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Knowledge Spillovers from Product and Process Inventions in Patents and their Impact on Firm Performance*

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1 Introduction

Although neoclassical economic models build on cost-saving process inventions (Tirole, 1988) and other theoretical contributions have investigated the choice of product or process innovation depending on the competitive setting (Bonanno & Haworth, 1998; Boone, 2000; Lin & Saggi, 2002; Rosenkranz, 2003), public interest generally focuses on product 'stories'. Accordingly, the empirical research mainly focuses on product inventions and there are only few studies that investigate process inventions (see, e.g., Adner & Levinthal, 2001; Hatch & Mowery, 1998; Reichstein & Salter, 2006; Trantopoulos, von Krogh, Wallin, & Woerter, 2017). Therefore, important elements of fundamental theories have remained untested. This negligence mainly comes from the lack of empirical data. Because of the availability of large-scale patent data, a natural approach would be to identify product and process inventions in patent data. However, apart from few attempts to distinguish between product and process patents in the past (Cohen & Klepper, 1996; Scherer, 1982), we are only aware of few recent studies that try to distinguish between products and processes in patents. They all used a keyword search in claims from patent filings at the United States Patent and Trademark Office (USPTO) (Bena, Ortiz-Molina, & Simintzi, 2018; Bena & Simintzi, 2019; Ganglmair & Reimers, 2019).

Against this background, our project pursues three main objectives:

First, we want to categorize patents according to whether they reflect product or process inventions. For this purpose, we identify keywords in patent abstracts and claims that are related to processes, which allows us to classify the universe of European Patent Office (EPO) and USPTO patents. We make the data available to the public so that future research can draw on more comprehensive data than hitherto possible. Our patent classification covers patent documents from two large patent offices, the USPTO (grants and applications after 2000) and the EPO (A and B documents), from 1980 to 2014 (for the EPO until 2016), which is a big advantage if studying invention activities of European countries and firms. In addition to a very detailed keyword classification that applies heuristic rules, we use text-mining methods in order to classify the patent records, which allows us to determine the 'core' process keywords. The report contains a detailed descriptive analysis for the development of the share of product and process patents over time, across different countries and technologies. In the descriptive analysis, we try to understand the development of product and process patents along technological life cycles that we study in more detail in the econometric part.

Second, we validate the indicators with firm-level survey data from Germany and Switzerland. Several seminal studies have shown that patent protection is only essential for a limited share of inventions (mostly in pharmaceuticals and chemicals, sometimes in medical instruments, and in parts of the machinery sector) and that patent protection is more effective for product than for process inventions. Moreover, secrecy is often used as an appropriation mechanism for process inventions (for a review, see Hall, Helmers, Rogers, & Sena, 2014). Thus, it is even more important whether patent-based indicators of products and processes can predict product and process innovations at firm level and whether their relative shares show a similar distribution as product and process innovations.[1]

Third, we investigate the relationships between a firm's patent stock, spillovers from other firms' patent stocks and two performance indicators econometrically, namely the number of new patented inventions and firm productivity. We use firm-level survey data from Germany and Switzerland to investigate these relationships. While the question whether a firm's R&D stock yields positive returns with respect to follow-on innovation and productivity has been studied and confirmed extensively in innovation economics (for literature reviews on returns from R&D see, e.g., Hall, Mairesse, & Mohnen, 2010; Ortega-Argilés, Piva, & Vivarelli, 2015), distinguishing product-related from process-related knowledge has been only possible by using binary indicators (Mohnen & Hall, 2013). We are able to do it in a more nuanced way by distinguishing between a firm's product and process-related technological knowledge (measured by a firm's product and process patent stocks) and product-related and process-related spillovers (measured by other firms' product and process patent stocks). Because we cannot observe to which degree a firm has invested in R&D directed toward new production methods (process R&D) and R&D directed toward the development of new and improved goods (product R&D), we use our patent classification in order to measure the intermediate output of process and product R&D. For this, we conduct a set of econometric estimations that capture the influence of product and process-related knowledge on new inventions and productivity. The patent classification provides a comprehensive data source for investigating the returns from technological knowledge in a more detailed and comprehensive way than before.

In summary, we investigate the following research questions with econometric methods:

1. Do process and product knowledge stocks contribute to new patent applications in a different way?
2. Do product and process knowledge stocks show a different influence on the productivity of companies?

By using firm-level data from two countries, we try to provide robust empirical evidence for the investigated research questions and to shed light on important structural differences between both countries at the same time.

The main results of our study are the following:

Product patents (we define product patents as patents with only product claims) are much more common than process patents (patents with only process claims), but 'mixed' patents (patents with both product and process claims) have become more important over time. In many technologies,

[1] The term product innovation refers to new or essentially modified products that have been introduced onto the market by a firm. The term process innovation refers to the introduction of new or essentially modified production processes.

mixed patents have become the predominant form of patenting already in the nineties. We see rather large differences across countries and technologies. The trend towards including more and more process claims in addition to product claims can have many reasons, such as a larger complexity of the underlying technologies, a general technological exhaustion, strategic patenting behavior of large firms, or specific requirements from the patent offices and examiners. Our analysis shows that it is not plausible to assume that additional claims are only added for strategic reasons. However, much more research is needed to understand the trends in the claim structure across different technologies and countries.

Furthermore, we uncover a significant correlation between process technological knowledge and the probability that a firm introduces a process innovation. Mixed patents with both product and process claims are an even stronger predictor of innovation at firm level. The shares of product, process and mixed patents that we obtain from our calculations seem to be in line with information from firm surveys on firm patenting and firm innovation activities. Even though claim texts use a very structured language that mainly represent requirements from the examination procedure, the information appears to be well suited in order to uncover process and product components of a patented invention.

The econometric analysis shows that product knowledge increases the number of further patent applications filed by a firm in Germany and Switzerland. Process knowledge is significantly and positively related with total factor productivity in both countries, which makes sense because process knowledge might help saving production costs. Spillovers from product knowledge are associated with new inventions in the high-tech sector, whereas we do not find a clear pattern of spillovers for productivity. Process knowledge seems to work in different directions for the generation of new inventions in Germany and Switzerland, which might be due to differences in the industrial structure and the demand for process technologies.

In a further analysis, we show that product knowledge seems to have a positive return when a company files patent applications in technological combinations with a growing number of patent applications (i.e. growing technologies), which is usually the case at the beginning of a technological life cycle. The positive return for process patents can be observed for firms also patenting in combinations with stable or negative growth (for example, exhausted technologies), which is usually the case towards the end of a technological life cycle. These results add some credibility on the technological life cycle story that process inventions become more important along the life cycle because firms increasingly invest in cost reductions if the technology matures.

Finally, we find that firms with trade secrets have positive returns from process patents, firms without trade secrets not. This hints at a possible complementarity between trade secrets and process patents with respect to productivity effects.

2 Identification of product and process patents

We conducted the identification of product and process patents with two different methods applied to three different text fields in the patent records (title, abstract, claims). The first method is based on an automated search of keywords within abstracts and claims.[2] The second method is a text-mining/machine learning approach to identify the classes (product or process) of a patent and claim, respectively. The method is applied on abstracts and claims. To provide a learning dataset, student assistants manually classified abstracts and claims for a sample of patents. This was used to train an algorithm, which classified all abstracts and claims. In order to conduct the learning and classification part, we collaborated with the Chair of Management Information Systems at ETH Zurich (MIS-ETH) who implemented the algorithms.

The chapter provides detailed information about the implementation of both methods, as well as a comparison of the results from applying the keyword search on different text fields.

2.1 Method A: Keyword search in abstracts and claims

For the classification of abstracts, we used the full-text abstract data available in PATSTAT (autumn 2017). Since PATSTAT does not provide full-text data of patent claims, claim texts for EPO patents were obtained from the EPO backfile containing EP-A and EP-B documents from 1978 to 2016 and 1980 to 2016, respectively.[3] Claim texts for USPTO patents were obtained from the 'Patent and Patent Application Claims Research Dataset' provided on the USPTO's Bulk Data Storage System containing full-text claims from US patents granted between 1976 and 2014 and US patent applications published between 2001 and 2014.[4] The data are available in XML and CSV format. We parsed the XML files and imported all data into a PostgreSQL database using a Python program. The keyword search was implemented in PostgreSQL.

Although we can already cover a quite comprehensive spectrum of important patent applications and grants worldwide, the data coverage could be of course improved by including full-text data from further patent offices such as the World Patent Office (WIPO) or the German Patent Office

2 We also did a keyword search in titles. We provide the classified titles in our data, but we did not further use nor mention classified titles in the study.

3 https://www.epo.org/searching-for-patents/data/bulk-data-sets/data.html#tab-2 (accessed on 2019/09/27)

4 https://bulkdata.uspto.gov/ (accessed on 2019/09/27).

(DPMA). Our keyword search (and with some limitations the text mining approach) can be directly applied on other full-text data that is available in CSV format or otherwise parsed data.[5]

The set of keywords we use to classify abstracts and claims were determined by a manual search process in EPO patents. The identification of product patents by keywords is incomplete as in many cases the labeling of the specific product is used instead of more abstract terms. In contrast, the identification of processes is quite complete if using the extracted keywords.[6] Since patent applications at the EPO can be filed in English, German or French, and not all patent filings are available in English, we had to conduct keyword searches in all three languages because we apply the keyword search on all EPO documents. The extracted keywords to distinguish between product and process patents for all three languages are listed in Table 1. For USPTO patents, we use the same set of keywords only in English.[7]

We implemented the classification as an exclusion process, meaning that every abstract or claim was checked for the occurrence of one of the process keywords. If one of the keywords occurs, the item (abstract or claim) is considered as belonging to the process class. On the contrary, if an item does not contain any of the process keywords, it is considered as belonging to the product class. This keyword search takes into account that the set of product keywords is incomplete and therefore does not use them explicitly. In this way, an unambiguous classification of claims is possible: If a claim is not a process claim, it must be a product claim by definition.[8] In contrast, abstracts are often ambiguous: If both products and processes show up in the text at the same time, we can only identify the process by applying the keyword search, i.e. abstracts are assigned to the process class whenever a process keyword appears in the abstract text. The classification of claims thus offers a more granular classification of each patent by considering that a substantial part of patents contains both products and processes.

5 A significant portion of patents is filed at Asian patent offices (Japan, China, South Korea). Including full-text data from these offices would have been of course much more difficult because the keyword search would have had to be applied using Asian languages. However, one can argue that many commercially valuable patents (especially from big firms) are also filed at the USPTO and EPO.

6 The keywords were extracted and verified by Ulrich Schmoch from the ISI Fraunhofer Institute. We added further keywords in order to identify use claims that should be equivalent to process claims. For example, “the use of substance X as an insecticide” is equivalent to a process claim of the form “a process of killing insects using substance X” (European Patent Office, 2017).

7 Bena & Simintzi (2019) use very similar process keywords in order to classify claims from the USPTO.

8 See the examination guidelines (EPO, 2017; USPTO, 2018). So-called ‘product-by-process’ claims are product claims as well, but the difference to a standard product claim is that the product they relate to is defined by the process for producing it.

Table 1: Keywords for classification into product and process patents.

	Typical Product Keywords	Process Keywords
English	• device • machine • material • tool • apparatus • vehicle • compound • composition • substance • article	• method • process • procedure • use • utilization / utilisation • usage
German	• Vorrichtung • Einrichtung • Werkzeug • Material • Apparat • Fahrzeug • Verbindung • Zusammensetzung • Substanz • Artikel	• Verfahren • Methode • Prozess • Prozedur • Verwendung • Anwendung • Benutzung • Nutzung
French	• outil • machine • support • materiel • dispositiv • assemblage • véhicule • composé • composition • substance • article	• procédé • méthode • procedure • processus • utilisation • usage

2.1.1 Keyword search in abstracts

We conducted the classification based on the abstract full-text data that is available in PATSTAT (PATSTAT table: tls203_appln_abstr), marking every abstract in English, German and French as a member of either the product or process class. The exclusion process described above was applied so that every abstract without process keywords has been classified as product abstract. This means, whenever a process keyword could not be found in the abstract, it was considered as belonging to the product class – no matter if product keywords from Table 1 appear in the abstract or not. With this search strategy, we can classify abstracts as belonging to only a single category even though many abstracts mention both product and process keywords.

In a technical sense, we implemented our classification procedure with a regular expression match operator in order to search for keywords within abstracts. A lower-case version of the abstracts in our PostgreSQL database was compared against the relevant keywords (in singular and plural) with the help of constraint escapes marking the beginning and end of a word (e.g., ~'\mprocess\M'). For abstracts in French language, letters with accents where replaced with their non-accent counterparts in both the abstract and the keywords, as accents and umlauts are often used inconsistently (e.g., à => a).

PATSTAT does not provide a full-text abstract for every single patent within a patent family. Therefore, it was necessary to impute part of the abstract texts using patent family links. We used the information from other family members' abstracts when no full-text data was available for a respective patent publication. We always preferred English abstracts. Only if no English abstract was available in the family, we used a German or French abstract.

In the Appendix A.2, we provide two examples of how abstracts have been classified.

2.1.2 Keyword search in claims

The classification of claims is in principle similar to the classification of abstracts as described above. However, since PATSTAT does not contain full-text data for claims, the process of data collection and aggregation was much more involved. One should also keep in mind that patents have multiple claims (in most of the cases between 5 and 50), and we classified each claim individually as belonging to the process or the product class. For the claim-based classification, we defined additional heuristic rules to exploit the structure of the claims.

In order to apply the rules, we had to pre-process the raw claim texts: We defined a set of stop words that we removed from the raw claim texts (see Appendix A.1), we removed all accents and umlauts, all numbers, and set everything to lower cases. The most important rule says: Restrict the keyword search to the first two or five words of a processed claim text in order to identify process claims and restrict the keyword search to the first word of a preprocessed claim text in order to identify use claims." This was necessary because otherwise we would have classified many product claims as processes by mistake, for example "The toner (…), wherein, in a distribution of particle diameter measured by a Coulter method, the content of large grains having a particle diameter of 8 µm or more is 2% by mass or less."[9]

In most cases, the process keyword comes right at the beginning of the claim, e.g., "The method of manufacturing an SOI substrate according to Claim 3, wherein the second insulating film is formed of a single-layer structure formed of a single layer or a stacked-layer structure formed of a plurality of layers (…)."[10]. In rare cases, other words precede the process keyword, e.g., "The digital rights method of claim 2, wherein modifying the existing digital rights comprises setting the DRM method to the Forward-Lock method if the DRM methods applied to the digital rights and existing digital rights are different, (…)."[11] The thresholds of two resp. five words were chosen after inspecting thousands of claims manually and they apply to processed claim texts where articles preceding the keywords have been removed. In the end, for aggregate indicators at patent or firm

9 EP2423755B1
10 EP1986230A2
11 EP1942429A2

level it does not make a significant difference whether we use two or five words. For use keywords, we could not find any claims where other words precede the keyword. That is why we identify use claims based on the first word. We always searched for both the singular (‘method’) and plural (‘methods’ or ‘methoden’ in German).

After the classification had been completed, we computed the total number of claims, the number of product, process, and use claims, as well as the share of process claims and use claims for each patent. These numbers serve as the basis for the identification of product and process patents that we use in this report. The data were joined with PATSTAT data based on their patent numbers (‘publn_nr’ or ‘publn_nr_original’ together with ‘publn_kind’ from PATSTAT table tls211_pat_publn).[12]

In a final step, we imputed missing EPO (USPTO) claim information from within the family by prioritizing information from other EPO (USPTO) patents over USPTO (EPO) patents because claims from another EPO (USPTO) publication should be closer to the focal EPO (USPTO) patent than a USPTO (EPO) publication.[13]

The main advantage of using the process share in claims per patent is that it is able to reflect the different degrees of patents being both products and processes at the same time rather than only delivering a binary indicator as in the case of abstracts. In the Appendix A.2, we provide two examples of how claims have been classified and the corresponding process shares have been calculated.

2.1.3 Identification of independent and dependent claims

The difference between independent and dependent claims is that a dependent claim cannot stand alone, this means it references another claim (independent claim) that is directed to the essential features of the invention, e.g., “The method of manufacturing an SOI substrate according to Claim 3 (…)”[14]. The distinction might play a role for aggregated claim-based indicators. From an economic point of view, an applicant wants to include as many claims as possible in order to increase the patent’s breadth. Measures only based on independent claims might therefore have the advantage of considering only “relevant” product and process features and filtering out content that has been added for strategic reasons. We therefore provide all measures in our database also calculated based on only independent claims.

12 For USPTO patents, the publication number from the claims dataset turned out to be only partly consistent with the publication number in PATSTAT. Therefore, we did the matching in three steps: First, we joined patents on their publication number (publn_nr). Second, if not successful, we joined them on the publication number only used at the USPTO (publn_nr_original). Third, if still not successful, we accounted for systematic inconsistencies between the publication number in PATSTAT and the one in the USPTO data by adding an additional zero-digit at fifth position of the publication number on which we join.

13 In some cases, if several publications of the same invention are available and the claims structure is the same across publications within a family, the claims are only published once.

14 EP1986230A2

The most common phrases used in dependent claims are ‘according to [independent claim]’, ‘according to (any) one of the preceding claims’, ‘as claimed in [independent claim]’, ‘in accordance with [independent claim]’. The identification of dependent claims is easy: Whenever the word ‘claim’ or ‘claims’ appears in the claim text but not in the first word, it must be a dependent claim. Accordingly, all other claims have been classified as independent claims. We also applied this strategy on all claims in German and French using a different set of keywords ('anspruch', 'anspruche', ‘anspruech', 'ansprueche', 'anspruchen', 'anspruechen', ‘revendication', 'revendications').

2.1.4 Identification of product-by-process claims

A product-by-process claim defines a product in terms of a new process (for example, “an article A, characterized by being the product of process B“, or “an article A obtained by process B”). Product-by-process claims are product claims. We need to classify them separately because otherwise we would run the risk of classifying them as process claims based on the process keywords appearing in the same claim.

The typical product-by-process claim includes words such as “according to [process keyword]”, “obtainable by [process keyword]”, “produced by [process keyword]”, “purified from [process keyword]”, “the product of the [process keyword] comprising the steps of”, “prepared in accordance with the [process keyword]”, “by a [process keyword] which comprises the steps of” (Chang & Wang, 2016). We checked a random sample of claims for further phrases indicating product-by-process claims. We are confident that we have identified the bulk of phrases so that we can classify most of the product-by-process claims correctly. We applied an exclusion strategy to increase the likelihood of true positives: We did not allow for any of the process (or use) keywords from Table 1 to show up in the first two words of the pre-processed claim text. Thus, we make sure that a product label must appear in the first two words. In addition, we searched for all extracted phrases which need to be followed by a process keyword (for example, the product showing up at the beginning has to be produced ‘according to’ or ‘obtainable from’ a process). We also run the code with phrases and keywords in German and French.

2.2 Method B: Manual classification (claims and abstracts) and text-mining

In addition to the keyword search, we classified the EPO and USPTO patent records (their abstracts and claims) based on a text-mining algorithm. For this purpose, three students from ETH Zurich with backgrounds in engineering and natural sciences classified a sample of about 1’100 randomly selected granted USPTO and EPO patents manually as to whether they refer to products or processes. We instructed them carefully about what identifies a process or product in a patent. About 10% of the patents were classified twice by two different persons in order to calculate the interrater reliability.[15] We focus on granted patents as the claims can change during the examination process and the claims in granted patents already passed a revision process.

2.2.1 Manual classification based on keywords and examination guidelines

Each student got a list with 390 patents. We asked them to search for the patents in Espacenet (https://worldwide.espacenet.com/?locale=en_EP) and to classify both the abstract and all claims of each granted patent. First, the students looked at the abstract of each patent and classified it as referring either to a product or process or both. Second, they classified each claim individually as referring to a product or process.[16] The students were also asked to note the main phrase from the abstract or claim text underlying their classification decision.

Although the students had a technical or natural scientific background, they needed a detailed introduction into the subject, the terms used in patent documents and the search engine. We prepared detailed coding guidelines for them on which they could base their decisions. In many cases, the classification is straightforward, especially if keywords as depicted in Table 1 show up. Accordingly, the students were asked to look for the already known keywords in a first scan.

The EPO and USPTO (European Patent Office, 2017; United States Patent and Trademark Office, 2015) examination guidelines for patent examiners define how a patent examiner has to deal with claims and, more specifically, how product and process claims are exactly defined. We included an excerpt from the very comprehensive guidelines in the coding guidelines in order to support them in their decision. For illustrative purposes, the main points are shown in Box 1. There are some more fine-grained definitions not included there, e.g., on Computer-implemented Inventions where computer programs (products) have to be distinguished from Computer-implemented Methods (processes).

One has to note that the language used in the examination guidelines differs from the language used by economists that define new products and processes in terms of their potential of serving a market or of reducing costs. The examiners' language appears to be much more formal and technical. Just from reading patent claims, it is very difficult to determine whether product and process claims as defined by the guidelines can serve the typical functions economists have in mind when talking about product and process inventions.

15 Both students came to the same result for 94.2% of the abstracts and 98.2% of the claims.

16 We could not further distinguish products from product-by-processes and processes from use claims. All product-by-process claims have been classified as product claims and all use claims as process claims.

Box 1: Main points from the examination guidelines referring to the definitions of product and process claims (EPO Examination Guidelines, Part F Chapter IV-3 and USPTO Manual of Patent Examining Procedure, Chapter 2100)

- In general, product claims refer to a physical entity and process claims to an activity.

Product claims

- **Product claims** include products, apparatuses, substances or compositions (e.g., a chemical compound or a mixture of compounds) as well as any physical entity (e.g., object, article, machine, or systems of co-operating apparatuses) which is produced by a person's technical skill (EPO definition).
- **Product claims** are directed to either machines, manufactures or compositions of matter (USPTO definition)
    - **Machine** – a concrete thing, consisting of parts, or of certain devices and combination of devices; includes mechanical devices or combinations of mechanical powers and devices to perform some function and produce a certain effect or result.
    - **Manufacture** – an article produced from raw or prepared materials by giving to these materials new forms, qualities, properties, or combinations, whether by hand labor or by machinery.
    - **Composition of matter** – all compositions of two or more substances and all composite articles; they can be results of chemical union, of mechanical mixture, or they can be gases fluids, powders or solids.
- **Examples:** "a steering mechanism incorporating an automatic feed-back circuit", "a woven garment comprising…", "an insecticide consisting of X, Y, Z", "a communication system comprising a plurality of transmitting and receiving stations".

Process claims

- Include all kind of activities in which the use of some material product for effecting the process is implied; the activity may be exercised upon material products, upon energy, upon other processes (as in control processes) or upon living things (EPO definition).
- **Process claims** define steps, acts or methods to be performed and include a new use of a known process, machine, manufacture, composition or material (USPTO definition).
- **Two types of process claims**
    - The use of an entity to achieve a technical effect (e.g., 'a method in order to contact polypeptide X with a compound to be screened').
    - A process for the production of a product (e.g., 'a method to determine whether a compound affects the activity of polypeptide X and to transform any active compound into a pharmaceutical composition').

2.2.2 Text mining

The abstract texts sometimes contain keywords indicating both products and processes. In order to obtain a binary classification label, we assert that an abstract corresponds to a product patent if the number of product labels is greater or equal to the number of processes described in the abstract; otherwise it is labeled as a process. With respect to model training, we thus eliminated all duplicated texts and kept only the unique texts with the corresponding majority label. We restricted the text mining to patent texts in English so that we can only classify EPO patents that are available in English in the full-text data by means of this method.

The following pre-processing that is common in text mining was applied to the plain document text:

- Stripping white space
- Removing punctuations
- Making all characters lower case

- Removing numbers
- Removing stop words
- Stemming, i.e., reducing words to their word stem
- Removing words with fewer than four characters.

For the purpose of our analysis, we used a term-document matrix. The general concept is to compute the frequency f_{ik} of term t_i in document d_k and store the combined result in a DxN matrix *M*, where *D* is the number of documents and *N* is the number of unique terms appearing in the documents.

Our labeled dataset (based on the students' manual classification of abstracts and claims) used for model training and evaluation included 901 abstracts and 6'994 claims in English, which is a comparably small proportion of the over 40 million abstracts and 190 million claims that we wished to classify. As a result, the term frequencies in our labeled data are potentially not entirely representative of the term frequencies in our full set of data. This can lead to model overfitting and in response, we chose to model our term-document matrix with a regularized logistic regression that adds a *l1* (lasso) and *l2* (ridge) penalty; a so-called elastic net (Zou & Hastie, 2005). The intuition of l1-regularization is to set some parameters to zero, effectively reducing the number of features (terms) in the model. Instead, *l2*-regularization results in smaller, but non-zero parameter estimates. We used the glmnet package by Friedman, Hastie, & Tibshirani (2010), which implements fast algorithms for elastic nets in the statistical programming language R.

2.2.3 Results

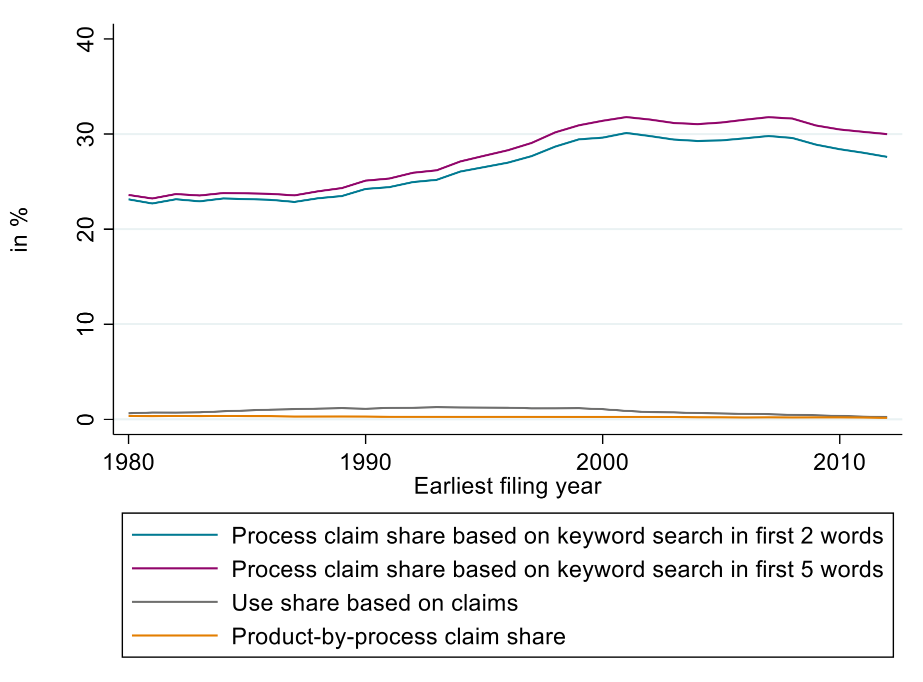
The labeled data was split into a training (70% of all rows) and test set (30%). This resulted in 632 (4'897) abstracts (claims) for training and 269 (2'097) abstracts (claims) for testing. Hyper-parameters were tuned on the training set and based on 10-fold 5-times repeated cross-validation. More details on the text mining analysis can be found in Appendix A.3.

After parameter tuning, the elastic net was re-fitted with the optimal hyper-parameters on the full training set and the resulting model was then used for predicting the test set labels. Based on a good out-of-sample performance on the test set, the models were subsequently applied to the full list of over 40 million abstracts and 190 million claims, respectively.

2.3 Results from keyword search

The chapter provides an evaluation of the keyword search-based classification method described in chapter 0. Figure 1 shows the development of the process share per patent (calculated based on the classification of claims) over time by the earliest filing year within the family. In this figure, we distinguish between the process and use share as the use share can be calculated separately based on the occurrence of “use”-keywords in the claims. The use share per patent is very small and does not change significantly over time. For the most part of the report, we will not separate the process and use share in our definition of process patents, but will add them up to a process-use share. As already mentioned, product-by-process claims are in fact product claims. Consequently, we will treat them as product claims throughout the analysis, i.e. we will add them to a patent’s product share.

Figure 1: Share of process, use, and product-by-process per patent (USPTO and EPO filings)



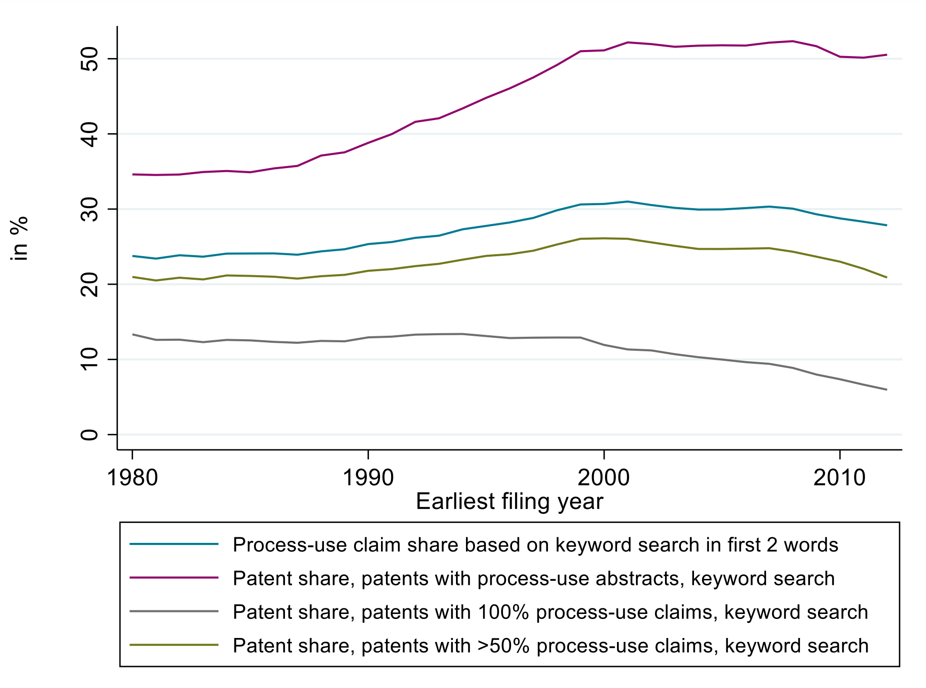
Concerning the process share, there has been a trend towards including more process claims since 1990. The share amounts to about 30% nowadays. There is only a slight difference between process shares based on keyword searches in the first two words and in the first five words. Searching only in the first two words is a more restrictive search strategy and we will use this classification throughout the report.[17]

Figure 2 compares the process-use share based on a keyword search in claims with the share of process-use patents based on a keyword search in abstracts. It is important to be aware of the fact that the classification of abstracts results in a binary value, while the classification of claims leads to a share per patent, which can be expressed as a percentage value at patent level. The line for ‘Abstract’ (red line) represents an overall average of the share of patents classified as process-use patents per year. The ‘Claims’ line (blue) represents the average share of claims classified as

17 We make both classifications available. Figure 1 looks very similar if we only plot shares based on independent claims.

process claims in a certain year. Since the line of the share of process-use patents based on keyword search in abstracts is comparable with the share of process-use claims per patent only to a limited extent, we provide a binary measure based on the claims. The line 'Claims 50%' (green) hence shows the share of process-use patents if we define a patent as being a process patent under the condition that more than 50% of a patent's claims are process or use claims. Finally, the grey line shows the share of process-use patents if we define a patent as being a process-use patent under the condition that it only has process or use claims (100%). The figure shows that much more patents are classified as processes if we apply the keyword search on abstracts. The reason lies in the fact that many patent abstracts mention a 'method' so that the patent is classified as being a process patent, but in fact the method only constitutes a small part of the invention. In contrast, the measures based on claims can capture the process relatedness more accurately. For example, if a patent has nine claims referring to an apparatus, but only one referring to a new method, the ratio of product vs. process-related parts is 9:1.

