A new Dataset to Study a Century of Innovation in Europe and in the US*

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Abstract

Innovation is an important driver of potential growth but quantitative evidence on the dynamics of innovative activities in the long-run are hardly documented due to the lack of data, especially in Europe. In this paper, we introduce PatentCity, a novel dataset on the location and nature of patentees from the 19^{th} century using information derived from an automated extraction of relevant information from patent documents published by the German, French, British and US Intellectual Property offices. This dataset has been constructed with the view of facilitating the exploration of the geography of innovation and includes additional information on citizenship and occupation of inventors

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1 Introduction

The availability of new quantitative data has led to numerous studies that analyze the social and economic implications of innovation activities and the enabling environment for strengthening innovation (see Hall and Harhoff, 2012 for a review). Most of these studies use patent documents as a means of measuring innovation across time and space. While patents are imperfect and incomplete proxies for innovation due to the heterogeneity in patenting propensity across countries, time, sectors, and firm size (see Arundel and Kabla, 1998; Mansfield, 1986), they are widely used in economic literature because of the rich quantity of information they contain. Additionally, despite their limitations, evidence shows that patents as a measure of innovation provide a relevant signal (they are, in particular, well-correlated with R&D activities, see Pakes and Griliches, 1980; Acs and Audretsch, 1989).

The patent system has been in place for a very long time. It is commonly acknowledged that the first British patent was granted to John of Utynam in 1449 (Plasseraud and Savignon, 1983). Yet only limited information is available before the 1980s and actual publications did not systematically exist before the end of the 19^{th} century in most countries (see Appendix C for a short history of the patent systems). One important exception is the United States Patent and Trademark Office (USPTO) which consistently published patents since 1836 and made them publicly available.[1] In this specific case, extracting the information of interest (e.g., inventors, assignees, locations...) can therefore be performed in a single step; either manually or using simple semantic rules. This has motivated early efforts to exploit and study parts of this rich corpus of documents (e.g. Lamoreaux and Sokoloff, 1997, 2000; Sokoloff, 1988) which were nonetheless limited by the quantity of USPTO documents. Recent improvements in large data handling and text data processing have stimulated a renewed interest in large scale use of historical patents (see in particular Packalen and Bhattacharya, 2015; Petralia et al., 2016; Akcigit et al., 2017a; Berkes, 2018; Sarada et al., 2019). Thus far, this momentum has mostly been restricted to US patents - notably due to the public availability of US patents *text* data.[2]

Consequently, our understanding of the long-term development of innovative activities is largely based on a US perspective. In contrast, we do not know much about the forces at

[1] USPTO patent publication texts are publicly available for bulk download from the USPTO website and the Google Patents public dataset. USPTO publications existed before 1836 but a fire burned an unknown number of them.

[2] With some notable exceptions that restrict to patents published before the 19^{th} century, see e.g. Hanlon (2016); Nuvolari and Tartari (2011); Nuvolari et al. (2020, 2021). These studies however do not focus on the geography of patentees.

stake in other major innovative countries, namely European technological leaders, before the 1980s. In particular, the location, occupation and citizenship of patentees (inventors or assignees), which are key to the study of innovation dynamics, are unavailable from standard patent datasets such as PATSTAT and Claims before the 1980s. However, most historical patent documents are available as scanned images. Starting from these images and using a pipeline of data science and Natural Language Processing (NLP) steps, we extend previous work restricted to US patents, both in terms of coverage and methodology. Specifically, we used raw images of patent documents as our input, extracted and structured the embedded information and produced a relational database covering patents published in Germany (including East Germany), France, the United Kingdom, and the US since the 19^{th} century.

To the best of our knowledge, our database PatentCity is the largest of its kind, both in terms of time-space coverage and scope of applications. We make it open access with open source tools to help the community build on/extend our work.[3] Despite the large number of efforts in the field for US data, we are not aware of any other publicly available database to date with similar coverage. We have also made the database as interoperational as possible. Each patent and its geographical information are associated with standard identifiers that should facilitate the matching of PatentCity with other data source. We hope that this work will encourage researchers to use and extend our work to complete our knowledge on innovation in the 20^{th} century and earlier.

Our project relates to the growing and recent literature that aims at overcoming the lack of historical data on the location of innovative activities using patent documents. We have already mentioned early efforts by Lamoreaux and Sokoloff (1997, 2000); Sokoloff (1988) which are based on a small sample of patents that are manually classified and geocoded. More recently, Nicholas (2010) studied innovation activities between 1880 and 1930 in the US thanks to the construction of a new dataset that restrict to a 10% sample of USPTO patents that were not associated with a specific assignee. Since then, other datasets have extended this work by implementing automatic rules to the text of the patent publications to extract relevant information, namely Sarada et al. (2019); Packalen and Bhattacharya (2015); Berkes (2018); Berkes and Gaetani (2019); Akcigit et al. (2017a, 2018) and Petralia et al. (2016). These datasets follow different purposes. For example Akcigit et al. (2018) use patent data to measure the impact of taxes on individual inventors and firms, Berkes and

[3]The pipeline code base is publicly available and fully documented on the GitHub repository of the project at www.github.com/cverluise/patentcity. Non technical additional material is also available on the project website at https://cverluise.github.io/patentcity/.

Gaetani (2019) look at the geographical concentration of innovation in history and Packalen and Bhattacharya (2015) analyze the role of physical proximity as an engine for new ideas and innovation. They also differ in the nature of the information they focus on, their time frame and the way they collect the data. The accuracy of these databases is usually high based on different criteria and despite their differences, they paint a consistent picture of the nature of inventions in the history of the US (see Andrews, 2019 for a comparison of existing datasets). However, all these datasets focus on USPTO patents only and do not include information on patents filed in other patent offices. Of course, some scholars have studied innovation in Europe and before WW2 in the past, either using alternative data (e.g., Moser, 2005) or using a subset of patents (e.g. Nuvolari and Tartari, 2011; Nuvolari and Vasta, 2017; Andersson and Tell, 2018). However, none of these projects attempted to add geographical information to a comprehensive set of patents. For the more recent period, de Rassenfosse et al. (2019) used information available from the patent office registers on the address of patentees to geocode assignees and inventors' locations all over the world since the 1980s. This of course includes the four countries we are focusing on. We view our work as completing these projects by extending these works either in time or in space thanks to substantial methodological novelties.

In addition to providing information on the location of inventors and assignees, we also extract additional details such as the occupation and citizenship of the inventors when applicable. These are often available in the text of patents, especially for British publications and can be used to extend our understanding of who are the actors of innovation over the 20^{th} century. This relates directly to a recent literature that has looked at how innovative activities have changed over time (see e.g., Akcigit et al., 2017a; Berkes, 2018), in particular in time of crisis (Babina et al., 2020). Akcigit et al. (2017b) and Sarada et al. (2019) have both documented that most US inventors are white males but that this pattern changes slightly over time. Sarada et al. (2019) also reports that the typical occupation of an inventor moves away from farming to engineer and scientists. By collecting information on the citizenship of inventors, our dataset can also speaks to the literature on the relation between immigration and innovation. This literature typically finds that immigration is a privileged vehicle for importing knowledge.[4] In terms of historical trends, Akcigit et al. (2017a) and

[4]For example, Bahar et al. (2020) uses a large set of countries and recent data and document that the probability of a country to experience an abnormal momentum in patenting activity in a technological field is positively affected by an increase in the influx of migrants coming from a country with a patenting advantage in this field. Bernstein et al. (2018) show evidence for this using data for the US since the 1990s. In addition to relying on different knowledge and being more productive than their domestic counterparts, foreign-born inventors also generate larger spillovers. This was notably the case for Jewish chemists fleeing the Nazi as studied by Moser et al. (2014) whose overall impact on innovation largely exceeded their per-

Arkolakis et al. (2020) provide large scale historical research stressing the crucial role of the 1880-1940 immigration on the dynamics of US innovation. Specifically, Arkolakis et al. (2020) find that European immigrants spurred more radical innovations compared to domestic inventors while Akcigit et al. (2017a) find that the specific expertise brought by immigrants during the 1880-1940 period resulted in more patenting in these areas in the 1940-2000 period. In these different studies, information on the citizenship and occupation of inventors are usually the results of a complex matching of patent publication data with different vintages of the census. Our database offer an alternative perspective by looking at the information directly reported in patent publications.[5]