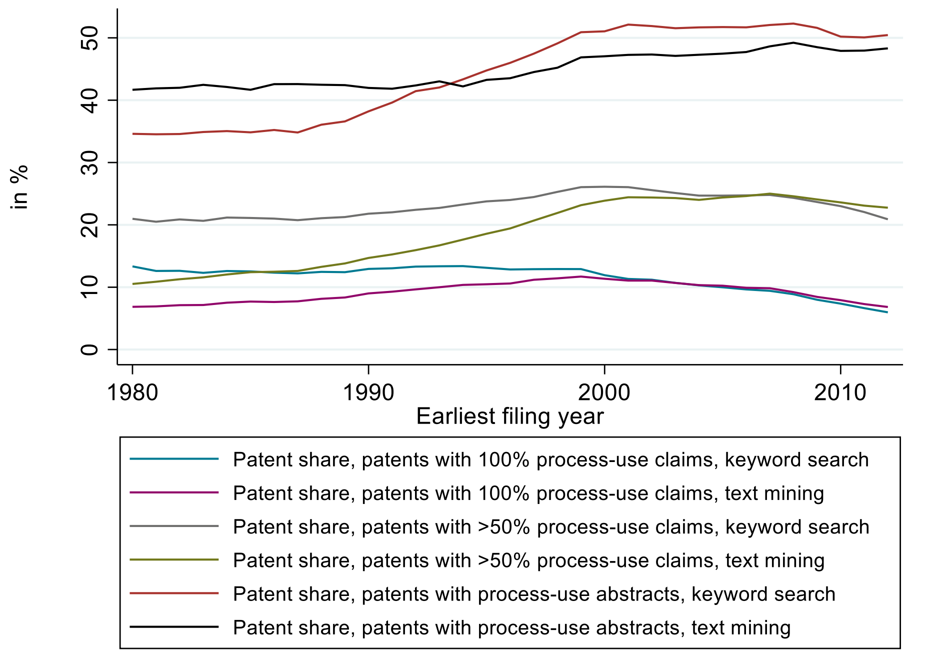
Figure 2: Share of process claims / patents (USPTO and EPO filings)



2.4 Results from text mining

Figure 3 compares the results from text mining with results from the keyword search for different process-use patent shares. The black line shows the share of patents categorized as process-use patents by the text mining algorithm based on abstracts. The share is slightly lower than the share obtained from keyword search for recent years. As the keyword search is likely to overestimate the number process patents based on abstract classification (see above), the text mining algorithm might be superior here. For the classification of abstracts, glmnet delivers indeed a slightly higher accuracy (73) compared to the keyword search (accuracy: 71).[18] For the share of patents with at least 50% (100%) process-use claims, the text mining algorithm delivers a significantly lower share until 2000, but the shares from both methods have converged in recent years. For the classification of claims, the keyword search delivers a higher accuracy (98) compared to glmnet (93).

Figure 3: Comparison of results from keyword search and text mining



An elastic net that has been used in text mining approach is a regularized regression where coefficients can become zero due to lasso penalty (Friedman, Hastie, & Tibshirani, 2001). This is the case for the claims data where all coefficients become zero except for the coefficient of the term “method”. The text mining analysis therefore shows that “method” is the only decisive keyword for the classification of patents at claims level. At abstract level, more terms are in the model, but the dataset is smaller which increases the risk of overfitting. The out-of-sample performance on the test data is strong which increases the credibility in the result that “method” is the most decisive process keyword.

The major advantages of the text mining approach are that it does not require manually configured keywords and heuristic rules and that the performance has been evaluated based on an out-of sample test. Since the accuracy for the classification of claims is higher using the keyword search

18 The Accuracy is calculated as the share between the sum of ‘true positives’ and ‘true negatives’ and the sum of ‘true positives’, ‘true negatives’, ‘false positives’, and ‘false negatives’. For the calculation, we compared the outcome of the keyword search and the text mining approach with the ‘true’ outcome from the labeled dataset, i.e., we assumed that the manual classification provides the Ground Truth. The Accuracies reported in the main text of this study have been calculated after imputation of missing classification labels for the keyword and text mining results (based on information in the patent family).

and we prefer a claims-based indicator, we will use indicators based on the keyword classification of claims throughout the report.[19] We make the text mining results together with the code available for interested researchers.

Table 2 shows the correlations between the different classifications: keyword search in abstracts and claims and text mining of abstracts and claims. In order to make the abstract and claim classification comparable, we define a patent as being a process patent if either the abstract has been classified as process-use, more than 50% of the claims have been classified as process-use, or all claims have been classified as process-uses ('100% rule'). The highest correlations can be seen between the classification of claims from the text mining approach and from the keyword search according to both the '50%' (0.81) and '100% rule' (0.76). The classifications of abstracts are correlated to a lower degree (0.594).

Table 2: Correlation between different classification methods (all classified filings)

		Keyword search			Text mining		
		Abstract	Claims 50% rule	Claims 100% rule	Abstract	Claims 50% rule	Claims 100% rule
Keyword search	Abstract	1					
	Claims 50% rule	0.4266	1				
	Claims 100% rule	0.2743	0.6160	1			
Text mining	Abstract	0.5936	0.3531	0.2455	1		
	Claims 50% rule	0.3995	0.8091	0.4608	0.3106	1	
	Claims 100% rule	0.2599	0.5348	0.7626	0.2201	0.6115	1

2.5 Definition of product and process patents

For the subsequent analyses, we use a consistent definition of process and product patents. We identified product and process patents based on the '100% rule': If a patent filing only contains product claims (i.e., the share of product claims is 1), it is considered a product patent. If it only contains process or use claims or process and use claims, it is a process-use patent. Patents with both product and process-use claims are 'mixed patents'. This definition is admittedly narrow and we lose information on the exact share of process and product claims in mixed patents. However, it has the advantage of being clear-cut and that we do not need to establish arbitrary thresholds (such as a 50% rule etc.).

In addition, we saw that clear-cut indicators worked best in the econometric analysis because the correlation between the indicators is somehow reduced.

19 In contrast to abstracts, claims are very well structured. Our set of heuristic rules were able to fully exploit their structure and consequently lead to a slightly better result as compared to the text-mining approach.

3 Descriptive results

In this chapter, we provide descriptive results for the development of product, process-use and mixed patents based on the keyword search in claims by inventor countries and technologies. Data on inventor countries and technologies come from PATSTAT (version: autumn 2017).[20] We look at patents granted at either the EPO or USPTO with priority years between 1980 and 2010.

Figure 4 and Figure 5 show the number of granted patents at the EPO and USPTO, respectively, along with the share of product, process-use, and mixed patents in all granted patents. At the EPO, the share of pure product patents is around 50%, at the USPTO, it is slightly lower. Interestingly, the share of product patents has decreased considerably at the USPTO. The share of pure process-use patents is generally much lower and slightly decreasing at both offices. In contrast, the share of mixed patents has increased considerably over time.

In a recent EPO study on the 'Market success for inventions', the results from interviews with SMEs on the type of a specific patented invention are presented (European Patent Office, 2019). Interestingly, the shares of pure product, pure process, and mixed patents are very close to our figures (according to the survey, 47% of the patent applications refer to pure product inventions, 38% to inventions combining product and process features, and 15% to pure process inventions). Even though the applied methods are completely different (interviews with a sample of SMEs vs. keyword classification of the universe of EPO patents), the interview results can provide confidence in the classification approach and can help allay concerns regarding the use of claim texts (e.g., because they might reflect the examiners' point of view rather than the firms' inventions).

Looking at the average number of claims per patent, we can see that the number has increased from about 9 to 12 at the EPO and from 11 to 17 at the USPTO (Figure 6 and Figure 7). Interestingly, the number of independent claims has not changed by much; especially at the EPO, it does not show any upward trend. The increase in the number of dependent claims might be due to strategic reasons (such that firms try to make their patents as broad and vague as possible in order to sue competitors that infringe the patent), to increasing technological complexity, or to legal requirements at the patent offices.[21] Indicators based on independent claims only might get closer to 'true' product or process shares of inventions by filtering out claims that have been added for those reasons.

20 Inventor countries and technologies can be retrieved from the PATSTAT tables TLS906_PERSON and TLS230_APPLN_TECHN_FIELD. Because PATSTAT contains missing values for a considerable amount of fields, we applied the imputation algorithm described in de Rassenfosse, Dernis, Guellec, Picci, & de la Potterie (2013) and (Seliger, Kozak, & de Rassenfosse, 2019) on both country codes and technologies.

21 Van Zeebroeck, de la Potterie, & Guellec, (2009) studied the contribution of the diffusion of national practices, technological complexity, emerging sectors and patenting strategies in explaining the number of claims of EPO patents. Even though all elements are important, they found that institutional influences and the international harmonization are the most important factors.

Figure 4: Share of product, process-use, and mixed patents, EPO

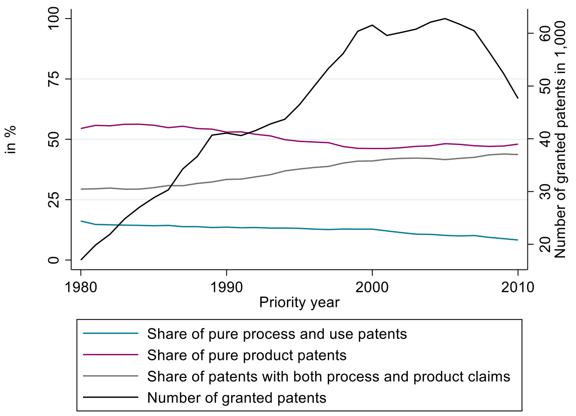


Figure 5: Share of product, process-use, and mixed patents, USPTO

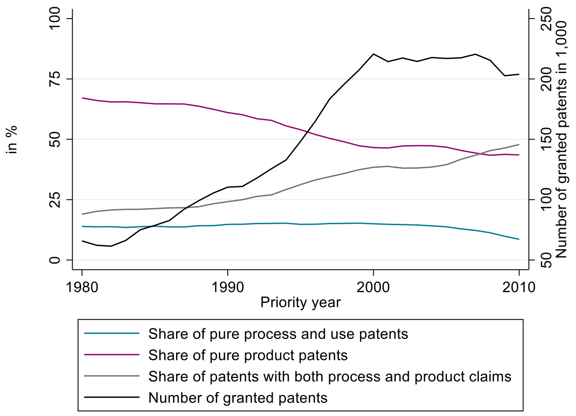


Figure 6: Average number of claims per patent, EPO

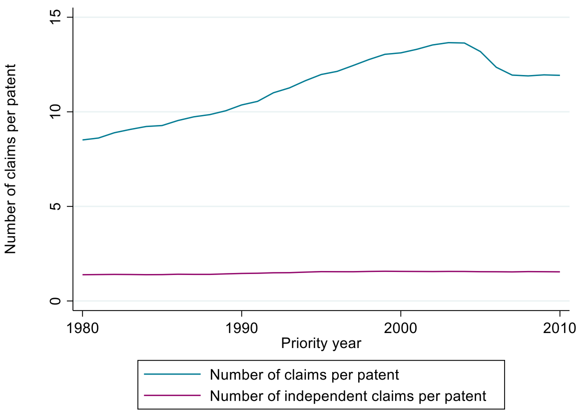


Figure 7: Average number of claims per patent, USPTO

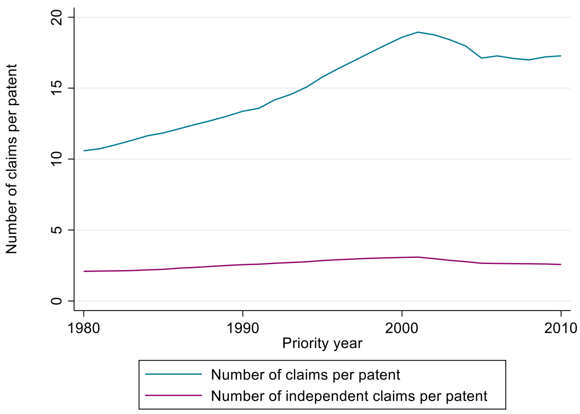


Figure 8: Share of product, process-use, and mixed patents, EPO, based on independent claims

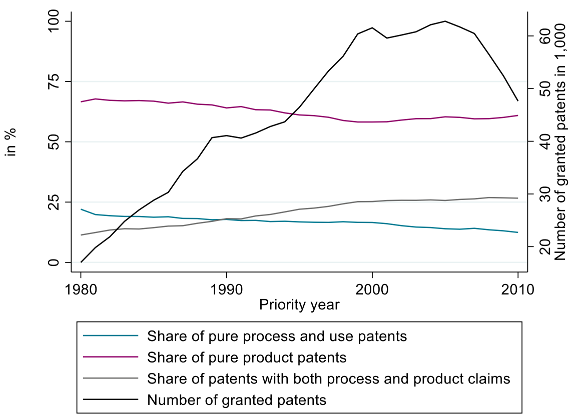
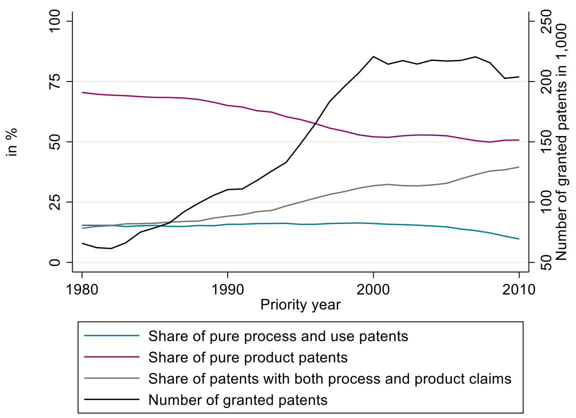


Figure 9: Share of product, process-use, and mixed patents, USPTO, based on independent claims



For this reason, we also report the share of product, process-use and mixed patents calculated only based on independent claims (Figure 8 and Figure 9). The share of product patents calculated in this way is higher at the EPO (between 61% and 67%). At the USPTO, we can again observe a tremendous decrease in product patents from 71% (1980) to 51% (2010).

3.1 Product and process patents in different countries

We show the development of the share of product, process-use and mixed patents in all granted patents and the number of granted patents for a selection of countries, namely Germany, Switzerland, Sweden, the United States, China, and Japan.[22] "Country" in this context means the country of inventor, not the jurisdiction where the patent is filed. In order to determine the number of granted, product, process, and mixed patents per country, we use a fractional count based on summing up the patents' share of inventors by country.[23] We plot EPO and USPTO granted patents separately and show the shares calculated based on independent claims in addition to the shares based on all claims.

22 We have prepared plots for many more countries. For the purpose of the report, it was not possible to include them all. However, interested readers can found them in our data repository: https://doi.org/10.7910/DVN/7JFRNL.

23 If for a specific patent one out of three inventors is located in Germany, the patent counts one third to the German patent count.

3.1.1 Germany

Figure 10: Share of product, process-use, and mixed patents invented in Germany, EPO

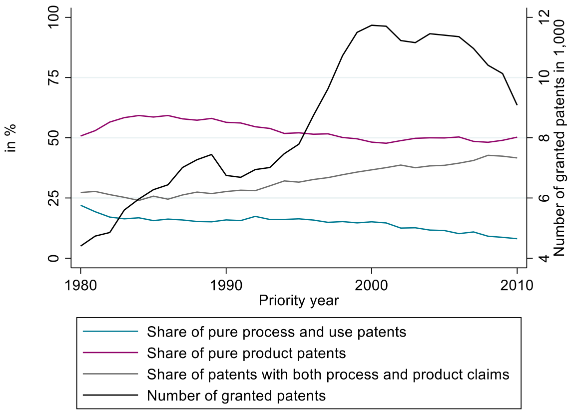


Figure 11: Share of product, process-use, and mixed patents invented in Germany, USPTO

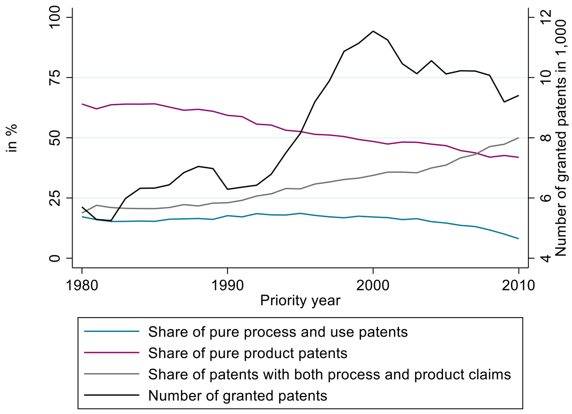


Figure 12: Share of product, process-use, and mixed patents invented in Germany, EPO, based on independent claims

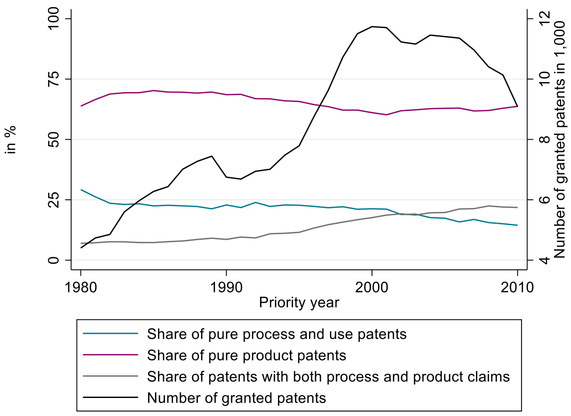
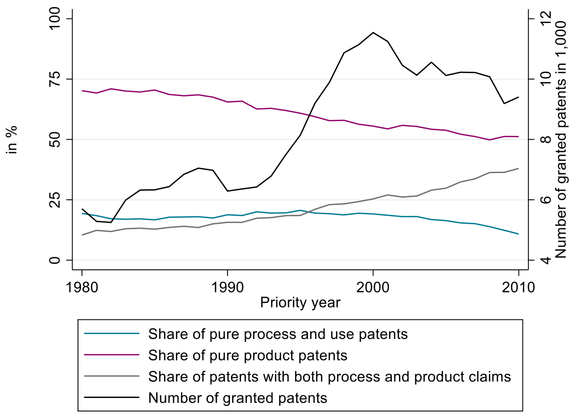


Figure 13: Share of product, process-use, and mixed patents invented in Germany, USPTO, based on independent claims



The development of Germany's product and process-use patents follows the total development closely (Figure 10 to Figure 13). For patent applications filed at the EPO, this does not come as a surprise because patents from Germany account for a large share of EPO patents.

3.1.2 Switzerland

Figure 14: Share of product, process-use, and mixed patents invented in Switzerland, EPO

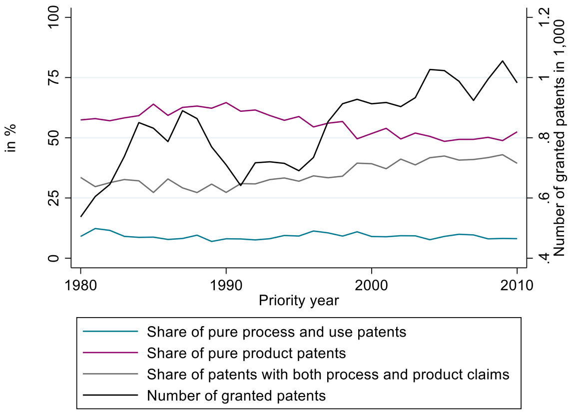


Figure 15: Share of product, process-use, and mixed patents invented in Switzerland, USPTO

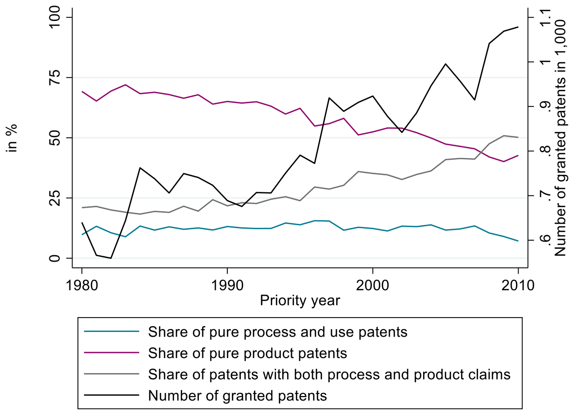


Figure 16: Share of product, process-use, and mixed patents invented in Switzerland, EPO, based on independent claims

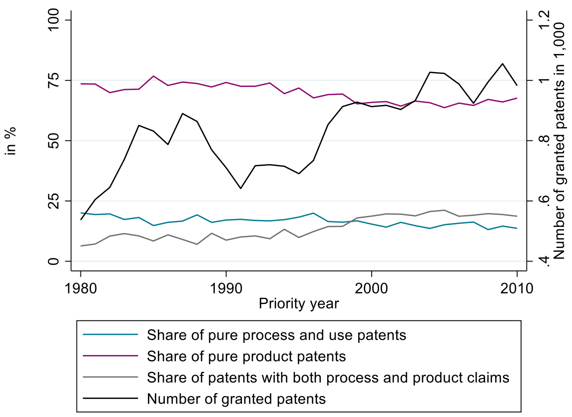
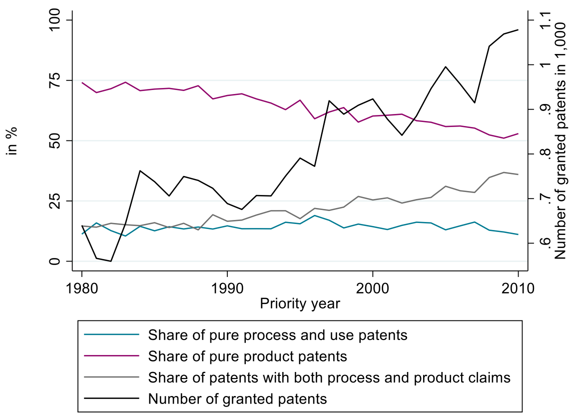


Figure 17: Share of product, process-use, and mixed patents invented in Switzerland, USPTO, based on independent claims



Switzerland is a small country and its economy shares some features of the German economy (for example, the fact that small and medium-sized high-tech firms employ a large part of the labor force). However, there are also important structural differences: For example, the largest companies in the manufacturing sector are pharmaceutical and food companies that account for a large share of the patenting activities in the economy. With respect to process and product patenting, Switzerland shows a very similar picture as Germany (Figure 14 to Figure 17).

3.1.3 Sweden

Figure 18: Share of product, process-use, and mixed patents invented in Sweden, EPO

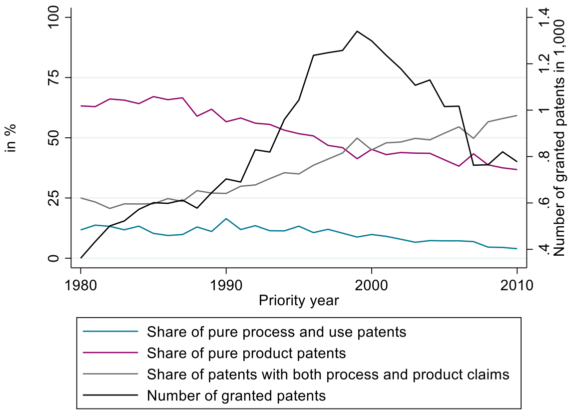


Figure 19: Share of product, process-use, and mixed patents invented in Sweden, USPTO

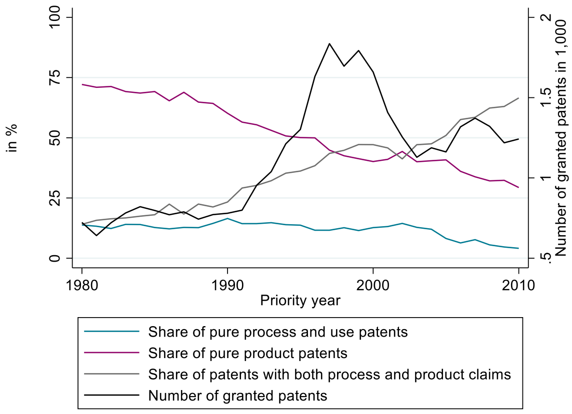


Figure 20: Share of product, process-use, and mixed patents invented in Sweden, EPO, based on independent claims

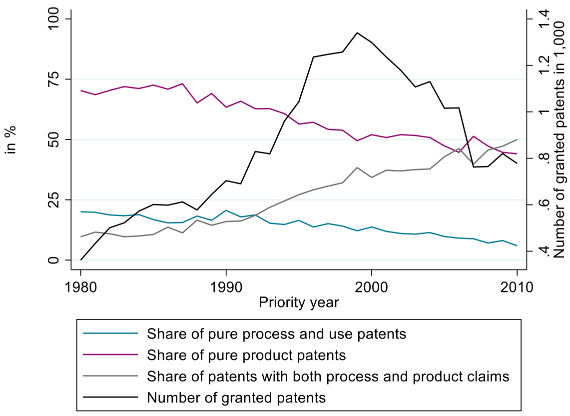
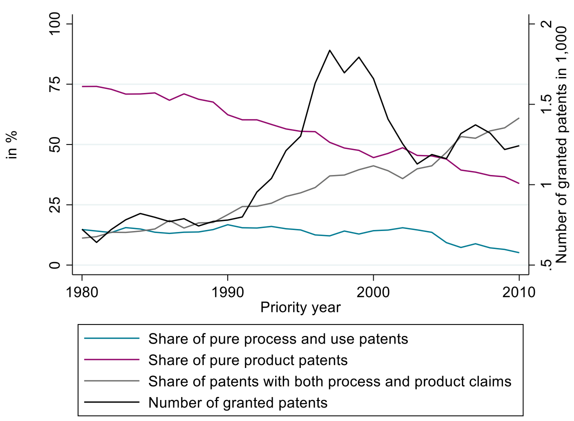


Figure 21: Share of product, process-use, and mixed patents invented in Sweden, USPTO, based on independent claims



As a further European inventor country, we have selected Sweden that is known for its strong manufacturing sector. However, in terms of process and product patenting and granted patents, it shows a different picture than Germany and Switzerland (Figure 18 to Figure 21). First, the number of granted patents at both the EPO and USPTO has decreased considerably since 2000. Second, Sweden seems to be much more “process-driven” as indicated by the increasing share of mixed patents. The share of product patents has decreased considerably and mixed patents now dominate Sweden’s patent portfolio (59% in 2010).

3.1.4 United States

Figure 22: Share of product, process-use, and mixed patents invented in the United States, EPO

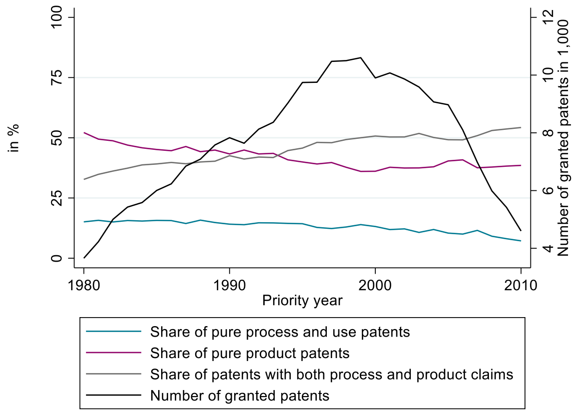


Figure 23: Share of product, process-use, and mixed patents invented in the United States, USPTO

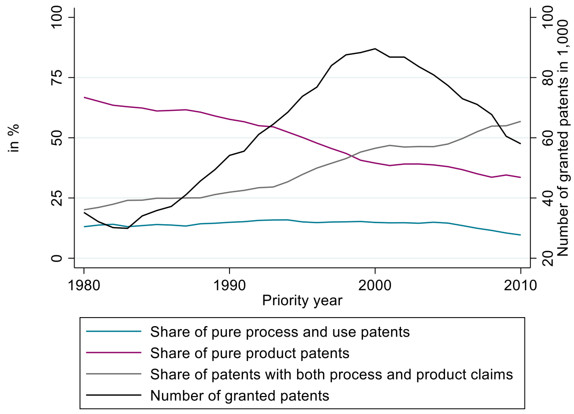


Figure 24: Share of product, process-use, and mixed patents invented in the United States, EPO, based on independent claims

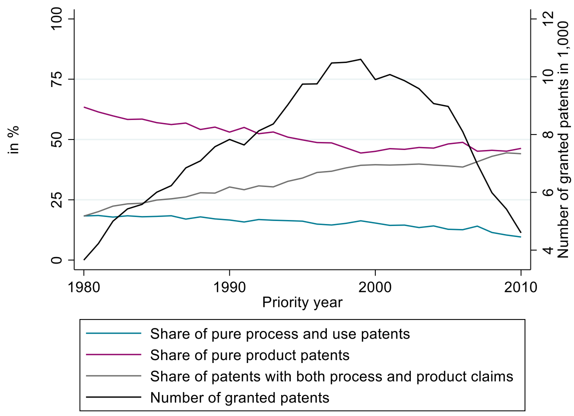
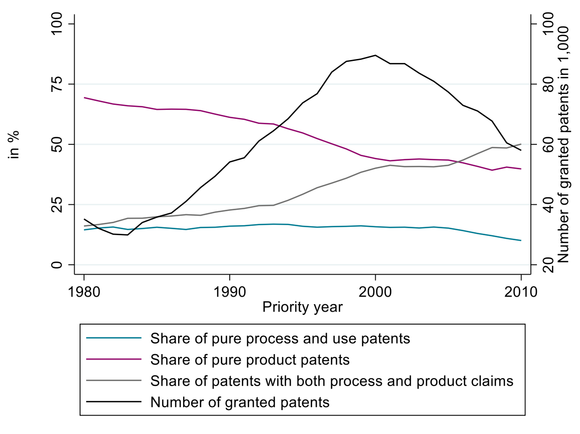


Figure 25: Share of product, process-use, and mixed patents invented in the United States, USPTO, based on independent claims



In the U.S., the share of mixed patents topped the share of product patents already in the nineties (Figure 22 to Figure 23). Many of the process claims must have been added as dependent claims as the share of mixed patents has passed the share of product patents only recently when looking at shares calculated based on independent claims only. Nevertheless, patents from U.S. inventors are much less dominated by products compared to Germany and Switzerland, perhaps reflecting a different technological orientation or strategic behavior of firms. Similar to Sweden, the number of granted patents peaked around 2000 with a pronounced decline afterwards.

3.1.5 China

Figure 26: Share of product, process-use, and mixed patents invented in China, EPO

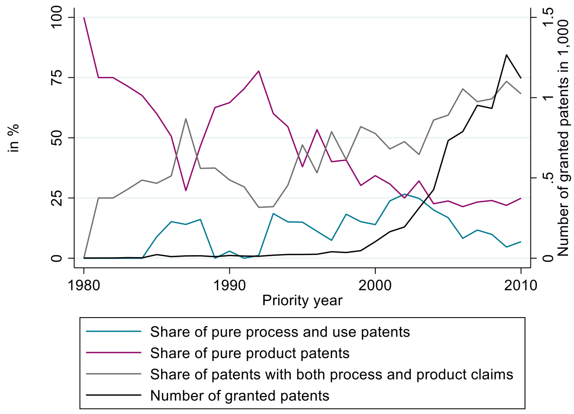


Figure 27: Share of product, process-use, and mixed patents invented in China, USPTO

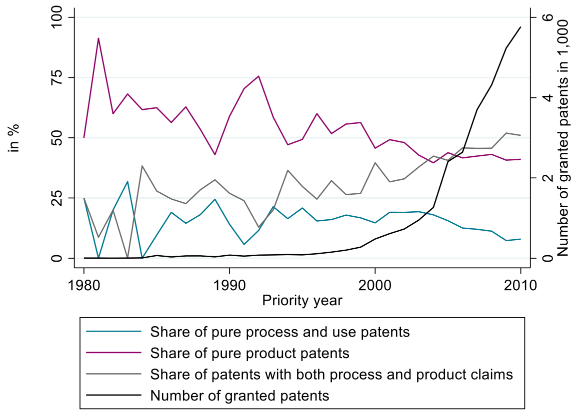


Figure 28: Share of product, process-use, and mixed patents invented in China, EPO, based on independent claims

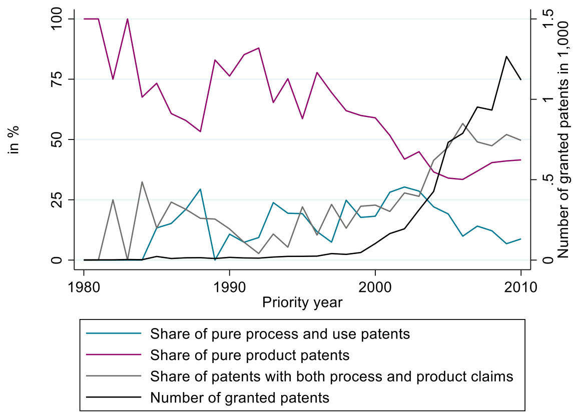
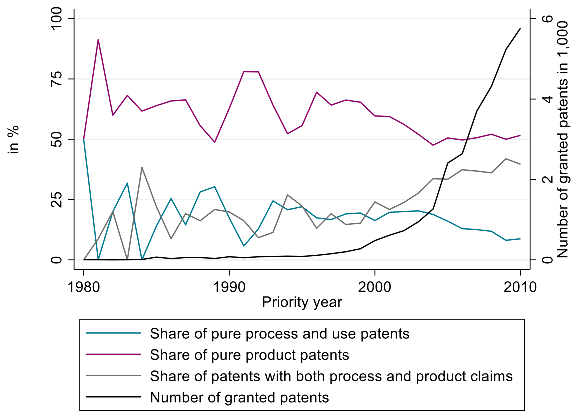


Figure 29: Share of product, process-use, and mixed patents invented in China, USPTO, based on independent claims



China's patenting activities took off around 2000. Since then it has increased the number of granted patents at the EPO and USPTO at very impressive rates from year to year (Figure 26 to Figure 29). China shows remarkable differences regarding the shares based on all claims and on independent claims only and across the two patent offices. The trends are difficult to interpret and it is not clear yet to what degree China's patent activities are process or product-driven.

3.1.6 Japan

Figure 30: Share of product, process-use, and mixed patents invented in Japan, EPO

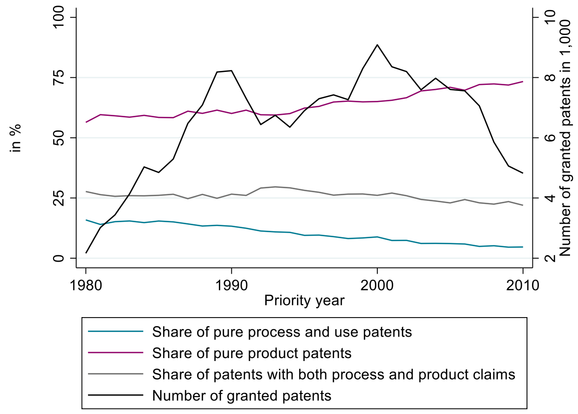


Figure 31: Share of product, process-use, and mixed patents invented in Japan, USPTO

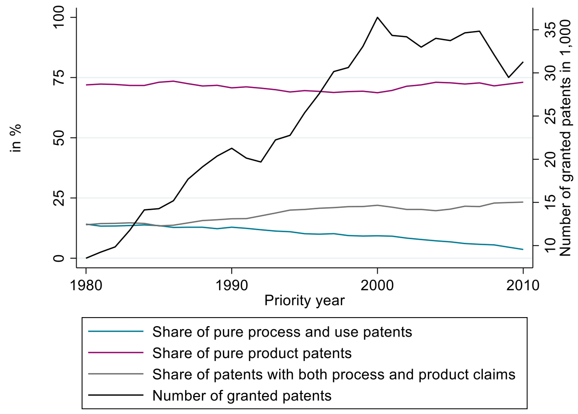


Figure 32: Share of product, process-use, and mixed patents invented in Japan, EPO, based on independent claims

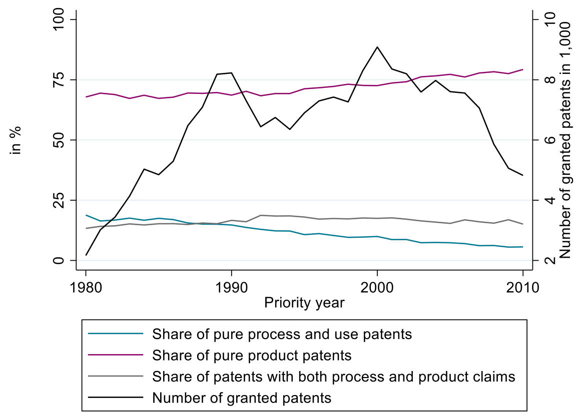
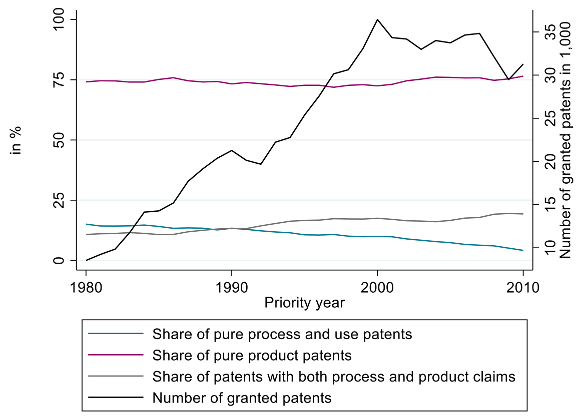


Figure 33: Share of product, process-use, and mixed patents invented in Japan, USPTO, based on independent claims



Japan seems to be a special case in every respect: Not only does it have a very large number of granted patents at both the EPO and the USPTO, but it also has a share of product patents of around 75% at both offices – and in contrast to other countries, this share is still increasing.

3.2 Product and process patenting in different technologies

In this chapter, we show the development of the shares of product, process-use and mixed patents in selected technologies.[24] For this purpose, we use the mapping between technology fields and the International Patent Classification (IPC) that is available in PATSTAT, a classification of 'breakthrough technologies' from the WIPO and ISI Fraunhofer Institute, and finally IPC 4-digit codes with large increases in the number of patent applications over time in order to analyze the development in technological space.[25]

We will discuss the descriptive findings in light of the question whether product and process patents can be used to trace technological life cycles. Technology life cycle models assume that after an early stage with intense competition a so-called dominant design emerges. Utterback and Abernathy (1975) described a prototypical life cycle where firms devote more and more effort to process inventions over time in order to improve the production process and to decrease the production costs. Firms first try to compete in the market by introducing new products. Later on, they compete in prices, only incremental changes happen and they introduce process inventions in order to sell into mass markets. Some researchers have noted that this model only works for some industries where the focus of follow-on innovations is on vertical product differentiation (see Huenteler, Schmidt, Ossenbrink, & Hoffmann, 2016). The slope of a life cycle curve might depend on many factors, e.g., the technological complexity of the inventions in the respective field and the state of competition.[26] Empirical evidence on technological life cycles is scarce due to a lack of data.

24 Plots for all technology fields are deposited here: https://doi.org/10.7910/DVN/IL0LUE.

25 PATSTAT table tls901_techn_field_ipc contains a mapping between 35 technology fields and the much more detailed IPC classification. The content is derived from http://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/xls/ipc_technology.xls (Schmoch, 2008). We sum up the weights from this table by technology field and priority year. The weight accounts for the degree to which a patent belongs to a certain technology as a patent usually has several IPC codes that might belong to different technologies. The classifications of breakthrough technologies are based on keyword searches in abstracts and titles and IPC and CPC codes and were kindly provided by Julio Raffo (WIPO) and Ulrich Schmoch.

26 Klepper (1996) shows in a model that the ability to appropriate the returns to process R&D depends on the size of the firm. As industries mature and firms get bigger, incentives to pursue process innovations increase.

3.2.1 Selected technological fields

Biotechnology

Figure 34: Share of product, process-use, and mixed patents in Biotechnology, EPO

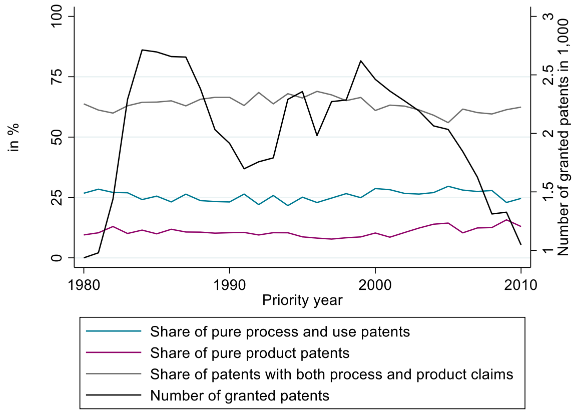


Figure 35: Share of product, process-use, and mixed patents in Biotechnology, USPTO

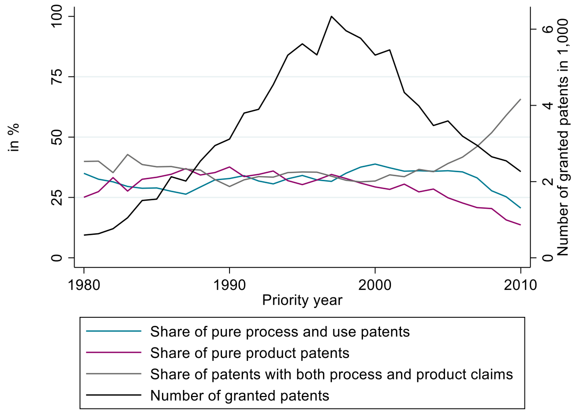


Figure 36: Share of product, process-use, and mixed patents in Biotechnology, EPO, based on independent claims

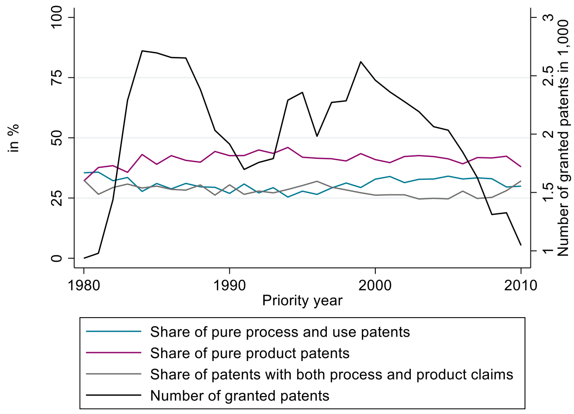
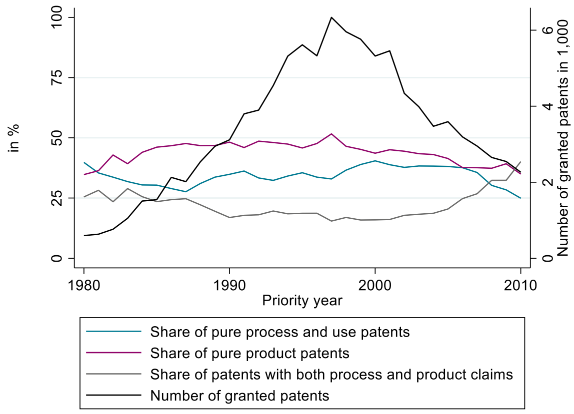


Figure 37: Share of product, process-use, and mixed patents in Biotechnology, USPTO, based on independent claims



The number of granted patents in biotechnology has been declining since many years, which might indicate technological exhaustion in this field. Whereas the share of product, process-use and mixed patents has remained almost stable at the EPO, there has been a recent increase in the share of mixed patents and a decline in pure product and process_use patents at the USPTO. The shares of mixed patents are smaller and the share of product patents higher when looking at shares based on independent claims. This indicates that many process and use claims are added as dependent claims in this technology.

Computer technology

Figure 38: Share of product, process-use, and mixed patents in Computer technology, EPO

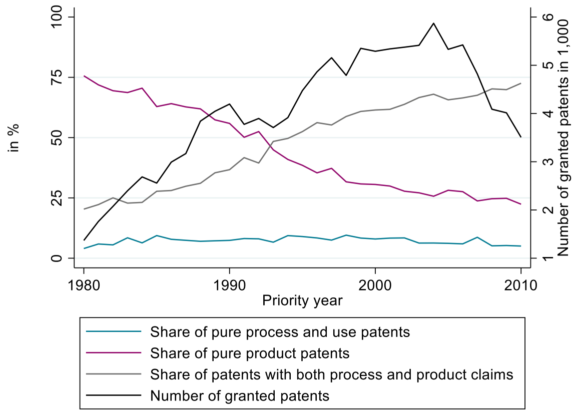


Figure 39: Share of product, process-use, and mixed patents in Computer technology, USPTO

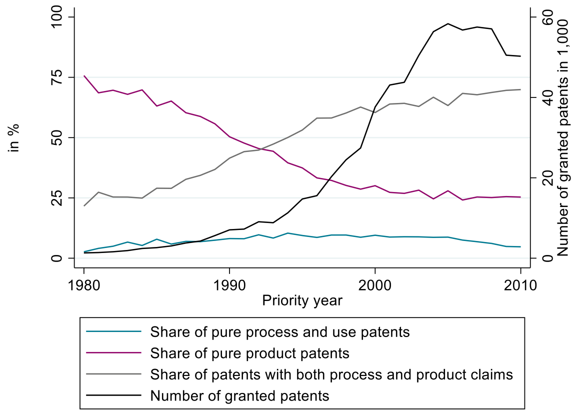


Figure 40: Share of product, process-use, and mixed patents in Computer technology, EPO, based on independent claims

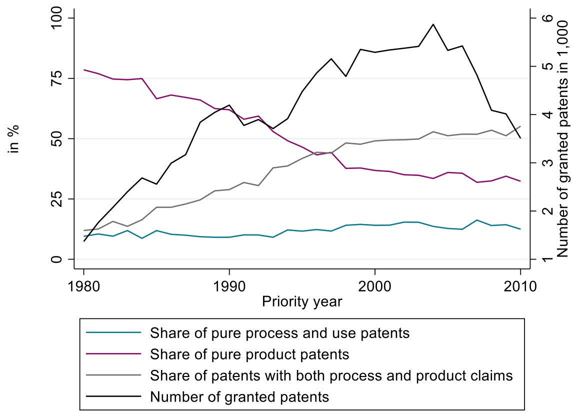
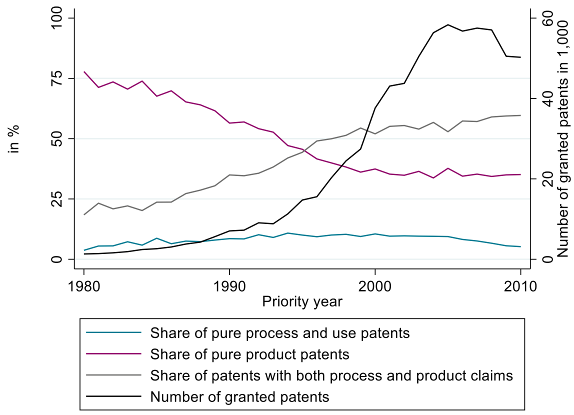


Figure 41: Share of product, process-use, and mixed patents in Computer technology, USPTO, based on independent claims



The number of granted patents in computer technology has peaked very recently. At the same time, there has been a quite pronounced decrease in the share of product patents and an increase in the share of mixed patents. This can mean that inventions in the field of computer technology have become more complex and increasingly need accompanying methods. Of course, it can also mean that process claims have been added in order to increase the patentability, but the indicators based on independent claims show a similar picture (even though the difference between the share of mixed patents and product patents is smaller) which makes this interpretation less likely. Altogether, the curves seem to suggest a prototypical life cycle. However, we have to keep in mind that they might not necessarily coincide with life cycles à la Utterback and Abernathy: computer technology is a complex technology and process technologies might complement computer programs etc. These must not necessarily be cost-saving technologies that improve the production process.

Transport

Figure 42: Share of product, process-use, and mixed patents in Transport, EPO

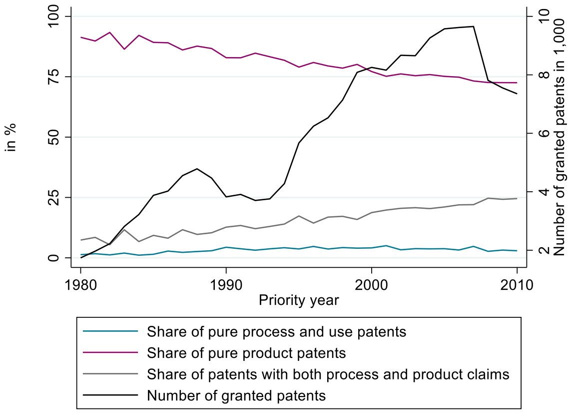


Figure 43: Share of product, process-use, and mixed patents in Transport, USPTO

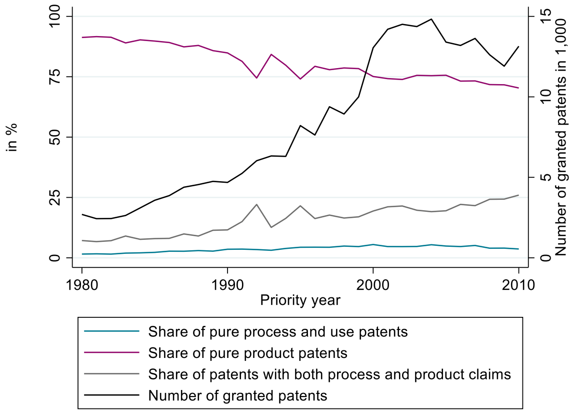


Figure 44: Share of product, process-use, and mixed patents in Transport, EPO, based on independent claims

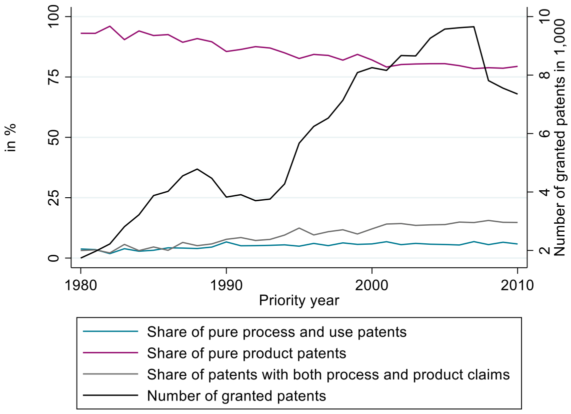
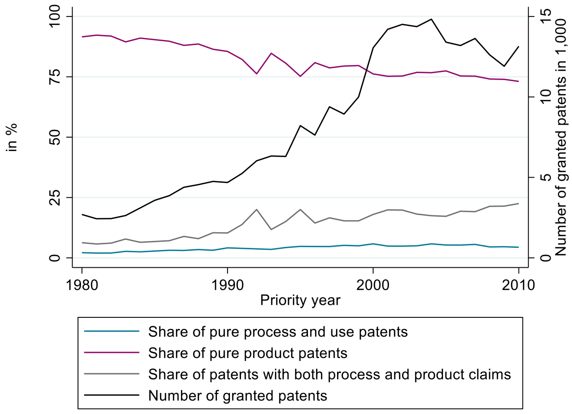


Figure 45: Share of product, process-use, and mixed patents in Transport, USPTO, based on independent claims



The transport technology is a field that is widely dominated by product technologies. However, the share of mixed patents has increased continuously over time and the proportion of pure process and use patents is continuously low.

Semiconductors

Figure 46: Share of product, process-use, and mixed patents in Semiconductors, EPO

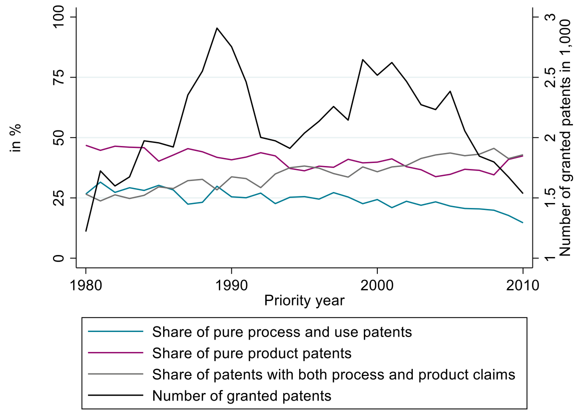


Figure 47: Share of product, process-use, and mixed patents in Semiconductors, USPTO

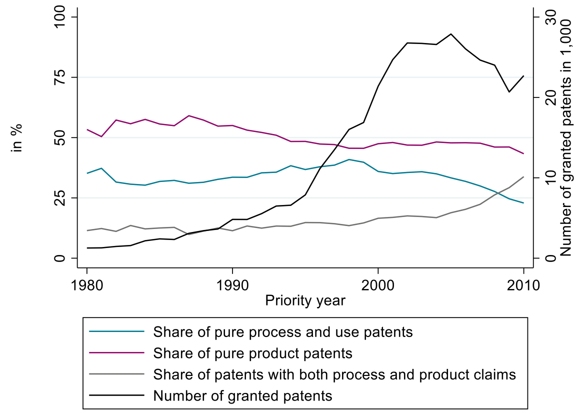


Figure 48: Share of product, process-use, and mixed patents in Semiconductors, EPO, based on independent claims

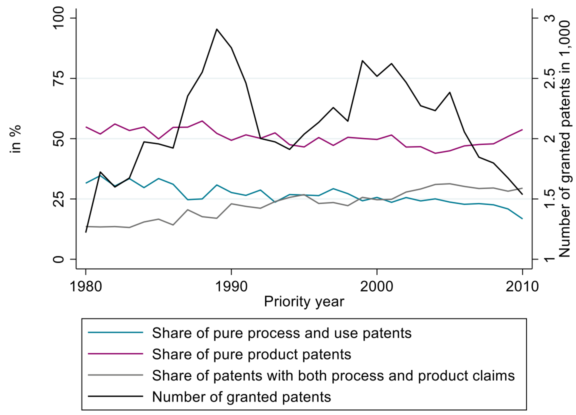
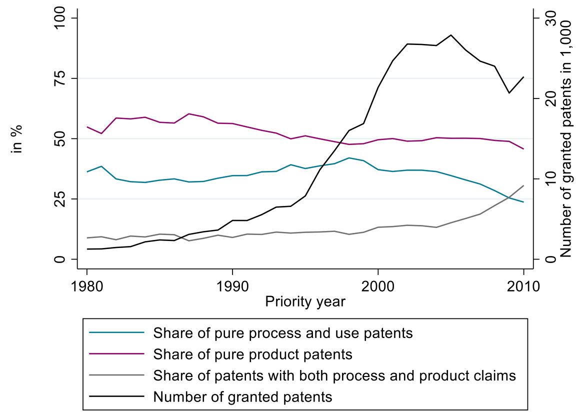


Figure 49: Share of product, process-use, and mixed patents in Semiconductors, USPTO, based on independent claims



In semiconductors, the share of mixed patents is slightly increasing and the share of process-use patents decreasing. This development is difficult to interpret against the background of the life cycle theory since it is unclear what an increasing fraction of mixed patents and decreasing faction of process-use patents mean for the technological dynamics in this field.

Pharmaceuticals

Figure 50: Share of product, process-use, and mixed patents in Pharmaceuticals, EPO

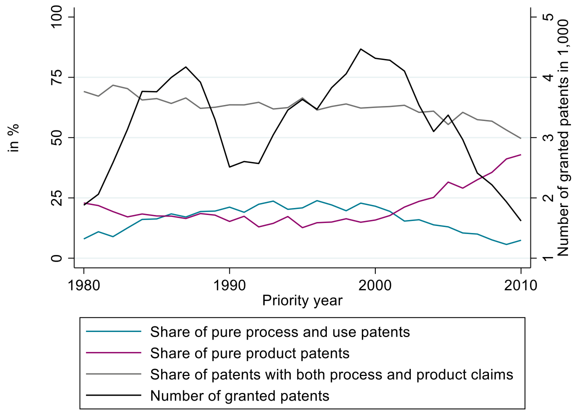


Figure 51: Share of product, process-use, and mixed patents in Pharmaceuticals, USPTO

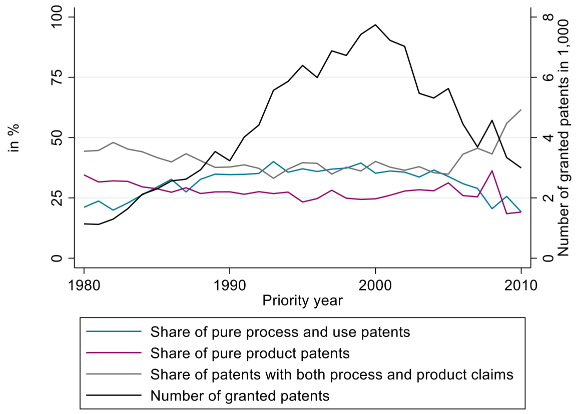


Figure 52: Share of product, process-use, and mixed patents in Pharmaceuticals, EPO, based on independent claims

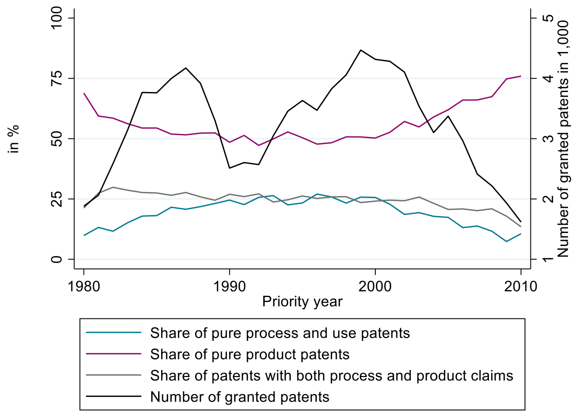
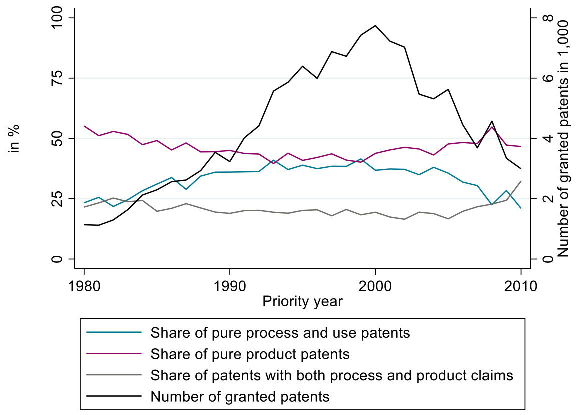


Figure 53: Share of product, process-use, and mixed patents in Pharmaceuticals, USPTO, based on independent claims



Pharmaceuticals is driven by products if the shares are calculated based on independent claims. However, many patents at the EPO seem to include many dependent process and use claims as can be seen from Figure 50, thus delivering a completely different picture if we consider all claims. The big differences between the EPO and USPTO might have to do with different legal requirements in drafting the claims.

Telecommunications

Figure 54: Share of product, process-use, and mixed patents in Telecommunications, EPO

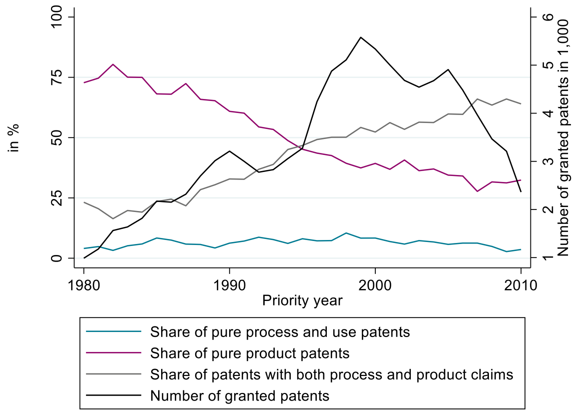


Figure 55: Share of product, process-use, and mixed patents in Telecommunications, USPTO

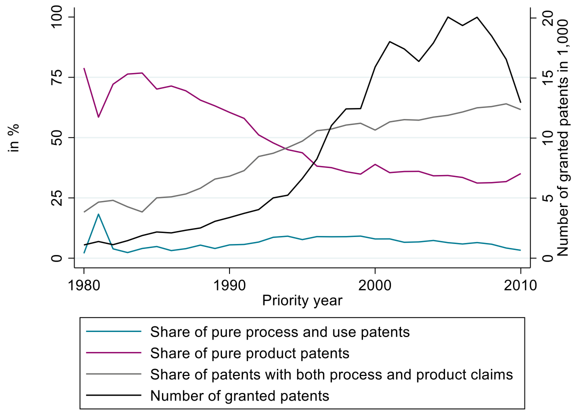


Figure 56: Share of product, process-use, and mixed patents in Telecommunications, EPO, based on independent claims

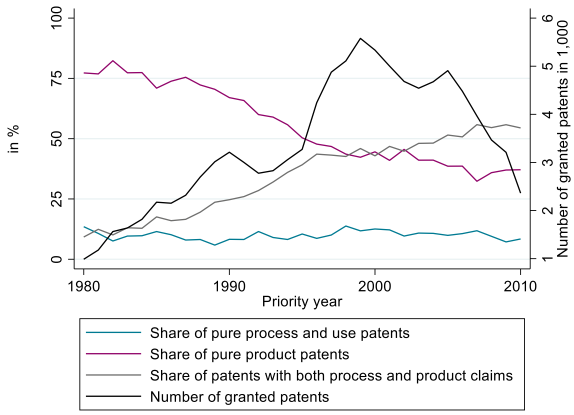
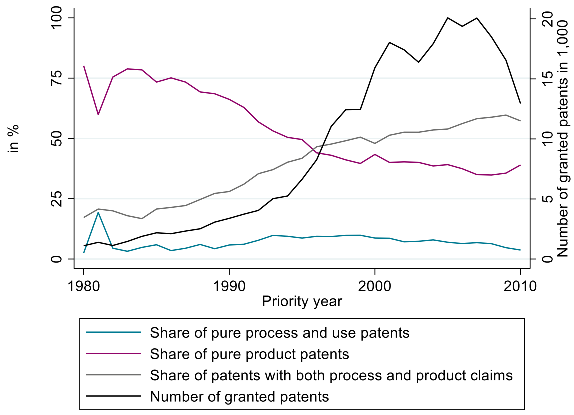


Figure 57: Share of product, process-use, and mixed patents in Telecommunications, USPTO, based on independent claims



Telecommunications shows a pattern similar to computer technology: Starkly increasing shares in mixed patents and decreasing shares in product patents. It is unclear what this pattern tells us in the context of the technological life cycle theory. It could indicate both technological exhaustion and increasing complexity in this technological field.