From a data perspective, our work borrows extensively from modern NLP, in particular to the Named Entity Recognition (NER) field. This strand of literature seeks to develop algorithms to detect mentions of predefined semantic types, either generic (e.g., person, organization, location, etc) or domain specific (e.g., assignee, inventor, occupation, etc). Two approaches coexist in the literature. First, the rule-based and statistical methods (see Li et al., 2020 for an in-depth survey of the NER literature). Rule based approaches usually leverage large domain specific gazetteers (Etzioni et al., 2005, Sekine and Nobata, 2004) and syntactic-lexical patterns (Zhang and Elhadad, 2013). However, this approach is largely unable to handle inherent ambiguities of natural language and to generalize to new documents. To overcome these limitations, the literature has introduced statistical approaches. Starting with text data annotated by humans with entity labels, machine learning algorithms are trained to learn a model to recognize similar patterns from unseen data. The first generation of this class of algorithms, notably including Hidden Markov Models (Eddy, 1996) and Conditional Random Fields (Lafferty et al., 2001), typically rely on feature engineering. More recently, statistical approaches leveraging deep learning have repeatedly advanced the state-of-the-art performance in the field. Such models are able to exploit non linearity to uncover complex and hidden features automatically, without the need for feature engineering or built-in domain expertise (Collobert et al., 2011; Huang et al., 2015; Lample et al., 2016; Chiu and Nichols, 2016; Peters et al., 2017). The class of models we use to extract relevant data from the patent documents belongs to this latter group.

The rest of the paper is organized as follows. Section 2 discusses the main steps of the

sonal contribution. On the other hand, Borjas and Doran (2012) show that immigration of scientists can have a negative business-stealing effects on the productivity of domestic scientists, but this adverse effect is more likely to materialize in very constrained labor markets (in their case, mathematicians in academia).

[5]In a recent work, Diodato et al. (2022) also use the declared citizenship in the patent text in the case of the USPTO.

construction of the dataset and we refer the reader to the Online Appendix and to the GitHub repository for more technical details. Section 3 provides an overview of the dataset and sketches some potential applications for economic analysis. Section 4 concludes.

2 Data

We now detail the construction of the database. The key steps are the following. We start by collecting the patent document images. We convert these document into text data using Optical Character Recognition (OCR). We then leverage modern Named Entity Recognition techniques to extract the relevant information from the patent text: the name of inventors and assignees, and, if available, their locations, occupations, and citizenship. These attributes are then tied together using a simple relationship prediction algorithm (e.g., an inventor is linked to his or her location). Finally, we enrich the dataset by converting extracted natural language text spans into harmonized attributes. In particular, we geocode the locations and provide administrative codes to facilitate the interoperability of the database with other sources. Figure A13 summarizes the workflow that we describe in detail in this section.[6]

2.1 Data collection and coverage

Contrary to the USPTO, patent publications from the German, French and British intellectual property offices are not publicly available for bulk download in text format.[7] To overcome this obstacle, we scraped the patent document images and extracted the embedded text using `Tesseract v5.0` (Kay, 2007), a popular open-source OCR software. A qualitative assessment of the results showed that the quality of the text of USPTO patents could be improved by using the latest version of `Tesseract` compared to the text provided by the USPTO itself and generated by former OCR technologies. Hence, we used the patent images made available by the USPTO and implemented in-house OCR in order to maximize the quality of the text and to make our dataset more consistent across different patent offices.

We restrict attention to utility patents. Utility patents are the class of patents which cover the creation of a new or improved –and useful– product, process, or machine. Appendix

[6]The codebase is open source and fully documented on the project GitHub repository.

[7]Patent search engines such as EspaceNet and Google Patents enable manual patent download on a per-document basis. Unfortunately, both of them impose quotas on the daily number of downloads.

A.1 reports the list of kind codes selected as referring to utility patents for each patent office.[8] For the sake of brevity, we refer to utility patents as patents thereafter. As previously mentioned, we focus on patents published by the East German, German, French, British and US patent offices. Data collection is subject to two conditions. First, we need patent publications to exist and to be available in a digital image format. Second, we need these documents to include at least some geographical information. These conditions have been met consistently for patents published between 1950 and 1992 for East-German patents (with the exception of the period 1973-1976), from 1877 for German patents, from 1903 for French patents, from 1893 for British patents and from 1836 for US patents. Starting from those publication dates, we collect all patents published until 1980. Overall, this represents around 8.9 million documents.

After 1980, we complete our data using the work of de Rassenfosse et al. (2019) which reports the patentees location for a very large corpus of patents, including publications from the patent offices we are interested in. When necessary, we completed their corpus with patents published after 1980 but missing from their dataset to make sure that the transition between the two datasets is smooth.[9] Our dataset comprehensively[10] spans over the following periods: 1877-1980 for German patents, 1950-1972 and 1977-1992 for East German patents,[11] 1903-1980 for French Patents, 1893-1980 for British patents and 1836-1980 for US patents. After 1980, our dataset smoothly splines over de Rassenfosse et al. (2019)'s which provides data up until 2013 included.

2.2 Information extraction

Our information extraction pipeline is made of two layers. First, a NER model in charge of extracting the entities of interest. Second, a relationship prediction model that resolves the relations between extracted entities. Both layers are crucial to fully exploit the potential of patent texts.

[8] Utility patents cohabit with other types of patents. They are usually identified by a set of kind codes, that is the last letter of the DOCDB publication number.

[9] In particular, we collected patents from the East German patent office until the last one in 1992.

[10] Depending on the office, our coverage varies between 98% and 100% of the utility patents listed in the Google Patents Public Data, the largest publicly available bibliographic dataset of patent publications.

[11] To our knowledge, digitized copies of East German patent documents published between 1973 and 1976 are not available. However, recent efforts have been made to bridge this gap, see Hipp et al. (2022).

2.2.1 Main challenges

Constructing structured data from patent text presents a significant challenge due to the vast variability in document formats. One of the main difficulties lies in establishing a strategy that can effectively extract relevant information, such as the inventor's name or geographical location, which is often presented in varying formats across different patent offices and countries, and even over time. In the case of the US, Berkes (2018) and Petralia et al. (2016) discuss in details how the changing structure of patent documents requires to adapt the rules used to extract information. In our case, patent document formats can vary greatly across different countries, which makes it inefficient to use rules that rely on the structure of the document (Table 2 provides some examples).

2.2.2 Entities

Our goal is to extract the names of the inventors, the names of the assignees but also their location, occupation and citizenship when applicable. The exact definition and actual examples by countries are reported in Table 1 and discussed in Appendix A. This is naturally subject to the actual reporting of these entities in the text of the patent. The reason why we focus on this set of information is largely influenced by the last decades of the innovation literature. The relation between geography and innovation occupies a central place in this literature. The occupation of inventors also constitutes a valuable asset to study their socio-economic characteristics. Eventually, the combination of inventors' citizenship and location provides their immigration status, which appears to be key to understand innovation dynamics. One important remark is that the very notion of inventor and assignee is mainly a US and modern times terminology. In many offices and at many points in time, there is no explicit distinction between the two. In this case, we called inventors any human being involved in the invention and assignee any company related to the invention.[12]

Table 1 summarizes the entities extracted by patent office. We were able to extract the names of the inventors and assignees and their locations from all patent offices. In contrast, the occupation and citizenship are only available for some countries. Specifically, the

[12]This is a necessary but arbitrary point which has important implication for comparability across countries (see also Section 3.1.3 for more on this point). For example: French patents most of the time did not explicitly report the name of the inventor but only the name of the "déposant" (applicant). In some cases, this applicant is a firm and in other cases a physical person. In rare instances, the name of the inventors are given in addition to the name of the applicant. For this reason, we chose to define this applicant as an assignee. See Appendix A.3 for more details. Additionally, some patents mention additional individuals such as the name of the patent attorney, the representative of the inventor, witnesses etc... In principle, these entities are not reported in PatentCity and therefore cannot be wrongly considered as inventors.

occupation is reported in East-Germany, Germany and the United Kingdom while the citizenship is reported in the United Kingdom and the US. Importantly, even within a given patent office, the reporting of a given entity can vary over time. See Appendix A.4 for more details on the share of patents from which we extracted at least one entity of each category by publication year and countries. Similarly, the level of precision of the location (i.e. country, state, county, ...) changes across time and countries. More details are provided in Figure A7.