In sum, we find some developments that seem to be in line with the life cycle theory. However, as the technology fields depicted here are very broad, it might be difficult to say anything about the state of the technology (how 'mature' it is).

3.2.2 Breakthrough technologies

The term 'breakthrough technologies' is lent from the World Intellectual Property Report 2015 (WIPO, 2015). They study three historical innovations (airplanes, antibiotics, and semiconductors) and three current innovations (3D printing, nanotechnology, robotics). We applied their keyword search and IPC mapping and show the development of the share of product, process and mixed patents for three of them (the development for Semiconductors can be found in Section 0). In addition, we show the development for 'combustion engines' (IPC subclass F02B) and 'batteries' (H01M) which also appear interesting to us.

Robotics

Figure 58: Share of product, process-use, and mixed patents in Robotics, EPO

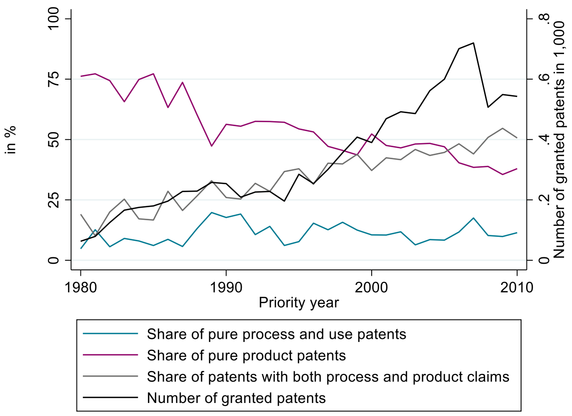


Figure 59: Share of product, process-use, and mixed patents in Robotics, USPTO

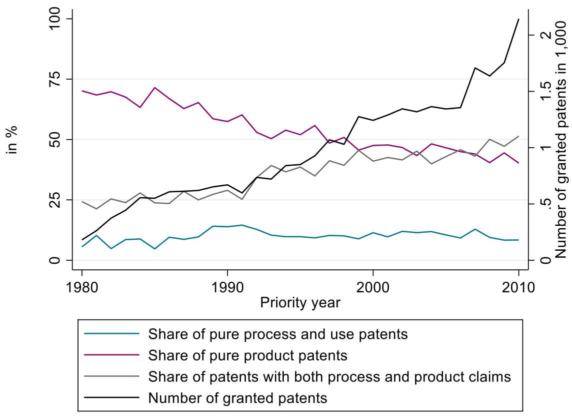


Figure 60: Share of product, process-use, and mixed patents in Robotics, EPO, based on independent claims

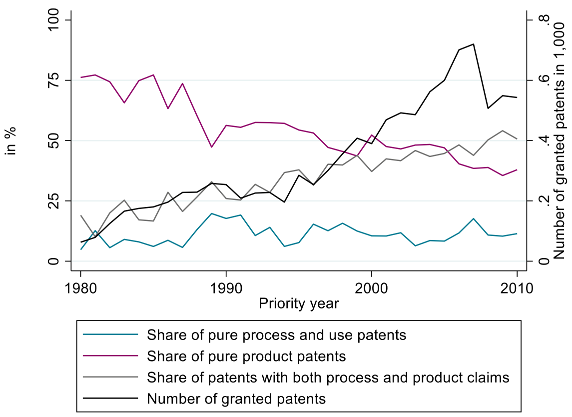
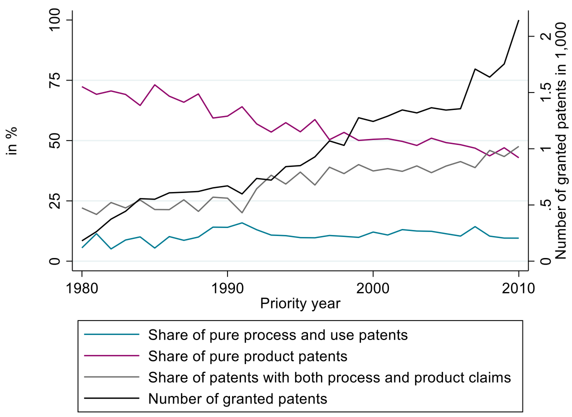


Figure 61: Share of product, process-use, and mixed patents in Robotics, USPTO, based on independent claims



Robotics is a technology that is characterized by a fast growth in patenting activities. What is remarkable is that the share of pure product patents has decreased considerably. We can observe a similar trend in the complex technology fields 'Telecommunications' and 'Computer technology'.

At the EPO, the shares we obtain based on independent vs. all claims are indistinguishable from each other.

Nanotechnology

Figure 62: Share of product, process-use, and mixed patents in Nanotechnology, EPO

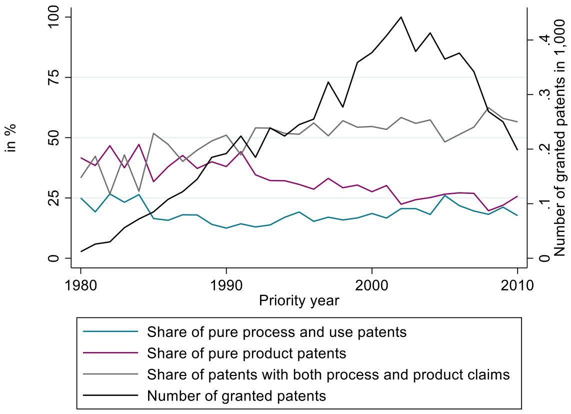


Figure 63: Share of product, process-use, and mixed patents in Nanotechnology, USPTO

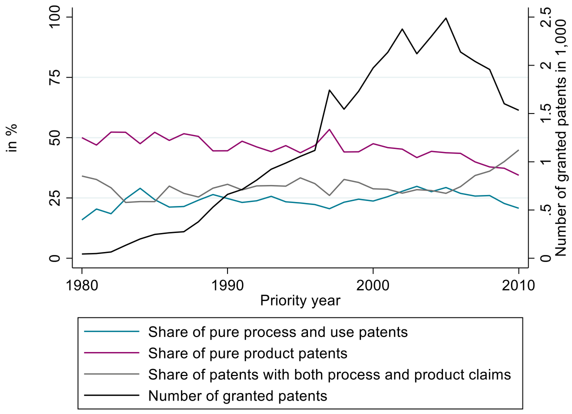


Figure 64: Share of product, process-use, and mixed patents in Nanotechnology, EPO, based on independent claims

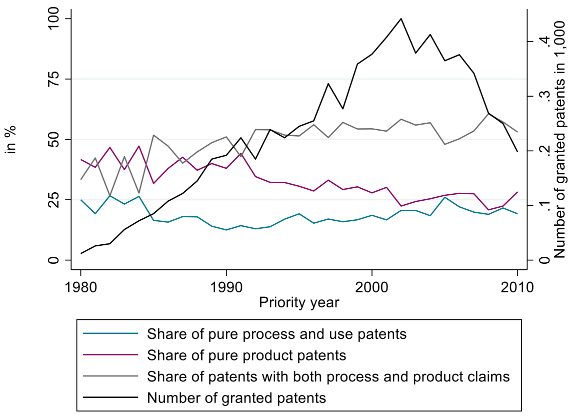
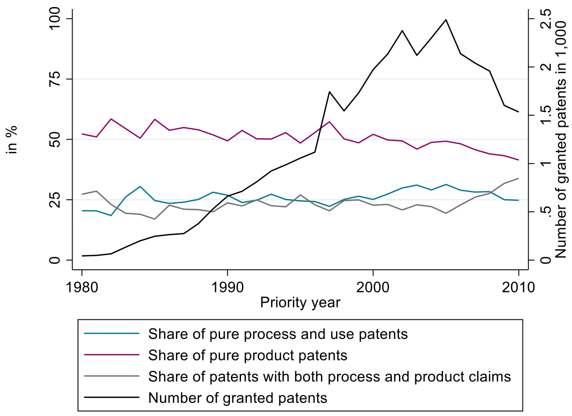


Figure 65: Share of product, process-use, and mixed patents in Nanotechnology, USPTO, based on independent claims



In nanotechnology, mixed patents have gained in importance for granted patents at the USPTO only very recently. There are significant differences between the EPO and USPTO, with the EPO having much higher shares of mixed patents. Again, we get very similar figures for the EPO for both independent and all claims.

Airplanes

Figure 66: Share of product, process-use, and mixed patents in Airplanes, EPO

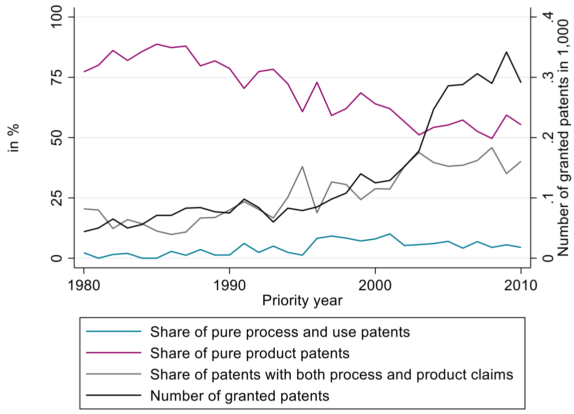


Figure 67: Share of product, process-use, and mixed patents in Airplanes, USPTO

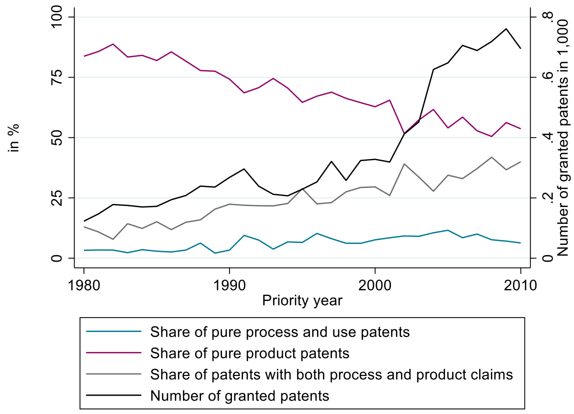


Figure 68: Share of product, process-use, and mixed patents in Airplanes, EPO, based on independent claims

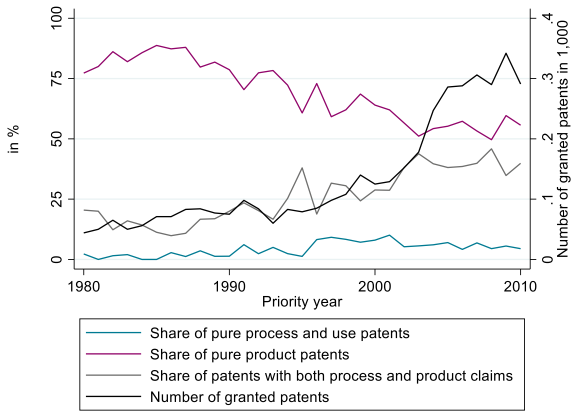
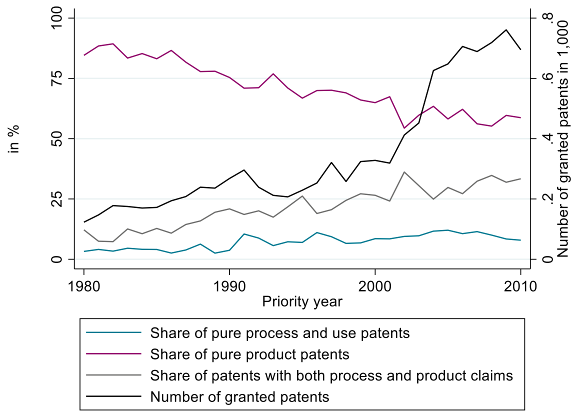


Figure 69: Share of product, process-use, and mixed patents in Airplanes, USPTO, based on independent claims



Even though airplanes have been characterized as historical, the technology still shows a growing number of granted patents. The technology is dominated by product technologies, but the shares of product patents are decreasing and the share of mixed patents increasing which might indicate a relatively high degree of technological maturity or complexity.

Combustion engines

Figure 70: Share of product, process-use, and mixed patents in Combustion engines, EPO

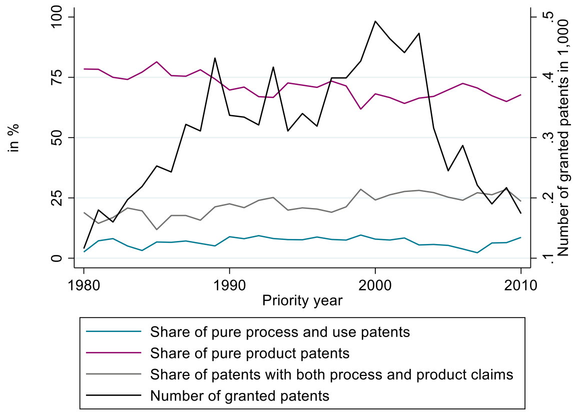


Figure 71: Share of product, process-use, and mixed patents in Combustion engines, USPTO

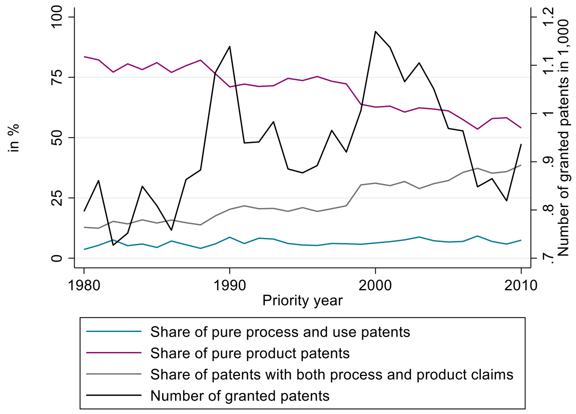


Figure 72: Share of product, process-use, and mixed patents in Combustion engines, EPO, based on independent claims

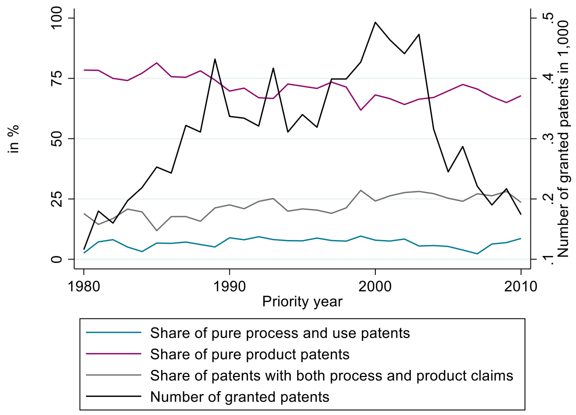
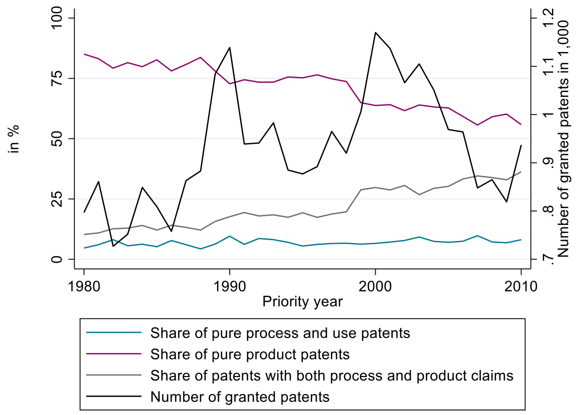


Figure 73: Share of product, process-use, and mixed patents in Combustion engines, USPTO, based on independent claims



Combustion engines might be a prototypical example of an exhausted technology in light of the debate on switching to electric engines in cars. Indeed, patent activities have decreased tremendously. Nevertheless, it is still largely dominated by product patents even though the share is slightly decreasing.

Batteries

Figure 74: Share of product, process-use, and mixed patents in Batteries, EPO

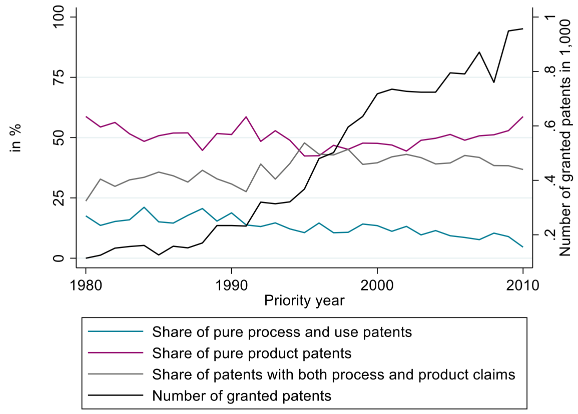


Figure 75: Share of product, process-use, and mixed patents in Batteries, USPTO

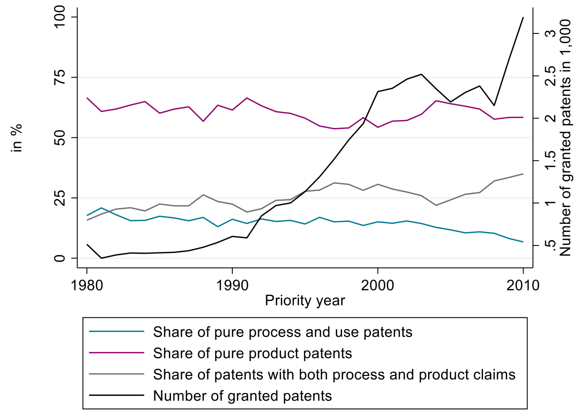


Figure 76: Share of product, process-use, and mixed patents in Batteries, EPO, based on independent claims

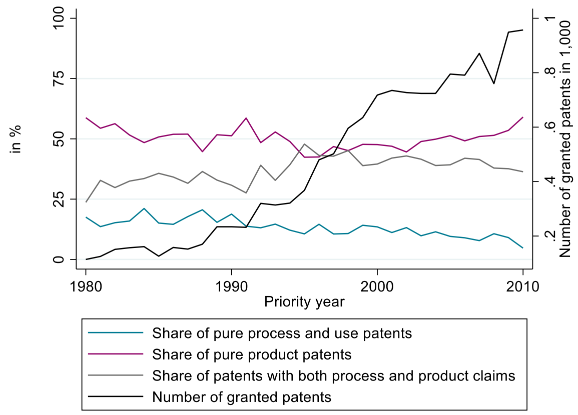
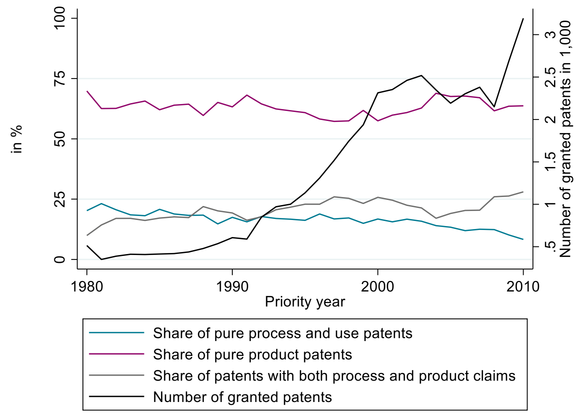


Figure 77: Share of product, process-use, and mixed patents in Batteries, USPTO, based on independent claims



Technological progress in batteries is very important for the diffusion of electric vehicles. Indeed, batteries is a high-growth technology in terms of patenting activities. This dynamic is characterized by stable shares of product patents and a decreasing fraction of process patents. The share of mixed patents is slightly decreasing at the EPO.

3.2.3 Dynamic technologies

Finally, we want to depict four highly dynamic technologies, defined as IPC subclasses where the difference between the maximum number of patent applications in a given year and the minimum number in another year is extraordinarily high, thus indicating large dynamics. All subclasses show a similar picture: an increasing share of mixed patents that has outperformed the share of product patents since the nineties.

H04N Pictorial communication, e.g. television

Figure 78: Share of product, process-use, and mixed patents in H04N, EPO

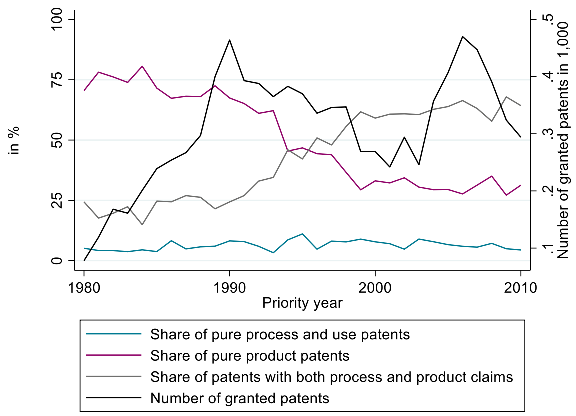


Figure 79: Share of product, process-use, and mixed patents in H04N, USPTO

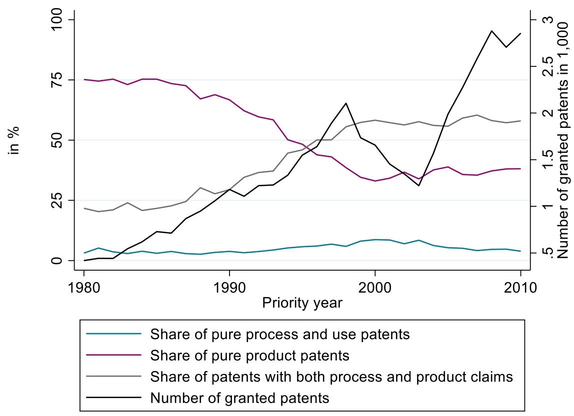


Figure 80: Share of product, process-use, and mixed patents in H04N, EPO, based on independent claims

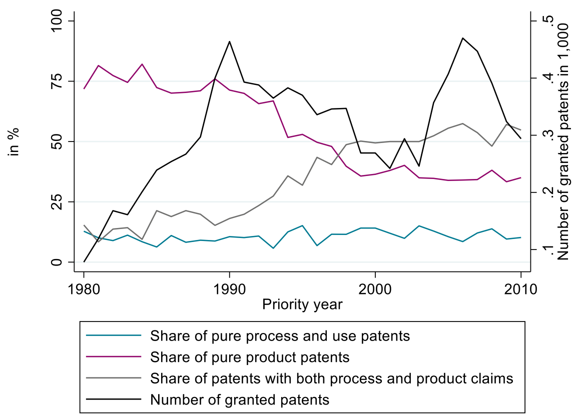
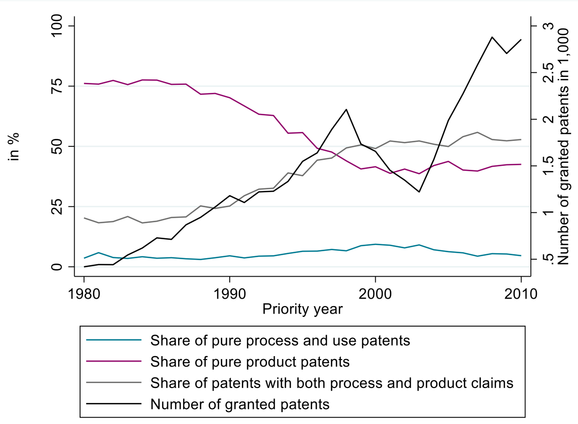


Figure 81: Share of product, process-use, and mixed patents in H04N, USPTO, based on independent claims



The technological field of pictorial communication shows an interesting pattern. First, we see that the number of granted patents peaked earlier at the EPO than at the USPTO. Second, the overall patent dynamic seems to be driven by the mixed patents. The recent increase in the number of patents granted at the USPTO is not reflected in a change in the proportion of different patent types.

G06F Electric digital data processing

Figure 82: Share of product, process-use, and mixed patents in G06F, EPO

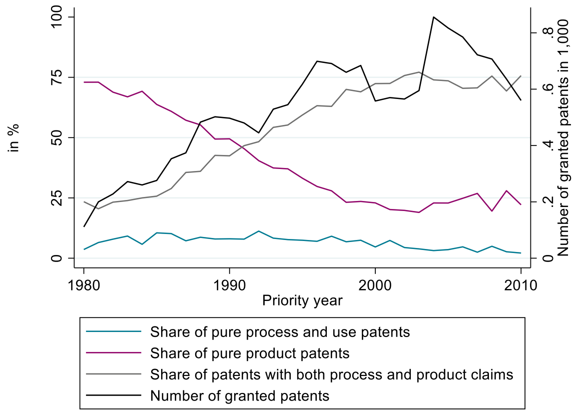


Figure 83: Share of product, process-use, and mixed patents in G06F, USPTO

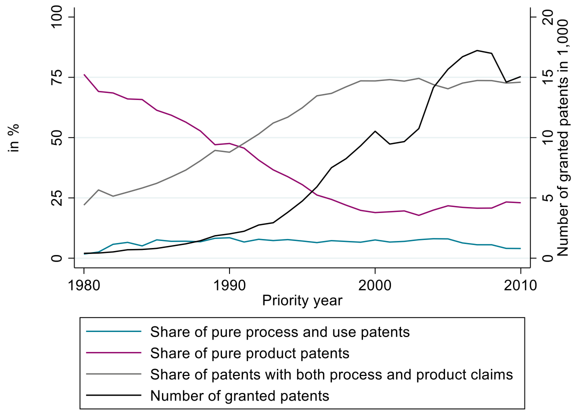


Figure 84: Share of product, process-use, and mixed patents in G06F, EPO, based on independent claims

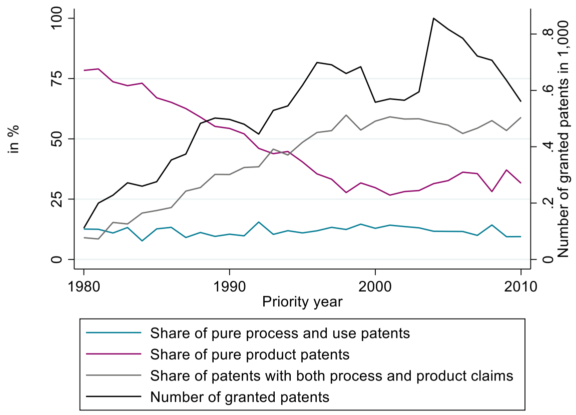
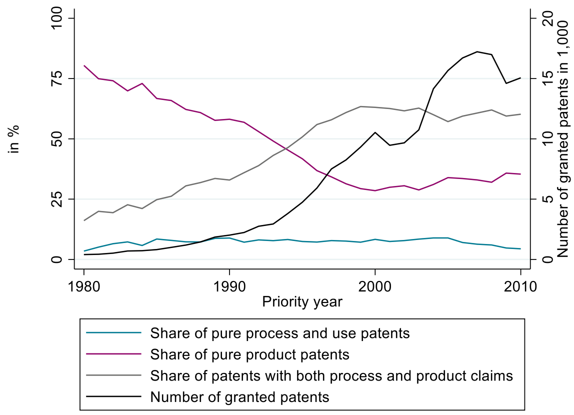


Figure 85: Share of product, process-use, and mixed patents in G06F, USPTO, based on independent claims



We see a similar picture for electrical digital data processing technologies. The fraction of product patents was decreasing until 2000 and the fraction of mixed patents increasing. Mixed patents drive the overall dynamic over the complete period of the technological life cycle. Moreover, we see a remarkable decrease of product patents irrespective of the patent office and whether the claims are independent or not.

H04L Transmission of digital information, e.g. telegraphic communication

Figure 86: Share of product, process-use, and mixed patents in H04L, EPO

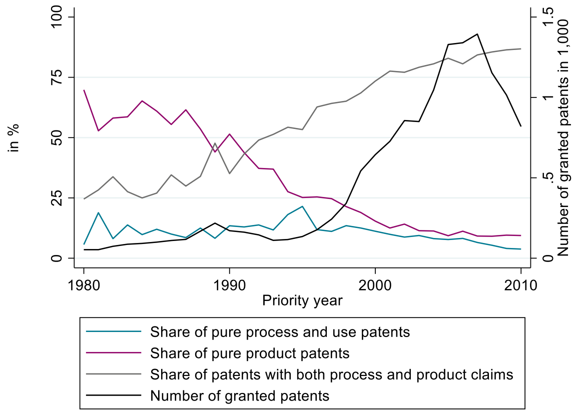


Figure 87: Share of product, process-use, and mixed patents in H04L, USPTO

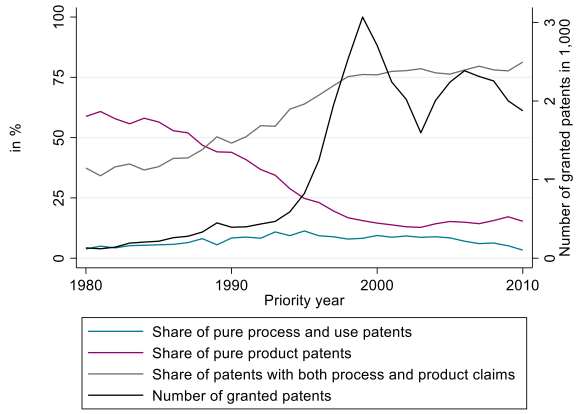


Figure 88: Share of product, process-use, and mixed patents in H04L, EPO, based on independent claims

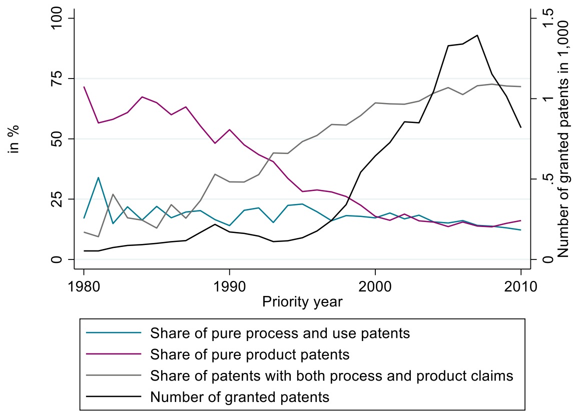
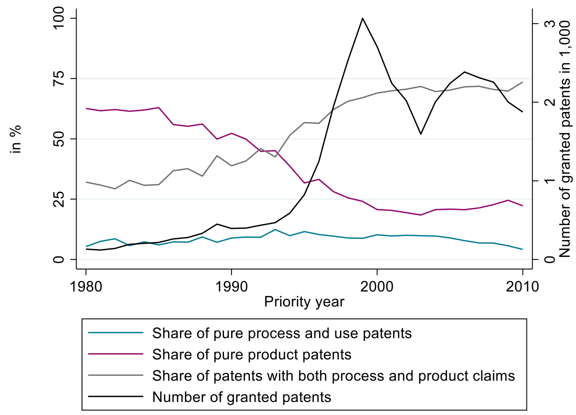


Figure 89: Share of product, process-use, and mixed patents in H04L, USPTO, based on independent claims



The fraction of mixed patents also dominates the development of granted patents in transmission of digital information. However, compared to other technologies, there is a longer time lag between increasing the share of mixed patents and increasing the number of patents overall. There was a rather sharp decline in the share of product patents. In the case of EPO patents, and in particular for shares based on independent claims, they reach the level of the share of process patents nowadays.

3.2.4 Summary

For complex and dynamic technologies, the descriptive evidence delivers a clear picture: Mixed patents have become predominant, whereas product patents loose in significance. Pure process patents only play a minor role. As those developments are consistent across offices and the unit of analysis (based on either all or only independent claims), we might interpret this as reflecting a kind of technological life cycle. However, the reasons for those developments remain unclear and require more detailed analyses. It is likely that technologies have become more complex over time or that firms add additional process claims in order to fulfil legal requirements or for strategic reasons. That being said, the increase in mixed patents might be hardly attributed to cost reductions or improvements in the production process alone.

For technologies that are characterized by very high shares of product patents such as transport technologies, there is also a trend towards more mixed patents (and less product patents), perhaps indicating technological exhaustion within a technological paradigm (Dosi, 1982), but the share of product patents is still much higher.

Discrete technologies such as pharmaceuticals show less clear patterns: The developments are quite inconsistent across offices and the unit of analysis.

In sum, even though we can detect clear patterns for some technologies, the technological life cycles seem to be affected by the degree of complexity and other (institutional) factors for which we cannot control here. Therefore, life cycles traced with product and process patents have to be interpreted with caution. Nevertheless, our data offer the unique opportunity to study questions related to technological developments on a very large scale.

In the econometric part of the study, we will try to identify the relationship between the state of a technological life cycle and product and process patenting more rigorously by examining performance effects of product and process patents in firms characterized of being in different states of a life cycle.

3.3 Firm-level characteristics and product and process patenting

In the remainder of the report, we use our indicators of product and process patents together with firm data from Germany and Switzerland. By using firm-level data, we get additional information on whether the indicators are good predictors of process and product innovations at firm level. In addition, we get insights into the distribution of product and process patents by industries, firm age, size, and R&D intensity.

3.3.1 Description of the firm-level datasets

Dataset for Switzerland

The firm data for Switzerland is based on the KOF Swiss Enterprise Panel. This panel of companies is used to conduct the Swiss Innovation Survey (SIS). The SIS was funded by the State Secretariat of Economic Affairs until 2015 and is funded by the State Secretariat for Education, Research, and

Innovation since then. The surveys take place every two to three years. The sample is representative for the Swiss corporate landscape, stratified by industry and three size-classes and consists of about 6,000 companies that cover the most important branches of the manufacturing sector, the construction sector, and the service sector. The KOF Innovation Survey is comparable to the Community Innovation Surveys (CIS) in EU countries with regard to essential questions, method and relative sample size. In addition to innovation related questions, the survey also collects information on other economic indicators of companies like turnover, intermediate inputs, employment, etc. The response rate is between 30% and 40%. For this study, we use survey data from the 1996, 1999, 2002, 2005, 2008, 2011, 2013 and 2015 survey.

We matched firm names and addresses with applicant names and (if available) addresses from PATSTAT after pre-processing of the respective fields. The results from the fuzzy matching were checked carefully. The firm-patent mapping includes the firm identifier from the survey and all patent families in which a firm has filed a patent application in a given year. For the purpose of this study, we assigned the USPTO and EPO filings to the respective family and merged the USPTO and EPO filings with the classification of product and process patents afterwards. In order to avoid double counting within a family, we only kept the first USPTO and/or EPO filing within each family.

Dataset for Germany

The firm data for Germany is taken from the German CIS. In contrast to other national CIS, the German survey is conducted annually, employing a panel sample. The survey is conducted by the Centre for European Economic Research (ZEW) in Mannheim on behalf of the Federal Ministry of Education and Research and is called the ‘Mannheim Innovation Panel’, MIP. The stratified random sample includes firms with 5 or more employees in the production sector (sections B to E of Nace rev. 2) and a large number of service sectors (division 46, 49 to 53, 58 to 66, 69 to 74, 78 to 82 of Nace rev. 2). In addition, the panel sample also includes a larger number of firms from Nace rev. 2 divisions 41 to 45, 47, 68 and 77. The size and sector coverage is hence very similar to the Swiss data. The number of firm observations per year is about 18,000.

The ZEW has matched the firms surveyed in the MIP with EPO patents in the PATSTAT database based on a name and address search, which was checked manually. We added the classification for product, process and mixed patents, and kept only the first filing within each family if there are multiple EPO filings. Out of all the EP patents filed in this period, German applicants (i.e. firms residing in Germany) account for the largest share of patents (just over 50%), which makes a specific analysis of Germany an interesting one. This also means that we cover quite a large share of the EP patents by matching the German firms and their patents; 235’178 EP patents out of a total of around 2’614’000 EP applications filed since 1992, corresponding to around 9%.

3.3.2 Distribution of product and process patents by firm characteristics

In this section, we provide descriptive evidence on the distribution of product, process-use, and mixed patents as defined according to the ‘100% rule’ across selected industries, across different firm age and firm size groups, and by different percentiles of R&D intensity. We use the Swiss firm dataset for this analysis. We provide similar figures for the distribution of product innovators, process innovators, and mixed innovators according to survey information and across the same firm characteristics. In order to make the innovation categories mutually exclusive, product innovators are defined as firms having only introduced at least one product innovation during the last three years (and not a process innovation), process innovators as firms having only introduced at least one process innovation (and not a product innovation), and mixed innovators as firms having introduced both product and process innovations (at least one from each category).

It should be noted that the figures are not directly comparable: A firm can have multiple patent applications in each year and we can observe all of them. In contrast, the survey information on product and/or process innovation is a binary indicator, i.e. we do not know the overall number of product and/or process innovations a firm has introduced. The binary indicator only allows us to calculate the average propensity of firms (in a given industry, a size group etc.) to innovate. The number of patents allows us to calculate a firm’s average number of patents in a given industry, a size group etc. Further complications arise from the fact that the reference period is different as the survey information refers to a three-year period before the survey year and the patent applications refer to the priority year.

When interpreting the charts, it should be also noted that the data represent the industry structure in Switzerland, where, e.g., a firm in the pharmaceutical industry has more patents than a firm does in the machinery industry on average. This is not only driven by the technological orientation of the industry, which determines the affinity to seek for patent protection, but also by structural features such as the dominance of very big companies (in the pharmaceutical industry) with a higher propensity to patent, or of SMEs (in the machinery industry) with a lower propensity to patent. Nevertheless, we hope to provide further insights with this analysis. All bar charts are shown for both the subsample of firms with patents and all firms.

As can be seen from the charts below, innovations at firm level follow the patenting activities in at least two important points: Innovating with both product and process innovations at the same time is much more common across all industries, size groups, age groups etc. than innovating in a single category. The same is true for patenting activities, where mixed patents dominate across all characteristics except for SMEs (see Figure 98). Mixed patents seem to be especially common for younger firms, larger firms, and firms with higher R&D intensity. In the same vein, pure process-use patenting and pure process innovations play a minor role across all characteristics.

Selected industries

Figure 90: Average number of product, process-use and mixed patents for selected industries, firms with patents

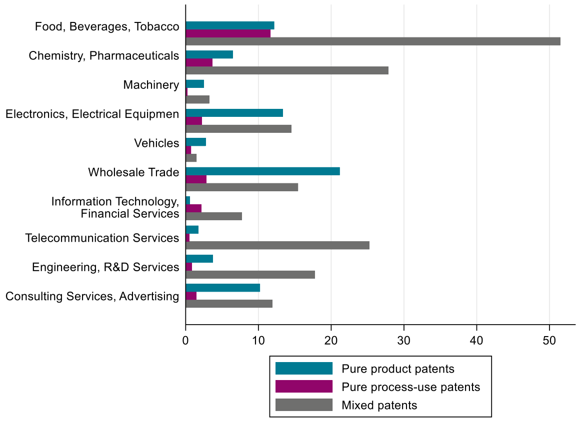


Figure 91: Average propensity of being a product, process or product and process innovator for selected industries, firms with patents

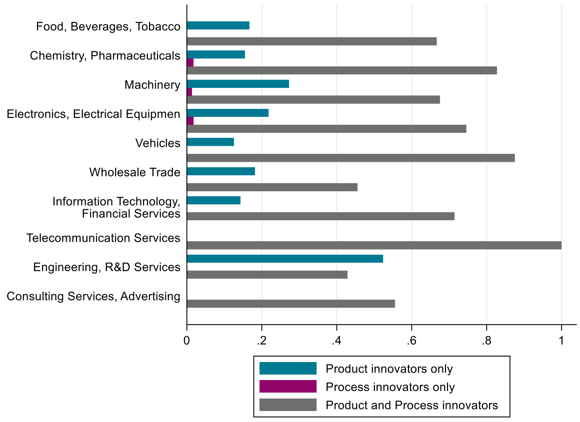


Figure 92: Average number of product, process-use and mixed patents for selected industries, all firms

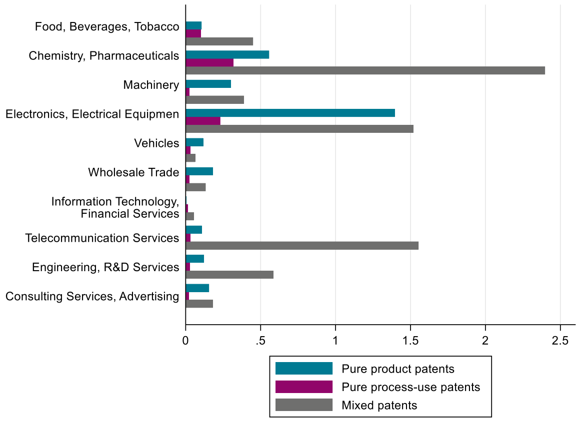
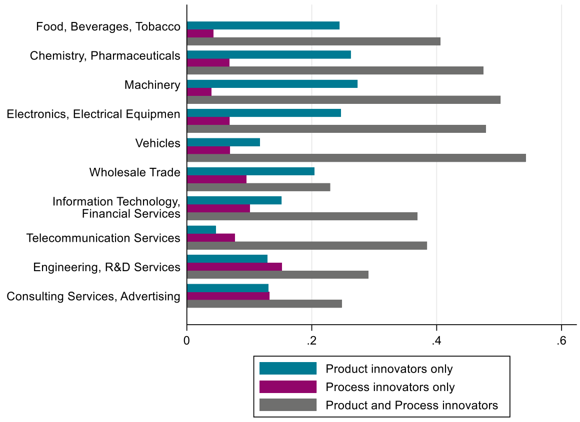


Figure 93: Average propensity of being a product, process or product and process innovator for selected industries, all firms



Firm age

Figure 94: Average number of product, process-use and mixed patents by firm age, firms with patents

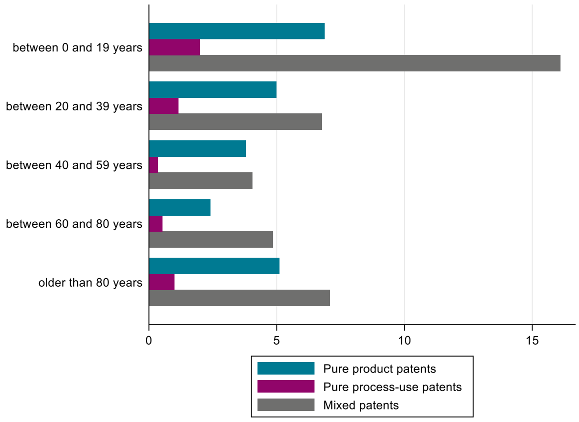


Figure 95: Average propensity of being a product, process or product and process innovator by firm age, firms with patents

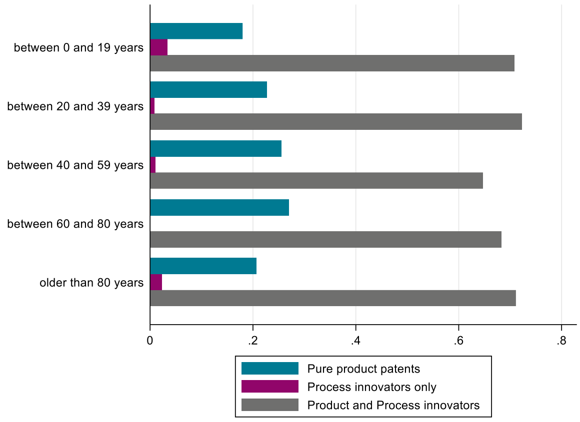


Figure 96: Average number of product, process-use and mixed patents by firm age, all firms

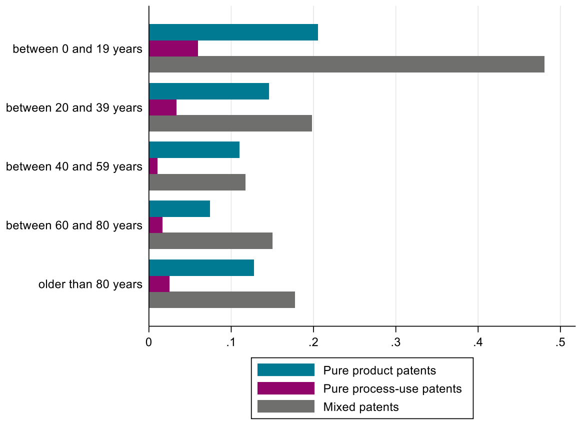
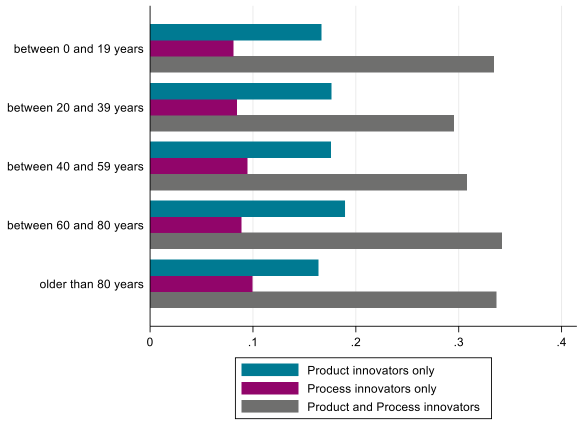


Figure 97: Average propensity of being a product, process or product and process innovator by firm age, all firms



Firm size

Figure 98: Average number of product, process-use and mixed patents by firm size, firms with patents

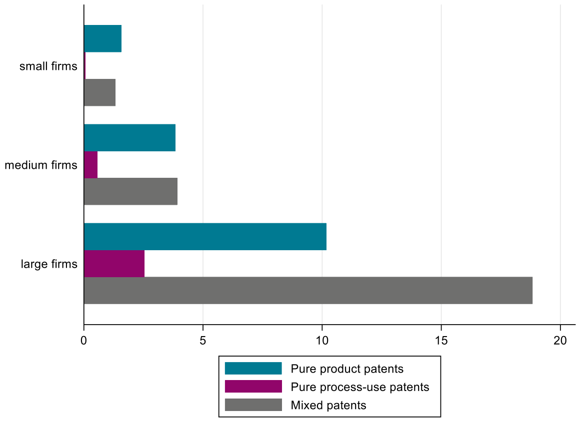


Figure 99: Average propensity of being a product, process or product and process innovator by firm size, firms with patents

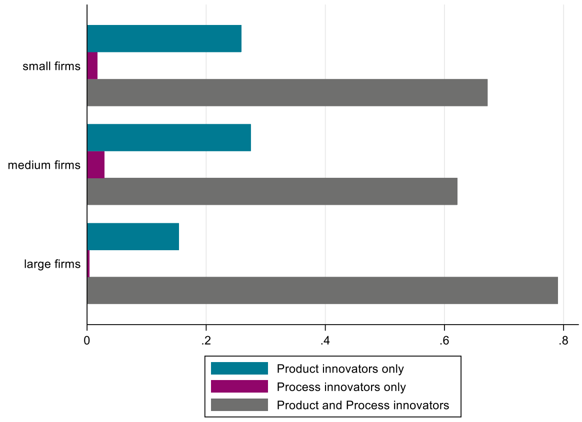


Figure 100: Average number of product, process-use and mixed patents by firm size, all firms

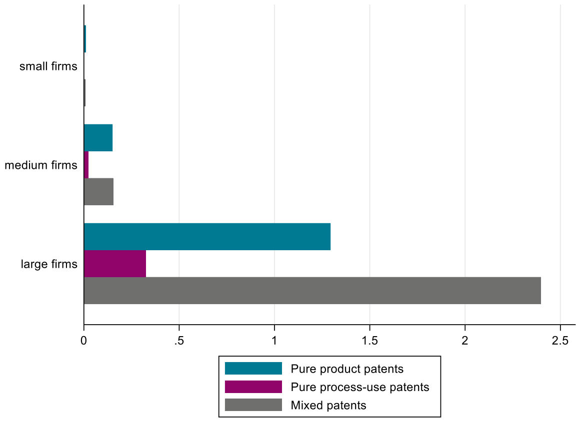
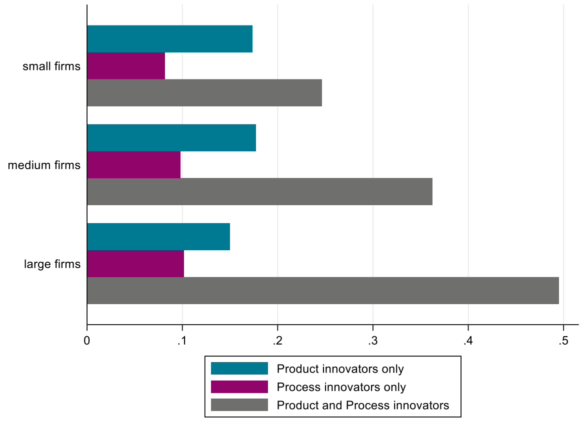


Figure 101: Average propensity of being a product, process or product and process innovator by firm size, all firms



R&D intensity

Figure 102: Average number of product, process-use and mixed patents by percentiles of R&D intensity, firms with patents

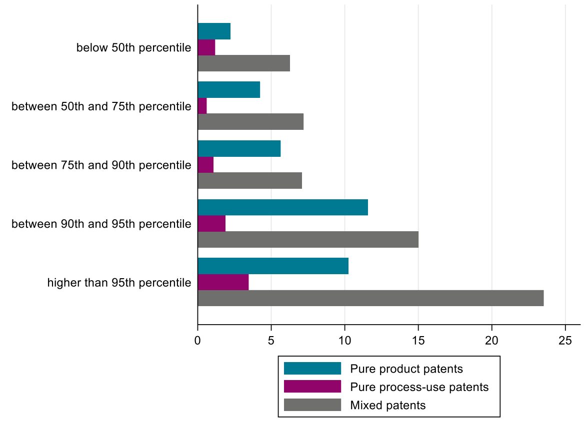


Figure 103: Average propensity of being a product, process or product and process innovator by percentiles of R&D intensity, firms with patents

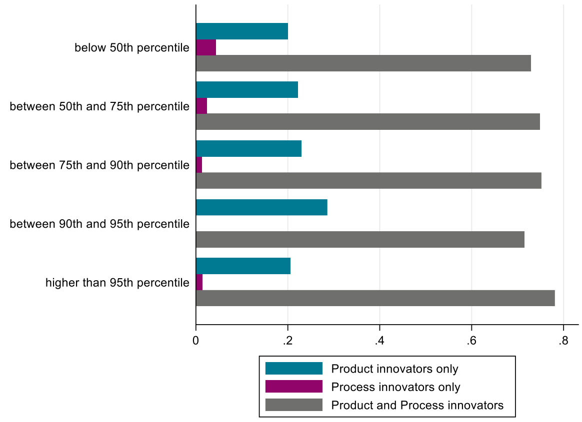


Figure 104: Average number of product, process-use and mixed patents by percentiles of R&D intensity, all firms

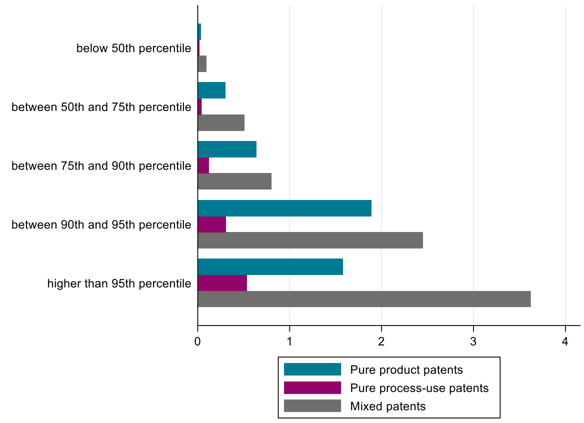
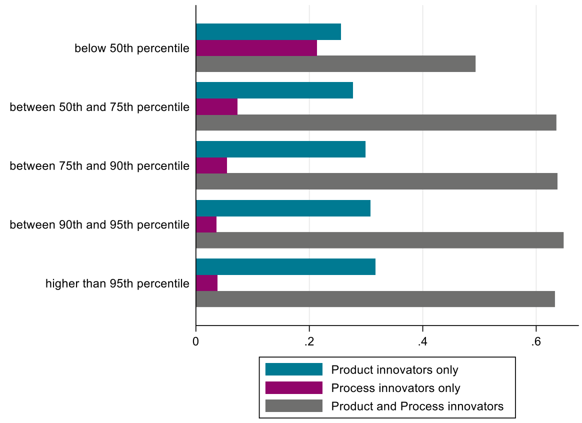


Figure 105: Average propensity of being a product, process or product and process innovator by percentiles of R&D intensity, all firms



3.3.3 Calculation of product and process-use patent stocks

We proxy a firm's product and process-use knowledge stock (i.e., the technological knowledge of a firm with respect to product and process technologies) with the patent stock consisting of pure product patents and pure process (and use) patents, respectively. The overall knowledge stock is measured by the number of patent applications at the USPTO or EPO accumulated over time. We use the "perpetual inventory method" with a depreciation rate of 15%.[27] We differentiate between patent applications that only contain product claims, only contain process-use claims, and both product and process claims (mixed). The knowledge stock can be written as follows:

[27] The initial knowledge capital is the number of patent applications in the earliest year we can observe (1980) if a firm already had patent applications at that time.

$$K_{ilt} = (1 - d)K_{ilt-1} + R_{ilt}$$
$$\text{where } l \in \{ALL, PROD, PROC, MIXED\}. \quad (1)$$

K_{ilt} is the patent stock of firm *i* in year *t*, *d* the depreciation rate, and R_{ilt} new patent applications in *t*. *l* denotes whether we consider the total patent stock (ALL), the patent stock based on product patents (PROD), the patent stock based on process-use patents (PROC), or the patent stock based on mixed patents (MIXED).

3.3.4 Calculation of product and process spillover variables

In the econometric part, we include variables that should proxy for knowledge spillovers from product and process technologies that have been developed by other firms. Karlsson et al. (2018) define knowledge spillovers' contents as "news, information, ideas, knowledge, experience and similar intangible things, which can be embodied in human beings, real capital and software". The extent of knowledge spillovers is a function of the interaction between individuals and organizations. They are externalities from which other firms can benefit if they absorb the knowledge – usually without paying for it.

In contrast to existing literature, we distinguish between different forms of knowledge spillovers based on the distinction of product and process patents. From the outset, we would expect a lower spillover effect from processes than from products because knowledge leakage to other firms should be lower and imitation of processes more difficult. First, knowledge about processes less visible and is assumed to be more difficult to appropriate with patents than knowledge about products (Cohen, Nelson, & Walsh, 2000; Levin et al., 1987). Firms can keep most of the process inventions hidden from competitors. In contrast, once a product is on the market it can be reverse-engineered by competitors (Arundel, 2001). In addition, new product features are often publicized in order to generate interest in the market (Cohen & Klepper, 1996). Second, according to Cohen & Klepper (1996) firms use process inventions internally and do not sell or license them.

The usual approach is to include the weighted knowledge capital of firms other than the focal firm in an estimation equation. Jaffe (1986) has proposed a weight, where the share of patents of a firm in different technologies are proxies for the unobservable share of researchers in a company in different research fields. The degree of similarity of technological profiles (technological proximity) between all possible company pairs (for example, all firms based in Switzerland) leads to a so-called measure of proximity which measures how close or how far two companies are technologically. The smaller the measure, the more different are firms technologically. The Jaffe proximity measure is calculated for all possible firm pairs and can be written as follows:

$$TECH_{ij} = \frac{T_i T_j'}{(T_i T_i')^{\frac{1}{2}} (T_j T_j')^{\frac{1}{2}}}; i \neq j \tag{2}$$

where T_i and T_j are vectors containing the shares of patents of firm *i* and *j* in each IPC subclass. In a further step, weighted sums of knowledge stocks of all firms in the respective dataset other than focal firm *i* are calculated using weights as defined in equation (2) and the knowledge stock for firm *j* as defined in (1). This pool of spillovers that is available to focal firm *i* in year *t* can be written as

$$SPILL_{it} = \sum_j TECH_{ij} K_{jt}; i \neq j \tag{3}$$

In contrast to most of the existing literature, we allow $TECH_{ij}$ to vary over time (in fact, we use $TECH_{ijt}$). This approach seems to be more convenient to us because we do not see any reason why the technological position of a firm should remain constant. Because we have many small firms in both the Swiss and the German data that do not patent regularly, we use the annual information on patent stocks in IPC subclasses rather than pure patent counts in order to calculate the firm's share of patents in each technology.[28]

As we are interested in knowledge spillovers from products and processes, we calculated the spillover measure in (3) with other firms' product patent stocks, process-use patent stocks, and mixed patent stocks, respectively:

$$SPILL_{ilt} = \sum_j TECH_{ijt} K_{jlt}; i \neq j \tag{4}$$

where $l \in \{PROD, PROC, MIXED\}$.

3.3.5 Relationship between product and process patents and product and process innovation

An important part of the project is to bridge the gap between process and product innovations in economics and in patent applications (patent attorney and examination view). Even though our indicators seem to reflect the overall picture from survey information quite well (see again European Patent Office, 2019, and section 3.3.2) a further step is to establish correlations between the patent-based indicators and firm-level measures of process and product innovations.

It must be kept in mind that not every innovation is patented and intellectual property protection is probably less essential for process innovations than for product innovations because processes

28 Using patent stocks implies that we have a non-zero patent share for all periods following the period where a firm had its first patent application. Our econometric results are robust if we use a time-invariant weight based on patent counts over all periods.

are harder to imitate. This means that it is not unlikely that firms are process innovators without patenting the underlying inventions. This might make it more difficult to detect any relation between the indicator of process patents and process innovations, e.g. from survey information.

Ideally, the firms' process patent stocks should have good descriptive power for the process innovations of companies, but not for product innovations. For this, we performed Probit regressions using MIP data with two different binary dependent variables: First, whether a firm has introduced a product innovation (or not) and, second, whether a firm has introduced a process innovation.

The regression results in Table 3 show that a statistically significant correlation exists between the process-use patent knowledge stock (Process Use KS) and the likelihood of the firm to introduce a process innovation. However, the magnitude is relatively small. As the process patent stock increases by one unit, the probability of being a process innovator increases by 0.036 (i.e. 4%). Interestingly, there is also a negative correlation between the product patent stock and the likelihood to introduce a process innovation.

The statistically significant relationships do not hold for product innovations (i.e. if the firm has introduced a new or significantly improved product in the past three years). However, the mixed patent capital is highly significant for both dependent variables. According to the results from section 3, mixed patents have become more and more important over time and are now the dominant type of patents. The finding that they are associated with innovation in firms implies that they cannot be only patents where additional claims have been added for strategic reasons, but that a significant part of the mixed patents must contain valuable inventions. This makes it more credible that the share of mixed patents have risen due to a higher complexity of underlying technologies and due to institutional factors.

Table 3: Probit estimates – dependent variable process innovation or product innovation

	Process innovation	**Process innovation (margins)**	**Product innovation**	**Product innovation (margins)**
Product KS	-0.061*	-0.017*	0.011	0.002
	(0.036)	(0.010)	(0.047)	(0.007)
Process Use KS	0.125**	0.036**	-0.099	-0.014
	(0.052)	(0.015)	(0.070)	(0.010)
Mixed KS	0.107**	0.031**	0.205***	0.029***
	(0.042)	(0.012)	(0.059)	(0.009)
Year fixed effect	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes
Observations	2462	2462	2372	2372
Wald chi2	379.172		240.597	
P > chi2	0.000		0.000	

Note: The dependent variable is a dummy variable equal to one if the firm invented a new product or process in the last three years. Heteroscedasticity-robust standard errors are in brackets. Controls include firm age, size, academic employees share, technological potential, price competition, foreign ownership and appropriability.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4 Description of the publicly accessible dataset

In order to stimulate further research and to enrich existing databases, we make the classification of patent abstracts and claims publicly available at 'patent filing level', i.e. we provide Boolean indicators for patent abstracts and the share of process claims for each USPTO and EPO patent we could classify with the methods described above. The dataset will be available at https://doi.org/10.7910/DVN/CBSK2W together with the PostgreSQL code and the R code we used in order to implement the keyword search, the text mining, and the aggregation at patent level.