Table 1: Entities extracted by countries

	DD	DE	FR	GB	US
E-Inventor	✓	✓	✓	✓	✓
E-Assignee	✓	✓	✓	✓	✓
E-Location	✓	✓	✓	✓	✓
E-Occupation	✓	✓		✓	
E-Citizenship				✓	✓
Time span	1950-1992	1877-1980	1903-1980	1893-1979	1836-1976

Notes: The prefix E refers to "Entity" and is added to make sure that they entities not confounded with relationships designated with similar names and reported with a R prefix. The actual reporting of the entities can vary over time. See Appendix A for more details on the share of patents from which we extracted at least one entity of each category by publication year and countries. This table only reports the entities extracted in the course of this project. Later results incorporate de Rassenfosse et al. (2019) dataset which provides the names and locations of German, French, British and US patentees after the end of our dataset. DD stands for East Germany, DE for Germany (which only includes West Germany during the 1950-1989 period), FR for France, GB for the United Kingdom and US for the United States of America.

2.2.3 Named Entity Recognition

Meta-data (e.g., patentees' names and locations) on historical patents are reported in an unstructured way, most often as part of the preamble or in the header of the document. Table 2 shows typical examples for each patent office. To our knowledge, previous historical patent data projects used rule-based methods to extract such domain-specific data. Instead, we use deep-learning based statistical NER. As previously explained in the literature review, this class of models have been conceived by the NLP community specifically to improve on rule-based approaches and have repeatedly advanced the state-of-the-art since their introduction. In our specific case, they also present the advantage to have considerable generalization abilities based on a relatively small amount of examples - making them robust to typographical errors and variations in word-use which can be very frequent at some patent offices and would give rule-based models a hard time. It is also worth noting that, contrary to most previous works, we produced and released manually annotated data

which supports rigorous and transparent performance evaluation and future extensions.[13]

Table 2: Example of patent documents with embedded entities

Country	Example	Source
DD	*Erfinder: Wilhem Uhrig, WD. Inhaber: Dr. Plate GmbH, Bonn, WD.*	DD-79836-A
DE	*Bela Barenyi, Stuttgart-Rohr, ist als Erfinder genannt worden. DAIMLER-BENZ Aktiengesellschaft, Stuttgart-Unterturkheim*	DE-869602-C
FR	*MM. Joseph MARTINENGO et Jean-Baptiste GAUDON résidant en France (Loire)*	FR-504101-A
GB	*We William Christopher Fanner, and Henry Elfick, trading together as De Grave, Short, Fanner & Co., of Farringdon Road in the County of London, Scale and Balance Manufacturer, do hereby declare the nature of this invention...*	GB-189704983-A
US	*Be it known that I, PAUL SCHMITZ, a subject of the King of Prussia, German Emperor, residing at Cologne-Niehl, in the Kingdom of Prussia, German Empire, have invented...*	US-1108402-A

Notes: Examples of patent document for each of the five patent offices considered. Colored text correspond at the entities that we seek to extract: red for inventors, purple for assignees, olive for locations, brown for citizenship and blue for occupations.

In practice, the NER models were trained using `spaCy v3` (Honnibal et al., 2020), a popular Python NLP library offering an efficient framework for reproducible custom domain NLP models. The manually labeled dataset was split in two subsets, the training set used for model training and the test set used for model's performance evaluation. The goal of this approach is to avoid over-fitting, that is the tendency of the model to "learn training data by heart" which can produce very high performance on the training set while harming its ability to generalize to other data. Each office was treated independently from one another and multiple models were trained for offices to account for the large changes in the format of the patents (see Appendix A.2). More details are provided in Appendix D.

In Table 3, we report the performance of the models on the test sets for each entity of interest. The performance metrics are respectively: the precision, that is the share of *extracted* entities which are *actual* entities; the recall, that is the share of *actual* entities which are indeed *extracted* and the F1-score, the geometric mean of the precision and the recall. In short, the higher the F1-score, the better the reliability of the model. For the sake of brevity,

[13]For the labeling tasks, we used `Prodigy v1.10` (Montani and Honnibal, 2018). Data and annotation guidelines are available on the project GitHub repository at https://github.com/cverluise/patentcity.

we average over models performance when there was more than one data format, hence models, for a given office. We report in brackets the underlying number of models. The average F1-score over all extracted entities ranges from 0.94 to 0.98 on the test set which indicates a high level of performance.

Table 3: Performance of the NER models

	DD (2)	DE (2)	FR (2)	GB (1)	US (4)
E-Inventor	0.95/0.95/0.96	0.98/0.97/0.98	0.99/0.99/0.98	0.95/0.96/0.96	0.99/0.99/0.99
E-Assignee	0.97/0.97/0.97	0.98/0.98/0.98	0.98/0.98/0.98	0.93/0.92/0.93	0.96/0.96/0.96
E-Location	0.98/0.97/0.97	0.99/0.99/0.99	0.99/0.99/0.99	0.92/0.92/0.92	0.98/0.98/0.98
E-Occupation	0.96/0.97/0.96	0.97/0.97/0.97	-	0.90/0.86/0.88	-
E-Citizenship	-	-	-	0.96/0.96/0.96	0.98/0.98/0.98
E-All	0.97/0.96/0.97	0.99/0.98/0.98	0.97/0.97/0.97	0.93/0.94/0.94	0.98/0.98/0.98

Notes: The prefix E refers to "Entity" and is added to make sure that they entities not confounded with relationships designated with similar names and reported with a R prefix. Reported performance metrics were computed on the test set - unseen during training. The figure in brackets indicates the number of different models used for the office. For example, for the German office, there was a major shift in the patent information display in 1881 forcing us to train two different models (see Appendix A.2). Performance metrics are reported as follows: precision/recall/F1-score. Model by model performance for each patent offices can be found in Appendix D.

2.2.4 Relationship prediction

At this stage, we have extracted the information of interest from a patent with a high level of reliability but the output is essentially a "bag" of entities. For example, assuming that we have extracted one inventor, one assignee and two locations, we still don't know how these entities are related to one another. Such relationships can be extremely detrimental to the analysis. For instance, if we want to know whether an inventor is an immigrant, we need to link their name to a citizenship and to a location. This case of multiple patentees in a given publication is a well identified additional difficulty to the conversion of unstructured patent documents into a set of entities (see Berkes, 2018). For this reason, we go one step further and reconstruct the latent relationships between our different entities. That is what we call relationship prediction.

In our case, there are three different kinds of relationships: the *location* which relates the patentee to her address, the *occupation* which relates the patentee to her occupation, or academic title and the *citizenship* which relates the patentee to citizenship or country of origin. There are many different ways to implement such relationship prediction but we found that a simple algorithmic approach leveraging the relative position and the absolute distance of the attributes (location, occupation, citizenship) to the patentees (inventor, assignee) with a slight level of hyperparameter fine tuning performs surprisingly well. Our approach is

the following: we iterate over extracted patentees, harvest all attributes positioned either at the right or left of the patentee within a distance expressed in terms of number of words (or tokens) and keep the closest element of each attribute family (if any). In this algorithm, two hyperparameters need to be chosen: the position (right, left, both) and the size of the window (expressed in tokens).

We evaluate the performance of this procedure on a set that has been manually annotated in Table 4. Since parameter fitting remains minor, we considered that the risk of overfitting is relatively small and did not split the labeled set in a training and test set and report performance on the former. As before, we average performances over the different models for each patent offices for simplicity. The overall F1 score varies from 0.93 to 0.98 depending on the office, which guarantees a high level of confidence.

Table 4: Performance of the relationship prediction models

	DD (2)	DE (2)	FR (2)	GB (1)	US (4)
R-Location	0.98/0.96/0.97	0.99/0.99/0.99	0.98/0.97/0.98	0.97/0.92/0.94	0.98/0.93/0.95
R-Occupation	0.88/0.86/0.87	0.98/0.99/0.98	-	0.96/0.94/0.95	-
R-Citizenship	-	-	-	0.92/0.93/0.92	0.98/0.97/0.97
R-All	0.94/0.93/0.93	0.98/0.99/0.98	0.98/0.97/0.98	0.95/0.93/0.94	0.97/0.93/0.95

Notes: The prefix R refers to "Relationship" and is added to make sure that relationships are not confounded with entities designated with similar names and reported with a E prefix. The number in brackets indicates the number of different models used for the office (see Appendix A.2). For example, for the German office, there was a major shift in the patent information display in 1881 forcing us to train two different models. Performance metrics are reported as follows: precision/recall/f1-score. Model by model performance for each patent offices can be found in Appendix D.

2.3 Data enrichment

At this stage, each patent is characterized by a set of extracted inventors and/or assignees who are themselves characterized by a set of attributes, as is usual in modern patent datasets. Most importantly both the extracted entities and predicted relations exhibit a high level of reliability. However, some limitations remain for research usage. Extracted attributes are reported in raw text, which requires geocoding for locations and further disambiguation for the citizenship. The publication dates from German patents published before 1919 and East German patents published before 1972 are missing from standard datasets, which calls for some additional effort as well. In this section, we detail how we overcame these limitations and the resulting data enrichment process.

2.3.1 Location geocoding

Our first task is to turn natural language attributes into high quality and harmonized variables. The most challenging and crucial task was certainly the geocoding of natural language locations, that is the translation of free-text locations such as "Farringdon Road in the County of London" (from patent GB-189704983-A) into well defined geographic attributes (country, state, county, ...) and coordinates. This "geocoding" exercise is well known as challenging and resource intensive due to the many ambiguities and typographical errors that can be found in natural language addresses and the size of the universe of worldwide addresses. In our case, there are the additional difficulties of multiple languages and changing names and borders over the time span considered. For all these reasons, we found that the best output quality was only achievable using a commercial geocoding supplier. Having close to 3 million unique addresses to geocode we mixed two providers (HERE and Google Maps) to maximize efficiency. Specifically, we leverage the specific features of the two services: on the one hand, HERE tends to have a low rate of errors but a relatively high rate of "unmatched" locations; on the other hand, Google Maps tends to have a very low rate of unmatched locations, notably thanks to a better understanding of locations expressed in plain language and of historical entities which have changed names (e.g., "Karl-Marx Stadt" in East Germany now known as "Chemnitz"). This is however sometimes done at the expense of a slightly higher error rate (see Perlman et al., 2016 for a discussion of the geocoding of historical patent using modern Geographic Information System). With these specificities in mind, we decided to get the best of both worlds. We first processed locations through HERE batch geocoding API and then restricted Google Maps geocoding to the unmatched locations.[14] The two outputs were relatively straightforward to align in a common data structure.

Table 5 presents the share of matched locations together with the level of quality of the geocoding (conditional on match). Tthe geocoding output was validated by hand. The human annotator was given both the extracted location and the geocoded address. He would then choose from a set of options (country, state, county, ...) to select the finest geographic level at which the location was rightly geocoded. The share of locations matched varies from 88.3% for the British patents to 99% for French patents. Conditional on matching an address, more than 92% of the locations are rightly geocoded at the country level for all offices. This figure can even exceed 98% for French and US patents. Results at more detailed geographic levels vary depending on how detailed the location was in the patent

[14]Both APIs are respectively documented at the following addresses HERE API and Google Maps API.

document itself. It goes up to 95% at the city level for German and US patents versus only 33.5% for French patents.

Table 5: Performance of the geocoding

	DD	DE	FR	GB	US
Match	0.987	0.976	0.990	0.883	0.975
Country	0.927	0.971	0.986	0.934	0.985
State	0.576	0.957	0.483	0.924	0.982
County	0.569	0.953	0.456	0.910	0.968
City	0.569	0.950	0.335	0.887	0.951
Postal Code	0.116	0.251	0.006	0.727	0.185
District	0.109	0.226	0.006	0.690	0.085
Street	0.014	0.035	0	0.605	0.034
House number	0.007	0.010	0	0.394	0.002

Notes: The match rate is the share of locations for which either HERE or Google Maps found an address. The match rate is based on the *entire* dataset. Conditional on a match, other figures represent the share of locations which were rightly geocoded at a given geographic level based on the manually validated sample. For instance, for German patents, 97.6% of the extracted locations were matched and 95% of the matched addresses were right at the City level. These conditional figures are based on a *manually* annotated sample.

2.3.2 Citizenship disambiguation

Our second task consisted in turning citizenship statements (e.g., "a citizen of the United States of America", "a subject of the King of Great Britain"...) into harmonized and unambiguous country codes. This exercise can be seen as a translation task where we start from a finite (but large) set of possible citizenship statements which we want to map to another (smaller) finite set of country codes.[15]

A simple way to implement such mapping is to define a set of regular expressions which, when matched, trigger a pre-determined country code. We collected a list of citizenship and country names together with the corresponding country codes and authorized a small amount of edit distance between the target and the extracted text to account for typographical errors. Confronting the output with a set of manually annotated citizenship values, we find that this procedure achieves a satisfying level of accuracy defined as the share of initial citizenship statements mapped to the right country code. We achieve 98.7% and 92.9%

[15]This perspective borrows from the Finite Set Transducer which was developed in early attempts to automate natural language translation.

accuracy on British and US patents respectively.

2.3.3 Publication date approximation

The final data enrichment exercise was especially crucial for later analysis since it has to do with the time dimension of the dataset. As previously noted, standard datasets do not report the publication date of patents German patents published between 1877 and 1919 and East German patents published between 1950 and 1972. Fortunately, in both cases the publication number can be used in some way to overcome the issue. In the case of Germany, we use Patent Gazette published by the German patent office since 1877[16], take the last publication number reported under the section "*Erteilungen*" (i.e. "Publications") and define it as the last publication number of the year. We then iterate backward to fill the publication year until we hit the last publication number of the previous year. To our knowledge, East Germany did not generate such a Patent Gazette. Nevertheless, we were able to develop a similar approach based on publication numbers. First, we drew a random sample of undated East German patents. Second, we manually filled their publication date based on the information displayed on the patent itself. Third, we used the clear but imperfect relation between the publication number and the publication year to find thresholds similar to those found in the German Patent Gazette. Specifically, we chose the publication number thresholds so as to maximize the F1-score of the predicted publication year. Doing so, we obtain an overall 93% accuracy of the publication year.

3 Overview of the dataset

Having described the construction of PatentCity, we now illustrate some possible usages. We start by describing how the dataset can be used and and emphasize the importance of paying attention to differences between countries and over time before using the data to make comparisons. We then discuss in more details the three types of entities extracted from the patent files: location, occupation and citizenship.

[16]German Patent Gazette are available for download at the DPMA website.

3.1 What's in the database and how to use it?

3.1.1 Interoperability

We format the data into a ready-to-use database at the patent level with nested information. The database full schema is reported in Appendix A.7. Importantly, every patent entry in the dataset is identified by its DOCDB publication number. A DOCDB publication number has the following form: "CC-NNNNNN-KK" where CC is a two-letter country code, NNNNNN the publication number, and KK the kind code. In addition to identification, the DOCDB publication number also serves as the natural vehicle for interoperability with external datasets including useful variables (e.g., technological class, citations, ...) that are consistently collected by usual patent datasets.

We also harmonize the geographical information that we extracted. For each address, and in addition to field presented in Table 5, we give the official administrative code for the corresponding regions at different level. Specifically, we report the Nomenclature of Territorial Units for Statistics (NUTS) level 1, 2 and 3 when applicable for Germany, France and Great Britain, and the county, Commuting Zone (CZ) and state codes for the US.