We recommend importing the data into a SQL database. The data can be easily used together with PATSTAT or any other common database such as PatentsView. In the following, we list and describe all columns that can be found in our data:

Table 4: List of columns

Column name	data type	Description
pat_no	text	Patent Authority (*publn_auth*), publication number (*publn_nr*) and publication kind (*publn_kind*) from PATSTAT.*tls211_pat_publn*, merged to a single string
appln_id	integer	Application Id (*appln_id*) derived from PATSTAT's *tls211_pat_publn* table
earliest_filing_date	date	Earliest filing date (*earliest_filing_date*) from PATSTAT's *tls201_appln* table
process_count_2	integer	Number of process claims in patent (keyword within first *two* words)
process_count_2_ind	integer	Number of *independent* process claims in patent (keyword within first *two* words)
process_count_5_ind	integer	Number of process claims in patent (keyword within first *five* words)
process_count_pred	integer	Number of process and use claims in patent (according to text mining)
process_use_count_pred_ind	integer	Number of *independent* process and use claims in patent (according to text mining)
use_count	integer	Number of use claims in patent
use_count_ind	integer	Number of *independent* use claims in patent
product_by_process_count_2	integer	Number of product by process claims in patent (process keywords not allowed within first *two* words)

product_by_process_count_2_ind	integer	Number of *independent* product by process claims in patent (process keywords not allowed within first *two* words)
total_count	integer	Total number of claims contained in a patent
total_count_ind	integer	Total number of *independent* claims contained in a patent
process_ratio_2	numeric	The share of a patent's process claims (keyword within first *two* words)
process_ratio_2_ind	numeric	The share of a patent's *independent* process claims (keyword within first *two* words)
process_ratio_5	numeric	The share of a patent's process claims (keyword within first *five* words)
process_ratio_5_ind	numeric	The share of a patent's process claims (according to text mining)
process_use_ratio_pred	numeric	The share of a patent's process and use claims (according to text mining)
process_use_ratio_pred_ind	numeric	The share of a patent's *independent* process and use claims (according to text mining)
use_ratio	numeric	The share of a patent's use claims
use_ratio_ind	numeric	The share of a patent's *independent* use claims
product_by_process_ratio_2	numeric	The share of a patent's product by process claims (process keywords not allowed within first *two* words)
product_by_process_ratio_2_ind	numeric	The share of a patent's *independent* product by process claims (process keywords not allowed within first *two* words)
title_process	Boolean	The patent's title contained "process" keywords, when field is set to true
title_use	Boolean	The patent's title contained "use" keywords, when field is set to true
abstract_process	Boolean	The patent's abstract contained "process" keywords when field is set to true
abstract_use	Boolean	The patent's abstract contained "use" keywords when field is set to true
abstract_process_use_pred	Boolean	The patent's abstract classified as "process" or "use" according to text mining when field is set to true

5 Econometric estimations

5.1 Product and process knowledge and patent activities

In this section, we investigate the relationship between product and process knowledge and the generation of new inventions econometrically. For this purpose, we use product, process, and mixed patent stocks in order to proxy for product, process, and mixed technological knowledge respectively. New inventions or new technological developments are proxied with new patent applications filed by a firm.

5.1.1 Econometric model

Specification of the patent equation

In the main specification of the patent equation, we differentiate between knowledge capital that only comprises process technology knowledge (Process Use KS), knowledge capital that only comprises product technology knowledge (Product KS), and knowledge based on both (Mixed KS). We add proxies for the availability of spillovers for the respective type of knowledge (Products SO, Process Use SO, and Mixed SO), time fixed effects (*t*), firm fixed effects, and control variables (*X*) to improve the precision of the estimation.[29] The control variables in *X* comprise variables for the size of a company, the share of employees with an academic degree, the technological opportunities of a company, the intensity of price competition, the appropriability of knowledge, and whether a company is foreign owned or not (see Table 19 in the Appendix for the descriptive information of the Swiss data and Table 20 for the descriptive information of the German data). We can write the equation for new patent applications as follows:

$$\begin{aligned} Patent\ count_{it} = {} & \beta_0 + \beta_1 Product\ KS_{it-2} + \beta_2 Process\ Use\ KS_{it-2} \\ & + \beta_3 Mixed\ KS_{it-2} + \beta_4 Product\ SO_{it-2} + \beta_5 Process\ Use\ SO_{it-2} \\ & + \beta_6 Mixed\ SO_{it-2} + X\gamma_{it} + t_t + u_i + \varepsilon_{it} \end{aligned} \tag{5}$$

where *i* denotes the company and *t* the year of observation. We use a two-year lag (*t-2)* to identify the effects of the knowledge stocks because firms need some time in order to transform knowledge into new inventions. However, we also run estimations with a one-year lag. The results are very similar.

29 Details on the measurement of knowledge capital and spillovers can be found in sections 3.3.3 and 3.3.4.

Knowledge stocks and spillovers from technological activities of other companies

Based on the available literature it can be assumed that the size of the knowledge stock has a significant and positive effect on the number of future patented inventions (patent counts). Firms with large knowledge capital are generally more likely to develop subsequent new technologies while they are also more likely to benefit from external knowledge, which partly originates from spillovers (e.g., Arvanitis & Hollenstein, 2011; Bloom et al., 2013; Jaffe, 1986; Peri, 2005). The basic idea for this effect is that knowledge spillovers offer additional know-how to companies that are able to absorb such knowledge. Equation (5) includes several measures for spillovers, which allows us to distinguish between spillovers from product and process technologies. Since the patent-related literature has not distinguished between product and process technologies so far, the effects of the different spillover measures on patent propensity are unclear from an empirical point of view. However, we would expect a lower effect for process spillovers. On the one hand, processes are more difficult to protect with patents, but they are also more difficult to understand and to imitate by others.

Heterogeneity tests – patent equation

It is very likely that the effects of knowledge capital on the generation of patented inventions differ by different firm characteristics. To this end, we run a series of estimations as heterogeneity tests. In a first test, we investigated whether the competitive environment affects the relationship between the different types of knowledge stocks and the probability to develop new technologies. We split the sample into companies that perceive intense price competition in their main sales market worldwide (values 4 and 5 on a 5-point scale).[30] On the one hand, intense price competition reduces companies' sales margins and limits the availability of internal capital to develop new technologies. On the other hand, competition increases the incentives to escape this competitive pressure through inventions (Aghion, Bloom, Blundell, Griffith, & Howitt, 2005). Thus, price competition could have positive but also negative effects on the relationship between the knowledge stocks and the probability of invention. It is also unclear whether the effects depend upon the type of knowledge stock.

In a second heterogeneity test, we examine whether access to international markets influences the relationship between the different types of knowledge capital and the likelihood of invention. The literature shows a clear picture: innovation is positively related with export intensity (e.g. Cassiman & Golovko, 2011; Pla-Barber & Alegre, 2007). However, it is unclear whether the relationship depends upon the type of knowledge. We therefore split the sample at the mean level of export

30 In the German innovation survey data, there is no unique indicator for measuring price competition over time. The following indicators were used for the following years, 2013 to 2016: values 3 and 4 on a 4-point scale of the item "increase in product price directly leads to loss of customers"; 2007 to 2012: values 3 and 4 on a 4-point scale of the item "our products can easily be substituted by competitors' products"; 2005 and 2006: values 4 and 5 on a 6-point scale of the item "intensity of competition with respect to price"; 2003 and 2004: price is the most important competitiveness factor (out of a list of six factors: price, product quality, technological advance, service/flexible response to customer requests, product variety, marketing/design).

intensity and conduct an estimation for companies with a lower export intensity and one for companies with a higher export intensity.

In a third heterogeneity test, we analyze whether there are differences between companies in the high-tech and low-tech sector[31]. Given that technological knowledge is more important for the competitiveness of high-tech companies, we would expect a stronger relationship between knowledge accumulation and inventions in this sector. Again, it is unclear whether this relationship is driven by knowledge accumulation of product technologies or process technologies.

In a final heterogeneity test, we investigate whether public support affects the relationships between a company's different knowledge capital stocks and the likelihood of developing new inventions. Dependent on the pursued promotion policies, publicly supported companies might show different effects for product or process-related knowledge stocks. For instance, Switzerland's main promotion agency, Innosuisse, pursues a bottom-up approach and does not run program-oriented promotion activities (top-down). Hence, we hardly expect significant differences between publicly supported and not-supported companies. The promotion activities in Germany are much more heterogeneous. They apply both bottom-up and top-down designed policy instruments and we can expect differences between publicly promoted and non-promoted companies, for instance if promotion programs focus more on product development than on process development.

Estimation procedure

We use a Poisson estimator with firm-level fixed effects as our dependent variable has positive integer values. We estimate heteroscedasticity-robust standard errors that also correct for biased standard errors due to overdispersion (Cameron & Trivedi, 2010, p. 575). Although we control for unobserved time invariant heterogeneity (firm-fixed effects), coefficients cannot be interpreted causally. Unobserved time-variant factors might bias our coefficients. For instance, unobserved changes in the corporate's strategy or significant changes in the management of a company might influence both, the accumulation of certain knowledge stocks and the strategy to patent inventions. Even though we cannot control for such events, our comprehensive control vector takes into account the theoretically most important factors that drive the innovation activities of a company (Cohen, 2010).

5.1.2 Results

Table 5 and Table 6 present the estimation results for Switzerland and Germany respectively. Against the background of the existing literature (e.g., Bloom, Schankerman, & Van Reenen, 2013; Porter & Stern, 2000), we would expect a positive and significant relationship between the knowledge stock of a company and the number of new patent filings. This is indeed the case if we

31 High-tech industries: chemical, pharmaceuticals, machinery and equipment, electrical equipment, electronic and optical products, medical instruments, watches/clocks, vehicles. Low-tech industries: the rest of the manufacturing industries, e.g. food, textiles, wood, printing, rubber and plastics, basic metals.

look at the knowledge stock related to product technologies (Product KS) for both countries. Even the size of the effect is similar. An increase of Product KS by 10% increases the number of patents by around 3% in both countries if we look at the estimations with a 2-year lag of the knowledge stocks. Expressed as an incidence-rate-ratio[32], the estimates show that the incidence of an additional patent amounts to about 37 percentage points in Switzerland and 39 percentage points in Germany if we increase Product KS by one unit (2-year lag). The estimates with a one-year lag of the knowledge stocks yield similar results.

Table 5: Patent Counts - Main - CH

	1 Year Lag	2 Year Lag	Product Stock	Process Stock	Mixed Stock
Product KS - 1 L	0.333**				
	(0.161)				
Product KS - 2 L		0.313**	0.078		
		(0.136)	(0.108)		
Process Use KS - 1 L	-0.383*				
	(0.200)				
Process Use KS - 2 L		-0.794***		-0.501***	
		(0.194)		(0.176)	
Mixed KS - 1 L	0.386***				
	(0.099)				
Mixed KS - 2 L		0.168			0.022
		(0.139)			(0.139)
Product SO - 1 L	-0.142				
	(0.273)				
Product SO - 2 L		0.170	-0.310*		
		(0.298)	(0.173)		
Process Use SO - 1 L	-0.030				
	(0.309)				
Process Use SO - 2 L		-1.329***		-0.458***	
		(0.429)		(0.168)	
Mixed SO - 1 L	-0.202				
	(0.199)				
Mixed SO - 2 L		0.855**			-0.219
		(0.359)			(0.147)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	974	823	823	823	823
Wald chi2	10388.812	10249.249	7804.244	5599.493	5905.501
P > chi2	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable (Patent Count) measures the annual average patent count of a firm. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

32 IRR (incidence-rate-ratio): $e^{\beta_i \Delta x_i}$, where x is the variable and β the coefficient

Table 6: Patent Counts – Main – DE

	1 Year Lag	2 Year Lag	Product Stock	Process Stock	Mixed Stock
Product KS - 1 L	0.406***				
	(0.120)				
Product KS - 2 L		0.339***	0.449***		
		(0.110)	(0.088)		
Process Use KS - 1 L	0.259**				
	(0.116)				
Process Use KS - 2 L		0.222*		0.404***	
		(0.127)		(0.104)	
Mixed KS - 1 L	0.136				
	(0.090)				
Mixed KS - 2 L		-0.045			0.348***
		(0.120)			(0.057)
Product SO - 1 L	-0.081				
	(0.210)				
Product SO - 2 L		0.199	0.142		
		(0.215)	(0.169)		
Process Use SO - 1 L	0.171				
	(0.474)				
Process Use SO - 2 L		0.153		0.113	
		(0.466)		(0.127)	
Mixed SO - 1 L	-0.160				
	(0.475)				
Mixed SO - 2 L		-0.178			0.033
		(0.469)			(0.144)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	4301	4157	4157	4157	4157
Wald chi2	1207.652	787.571	671.992	640.062	692.188
P > chi2	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable (Patent Count) measures the annual average patent count of a firm. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Process knowledge stock effects

While the Process Use KS and Product KS are both positively associated with new patent applications in Germany, we observe a different pattern for Switzerland. Here, process technologies show a negative association with new patents. An increase in the Process Use KS by one unit decreases the incidence-rate-ratio of an additional patent by 47 percentage points (one-year lag). The contribution of process knowledge to new inventions thus turns out to be negative on average. The differences across countries also extend to the Mixed KS. While the coefficient of Mixed KS is significantly and positively related with new patents in Switzerland, the respective coefficient is insignificant in Germany.

One reason for these differences might be the smaller domestic market for Swiss companies, which makes it more difficult – for technologically advanced companies – to achieve economies of scale. This limits the gains from process optimizations, and consequently decreases the demand for highly advanced pure process technologies. Another reason could be the specialization of many smaller companies in technological niches, e.g., in the field of medical technology or optical instruments. These niches are usually characterized by relatively high product dynamics and lower process dynamics and play an important role in Switzerland (Arvanitis, 1997). One further scenario could be that a highly specialized (tool) producer develops new product-related technologies in Switzerland at its headquarters and optimize the production processes at its production premises abroad. Hence, it is likely to observe the positive process knowledge effect at the affiliation abroad and less so in Switzerland. In contrast, Germany's major industries such as the car industry have a relatively high share of firms with process innovations (Centre for European Economic Research, 2018). Since they assemble the cars in Germany for a mass market, cost aspects are very important. This might drive the positive knowledge accumulation effects for process technologies. As many Swiss companies focus on niche markets, there was less cost awareness until recently.[33]

Table 7: Patent Counts – Heterogeneity – CH

	High Compet.	Low Compet.	High Exports	Low Exports	High Tech	Low Tech	Support	No Support
Product KS - 2 L	0.573***	0.606	0.266*	1.312***	0.292**	-0.270	0.352	0.196
	(0.207)	(0.402)	(0.155)	(0.364)	(0.129)	(0.775)	(0.293)	(0.217)
Process Use KS - 2 L	-1.346***	-0.746***	-0.521***	-1.399***	-0.758***	0.177	-1.254***	-0.584***
	(0.390)	(0.275)	(0.159)	(0.540)	(0.175)	(0.392)	(0.349)	(0.226)
Mixed KS - 2 L	0.166	-0.095	-0.036	-0.779*	0.061	0.069	0.648*	0.021
	(0.167)	(0.440)	(0.143)	(0.461)	(0.146)	(0.447)	(0.379)	(0.165)
Product SO - 2 L	0.134	2.183*	0.407*	-0.424	0.571**	-1.861**	1.422	-0.149
	(0.461)	(1.177)	(0.245)	(0.952)	(0.275)	(0.742)	(0.908)	(0.408)
Process Use SO - 2 L	-0.447	-4.494***	-1.073**	-0.459	-1.181***	-1.715	0.239	-0.660
	(0.593)	(1.458)	(0.427)	(1.276)	(0.410)	(1.532)	(1.144)	(0.714)
Mixed SO - 2 L	-0.006	2.795	0.547	-0.010	0.538	2.701**	-1.899	0.799
	(0.437)	(1.816)	(0.392)	(1.045)	(0.384)	(1.318)	(1.296)	(0.592)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	572	98	532	220	518	209	163	451
Wald chi2	7279.43	889.74	5000.98	905.64	3878.88	3441.02	15742.61	1246.24
P > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable (Patent Count) measures the annual average patent count of a firm. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The main effects hold for Swiss companies regardless of whether they are exposed to high or low price competition (Table 7, columns 2 and 3). For both subsamples, the relationship between Product KS and Patent Counts is positive and the relationship between Process Use KS and Patent Counts is negative. The coefficient for Product KS and companies with low price competition is statistically insignificant. This can be however due to the low number of observations in this group of companies. For German companies, we find a significantly positive coefficient of the product knowledge stock for companies in environments with both high and low price competition. In

33 According to the official Swiss Innovation Survey, cost reduction in a company's production process has recently gained additional importance (Spescha & Wörter, 2018). Very likely, the strong appreciation of the Swiss franc played an important role (Kaiser, Siegenthaler, Spescha, & Wörter, 2018)

contrast, process knowledge only contributes to new technological development if firms face high price competition (Table 8, columns 2 and 3).

Table 8: Patent Counts – Heterogeneity – DE

	High Compet.	Low Compet.	High Exports	Low Exports	High Tech	Low Tech	Support	No Support
Product KS - 2 L	0.421***	0.281**	0.293***	0.221*	0.349***	0.204**	0.404***	-0.003
	(0.125)	(0.113)	(0.109)	(0.123)	(0.126)	(0.098)	(0.110)	(0.097)
Process Use KS - 2 L	0.369**	-0.047	0.385***	0.104	0.274**	-0.032	-0.023	-0.189
	(0.184)	(0.133)	(0.145)	(0.128)	(0.134)	(0.113)	(0.149)	(0.155)
Mixed KS - 2 L	-0.134	0.045	-0.078	-0.062	-0.064	-0.057	0.112	0.431***
	(0.194)	(0.125)	(0.123)	(0.137)	(0.136)	(0.106)	(0.122)	(0.139)
Product SO - 2 L	0.212	-0.163	0.514**	0.017	0.446**	-0.319	0.351	0.021
	(0.214)	(0.280)	(0.200)	(0.336)	(0.193)	(0.320)	(0.277)	(0.339)
Process Use SO - 2 L	-0.050	0.551**	0.124	-0.110	0.090	0.272	-0.996*	-0.895*
	(0.656)	(0.263)	(0.520)	(0.271)	(0.465)	(0.287)	(0.552)	(0.468)
Mixed SO - 2 L	-0.078	-0.172	-0.441	0.379	-0.349	0.136	0.924	1.102**
	(0.683)	(0.252)	(0.539)	(0.247)	(0.466)	(0.349)	(0.604)	(0.448)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2213	1844	2745	1304	2453	1704	845	1325
Wald chi2	1869.42	1300.4	1398.65	733.759	686.354	742.221	8318.39	- *
P > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable (Patent Count) measures the annual average patent count of a firm. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
* Implausibly high Wald chi2

We also split the sample into firms with lower export shares (below mean) and higher export shares (above mean) (columns 4 and 5). Regardless of the export level of a company, we see a positive relationship between the Product KS and Patent Counts in Switzerland and Germany and a negative relationship between Process KS and Patent Counts in Switzerland. The results for Germany mirror the knowledge effects for environments that are characterized by high competition and the process knowledge only contributes to new technological developments if the exports are high. For smaller countries like Switzerland, access to international markets is very important, however, the intensity of exports seems to be less important. The export level does not affect the overall negative relationship between Process KS and Patent Counts in Switzerland. In sum, export level and international competition makes a greater difference for the knowledge effects in Germany than in Switzerland.

Most importantly, high-tech companies drive the overall results that Product KS is significantly and positively related with Patent Counts in both countries, while the Process Use KS coefficient is negative for Switzerland and positive for Germany (see Table 7 and Table 8, columns 6 and 7). The result for Germany indicates that new technological developments are driven by both product and process knowledge for high-tech firms. As already mentioned, this might have to do with the industry structure in Germany where developing complementary process technologies and cost optimization might be important, e.g., in the car industry. In Swiss high-tech companies, new technological developments are only driven by product knowledge. This points at important structural differences compared to the German high-tech firms.

One of the most important features of the Swiss innovation support system is the absence of direct support measures. In contrast to Germany, companies can only benefit from public funding (indirectly) if they cooperate with university partners. This special feature of Switzerland can help explain why there are not any differences between funded and non-funded companies (Table 7, columns 8 and 9). The results for Germany show a different picture. The positive and significant relationship between Product KS and Patent Counts can be only found in the group of supported companies. Companies that are not supported, on the other hand, show a positive effect of Mixed KS. This supports the notion that promotion is mainly product-oriented.

Spillover effects

Generally, one would expect positive spillovers from R&D activities on further technological developments as spillovers represent knowledge externalities, i.e. external knowledge that can be used by other firms in their own technology development without paying for it. While an extensive part of the literature found a positive effect of spillovers on the generation of technology (Griliches, 1992; Jaffe, 1986), there can be also negative spillovers in relation to R&D – for example due to a market stealing effect (Bloom et al., 2013) or when R&D is used strategically to preempt competition (Jones & Williams, 1998).

The results in this study partly mirror these ambiguous findings. Furthermore, there are indeed differences related to the type of the underlying knowledge stocks. In the main estimations, we do not find any spillover effects for Germany, but we find such effects for Switzerland (Table 5). First, the time lag seems to be important. Effects are only visible with a 2-year-lag because it takes time to absorb and utilize external knowledge. Second, we find a negative and significant spillover effect for pure process technologies. Third, there is a significantly positive spillover effects of mixed technologies. This indicates that Swiss firms are less likely to generate new technological developments not only if they have invested in own pure process technologies, but also if other firms that generate spillovers have invested in pure process technologies, perhaps because pure process technologies from other companies are more difficult to absorb and utilize than it is the case for product or mixed technologies.

The heterogeneity tests reveal some interesting patterns. Technological developments in high-tech companies and companies with intensive export activities benefit from product technology spillovers in both Germany and Switzerland. The higher absorptive capacity of such companies in order to understand and exploit related technological activities of other companies and the strategic importance of new technological developments to position itself at the technological frontier might be reasons for these findings. Indeed, low-tech companies in Switzerland that have in general a lower absorptive capacity show significant and negative spillover effects from pure product technologies. Instead, low-tech companies benefit from spillovers from inventions that comprise both product and process technological elements (Mixed SO). Such technologies seem to better match the lower absorptive capacity of low-tech companies, maybe because they are less specialized and easier to absorb than pure product or process technologies as they require less additional development work from the adopting firm.

In Switzerland, we further find that the negative spillovers from process technologies can be attributed to firms in industries with low competition and high-tech products. In contrast, in Germany, we find a positive and significant coefficient for Process SO in industries with low competition, but not in industries with high competition.

In sum, the results for Switzerland shows some important differences as compared to Germany that refer to the presence of negative associations between process knowledge stocks and spillovers and new patented inventions. The Swiss high-tech industry seems to reflect a Schumpeter Mark I pattern with fewer incumbents and perhaps a lower degree of appropriability, whereas the German high-tech industry seems to follow a Schumpeter Mark II pattern to a higher degree. However, the results should be interpreted with caution, as there are not any theoretical guidelines on how to interpret differences in effects from product and process knowledge with respect to different patterns of innovation.[34]

5.2 Productivity effects of product and process knowledge

In this section, we investigate productivity effects of product and process knowledge econometrically where product and process knowledge is again proxied with the product and process patent stock, respectively.

5.2.1 Measurement and econometric model

Measurement

We use total factor productivity (TFP) as the measure for the economic performance of a company. TFP is defined as the part of gross production value (production output in physical units multiplied with market output prices), which cannot be explained by standard input factors. Therefore, TFP is not directly observable; it has to be calculated out of the residuals from the estimation of the respective production function. This is the main idea of the productivity concepts developed by

[34] “Schumpeter Mark II patterns (characterised by high degrees of concentration of innovative activities, high stability in the ranking of innovators and low relevance of new innovators) are related to high degrees of cumulativeness and appropriability, high importance of basic sciences and relatively low importance of applied sciences as sources of innovation. Schumpeter Mark I patterns (characterised by low concentration of innovative activities, low stability in the ranking of innovators and high relevance of new innovators) are related to low degrees of cumulativeness and appropriability, and high importance of applied sciences and an increasing role of external sources of knowledge.” (Breschi, Malerba, & Orsenigo, 2000).

Levinsohn & Petrin (2003) and Olley & Pakes (1996), and further developed by Doraszelski & Jaumandreu (2013) and Loecker & Frederic (2012), and most recently by Ackerberg, Caves, & Frazer (2015).[35]

We constructed the TFP variable according to Ackerberg et al. (2015). We specified a production equation based on value added (sales minus intermediate material and service inputs) as output variable and physical capital (calculated by the perpetual inventory method with a 5.6% depreciation rate based on annual investment data) and labor (number of employees in full time equivalents) as standard input factors. In order to calculate the initial physical capital stock, we used a growth rate of 1.8%.[36] Exogenous variation to identify TFP out of the residuals of the OLS estimates of the production function comes from the intermediate inputs as suggested by Levinsohn & Petrin (2003). Moreover, we followed Ackerberg et al. (ACF) (2015) to address the functional dependence problem of labor.[37] Here, it is assumed that labor is a dynamic input, meaning that the current choice has an impact on the future cost of input use. This prevents the labor coefficient from being estimated in the first stage.

Specification of the TFP estimation

The main explanatory variables are the measures for the accumulated knowledge in product technologies (Product KS), in process technologies (Process Use KS), and mixed technologies containing both product and process-related knowledge (Mixed KS). Following the literature on the importance of spillovers for the productivity of a company (Añón Higón, 2007; Bloom, Schankerman, & Van Reenen, 2013; Eberhardt, Helmers, & Strauss, 2013, and Ugur, Trushin, Solomon, & Guidi, 2016), we add proxies for spillovers resulting from the product (Product SO), process (Process Use SO), or mixed (Mixed SO) knowledge stocks of other companies.[38] We also included control variables to capture important unobserved factors that might bias the estimated relationship between the different knowledge stocks. This control vector (*X*) includes variables for technological potential, price competition, and appropriability (see Table 19 and Table 20 in the Appendix). Finally, we included time dummies (*t*) to capture time-specific unobserved economic shocks such as the financial crisis in 2008. ε_{it} is the stochastic error.

35 Levinsohn & Petrin (2003) extended the Olley & Pakes (1996) approach to solve the issue of endogenous labor and capital coefficients when estimating standard production functions. While Olley & Pakes (1996) used capital investments, Levinsohn & Petrin (2003) used intermediate inputs to proxy for the unobserved TFP term. Moreover, the Levinsohn and Petrin approach solved the truncation bias of the Olley and Pakes approach, which is caused by the fact that firm investments often take the value of zero. Olley and Pakes (1996, p. 1274) explicitly assumed that labor is the only variable factor. The De Loecker and Frederic (2012) approach allowed for relaxing the assumption of constant returns to scale and measuring the user cost of capital (p. 2438). Ackerberg et al. (2015) allowed for dynamic labor effects by further relaxing the assumptions in the above papers about the non-dynamic nature of labor, namely that it is the choice of a firm in period t and has no impact on future profits of the firm (p. 2417). This means that their model allows, e.g., for unobserved shocks on the price of labor or unobserved adjustment cost of labor input. Finally, Doraszelski and Jaumandreu (2013) included the innovation-productivity relationship in the TFP calculation and found higher elasticities of R&D expenditures on TFP.

36 We used the average growth rate and depreciation rate across all economic sectors (1991-2017) based on data from Germany. Physical capital stock data disaggregated at the industry-level are not available for Switzerland.

37 The functional dependence problem of labor means that labor is fully determined by capital and material. This implies that the contribution of labor to the output cannot be separately identified since productivity is also determined by these factors (Ackerberg et al., 2015, p.2422).

38 For the measurement of the knowledge stocks and the spillover variables, see sections 3.3.3 and 3.3.4.

$$TFP_{it} = \beta_0 + \beta_1 Product\ KS_{it-2} + \beta_2 Process\ Use\ KS_{it-2} + \beta_3 Mixed\ KS_{it-2} + \beta_4 Product\ SO_{it-2} + \beta_5 Process\ Use\ SO_{it-2} + \beta_6 Mixed\ SO_{it-2} + X\gamma_{it} + t_t + \varepsilon_{it} \quad (6)$$

Based on the available literature, it can be assumed that the returns from the accumulation of process knowledge are higher than those from product knowledge (Clark & Griliches, 1998; Griliches & Lichtenberg, 1984; Mohnen & Hall, 2013; Scherer, 1982, 1983). First, process technologies are most likely used internally in order to improve the production process (i.e., to reduce costs) and to improve products (i.e., to improve quality). Our descriptive analysis implies this, but it is also difficult to imagine how pure process patents that define new methods could be sold as product. Second, product technologies take longer than process technologies to show productivity effects. This is due to the fact that new products reach their sales peak a few years after market launch, while development costs are incurred immediately. This means that productivity effects of product technologies occur after a longer time lag. This makes their measurement difficult, especially with – as in this case – an 'unbalanced panel' of companies that are observed for a limited period of time. Third, product and process innovations are difficult to disentangle and are usually interdependent. When a company develops a new product, it frequently also changes its processes, and vice versa. However, the returns from product technologies are difficult to measure because new products are hardly reflected in official price indices and their return is therefore likely to be underestimated. New products can also cause undocumented adjustment costs that reduce productivity (Hall et al., 2010).

Spillovers from technological activities of other companies

The empirical literature does not yield a clear picture regarding the effects of spillovers on productivity. Añón Higón (2007) investigated a sample of UK manufacturing companies and only detected positive spillover effects for domestic R&D. Ugur et al. (2016) conducted a meta-regression analysis where they did not find any significant differences between firm-level private returns and within-industry social returns which points at insignificant spillover effects. They argue that either the underlying theoretical notions or the measurement of spillovers or both are inadequate. They agree with Eberhardt et al. (2013) that identification issues of private and social returns in the production function or measurement issues (Bloom et al., 2013) might play a role for these results. Consequently, we do not have a-priori expectations about the spillover effects.

Heterogeneity tests - TFP estimations

Similar to the patent equation, we estimate different specifications to investigate the heterogeneity of the main effects. In a first heterogeneity test, we investigate the significance of the competitive environment of a company for the returns from process or product-related technological activities. For that purpose, we split the sample into markets with high price competition (values 4 and 5 on a 5-point scale) and low price competition (values 1 to 3). We assume that intense price competition increases the incentive to invest in the development of both product and process technologies, however, it also decreases the opportunities to do so since companies in those markets lack financial resources (Czarnitzki & Hottenrott, 2017; Dasgupta & Stiglitz, 1980; B. H. Hall & Lerner, 2010; Martin, 1993). Hence, it is an open question whether it has an impact on the returns from product and process technologies.

In a second heterogeneity test, we investigate whether the importance of international sales markets impact the relationship between product/process technologies and TFP. For that purpose, we split the sample into companies with high-levels of export activities (above mean) and companies with no or lower levels (below mean) of exports. A greater exposure to large markets should increase the returns from innovation activities (Acemoglu & Linn, 2004; Becker & Egger, 2013; Cassiman & Golovko, 2011), however, we do not know anything about differences regarding product and process technologies so far.

In a third heterogeneity test, we analyse potential differences in the returns from product and process technologies between companies in high-tech industries and companies in low-tech industries.[39] We would assume that the returns from technological activities for high-tech companies are larger than for low-tech companies. They have a higher absorptive capacity (Cohen & Levinthal, 1990), are more exposed to international competition, develop technologies at the frontier, and dispose of complementary assets (e.g., international marketing and sales structure) (Cohen, 2010) that increase the potential returns from technological activities. Again, it is unknown whether there are differences for product and process technologies.