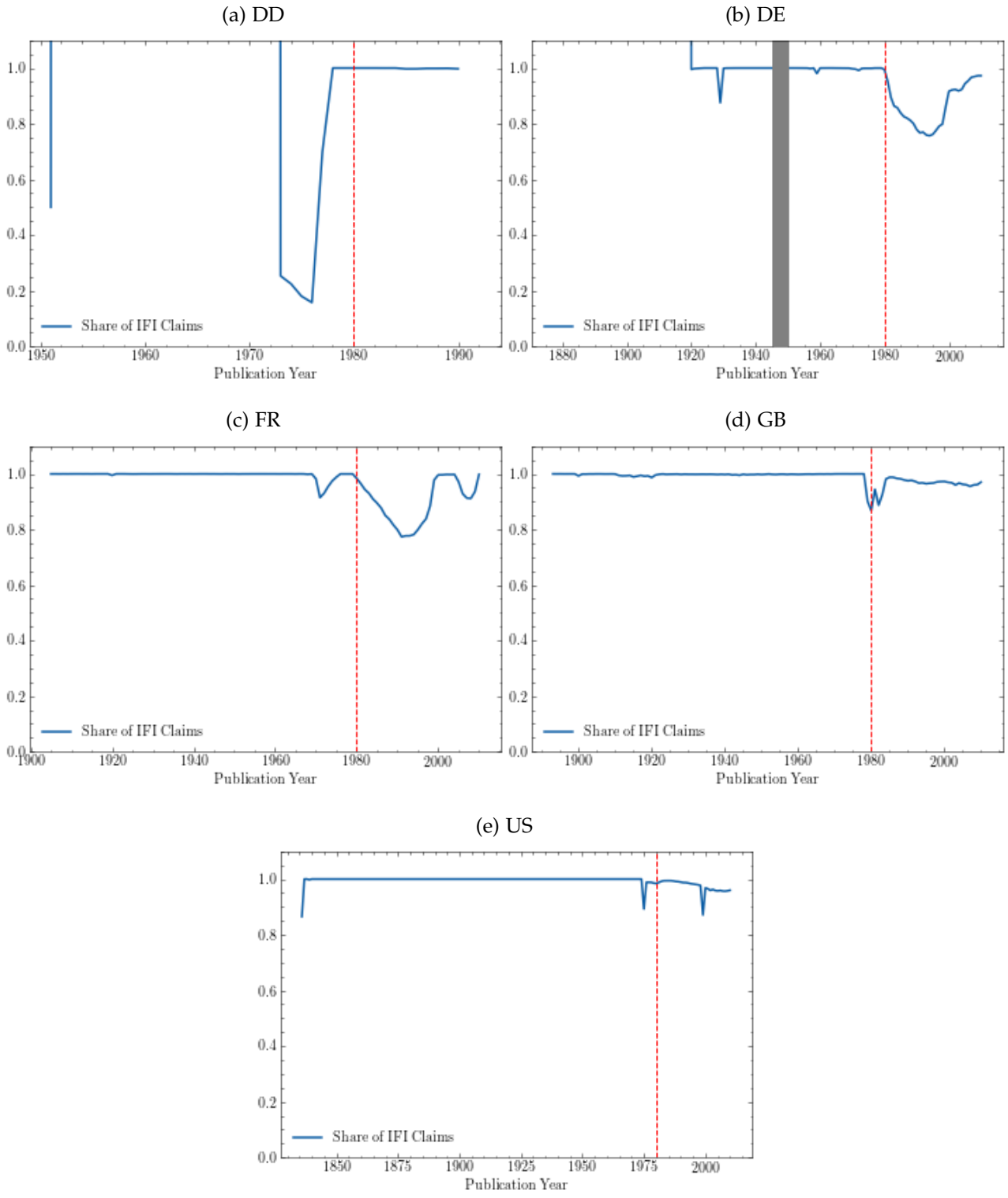
The database version we offer includes all patents that we collected with a kind code specified in Table A1, which pertains to utility patents. This database features over 16 million unique publication numbers; however, it contains multiple duplicates because a single patent can have several publications (e.g., first publication, second publication, reissue, and so on). Researchers who want to study patents at a specific stage might prefer to restrict the dataset to a corresponding set of kind codes. In general, most users of the database will likely need to eliminate duplicates and retain only one observation per patent, typically the earliest one. In Appendix A.1, we provide a simple procedure to accomplish this task.

3.1.2 Coverage

Benchmarking with commercial datasets In order to study the coverage of PatentCity, we compare it to two standard patent databases that are typically used in the literature: PATSTAT and IFI Claims (which is often referred to as Google Patent). Figure 1 reports the share of yearly observations in PatentCity compared to IFI Claims for publications that fall within the criteria defined in Table A1 (utility patents). Figure A11 in the Appendix provides a similar comparison with Patstat.

Overall, our coverage of patent documents is very high, and in some cases, exceeds that of IFI Claims. For example, in Germany, we have been able to recover missing publication dates before 1920 and for East Germany between 1952 and 1989, resulting in a higher

Figure 1: Number of patents in PatentCity compared as a share of IFI Claims (Google Patents)



Notes: these Figures report the share of patents included in PatentCity as a share of the number of patents included in IFI Claims. The vertical line indicates 1980, the beginning of the switch from PatentCity to de Rassenfosse et al. (2019).

number of observations. Some documents are however still missing, in particular after 1980 in France and Germany due to the data provided by patent offices to de Rassenfosse

et al. (2019). In Appendix A.4, we provide additional details on the coverage of our dataset and in particular the share of patents for which we detect at least one inventor, and similarly for all the entities that we extract. In particular, Figures A3 show that not all patents are associated with a location. This is generally due to the fact that during some subperiods, geographical information can be often missing from the patent publications (for example in France during the 1970-1980 period).

Benchmarking with other research datasets When assessing the extent of our coverage at the USPTO, it can be useful to compare our results to those of existing datasets. As a benchmark, we primarily rely on the Histpat dataset (Petralia et al., 2016), which is readily available for download and widely recognized for its quality. Histpat provides detailed information on both domestic and foreign patentees for USPTO patents up until 1975, and has been compared to other similar projects in Andrews (2019). Our analysis indicates that the coverages of PatentCity and Histpat are nearly identical for the period spanning from 1836 to 1975, differing by less than 0.1%. This is not surprising given that both datasets are sourced from the same USPTO Bulk Data Storage System. Furthermore, the two datasets are highly consistent in their classification of inventors and assignees by country, with approximately 92% of patents having the same location in both datasets.

For a more detailed assessment, we manually examined 350 patents that were filed with the USPTO and present in both PatentCity and Histpat, as well as in Berkes (2018)'s CUSP dataset[17]. While a comprehensive evaluation of the geocoding accuracy of these three datasets would require further investigation, we can report that the quality of CUSP, PatentCity, and Histpat appears to be very comparable. Specifically, we found that for more than 90% of the 350 patents examined, all three datasets identified the county-level location with consistency. Notably, our examination of the 350 patents revealed that errors in the three datasets seemed to have varying origins. For Histpat, the most common source of errors arose from inconsistent pairs of county-city. In contrast, CUSP frequently experienced issues with homonymous cities located in different states, while PatentCity primarily encountered problems with incorrectly geocoded entities. It is worth noting that such an assessment is particularly challenging since different datasets may use varying rules for reporting geographical locations (such as current names versus historical names). For further discussion and evaluation of previous datasets, we refer to Andrews (2019).

[17]We are grateful to Enrico Berkes for providing information on these 350 patents.