In a final heterogeneity test, we investigate the effectiveness of subsidies and split the sample into companies that have received public support and those that have not received it in order to detect whether it affects the relationship between product/process technologies and TFP. Many authors have reported lower returns from publicly-funded R&D compared to private R&D (Griliches, 1986; Levy & Terleckyj, 1989; Lichtenberg & Siegel, 1991). On the one hand, it can be the case that publicly financed R&D is carried out less efficiently, on the other hand, the type of projects may differ. First, public funds often go into riskier projects. Second, they are often directed towards projects with a significantly greater social than private value (e.g., some health technologies). Third, public funds should trigger additional private funds and consequently the effects are indirect and much more difficult to measure (Hall et al., 2010). The existing literature hardly distinguishes between the effects of subsidies for the development of product and process technologies.

Estimation procedure

In the main estimations, we use the dynamic panel estimator suggested by Blundell & Bond (1998). We use this complex estimation strategy for three reasons. First, productivity is correlated over time. Second, the impact of current R&D on future productivity depends crucially on current productivity (Doraszelski & Jaumandreu, 2013). Third, we cannot exclude the possibility that

39 High-tech industries: chemical, pharmaceuticals, machinery and equipment, electrical equipment, electronic and optical products, medical instruments, watches/clocks, vehicles. Low-tech industries: the rest of the manufacturing industries, e.g. food, textiles, wood, printing, rubber and plastics, basic metals.

unobserved time-variant heterogeneity biases the coefficients of the knowledge stock variables. Blundell & Bond (1998) address these estimation problems by using moment conditions in which lagged differences are used as instruments for the level equation in addition to the moment conditions of lagged levels as instruments for the difference equation. The Hansen test of overidentification restriction confirms the validity of the instruments in each equation. We apply a time lag of two periods for the knowledge capital variables to further reduce the possibility of reverse causality effects. We also include a set of control variables and time dummies to increase the precision of the estimates of the knowledge stock variables (see Equation (6)).

5.2.2 Results

Table 9 and Table 10 present the main results for the effects of different knowledge stocks on productivity, measured by TFP. For Switzerland, we can confirm the main results from literature: knowledge accumulation is significantly and positively related with productivity (column 2) (Hall et al., 2010). In Germany, the compound knowledge stock does not have a significant coefficient. This is however in line with findings from Crass & Peters (2014) who found that patents show only weak productivity effects in Germany.

In addition to those standard results, we find that the positive effect can be attributed to process-related knowledge (Process Use KS, column 3, Process KS column 4) and not pure product knowledge (Product KS). This result is in line with the a priori expectation of Mohnen & Hall (2013). They assume that process innovation has a clearer positive effect on productivity as new processes are often introduced in order to reduce production costs by saving some of the more costly inputs.

While in Switzerland the addition of Use KS to the Process KS yields a higher coefficient, the opposite is the case for Germany. Here, the coefficient of Process Use KS turns insignificant, while Process KS yields – similar to Switzerland – a significant and positive productivity effect. The reasons for these differences are unclear. In both countries, there are only few pure use patents and they are concentrated in few sectors (e.g. chemicals and pharmaceuticals, food industry). The usage of use patents by few companies might drive the results for Use KS in Germany, which might explain the differences. The results imply that it might be important to differentiate between process and use patents under certain circumstances. Because the results for Germany are affected by the Use KS, we estimated coefficients for the Process KS and the Use KS separately. In sum, the productivity effect of process knowledge in Germany is weaker as compared to Switzerland.

Table 9: Productivity (TFP) – Main – CH

	Patent Stock	All Stocks	All Stocks (Process & Use Separated)	Product Stocks	Process Stocks	Mixed Stocks
Patent KS - 2 L	0.063*					
	(0.033)					
Product KS - 2 L		-0.003	0.076	0.071*		

		(0.065)	(0.067)	(0.043)		
Process Use KS - 2 L		0.240***			0.202***	
		(0.090)			(0.061)	
Process KS - 2 L			0.146*			
			(0.084)			
Use KS - 2 L			-0.232			
			(0.353)			
Mixed KS - 2 L		-0.039	-0.042			0.058*
		(0.052)	(0.052)			(0.032)
Patent SO - 2 L	0.034					
	(0.044)					
Product SO - 2 L		0.062	0.153	0.046		
		(0.134)	(0.116)	(0.043)		
Process Use SO - 2 L		0.019			0.040	
		(0.132)			(0.048)	
Process SO - 2 L			-0.159			
			(0.140)			
Use SO - 2 L			0.126**			
			(0.058)			
Mixed SO - 2 L		0.004	0.005			0.030
		(0.176)	(0.151)			(0.045)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	786	786	786	786	786	786
Wald chi2	34.813	65.199	66.607	31.966	47.624	34.761

Note: The dependent variable (TFP) is estimated according to Ackerberg, Caves, Frazer (2015). Instruments for level equation are lagged differences. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability. The Arellano-Bond test for zero autocorrelation in first-differenced errors does not reject the null hypothesis of no serial correlation at order two. Hence, the moment conditions are valid. The Hansen test of overid restrictions confirms the validity of the instruments in each equation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Productivity (TFP) – Main – DE

	Patent Stock	All Stocks	All Stocks (Process & Use Separated)	Product Stocks	Process Stocks	Mixed Stocks
Patent KS - 2 L	-0.005					
	(0.036)					
Product KS - 2 L		0.028	0.004	-0.022		
		(0.038)	(0.028)	(0.046)		
Process Use KS - 2 L		-0.029			0.012	
		(0.099)			(0.051)	
Process KS - 2 L			0.086*			
			(0.045)			
Use KS - 2 L			-0.183			
			(0.170)			
Mixed KS - 2 L		0.020	0.011			-0.027
		(0.039)	(0.038)			(0.053)
Patent SO - 2 L	0.026					
	(0.067)					
Product SO - 2 L		-0.071	-0.028	-0.003		
		(0.066)	(0.106)	(0.077)		
Process Use SO - 2 L		-0.080			0.028	
		(0.099)			(0.046)	
Process SO - 2 L			-0.169			
			(0.137)			
Use SO - 2 L			-0.069			
			(0.063)			
Mixed SO - 2 L		0.154	0.277**			0.097
		(0.104)	(0.135)			(0.082)
Year fixed effect	3190	3190	3190	3190	3190	3190
Observations	223.183	324.239	451.184	212.184	223.933	162.610
Wald chi2	-0.005	0.028	0.004	-0.022	0.012	-0.027

Note: The dependent variable (TFP) is estimated according to Ackerberg, Caves, Frazer (2015). Instruments for level equation are lagged differences. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability. The Arellano-Bond test for zero autocorrelation in first-differenced errors does not reject the null hypothesis of no serial correlation at order two. Hence, the moment conditions are valid. The Hansen test of overid restrictions confirms the validity of the instruments in each equation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The investigation of the heterogeneity of the effects concerning the technological focus of an industry (high-tech, low-tech), price competition, export intensity, or public support yields very similar results for both German and Swiss companies and show that productivity effects are highly heterogeneous (Table 11 and Table 12).[40] In particular, companies exposed to high price competition show positive returns from process technologies, while this is not the case for companies in markets with low price competition. Similarly, companies with high export intensity benefit significantly from their process knowledge, but not companies with lower export intensity. It is perhaps more important to invest in process technologies if companies face tough competition which is the case for firms that are exposed to international markets. We also find a significantly positive Process KS coefficient for high-tech companies in Germany and a significantly positive Product KS coefficient for publicly supported companies in Switzerland. In the groups of companies

40 We again report coefficients for Process KS and Use KS separately for Germany.

that do not receive public funding, we again find positive productivity effects of process knowledge and negative ones for Mixed KS in both countries.

Table 11: Productivity (TFP) – Heterogeneity – CH

	High Compet.	Low Compet.	High Exports	Low Exports	High Tech	Low Tech	Support	No Support
Product KS - 2 L	0.007	0.073	0.030	-0.047	0.056	-0.094	0.141*	0.023
	(0.061)	(0.081)	(0.063)	(0.076)	(0.066)	(0.069)	(0.075)	(0.062)
Process Use KS - 2 L	0.307***	-0.007	0.208**	0.020	0.118	0.179	-0.002	0.183*
	(0.092)	(0.096)	(0.091)	(0.119)	(0.087)	(0.121)	(0.127)	(0.099)
Mixed KS - 2 L	-0.056	-0.005	-0.063	0.129	-0.051	-0.013	0.023	-0.089*
	(0.053)	(0.070)	(0.045)	(0.098)	(0.055)	(0.067)	(0.079)	(0.048)
Product SO - 2 L	0.086	0.023	0.059	-0.042	-0.220	0.252**	-0.504*	-0.097
	(0.138)	(0.106)	(0.149)	(0.109)	(0.143)	(0.106)	(0.272)	(0.111)
Process Use SO - 2 L	-0.134	0.129	0.136	-0.155	0.135	0.042	-0.051	-0.027
	(0.142)	(0.159)	(0.156)	(0.146)	(0.157)	(0.173)	(0.230)	(0.128)
Mixed SO - 2 L	0.113	-0.115	-0.130	0.234	0.138	-0.173	0.513	0.151
	(0.187)	(0.179)	(0.213)	(0.143)	(0.193)	(0.177)	(0.343)	(0.160)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	617	169	489	297	478	213	175	505
Wald chi2	69.238	27.831	93.041	35.001	54.810	75.147	25.842	92.662

Note: The dependent variable (TFP) is estimated according to Ackerberg, Caves, Frazer (2015). Instruments for level equation are lagged differences. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability. The Arellano-Bond test for zero autocorrelation in first-differenced errors does not reject the null hypothesis of no serial correlation at order two. Hence, the moment conditions are valid. The Hansen test of overid restrictions confirms the validity of the instruments in each equation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Productivity (TFP) – Heterogeneity – DE

	High Compet.	Low Compet.	High Exports	Low Exports	High Tech	Low Tech	Support	No Support
Product KS - 2 L	0.048	0.004	0.082	0.007	0.014	0.023	0.014	-0.014
	(0.113)	(0.037)	(0.068)	(0.040)	(0.058)	(0.026)	(0.043)	(0.037)
Process KS - 2 L	0.192**	-0.025	0.099*	0.121	0.202**	0.053	0.031	0.154**
	(0.075)	(0.046)	(0.052)	(0.083)	(0.093)	(0.049)	(0.049)	(0.073)
Use KS – 2 L	0.091	0.095	-0.292	-0.232*	-0.458	-0.029	0.012	-3.066
	(0.141)	(0.090)	(0.280)	(0.121)	(0.355)	(0.051)	(0.070)	(1.975)
Mixed KS - 2 L	-0.160	0.041	-0.121	0.104*	-0.047	-0.028	0.021	-0.153**
	(0.162)	(0.035)	(0.076)	(0.061)	(0.081)	(0.035)	(0.044)	(0.063)
Product SO - 2 L	0.014	-0.083	-0.049	-0.174*	0.054	-0.113*	-0.001	0.041
	(0.097)	(0.080)	(0.119)	(0.089)	(0.105)	(0.069)	(0.096)	(0.068)
Process SO - 2 L	-0.039	-0.152	-0.204	-0.018	-0.244*	-0.059	-0.059	-0.021
	(0.128)	(0.102)	(0.150)	(0.123)	(0.143)	(0.086)	(0.111)	(0.199)
Use SO – 2 L	-0.071	-0.086	-0.036	0.003	-0.076	0.074	0.009	0.042
	(0.084)	(0.056)	(0.082)	(0.058)	(0.091)	(0.055)	(0.058)	(0.079)
Mixed SO - 2 L	0.201	0.258**	0.386**	0.090	0.348**	0.102	0.075	0.083
	(0.127)	(0.129)	(0.180)	(0.143)	(0.166)	(0.118)	(0.128)	(0.191)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1759	1431	2065	1125	1956	1234	758	999
Wald chi2	379.759	580.214	536.468	478.260	416.224	601.256	1040.59	738.552

Note: The dependent variable (TFP) is estimated according to Ackerberg, Caves, Frazer (2015). Instruments for level equation are lagged differences. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability. The Arellano-Bond test for zero autocorrelation in first-differenced errors does not reject the null hypothesis of no serial correlation at order two. Hence, the moment conditions are valid. The Hansen test of overid restrictions confirms the validity of the instruments in each equation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Spillovers

Technological spillovers are of minor importance for productivity in both countries. This mirrors the general findings in the literature, where significant spillover effects for the productivity of companies occur only in specific circumstances or specific types of companies. This is also the case in the study at hand and the findings should be interpreted with great caution. However, we detect positive spillover effects from mixed patent stocks (Mixed SO) in the German sample (Table 10, column 4). According to Table 12, the mixed spillover effect can be attributed to low-tech and low-competition industries and companies with a high export intensity. Negative spillover effects are usually associated with a market steeling effect (Bloom et al., 2013). This refers to increased competition on the sales market due to spillovers. Such spillovers lower the profitability of new products and tend to decrease TFP. In Switzerland, this is only the case for Product SO in the subsample of publicly supported companies. Here, technological proximity and the associated spillovers are associated with lower productivity. Due to a larger domestic market and greater product market competition, negative spillover effects might be more frequent in the German sample. In particular, low-tech and low-exports companies that are more exposed to the domestic market characteristics show negative spillover effects from product technologies.

5.3 Life cycles

5.3.1 Measurement and econometric model

In addition to the descriptive analysis, we want to shed further light on the potential influence of technological life cycles on the relationships that we examined above. For this purpose, we constructed a unique variable that measures for each patent application whether it was filed in the upward slope of a life cycle or in the downward slope that might coincide with the end of a technological life cycle. We aggregated the information at firm level so that we are able to measure whether a firm files patent applications predominantly in technological life cycles showing an upward trend or not.

We started by querying all possible combinations of IPC subclasses available in PATSTAT, while many patents cover more than one IPC subclass. To give an example, the patent application EP2355317A1 filed by the Siemens AG has been assigned to 'H02M 1/12', 'H02M 5/458', and 'H02P 21/05'. Subclasses cover the first four digits of the IPC so that the patent application belongs to the subclass combination 'H02M, H02P' ('Electric machines not otherwise provided for', 'Control or regulation of electric motors electric generators or dynamo-electric converters; controlling transformers, reactors or choke coils'). In sum, we could find 1'193'770 combinations of IPC subclasses in PATSTAT.[41]

[41] We look at IPC subclasses rather than the complete IPC in order to keep the analysis tractable. There are of course many patents that only contain one subclass.

Combinations of technological fields have been often used in the literature on recombination and novelty (Strumsky & Lobo, 2015; Verhoeven, Bakker, & Veugelers, 2016). It is of course difficult to interpret combinations of IPC subclasses in this way and we do not claim to measure novelty or recombinatorial efforts accurately. Instead, we use the universe of combinations to trace the development of patent applications in each respective combination. We allocate each filing to the respective combination and determine whether the overall development of patent activities is positive or negative.

For each combination, we applied a 'kernel-weighted local polynomial regression' of the number of patent applications at the USPTO and EPO on filing year and stored the smoothed values *y*. Figure 106 and Figure 107 show the smoothed values for two exemplary technological combinations. We calculated the difference between the smoothed number of patent applications in year *t* and year *t-1* for each combination and created a variable with value -1 if the difference is negative, +1 if it is positive, and 0 if it is zero. This indicator allows us to determine for each combination and year if the difference of the number of patent applications shows an upward or downward trend. For example, for the technological combination in Figure 106, part of the years show an upward trend (+1) and part of the years a negative trend (-1). In contrast, the trend in Figure 107 is always positive (+1) or neutral (0).[42]

Figure 106: Patent applications (EPO and USPTO) in subclasses A61F, A61L, D04H

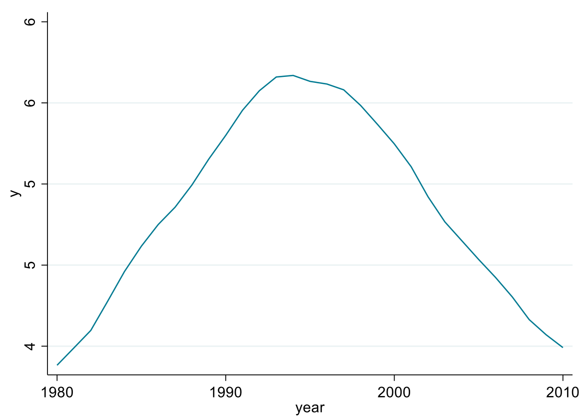
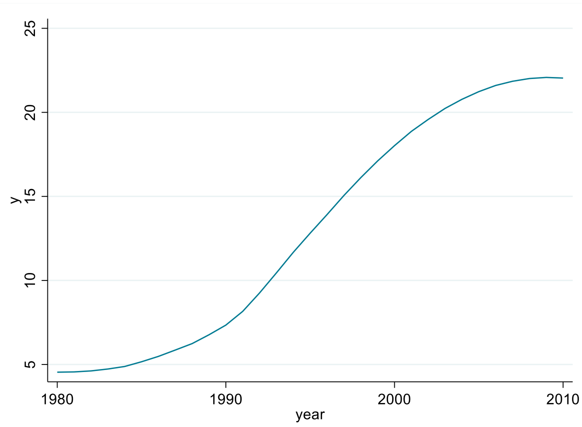


Figure 107: Patent applications (EPO and USPTO) in subclasses A61F, A63B



Afterwards we assigned each firm patent from the Swiss dataset to its particular technological combination, which results in a vector of -1s, 0s, and 1s for each firm-year. For example, (-1, 0, -1,1,1,1) means that a firm has filed six patent applications in year *t* with two being in the downward slope and three being in the upward slope of the respective curve of the technological combination. We then calculated the mean of these values for each firm and year (in this example, the mean is 3/6=0.5). The resulting variable allows us to position each firm according to whether its patents are

[42] The development in Figure 107 looks like a life cycle that is in its middle.

predominantly applied in growing technological combinations or declining technological combinations.

5.3.2 Results

Table 13 shows whether the state of the technological life cycle has an impact on the productivity effects of different knowledge stocks for Switzerland. Although there are only few companies in Switzerland that exclusively file their patents in growing technological life cycles (i.e., have a value of 1), we find that positive returns from the undifferentiated patent stock can be attributed to exactly those firms (column 2). If we distinguish between Product KS, Process Use KS, and Mixed KS and insert the differentiated patent stocks separately, we see the following pattern: Product KS shows a positive sign in case the company filed its product technology patents at the beginning of a technological life cycle with a positive and growing technological dynamic (==1) (column 6). Process Use KS, in contrast, only shows significant positive returns if the process technology patents are filed – at least partly – during decreasing technological dynamics towards the end of a technology life cycle (<1, column 9). For Mixed KS, we also find a positive coefficient if the technological dynamics are increasing (column 10).

Table 13: Productivity (TFP) – Technological Life Cycles – CH

	tech cycle == 1	tech cycle < 1	tech cycle == 1	tech cycle < 1	tech cycle == 1	tech cycle < 1	tech cycle == 1	tech cycle < 1	tech cycle == 1	tech cycle < 1
Patent KS - 2 L	0.282***	0.045								
	(0.105)	(0.031)								
Product KS - 2 L			0.129	-0.001	0.214**	0.064*				
			(0.100)	(0.058)	(0.095)	(0.039)				
Process Use KS - 2 L			0.039	0.380***			0.138	0.216***		
			(0.214)	(0.098)			(0.191)	(0.064)		
Mixed KS - 2 L			0.101	-0.106**					0.229**	0.048
			(0.081)	(0.048)					(0.100)	(0.031)
Patent SO - 2 L	-0.085	-0.009								
	(0.097)	(0.043)								
Product SO - 2 L			0.040	0.069	0.015	-0.002				
			(0.255)	(0.116)	(0.075)	(0.043)				
Process Use SO - 2 L			0.404	-0.051			0.065	-0.022		
			(0.277)	(0.127)			(0.088)	(0.047)		
Mixed SO - 2 L			-0.370	0.008					-0.053	-0.006
			(0.362)	(0.151)					(0.091)	(0.045)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94	690	94	690	94	690	94	690	94	690
Wald chi2	24.048	28.343	43.936	67.049	14.003	29.202	5.615	52.216	30.464	29.457

Note: The dependent variable (TFP) is estimated according to Ackerberg, Caves, Frazer (2015). Instruments for level equation are lagged differences. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability. The Arellano-Bond test for zero autocorrelation in first-differenced errors does not reject the null hypothesis of no serial correlation at order two. Hence, the moment conditions are valid. The Hansen test of overid restrictions confirms the validity of the instruments in each equation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The findings support the theoretical notions of Klepper (1996) and Utterback & Abernathy (1975), but to the best of our knowledge, benefits from product technologies and process technologies along a technological life cycle based on a comprehensive patent classification have never been investigated econometrically. With the data at hand, i.e. the classification of product and process patents and the fine-grained trace of technological life cycles in all possible IPC combinations combined with firm data, we are able to provide first evidence on the returns of product and process technologies against the life cycle theory.

5.4 Complementarity between trade secrets and process patenting

A further case study uses the survey question in the 2004, 2010, 2012, 2016 MIP surveys of whether a firm uses trade secrets in order to protect its inventions. We are interested in the question whether trade secrets that are used as complements of process patents can contribute to productivity. Crass, Garcia Valero, Pitton, & Rammer (2019) found that firms combining trade secrets with patent protection yield significantly higher sales with new-to-market innovations. In contrast, Ganglmair & Reimers (2019) studied the trade-off between secrecy and disclosure through product or process patents and their results seem to imply that trade secrets and patents (at least process patents) are rather substitutes than complements because stronger trade secrets protection result in a disproportionate decrease of process patents.

In this study, we can also distinguish whether the patent protection refers to product or process technologies. As noted above, firms often keep process technologies secret rather than patenting them. However, we can ask if the contribution of processes that are patented increases productivity if a firm also use trade secrets at the same time or if trade secrets substitute process patents.

To that end, we split the sample into companies that use trade secrets and companies that do not and run the TFP estimations for both samples of companies.[43] Otherwise, estimation procedures are identical to those applied in section 0. By comparing the results for firms with trade secrets in Table 14: (column 2) with the results for firm without trade secrets (column 3), we can see that the majority of companies with patent activities also use trade secrets to protect their knowledge. In addition, we find that the significantly positive relationship between Process KS and TFP can be only found for the subsample of firms with trade secrets. This suggests that trade secrets are a complement rather than a substitute for companies' process patent activities and their contribution to TFP. Of course, our approach is rather simplistic[44], but the results are a further indication that complementarities might exist regarding productivity effects.

43 Since the question on trade secrets is not available for all cross-sections, we interpolated the missing values for the respective cross-sections.

44 For example, we are not able to deal with the assignment problem; it is not clear whether trade secrets and process patents refer to the same invention.

Table 14: Productivity (TFP) and Trade Secrets – DE

	Trade Secrets	No Trade Secrets
Product KS - 2 L	0.024	-0.046
	(0.034)	(0.029)
Process KS - 2 L	0.092**	-0.015
	(0.044)	(0.089)
Use KS - 2 L	-0.165	-0.036
	(0.167)	(0.092)
Mixed KS - 2 L	-0.007	0.012
	(0.045)	(0.049)
Product SO - 2 L	-0.066	0.018
	(0.100)	(0.056)
Process SO - 2 L	-0.119	0.146
	(0.100)	(0.099)
Use SO - 2 L	-0.072	-0.016
	(0.071)	(0.037)
Mixed SO - 2 L	0.235**	-0.130
	(0.114)	(0.102)
Observations	2592	468
Wald chi2	529.886	4240.226

Note: The dependent variable (TFP) is estimated according to Ackerberg, Caves, Frazer (2015). Instruments for level equation are lagged differences. Heteroscedasticity-robust standard errors are in brackets. Controls include firm size, academic employees share, technological potential, price competition, foreign ownership and appropriability. The Arellano-Bond test for zero autocorrelation in first-differenced errors does not reject the null hypothesis of no serial correlation at order two. Hence, the moment conditions are valid. The Hansen test of overid restrictions confirms the validity of the instruments in each equation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusions

In this study, we developed an approach to distinguish product from process technologies based on full-text patent data from the EPO and USPTO. We applied both a keyword search and text mining methods on all available abstracts and claims which enabled us to differentiate product and process patents accurately. We showed that pure process patents that are defined as patents that only comprise process claims correlate with process innovations at firm level and that the shares of product, process and mixed patents (patents that contain both product and process claims) coincide with shares reported in interviews and more roughly with innovation activities reported in surveys.

In a comprehensive descriptive analysis, we showed that the share of mixed patents has become dominant in many inventor countries and technologies, especially in complex ones such as computers and telecommunications. Pure process patents play a minor role and the fraction of pure product patents decreases in many technologies across time. This pattern is particularly observable in technologies with a strong increase in patent activities (e.g. pictorial communication, electric digital data processing, transmission of digital information).

We make the resulting dataset publicly available in order to enable future research on topics such as technological life cycles and the improvement of existing patent-based indicators of technological innovations.

In the second part of this study, we combined the resulting classification of product and process patents with firm-level data from Germany and Switzerland. We estimated standard innovation and productivity equations in order to investigate differences regarding the product and process patent stock with respect to new technological developments and productivity. We were especially interested in whether a differentiation of product and process technological knowledge yields new insights.

In particular, we addressed the following research questions:

- Do process and product knowledge stocks differ in their contribution to **new patent applications**?
- Do product and process knowledge stocks show a different influence on the **productivity** of companies?
- Do **price competition**, **export intensity**, **industry affiliation** and **public innovation support** for innovation influence the relationship between the different knowledge stocks and the number of new inventions / productivity?
- Are the returns from product and process knowledge influenced by the **technological life cycle**?

- Are **trade secrets** a complement to process knowledge?

After having addressed these research questions, we can conclude that it is indeed useful to distinguish between product and process-related technological knowledge for several reasons:

a) **They show different effects on the number of newly generated patented inventions**. Our estimations confirm the standard results of a positive relationship between the knowledge stock of a company and the development of new technologies in the literature. This is true for product-related technological knowledge in both countries and for the process-related technological knowledge for German companies. Process-related technology knowledge in Switzerland shows a contrary effect. One likely reason for this country difference is the smaller domestic market for Swiss companies and their strategic focus on product niches, which limits the demand and need for process technologies.
b) **They show different spillovers for technological activities**. The estimations show that high-tech companies or companies with intensive export activities benefit from product technology spillovers but not from process technology spillovers. This is true for companies in both countries.
c) **They show different effects on the productivity of companies**. Although we can confirm the findings in the literature that the knowledge stock is significantly and positively related with productivity for the Swiss sample, we find that this overall effect is driven by process-related technological knowledge and not by product-related knowledge. We find very similar – albeit weaker – relationships in the sample of German companies. The productivity effect of process technological knowledge is driven by firms that are confronted with high price competition.
d) **Productivity effects of process and product knowledge depend on the state of the technological life cycle**. The empirical investigations confirm a positive relationship of product knowledge with productivity in the beginning of a technological life cycle and a positive relationship of process knowledge with productivity towards the end of life cycles.
e) **Trade secrets appear to be complements to patented process inventions rather than substitutes, but they are not complementary to patented product inventions**. We find that German companies with trade secrets show a significant and positive relationship between knowledge related to process technologies and productivity, while companies without trade secrets do not. This suggests that trade secrets are complements rather than substitutes to companies' process patent activities.
f) **Even though mixed patents have become more and more important in numbers, product and process patents often show larger effects on new inventions and productivity.** This confirms our approach of creating three mutually exclusive categories of patents, namely pure product patents (i.e. patents that have only product claims), pure

process patents (patents that have only process claims), and mixed patents (patents with both product and process claims).

It is important to mention the **limitations** of this study. First, it is important to note that the results mainly refer to the sample of companies observed in our data sets and are not generalizable to other countries. Second, the German and Swiss Innovation Panels are both highly unbalanced panels where we applied rather demanding estimation techniques, namely a dynamic panel estimator (DPE) to consider the persistence of productivity. The DPE (partly) balances the panel and reduces the number of observations considerably which might affect the representativeness of the results for the whole economy. Third, classifying the whole universe of patent filings comes at the cost of neglecting details in the drafting of patents that can be important to understand the inventions' contents. Fourth, the descriptive analysis shows a large heterogeneity across technologies and countries and for some technologies across patent offices and dependent on whether we consider dependent or independent claims. We are not yet able to fully comprehend all those complexities.

Future research should address these limitations by further improving the classification methods and available panel datasets and by including further countries in the econometric analysis. It is also important to better understand the development of process and product inventions in different technologies, especially why more and more patents have both product and process claims and how technological exhaustion can be measured. Finally, a large-scale technology study could analyze whether, e.g., process technologies in the field of semiconductors show different returns than in the field of transport technologies.