3.1.3 Comparison across countries and over time

The final format of PatentCity makes it easy to compare patent numbers across different patent offices over time in order to study the technological development of these countries. However, it is important to keep in mind that the definition of a patent, its legal scope, and the barriers to obtaining one can vary significantly from one decade to another, or from one country to another. Comparing patent counts internationally using historical data is very challenging, as patent laws were not as harmonized in the past as they are today (Moser, 2013). One significant difference is the cost of a patent and the stringency of the intellectual property system, which can vary significantly over time and across different patent offices. Khan and Sokoloff (2001) describe the different philosophies of various patent offices at the time of their creation and gives specific examples to caution against drawing hasty conclusions. For instance, they emphasize that while the German system was influenced by the USPTO it was generally more strict, resulting in fewer patent grants but with a likely higher average quality. They also presents the USPTO as being guided with the general policy of keeping patent fees particularly low compared to France or the United Kingdom in the 19^{th} century, and even for a large part of the 20^{th} century (De Rassenfosse and van Pottelsberghe de la Potterie, 2013). And even in a given country, these fees can suddenly collapse, resulting in a higher propensity to patent and in a quick increase in the number of new publications (Nicholas, 2011). For example, in Britain in 1852, the fee for obtaining a patent was dramatically reduced from 100 pounds - the average annual wage of a skilled worker - to 25 pounds, and then further reduced to 4 pounds in 1883, and finally to 1 pound in 1905 (Van Dulken, 1999). Appendix C provides a summary of the significant changes in patent laws in various patent offices during the 19^{th} and 20^{th} centuries. Patent offices have followed their own paths from their initial stages which were deeply rooted in domestic social, philosophical, and economic characteristics, to progressively converged around 1980 to more harmonized procedures and definitions.

Besides this challenge, comparisons of the extracted entities across countries can also be tricky. Patents do not always include the same information or level of detail. One illustration of this is the nature of the patentee. In the case of the US, inventors and assignees are clearly separated and declared as such. Almost all patents have an inventor, and this has been consistent over time (see Figure A1). In contrast, assignees are very rarely mentioned before 1924 and became then increasingly common (see Figure A2). This simple distinction is not as straightforward in other patent offices, and our definition of an assignee or an inventor has been adapted accordingly (see Appendix A.3). Another important distinction to note is the definition of "occupation" in German and British patents (see also Section

3.3). In British patents, inventors sometimes explicitly state their occupation in the patent's preamble. In contrast, German inventors often indicate their education and field of study through an academic title preceding their name. Although these provide different types of information, we have labeled both as occupations in PatentCity.

In summary, researchers interested in using PatentCity to produce a comparative analysis of patenting over time or space should be cautious about correcting for these differences. For example, to allocate a patent to a region, it might be useful to first consider the location of the inventor, and in case the inventor is missing, to look at the assignee.

In the next sections, we look at three different possible uses of the database in more details exploiting the various entities extracted from the patent documents.

3.2 Geographic distribution of patents

The first and more natural usage of PatentCity is to analyze the geography of innovation. Numerous studies have looked a this question and have usually reported that innovative activities are highly concentrated, even when population density is taken into account (see Feldman and Kogler, 2010 for a comprehensive review). With geographic information provided for each patentee, PatentCity can aid in identifying potential variations in the spatial distribution of innovation different periods and in different countries which could open doors for future investigations into the concentration of innovation over time and space.

Section 2.3.1 details the level of granularity achieved through our geocoding process (see also Figure A7 in Appendix A). However, this Table 5 includes all patentees, whether domestic or foreign. Restricting the dataset to domestic inventors and assignees increases the average granularity significantly as foreign patentees sometimes only report their country. More than 99% of domestic patentees are located at least at the county level (counties in the US and NUTS3 regions in other countries), with the exceptions of East Germany (98%) and France (90%).

This "county" level of aggregation is particularly useful as it usually allows to confront the number of patents with other information, drawn from example from the Census, such as population, income, education etc... To illustrate this, we constructed local population estimates from various sources and for each of our four countries (this required some minor border adjustments, see Appendix A.5 for more details and sources). From this we report in Figure 2 the logarithm of the number of patentees (regardless on whether they are assignees or inventors) and the logarithm of total population all taken as an average

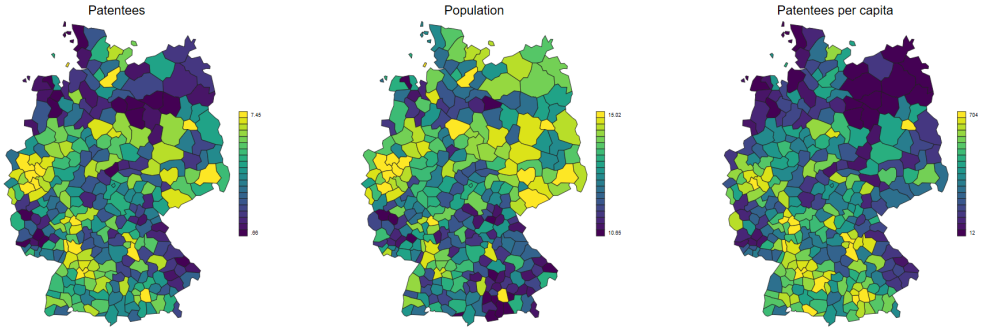
over time and for each of the 4 countries (pulling together East and West Germany). It shows that as expected inventors and assignees are mostly located around large urban areas. For example, the urban area of Paris accounts for 45% of all domestic patentees over the period 1900-2014, but only little more than 10% of the country's population in 2014. In the US, the six counties that make up the Silicon Valley account for 10% of all patentees over the same period for less than 1% of the population. This is also true for the UK as Inner London counts 27% of patentees for 5% of the population. The innovation in Germany is more uniformly distributed but large cities like Berlin or Munich concentrated an important share of the country's innovation activity over the 20^{th} century. To show more clearly the joint distribution of population and patenting across regions, we also map the average value of patentees per capita in Figure 2.[18]

County level analysis already provides a very granular picture of the geography of innovation which is likely to be sufficient for many analysis. However, the level of precision can be much finer in the case of British patents and 85% of patentees are located at the street or even house number level. This offers a very micro perspective on the location of inventors or assignees. We illustrate this in Figure 3 which reports the exact location of patentees in London. This Figure shows that most of the assignees are located in central London while inventors' locations are more widespread. Information at this level of precision can be useful for researchers interested in studying the role of the development of infrastructure to foster innovation, local technological clusters or the link between wealth and innovation.

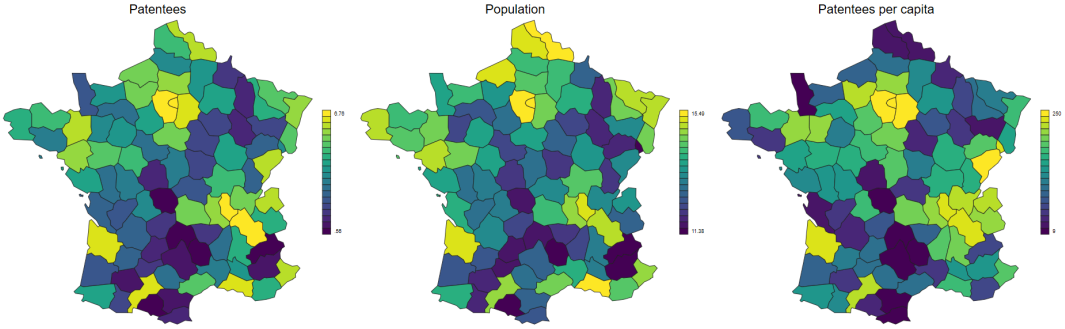
[18]While all these Figures consider the data without any restriction on the year of publication of the patent, one advantage of PatentCity is that it offers enough historical depth to study the evolution of these pictures over time. This is what we do in Appendix B for every decade.