7 References

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Appendix

A.1 Set of stop words

a|about|above|after|again|against|all|am|an|and|any|are|as|at|be|because|been|before|being|blow|
between|both|but|by|could|did|do|does|doing|down|during|each|few|for|from|further|had|has|have|
having|he|her|here|hers|herself|him|himself|his|how|i|if|in|into|is|it|its|itself|me|more|most|my|
myself|nor|of|on|once|only|or|other|ought|our|ours|ourselves|
out|over|own|same|she|should|so|some|such|than|that|the|their|theirs|them|themselves|
then|there|these|they|this|those|through|to|too|under|until|up|very|was|we|were|what|
when|where|which|while|who|whom|why|with|would|you|your|yours|yourself|yourselves|
i|me|my|myself|we|our|ours|ourselves|you|your|yours|yourself|yourselves|he|him|his|himself|
she|her|hers|herself|it|its|itself|they|them|their|theirs|themselves|what|which|who|whom|this|that|
these|those|am|is|are|was|were|be|been|being|have|has|had|having|do|does|did|doing|
a|an|the|and|but|if|or|because|as|until|while|of|at|by|for|with|about|against|between|
into|through|during|before|after|above|below|to|from|up|down|in|out|on|off|over|under|again|
further|then|once|here|there|when|where|why|how|all|any|both|each|few|more|most|other|some|such|no|nor|not|
only|own|same|so|than|too|very|s|t|can|will|just|don|should|now|wherein|thereof|
au|aux|avec|ce|ces|dans|de|des|du|elle|en|et|eux|il|je|la|le|leur|lui|ma|mais|me|même|mes|moi|mon|ne|nos|notre|
nous|on|ou|par|pas|pour|qu|que|qui|sa|se|les|ses|son|sur|ta|te|tes|toi|ton|tu|un|une|vos|
votre|vous|c|d|j|l|à|m|n|s|t|y|été|étée|étées|étés|étant|étante|étants|étantes|suis|es|est|
sommes|êtes|sont|serai|seras|sera|serons|serez|seront|serais|serait|serions|seriez|seraient|
étais|était|étions|étiez|étaient|fus|fut|fûmes|fûtes|furent|sois|soit|soyons|soyez|soient|fusse|fusses|fût|fussions|fuss
iez|fussent|ayant|ayante|ayantes|ayants|eu|eue|eues|eus|ai|as|avons|avez|
ont|aurai|auras|aura|aurons|aurez|auront|aurais|aurait|aurions|auriez|auraient|avais|avait|
avions|aviez|avaient|eut|eûmes|eûtes|eurent|aie|aies|ait|ayons|ayez|aient|eusse|eusses|eût|eussions|eussiez|
eussent|
aber|alle|allem|allen|aller|alles|als|also|am|an|ander|andere|anderem|anderen|anderer|anderes|anderm|
andern|anderr|anders|auch|auf|aus|bei|bin|bis|bist|da|damit|dann|der|den|
des|dem|die|das|daß|derselbe|derselben|denselben|desselben|demselben|dieselbe|dieselben|
dasselbe|dazu|dein|deine|deinem|deinen|deiner|deines|denn|derer|dessen|dich|dir|du|dies|
diese|diesem|diesen|dieser|dieses|doch|dort|durch|ein|eine|einem|einen|einer|eines|einig|
einige|einigem|einigen|einiger|einiges|einmal|er|ihn|ihm|es|etwas|euer|eure|eurem|euren|
eurer|eures|für|gegen|gewesen|hab|habe|haben|hat|hatte|hatten|hier|hin|hinter|ich|mich
|mir|ihr|ihre|ihrem|ihren|ihrer|ihres|euch|im|in|indem|ins|ist|jede|jedem|jeden|jeder|jedes|jene
|jenem|jenen|jener|jenes|jetzt|kann|kein|keine|keinem|keinen|keiner|keines|können|könnte
|machen|man|manche|manchem|manchen|mancher|manches|mein|meine|meinem
|meinen|meiner|meines|mit|muss|musste|nach|nicht|nichts|noch|nun|nur|ob|oder|ohne|sehr|sein|seine|seinem|
seinen|seiner|seines|selbst|sich|sie|ihnen|sind|so|solche|solchem|solchen|
solcher|solches|soll|sollte|sondern|sonst|über|um|und|uns|unse|unsem|unsen|unser|unses|
unter|viel|vom|von|vor|während|war|waren|warst|was|weg|weil|weiter|welche|welchem
|welchen|welcher|welches|wenn|werde|werden|wie|wieder|will|wir|wird|wirst|wo|
wollen|wollte|würde|würden|zu|zum|zur|zwar|zwischen|dadurch|dass|wobei|gekennzeichnet|

A.2 Examples of abstract and claim classification

(19) **United States**
(12) **Patent Application Publication** (10) **Pub. No.: US 2019/0329775 A1**
JUNGNICKEL et al. (43) **Pub. Date: Oct. 31, 2019**

(54) **CONTROLLER FOR A MOTOR VEHICLE, MOTOR VEHICLE, AND METHOD FOR CONTROLLING A MOTOR VEHICLE**

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(57) **ABSTRACT**

A controller for a motor vehicle (**1**) has an internal combustion engine (**3**), a transmission (**4**), and a cooling device (**5**) with a coolant (**5***b*) for cooling the internal combustion engine (**3**), wherein the controller (**2**) is configured to determine a target minimum rotational speed for the internal combustion engine (**3**) on the basis of the temperature of the internal combustion engine (**3**) and/or the temperature of the coolant (**5***b*) and to determine a target gear setting on the basis of the target minimum rotational speed.

Abstract does not contain any process keyword.
Based on the abstract classification, this is a product patent application.

1. A controller for a motor vehicle that has an internal combustion engine, a transmission and a cooling device with a coolant in order to cool the internal combustion engine, whereby the controller is configured to: determine a target minimum rotational speed for the internal combustion engine on the basis of the temperature of the internal combustion engine and/or on the basis of the temperature of the coolant; and determine a target gear setting on the basis of the target minimum rotational speed. **2**. The controller according to claim **1**, whereby the transmission is configured as an automatic transmission and the controller is configured to control the transmission on the basis of the determined target gear setting. **3**. The controller according to claim **1**, whereby the transmission is configured as a manual transmission and the controller is configured to issue a gear recommendation on the basis of the determined target gear setting. **4**. The controller according to claim **1**, whereby the target minimum rotational speed is determined in order to minimize the thermal loading of the internal combustion engine. **5**. The controller according to claim **1**, whereby the target minimum rotational speed is determined if the temperature of the internal combustion engine exceeds a temperature threshold value and/or if the temperature of the coolant exceeds a temperature threshold value. **6**. The controller according to claim **1**, whereby the controller has an engine control section and a transmission control section, whereby the engine control section determines the target minimum rotational speed and the transmission control section determines the target gear setting. **7**. The controller according to claim **6**, whereby the motor vehicle has a data bus, and whereby the engine control section transmits the target minimum rotational speed to the transmission control section via the data bus. **8**. The controller according to claim **1**, whereby the determination of the target minimum rotational speed is carried out incrementally. **9**. A motor vehicle that has an internal combustion engine, a transmission and a cooling device with a coolant in order to cool the internal combustion engine, as well as a controller according to claim **1**. **10**. A method for controlling a motor vehicle that has an internal combustion engine, a transmission and a cooling device with a coolant in order to cool the internal combustion engine, whereby the method comprises: determining a target minimum rotational speed for the internal combustion engine on the basis of the temperature of the internal combustion engine and/or on the basis of the temperature of the coolant; and determining a target gear setting on the basis of the target minimum rotational speed. **11**. The method according to claim **10**, whereby the transmission is configured as an automatic transmission and the method further comprises controlling the transmission on the basis of the determined target gear setting. **12**. The method according to claim **10**, whereby the transmission is configured as a manual transmission and the method further comprises issuing a gear recommendation on the basis of the determined target gear setting.	Patent application contains 6 claims with process keyword in the first two to five words. In sum, the patent application has 15 claims. It thus has a process share of 6/15. Moreover, it is a mixed patent according to the claim classification because it contains both product and process claims.

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13. The method according to claim **10**, whereby the target minimum rotational speed is determined in order to minimize the thermal loading of the internal combustion engine.

14. The method according to claim **10**, whereby the target minimum rotational speed is determined if the temperature of the internal combustion engine exceeds a temperature threshold value and/or if the temperature of the coolant exceeds a temperature threshold value.

15. The method according to claim **10**, whereby the determination of the target minimum rotational speed is carried out incrementally.

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(54) **COMBINATION COMPRISING AN MEK INHIBITOR AND A B-RAF INHIBITOR**

(57) A novel combination comprising the MEK inhibitor N-{3-[3-cyclopropyl-5-(2-fluoro-4-iodo-phenylamino)6,8-dimethyl;-2,4,7-trioxo-3,4,6,7-tetrahydro-2H-pyrido[4,3-d]pyrimidin-1-yl]phenyl}acetamide, or a pharmaceutically acceptable salt or solvate thereof, with a B-Raf inhibitor, particularly *N*-{3-[5-(2-Amino-4-pyrimidinyl)-2-(1,1-dimethylethyl)-1,3-thiazol-4-yl]-2-fluorophenyl}-2,6-difluorobenzenesulfonamide or a pharmaceutically acceptable salt thereof, pharmaceutical compositions comprising the same and methods of using such combinations and compositions in the treatment of conditions in which the inhibition of MEK and/or B-Raf is beneficial, eg. cancer.

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Abstract contains process keyword (‘methods’). Patent application is classified as process patent according to the abstract classification.

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Claims:
1. A combination comprising:(i) a compound of formula (I)
or a pharmaceutically acceptable salt or solvate thereof;
and
(ii) a compound of formula (II)
or a pharmaceutically acceptable salt thereof, for use in treating a cancer which is selected from: Barret's adenocarcinoma; billiary tract carcinomas; breast cancer; cervical cancer; cholangiocarcinoma; central nervous system tumors including primary CNS tumors such as glioblastomas, astrocytomas (e.g., glioblastoma multiforme) and ependymomas, and secondary CNS tumors (i.e., metastases to the central nervous system of tumors originating outside of the central

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One claim contains a use keyword. As the patent application has 15 claims, the use share is 1/15.
This is also a mixed patent according to our definitions.

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nervous system); colorectal cancer including large intestinal colon carcinoma; gastric cancer; carcinoma of the head and neck including squamous cell carcinoma of the head and neck; hematologic cancers including leukemias and lymphomas such as acute lymphoblastic leukemia, acute myelogenous leukemia (AML), myelodysplastic syndromes, chronic myelogenous leukemia, Hodgkin's lymphoma, non-Hodgkin's lymphoma, megakaryoblastic leukemia, multiple myeloma and erythroleukemia; hepatocellular carcinoma; lung cancer including small cell lung cancer and non-small cell lung cancer; ovarian cancer; endometrial cancer; pancreatic cancer; pituitary adenoma; prostate cancer; renal cancer; sarcoma; skin cancers; and thyroid cancers.

2. A combination for use according to claim 1 wherein the compound of formula (I) is in the form of the dimethylsulfoxide solvate and the compound of formula (II) is in the form of the methanesulfonate salt.

3. A combination kit or pharmaceutical composition for use in treating a cancer which is selected from: Barret's adenocarcinoma; billiary tract carcinomas; breast cancer; cervical cancer; cholangiocarcinoma; central nervous system tumors including primary CNS tumors such as glioblastomas, astrocytomas (e.g., glioblastoma multiforme) and ependymomas, and secondary CNS tumors (i.e., metastases to the central nervous system of tumors originating outside of the central nervous system); colorectal cancer including large intestinal colon carcinoma; gastric cancer; carcinoma of the head and neck including squamous cell carcinoma of the head and neck; hematologic cancers including leukemias and lymphomas such as acute lymphoblastic leukemia, acute myelogenous leukemia (AML), myelodysplastic syndromes, chronic myelogenous leukemia, Hodgkin's lymphoma, non-Hodgkin's lymphoma, megakaryoblastic leukemia, multiple myeloma and erythroleukemia; hepatocellular carcinoma; lung cancer including small cell lung cancer and non-small cell lung cancer; ovarian cancer; endometrial cancer; pancreatic cancer; pituitary adenoma; prostate cancer; renal cancer; sarcoma; skin cancers including melanomas; and thyroid cancers, wherein the combination kit comprises a combination defined in claim 1 or 2 together with a pharmaceutically acceptable carrier or carriers, or wherein the pharmaceutical composition comprises a combination defined in claim 1 or 2 together with a pharmaceutically acceptable diluent or carrier.

4. A combination for use according to claim 1 or 2, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the cancer is lung cancer.

5. A combination for use according to claim 1 or claim 2, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the cancer is small cell lung cancer.

6. A combination for use according to claim 1 or claim 2, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the cancer is non-small cell lung cancer.

7. A combination for use according to claim 1 or claim 2, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the cancer is BRAF<V600E> mutant skin or BRAF<V600E> mutant colon or BRAF<V600E> mutant lung cancer.

8. A combination for use according to claim 1 or claim 2, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the cancer is KRAS<G12S> mutant lung cancer.

9. A combination for use according to any one of claims 1 to 8, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the amount of the compound of formula (I) administered as part of the combination or combination kit is selected from 1mg to 7mg.

10. A combination for use according to any one of claims 1 to 9, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the amount of the compound of formula (I) administered as part of the combination or combination kit is 2mg.

11. A combination for use according to any one of claims 1 to 10, or a combination kit for use

according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the amount of the compound of formula (II) administered as part of the combination or combination kit is selected from 100mg to 200mg. 12. A combination for use according to any one of claims 1 to 11, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the amount of the compound of formula (II) administered as part of the combination or combination kit is 150mg. 13. A combination for use according to any one of claims 1 to 12, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein the compound of formula (II) is administered twice a day. 14. A combination for use according to any one of claims 1 to 13, or a combination kit for use according to claim 3, or a pharmaceutical composition for use according to claim 3, wherein one dose of the compound of formula (I) is administered simultaneously or separately with multiple doses of the compound of formula (II). 15. Use of a combination as described in claim 1 or claim 2 in the manufacture of a medicament for the treatment of a cancer which is selected from: Barret's adenocarcinoma; billiary tract carcinomas; breast cancer; cervical cancer; cholangiocarcinoma; central nervous system tumors including primary CNS tumors such as glioblastomas, astrocytomas (e.g., glioblastoma multiforme) and ependymomas, and secondary CNS tumors (i.e., metastases to the central nervous system of tumors originating outside of the central nervous system); colorectal cancer including large intestinal colon carcinoma; gastric cancer; carcinoma of the head and neck including squamous cell carcinoma of the head and neck; hematologic cancers including leukemias and lymphomas such as acute lymphoblastic leukemia, acute myelogenous leukemia (AML), myelodysplastic syndromes, chronic myelogenous leukemia, Hodgkin's lymphoma, non-Hodgkin's lymphoma, megakaryoblastic leukemia, multiple myeloma and erythroleukemia; hepatocellular carcinoma; lung cancer including small cell lung cancer and non-small cell lung cancer; ovarian cancer; endometrial cancer; pancreatic cancer; pituitary adenoma; prostate cancer; renal cancer; sarcoma; skin cancers; and thyroid cancers.	

A.3 Details on text mining analysis

In this section, we describe the analytical approach for classifying patent abstracts and claims into *product* and *process*. Our procedure is routine in predictive modeling and can be divided into four steps; data preprocessing (Section A.3.1), feature engineering (Section A.3.2), model selection (Section A.3.3) and hyper-parameter tuning (Section A.3.4).

A.3.1 Data preprocessing

Target label

The abstract texts sometimes contains both products and processes. In order to obtain a binary classification label, we assert that an abstract corresponds to a product patent if the number of products is greater or equal to the number of processes described in the abstract; otherwise it is labeled as a process. With respect to model training, we thus eliminate all duplicated texts and keep only the unique texts with the corresponding majority label.

Language

We restrict our analysis to claims and abstracts written in English language.

Text corpus

The following transformations are applied to the plain document text:

- Stripping white space.
- Removing punctuations.
- Making all characters lower case.
- Removing numbers.
- Removing stop words.
- Stemming, i.e., reducing words to their word stem.
- Removing words with fewer than four characters.

A.3.2 Feature engineering

The goal of extracting information from text in analytics is referred to as text mining. For the purpose of our analysis, we generate this information via a term-document matrix. The general concept is to compute the frequency f_{ik} of term t_i in document d_k and store the combined result in a $D \times N$ matrix M, where D is the number of documents and N is the number of unique terms appearing in the documents.

$$M = \begin{array}{c|cccc} & \text{method} & \text{product} & \cdots & \text{material} \\ \hline d_1 & 5 & 0 & \cdots & 1 \\ d_2 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_D & 10 & 0 & \cdots & 2 \end{array}$$

M is often a very sparse matrix containing many terms that rarely appear in documents and thus hardly provide useful information for differentiating the class label of documents. We address this issue by keeping only *5%* of the *N* unique terms. Furthermore, it is often advised to scale the term frequency in order to obtain better predictive results and help some machine learning models to converge faster. A common way to approach this, is to multiply the term frequency with the inverse document frequency w_i, which is computed as

$$\boldsymbol{w_i} = \boldsymbol{log}\left(\frac{\boldsymbol{D}}{\sum_{\boldsymbol{k=1}}^{\boldsymbol{D}} \prod(\boldsymbol{t_i} \in \boldsymbol{d_k})}\right), \tag{A.1}$$

where $\prod(t_i \in d_k)$ equals 1 if term t_i appears in document d_k, and 0 otherwise. However, for our final model, we chose *not* to scale the term frequency with w_i because estimating a *regularized* model on the unweighted term-document matrix yielded better predictive results.

A.3.3 Model selection

Our labeled dataset used for model training and evaluation includes 901 abstracts and 6994 claims, which is a comparably small proportion of the over 40 million abstracts and 190 million claims that we wish to classify by product and process. As a result, the term frequencies in our labeled data are potentially not entirely representative of the term frequencies in our full set of data. This can lead to model overfitting and in response, we choose to model our term-document matrix with a *regularized* logistic regression that adds a l_1 (lasso) and l_2 (ridge) penalty; a so-called elastic net (Zou and Hastie, 2005). The intuition of l_1-regularization is to set some parameters to zero, effectively reducing the number of features (terms) in the model. Instead, l_2-regularization results in smaller but non-zero parameter estimates.

Formally, given the linear model

$$E(Y|X = x) = \beta_0 + x^T\beta \,, \tag{A.2}$$

our goal is to minimize the loss function

$$L(x, y) = \frac{1}{2N}\sum_{i=1}^{n}\left(y_i - \beta_0 + x_i^T\beta\right)^2 + \lambda P_\alpha(\beta)\,, \tag{A.3}$$

where the first term is the sum of squared errors and the second term is the regularization term

$$P_\alpha = (1 - \alpha)\frac{1}{2}\|\beta\|_{l_2}^2 + \alpha\|\beta\|_{l_1}\,, \tag{A.4}$$

which is the weighted sum of penalties from ridge (α = 0) and lasso (α = 1) regression. The strength of regularization is determined by λ.

We use the `glmnet` package by Friedman et al., 2010, which implements fast algorithms for elastic nets in the statistical programming language R.

A.3.4 Hyper-parameter tuning

The optimal choice for λ and α is determined by repeated cross-validation. Thereby, the data is divided into K folds. The model is trained on $K - 1$ folds while leaving out 1 fold at a time for evaluation. This procedure is repeated N times and the data is shuffled before each repetition. Overall, this results in $E = N \cdot K$ evaluations of the model.

For our model selection, we try out the following hyper-parameter values

- $\alpha = [0.1, 0.5, 0.7, 0.9, 0.95, 0.99, 1]$ and
- $\lambda = [0, 0.1, 0.2, 0.3, \ldots, 10, 11, 12, 13, \ldots, 100]$,

which results in a tuning grid of $|\alpha| \cdot |\lambda| = 7637$. We choose the combination of α and λ with the highest average classification accuracy for 10-fold 5-times repeated cross-validation, i.e.,

$$\underset{\lambda,\alpha}{\arg\max} \; \frac{1}{50} \cdot \sum_{e=1}^{E=50} A_e \,. \tag{A.5}$$

A.3.5 Model evaluation

Binary classification performance is often illustrated in a 2x2 matrix as follows.

Table 15: Classification performance

		Prediction	
		Negative class	Positive class
Actual	Negative class	True negative (=TN)	False positive (=FP)
	Positive class	False negative (=FN)	True positive (=TP)

In our case, we set {Negative class: process; Positive class: product} and compute the following set of performance measures:

- *Accuracy* = $\frac{TP+TN}{TP+TN+FP+FN}$
- *BalancedAccuracy* = $\frac{1}{2}\left(\frac{TP}{TP+FN}+\frac{TN}{TN+FP}\right)$
- *Precision* = $\frac{TP}{TP+FP}$
- *Sensitivity* (or *Recall*) = $\frac{TP}{TP+FN}$
- *Specificity* = $\frac{TN}{TN+FP}$
- *F*1 = $2 \cdot \frac{Precision \cdot Recall}{Precision+Recall}$

In order to create the 2 x 2 classification matrix in the first place, we need to determine the threshold probability for classifying abstracts and claims as product or process. Here, we choose the top-left corner point of the receiver-operating characteristic (ROC) curve as illustrated in Figure 1. The ROC curve plots the true positive rate (Sensitivity) against the false positive rate (1 - Specificity) for various probability thresholds. As a result, the top-left corner point corresponds to the probability threshold that maximizes the sum of sensitivity and specificity, i.e,

$$\underset{t_p}{\arg\max} \quad \boldsymbol{Sensitivity} + \boldsymbol{Specificity}. \tag{A.6}$$

In addition to the performance measures derived from the 2 x 2 classification matrix, we also report the area under the ROC curve (AUC), which is often preferred when comparing the performance of binary classifiers because AUC is invariant of the probability threshold.

A.3.6 Results

In this section, we present the results of our methodological approach on the labeled data, which is split 70-30 into a training and test set. This results in 632 (4897) abstracts (claims) for training and 269 (2097) abstracts (claims) for testing. Hyper-parameters were tuned on the training set and the best parameter sets based on 10-fold 5-times repeated cross-validation are reported in Table 16.

After parameter tuning, the elastic net is re-fitted with the optimal hyper-parameters on the full training set and the resulting model is then used for predicting the test set labels. Table 17 shows the confusion matrices and Table 18 the performance measures. The corresponding ROC curves are depicted in Figure 108.

Based on this fairly good out-of-sample performance on the test set, both models were subsequently applied to the full list of over 40 million abstracts and 190 million claims respectively.

Table 16: Result of hyper-parameter tuning for labeled abstracts and claims training data

	Best α	Best λ	Training Accuracy
Abstracts	0.10	0.10	0.88
Claims	0.10	0.50	0.86

Shown are the optimal hyper-parameters for 10-fold 5-times repeated cross-validation and the corresponding accuracy on the abstracts (*N* = 632) and claims training set (*N* = 4897).

Table 17: Binary classification matrix of out-of-sample predictions for labeled abstracts and claims test data

Abstracts		Prediction	
		Process	Product
Actual	Process	42	9
	Product	69	149

Claims		Prediction	
		Process	Product
Actual	Process	427	188
	Product	119	1363

Shown are the predicted labels against the true labels for the abstracts (*N* = 269) and claims test set (*N* = 2097).

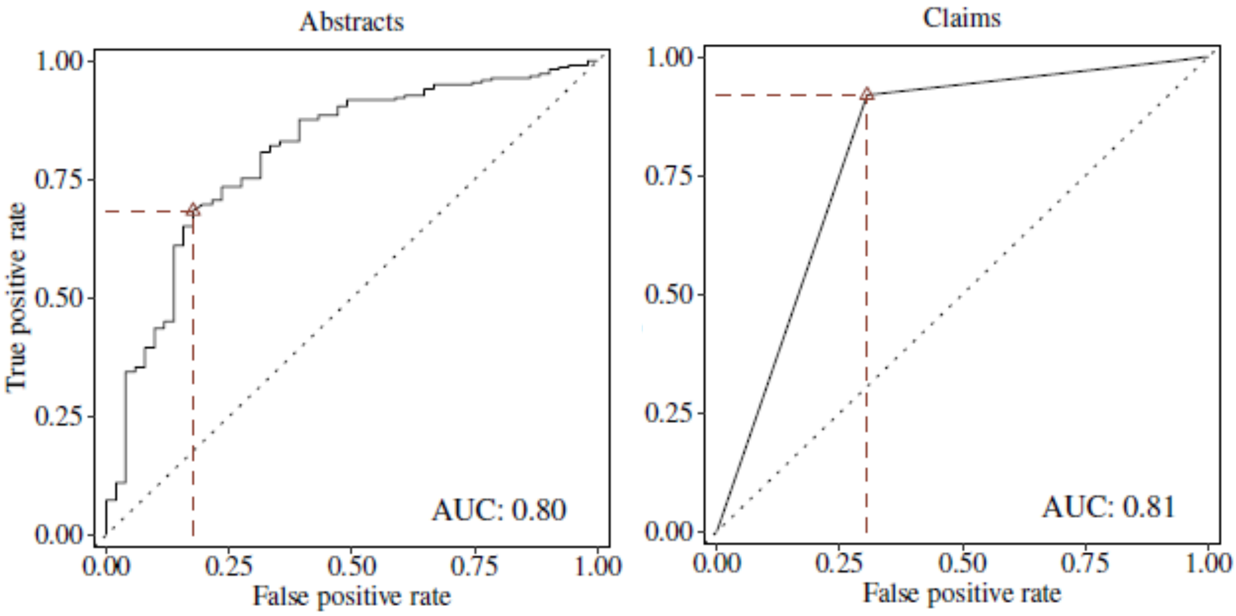
Table 18: Predictive out-of-sample performance for labeled abstracts and claims test data.

	AUC	Accuracy	Bal. Acc.	Precision	Sensitivity	Specificity	F1
Abstracts	0.75	0.71	0.75	0.94	0.82	0.68	0.79
Claims	0.81	0.85	0.81	0.88	0.69	0.92	0.90

Shown are area under the ROC curve (AUC), accuracy, balanced accuracy, precision, sensitivity, specificity and F1 score for the abstracts (*N* = 269) and claims test set (*N* = 2097).

Figure 108: Receiver-operating characteristic (ROC) curve for labeled abstracts and claims test data

Shown are the ROC curves and, in red, the point which maximizes the sum of specificity and sensitivity.



A.4 Variable description

Table 19: Variable Description – CH

	Description	Mean	SD	Min	Max	Obs
Patent Count	Patent count	8.63	35.70	0.00	396.00	974
Patent KS - 1 L	Knowledge stock based on patent counts, 1-year lag	2.27	1.55	0.01	7.83	974
Product KS - 1 L	Knowledge stock based on product patents, 1-year lag	1.66	1.39	0.00	6.90	974
Process KS - 1 L	Knowledge stock based on process patents, 1-year lag	0.53	1.01	0.00	5.35	974
Use KS - 1 L	Knowledge stock based on use patents, 1-year lag	0.04	0.25	0.00	3.35	974
Mixed KS - 1 L	Knowledge stock based on other patents, 1-year lag	1.57	1.53	0.00	7.27	974
Patent SO - 1 L	Spillovers based on patent counts, 1-year lag	5.72	1.24	1.37	8.04	974
Product SO - 1 L	Spillovers stock based on product patents, 1-year lag	4.84	1.09	0.83	6.84	974
Process SO - 1 L	Spillovers stock based on process patents, 1-year lag	3.21	1.20	0.09	5.88	974
Use SO - 1 L	Spillovers stock based on use patents, 1-year lag	0.63	0.79	0.00	3.82	974
Mixed SO - 1 L	Spillovers stock based on other patents, 1-year lag	4.97	1.40	0.51	7.66	974
Patent KS - 2 L	Knowledge stock based on patent counts, 2-year lag	2.29	1.55	0.01	7.81	874
Product KS - 2 L	Knowledge stock based on product patents, 2-year lag	1.65	1.40	0.00	6.89	874
Process Use KS - 2 L	Knowledge stock based on process and use patents, 2-year lag	0.55	1.02	0.00	5.39	874
Process KS - 2 L	Knowledge stock based on process patents, 2-year lag	0.54	1.01	0.00	5.35	874
Use KS - 2 L	Knowledge stock based on use patents, 2-year lag	0.05	0.25	0.00	3.51	874
Mixed KS - 2 L	Knowledge stock based on other patents, 2-year lag	1.59	1.53	0.00	7.24	874
Patent SO - 2 L	Spillovers based on patent counts, 2-year lag	5.76	1.23	1.22	8.04	874
Product SO - 2 L	Spillovers stock based on product patents, 2-year lag	4.87	1.10	0.33	6.83	874
Process Use SO - 2 L	Spillovers stock based on process and use patents, 2-year lag	3.31	1.21	0.10	5.99	874
Process SO - 2 L	Spillovers stock based on process patents, 2-year lag	3.26	1.20	0.10	5.87	874
Use SO - 2 L	Spillovers stock based on use patents, 2-year lag	0.67	0.81	0.00	3.90	874
Mixed SO - 2 L	Spillovers stock based on other patents, 2-year lag	5.03	1.36	0.50	7.65	874
Firm size	Firm size	5.52	1.25	1.61	10.09	974
Academic employees	Share of employees with college or university degree	9.97	12.75	0.00	90.00	974
Technological potential	Technological potential dummy	0.49	0.50	0.00	1.00	974
Price competition	Price competition dummy	0.79	0.41	0.00	1.00	974
Foreign ownership	Foreign ownership dummy	0.27	0.44	0.00	1.00	974
Appropriability	High appropriability dummy	0.46	0.50	0.00	1.00	974

All variables are per company and year. The summary statistics are sampled according to the sample used in the patent estimation (Table 5), meaning that we only consider company-years which are used in this estimation.

Table 20: Variable Description – D

	Description	Mean	SD	Min	Max	Obs
Patent Count	Patent count	6.58	20.62	0.00	375.00	4301
Patent KS - 1 L	Knowledge stock based on patent counts, 1-year lag	1.96	1.43	0.00	7.21	4301
Product KS - 1 L	Knowledge stock based on product patents, 1-year lag	1.45	1.31	0.00	6.31	4301
Process KS - 1 L	Knowledge stock based on process patents, 1-year lag	0.47	0.95	0.00	5.60	4301
Use KS - 1 L	Knowledge stock based on use patents, 1-year lag	0.07	0.31	0.00	3.22	4301
Mixed KS - 1 L	Knowledge stock based on other patents, 1-year lag	1.13	1.31	0.00	6.49	4301
Patent SO - 1 L	Spillovers based on patent counts, 1-year lag	7.10	1.04	0.11	9.07	4301
Product SO - 1 L	Spillovers stock based on product patents, 1-year lag	6.32	0.89	0.04	8.50	4301
Process SO - 1 L	Spillovers stock based on process patents, 1-year lag	4.78	1.26	0.00	7.56	4301
Use SO - 1 L	Spillovers stock based on use patents, 1-year lag	2.16	1.37	0.00	5.74	4301
Mixed SO - 1 L	Spillovers stock based on other patents, 1-year lag	6.07	1.28	0.00	8.59	4301
Patent KS - 2 L	Knowledge stock based on patent counts, 2-year lag	1.80	1.46	0.00	7.21	4300
Product KS - 2 L	Knowledge stock based on product patents, 2-year lag	1.33	1.30	0.00	6.31	4300
Process Use KS - 2 L	Knowledge stock based on process and use patents, 2-year lag	0.46	0.95	0.00	5.71	4300
Process KS - 2 L	Knowledge stock based on process patents, 2-year lag	0.43	0.92	0.00	5.60	4300
Use KS - 2 L	Knowledge stock based on use patents, 2-year lag	0.07	0.31	0.00	3.22	4300
Mixed KS - 2 L	Knowledge stock based on other patents, 2-year lag	1.02	1.29	0.00	6.49	4300
Patent SO - 2 L	Spillovers based on patent counts, 2-year lag	7.04	1.06	0.09	9.07	4181
Product SO - 2 L	Spillovers stock based on product patents, 2-year lag	6.26	0.90	0.04	8.50	4181
Process Use SO - 2 L	Spillovers stock based on process and use patents, 2-year lag	4.83	1.33	0.00	7.71	4181
Process SO - 2 L	Spillovers stock based on process patents, 2-year lag	4.74	1.30	0.00	7.56	4181
Use SO - 2 L	Spillovers stock based on use patents, 2-year lag	2.14	1.39	0.00	5.73	4181
Mixed SO - 2 L	Spillovers stock based on other patents, 2-year lag	5.99	1.31	0.00	8.59	4181
Firm size	Firm size	3920.00	18046.32	0.00	324203.00	4301
Academic employees	Share of employees with college or university degree	22.12	19.41	0.00	100.00	4301
Technological potential	Technological potential dummy	0.36	0.48	0.00	1.00	4301
Price competition	Price competition dummy (-1 if missing)	0.54	0.50	0.00	1.00	4301
Foreign ownership	Foreign ownership dummy	0.10	0.31	0.00	1.00	4301
Appropriability	High appropriability dummy (-1 if missing)	-0.73	0.60	-1.00	1.00	4301

All variables are per company and year. The summary statistics are sampled according to the sample used in the patent estimation Table 6, meaning that we only consider company-years which are used in this estimation.