Figure 2: Patentee location and population at the county level

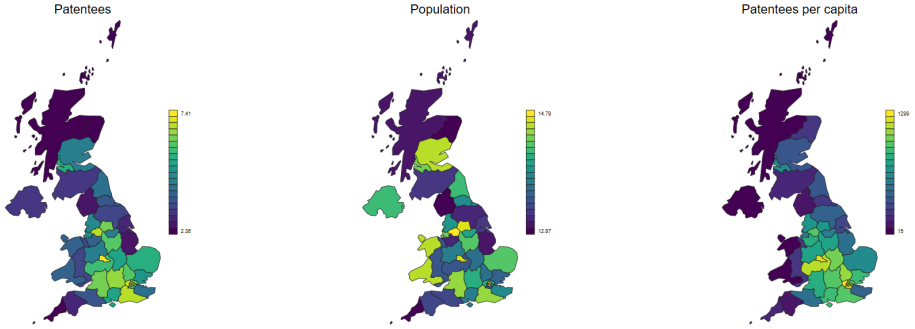
(a) Germany



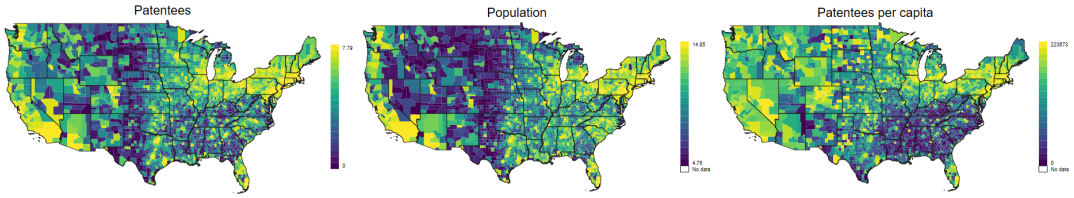
(b) France



(c) United Kingdom

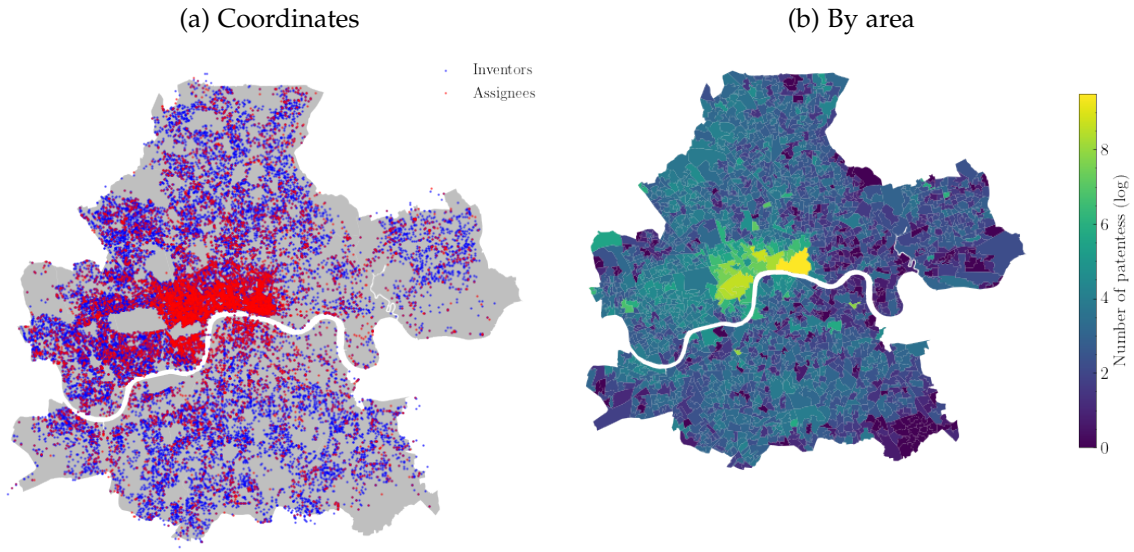


(d) United States



Notes: these Figures maps the number of patentees (whether assignees or inventors), in log, total population in log and the number of patentees divided by population (in millions) for each county in Germany, France, the UK and the US. In Germany and France a county is a NUTS3 region with minor border adjustments explained in Appendix A.5. In the UK, we used NUTS 2 regions. All variables are taken as yearly averages over the full period (see Table A1). West and East Germany are taken together as a single patent office when applicable. The number of patentees is taken as a total over the full set of domestic patentees that are located at least at the county level without restriction on the time period.

Figure 3: Location of patentees in London



Notes: these Figures maps the location of inventors and assignees of the UK patent office that are located in Inner London and for which the geocoding has been done at the street or house number level. Left-hand side map shows the coordinate of the house number reported or the centroid of the street. Right-hand side shows the number patentees (in log) by Lower Super Output Area.

3.3 Occupation of inventors

Patents filed in the UK patent office at the beginning of the 20^{th} century frequently report the occupation of the inventor. This represents a new source of information to document the professional activities of inventor and how this evolves over a 30 year window.

The denomination of occupation is free and as a result there is a very large number of distinct entities in the data. These can be highly precise, as for example, "Watchmaker and Jeweller", "Cemetery mason" or "Artificial limb manufacturer", or more vague like "Manufacturer" or "Engineer". The list of occupations covers a wide range of different skills. While the most frequently reported occupation is "Engineer" the list also include a large amount of low skilled occupations like "plumber", "worker" or "clerk" and more unexpected occupations like "Artist" or "professional mandolinist". At the same time, some inventors also declare to be "landowners", "gentlemen" or "inventor".

3.3.1 Reporting of occupation

The reporting of occupations in British patent is not systematic, but is fairly frequent over the period 1894-1920 with on average 50%-60% of inventors declaring one occupation. See Figure A5 in Appendix A.4. There is no legal obligation to disclose one occupation (Van Dulken, 1999, chapter 4.7) and this seems to be a practice inherited from earlier patents (MacLeod, 2002) which stopped around 1920. As explained in Van Dulken (1999), the occupation is often consistent with the nature of the innovation patented or the company's name.

Regarding inventors who did not choose to disclose their occupation, we follow Hanlon (2022) and characterize these occupations as "unknown". The corresponding patents do not seem to differ from others: the correlation between the relative weights of each technological class[19] in the groups of patents where inventors disclose their occupations and the other group over the period 1894-1920 is 96%. Similarly, the correlation in the relative weights of NUTS 3 regions is 88% for domestic patentees.

3.3.2 The rise of engineers?

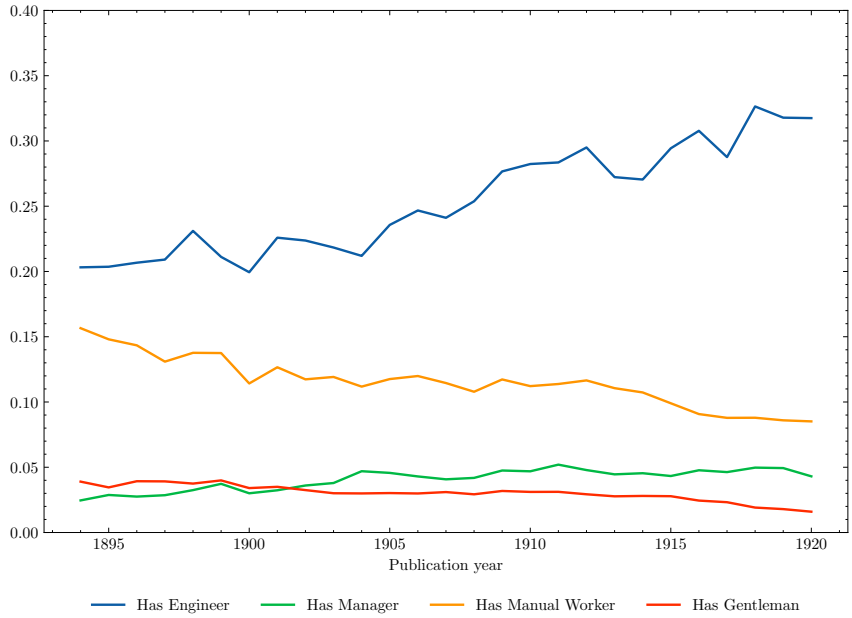
Hanlon (2022) recently examined British patents from 1700 to 1854 to explore the increasing importance of engineers in the country's technological landscape. With occupation infor-

[19]We use the International Patent Classification system at the 3-digit level, which counts 114 different categories.

mation available in PatentCity, we can conduct a similar analysis for various occupation groups over a later time period.

Figure 4 shows the share of patents with at least one inventor declaring an occupation in the following groups: engineer, manager, manual worker, and gentleman. The data indicates that the percentage of patents involving an engineer increased from approximately 20% to over 30% between 1895 and 1920. During the same period, fewer patents involved at least one manual worker. While the share of patents with an inventor reporting "gentleman" as an occupation decreased from 4% to 2%, the share of patents with a manager increased from 2% to 5%, albeit at a much lower level.

Figure 4: Occupation of inventors in the United Kingdom



Notes: This Figure reports the share of patents involving at least one engineer (Has engineer), one manager (Has manager), one manual worker (Has manual worker) or one gentleman (Has gentleman) in terms of the occupation of the inventor reported in the text. Time period: 1894-1920.

3.3.3 The case of Germany

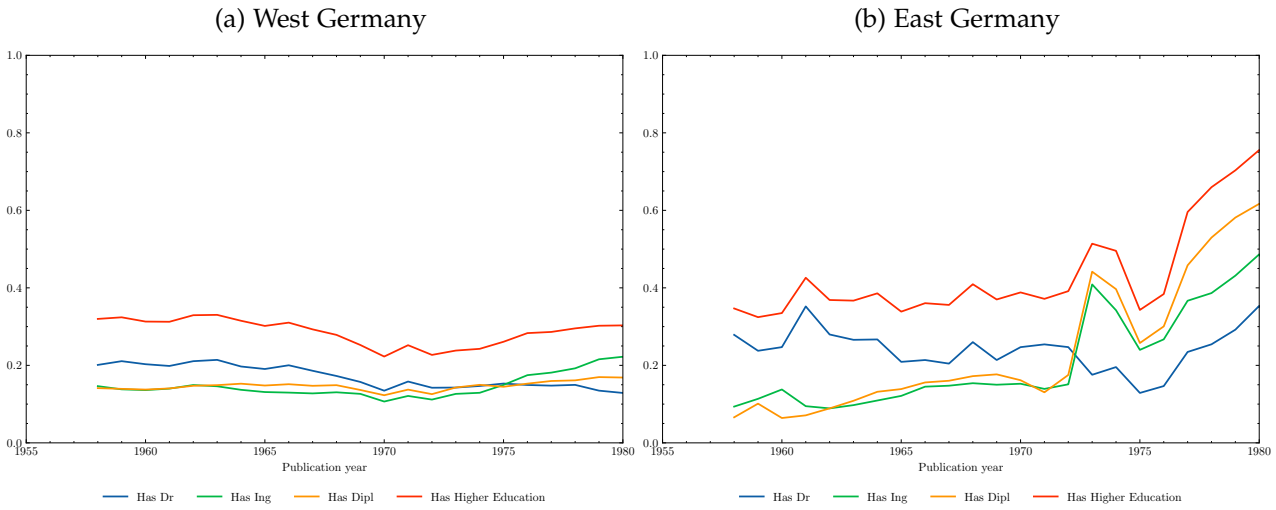
German patents (both East or West Germany) also offer a way to inform about the education of inventors as the names of the patentees are preceded by an academic title, when applicable. This includes the prefix "Dr.", but goes far beyond, with many different possibilities like "Dipl-Ing.", "Phy. Dr.", "Ing.", ... We consider the presence of these elements as indications that the inventor has some higher education.[20] Figure 5 reports the share of

[20] As already explained, this information does not directly relate to the occupation of the inventor but rather to its education level. Since many scholars consider occupation to construct a measure of the skill of workers, we chose to label this entity as occupation, i.e. under the same category as actual occupations reported in

patents where at least one inventor reports an academic title: Doctor (Has Dr), Engineer (Has Ing), Diploma (Has Dipl) and any the previous title (Has Higher Education). The time periods are restricted to 1955-1980 for West Germany and 1965-1980 in the case of East Germany due to limited reporting of inventors before those periods.

In both cases, Figure 5 shows that the share of patents involving an inventor who reports a title that indicates some higher education increases after the 1970s from around 25% to 35% in West Germany and from around 40% to 70% in East Germany. In addition, this increasing share seems to be driven by inventors who report to be engineers or to have a diploma, rather than doctors or professors whose relative importance has declined in time.

Figure 5: Share of inventors with an academic title in Germany



Notes: This Figure reports the share of patents with at least one inventor declaring an academic title: Doctor (Has Dr), Ingenior (Has Ing), Diploma (Has Dipl). We also define "Has Higher Degree" as the union of the previous variables. Time period: 1958-1980 for West Germany and 1965-1980 for East Germany.

3.4 Citizenship

The relationship between skilled immigration and innovation has been the subject of various studies, which have largely focused on recent immigration waves (e.g., Kerr and Lincoln, 2010). However, the information included in PatentCity provides an opportunity to investigate this question over a longer time period.

Most studies that examine the relationship between historical immigration and innovation (see e.g. Arkolakis et al., 2020 and Akcigit et al., 2017a) rely on external sources to identify immigrants, such as various US Census data or registers of inventors. In contrast,

British patents.

PatentCity uses the information on citizenship found in the text of patent publications in the US and the UK. This information is available during two distinct subperiods, 1920-1950 for the UK and 1880-1925 for the US, when the patent documents directly report the citizenship and location of some inventors. This approach enables us to classify inventors as "immigrants" based on the information available in the patents themselves.

Not all patentees declare a citizenship even during these subperiods. Among the set of patentee that are located in the United Kingdom, 87% report a citizenship for patents filed between 1920 and 1950. During the period 1950-1980, around 20% of inventors filing a British patent did declare their citizenship. For the US, this share is around 37% between 1880 and 1925 but is closer to 45% after 1910 (see Appendix Figure A6).

We find that between 4% and 5% of inventors who report an address in the US but are *not* Americans. In a recent work focusing on the USPTO, Diodato et al. (2022) reports a similar order of magnitude. In the United Kingdom, this share is lower, between 1% and 2%, at any point in time between 1920 and 1950. In Figure 6, we report this share every year for the two countries. We can see that the US experienced a sizeable increase in the share of immigrants during the 1910s. The United Kingdom experienced a similar upswing during the 1940s.

3.4.1 Immigrants in PatentCity

By nature, the concept of "immigrant" in PatentCity is different from the Census-based definition of being born abroad (used namely in Sarada et al., 2019; Arkolakis et al., 2020; Akcigit et al., 2017a) for at least three reasons. First, an inventor residing in the US or the UK but declaring to be a citizen of another country may only be a temporary visitor without any plan to settle permanently.

Second, our definition of immigrant only applies to individuals who are not yet citizens of their country of residence. Therefore, individuals who have obtained citizenship prior to filing their patents may not be identified as immigrants in our data. This second point is in particular critical in the US as the period during which USPTO patents sometimes report the citizenship status of the inventor corresponds to the "age of mass migration" during which naturalization was relatively easy to get in the US (typically after five year of residency). This could account for the lower shares of immigrant inventors reported in PatentCity or Diodato et al. (2022) compared to Akcigit et al. (2017a) or Sarada et al. (2019).

Third, our definition relies on the fact that the patentee disclosed its citizenship in the text of the patent. We did not find evidence from the regulation governing the functioning of the USPTO in the period 1880-1925 (e.g. Khan and Sokoloff 2001) and the British patent

offices in the 1920s (Van Dulken, 1999) regarding the citizenship of inventors, such as higher fees or specific requirements.[21] This has led previous attempt (e.g. Diodato et al., 2022; Campo et al., 2020) to assume that a non-reported nationality in the USPTO corresponds to a US citizen. To check this, we proceed as in Section 3.3. Specifically, we compared the distribution of technological classes and regions for domestic patents without disclosed citizenship (A) with patents filed by migrant inventors (B) and national citizen inventors (C) for the USPTO from 1880 to 1925 and the British patent office from 1920 to 1950. The correlation between A and C was higher than 99% in the US and equal to 97% in the UK for technological classes, and 97% and 95%, respectively, for regional shares. The correlations between A and B were 94% in the US and 95% in the UK for technological classes and 92% and 90%, respectively, for regional shares. Thus, patents without reported citizenship appeared to be closer to those filed by national citizens than those filed by immigrants.

In summary, the entity reporting the citizenship in PatentCity should be interpreted as evidence that the inventor has recently settled in their country of residence or have lived there without having the nationality. This definition differs from the one typically used in the literature. However, one advantage of this method is that it does not require the implementation of a complex matching process to external data, which usually relies on the name and location of inventors.

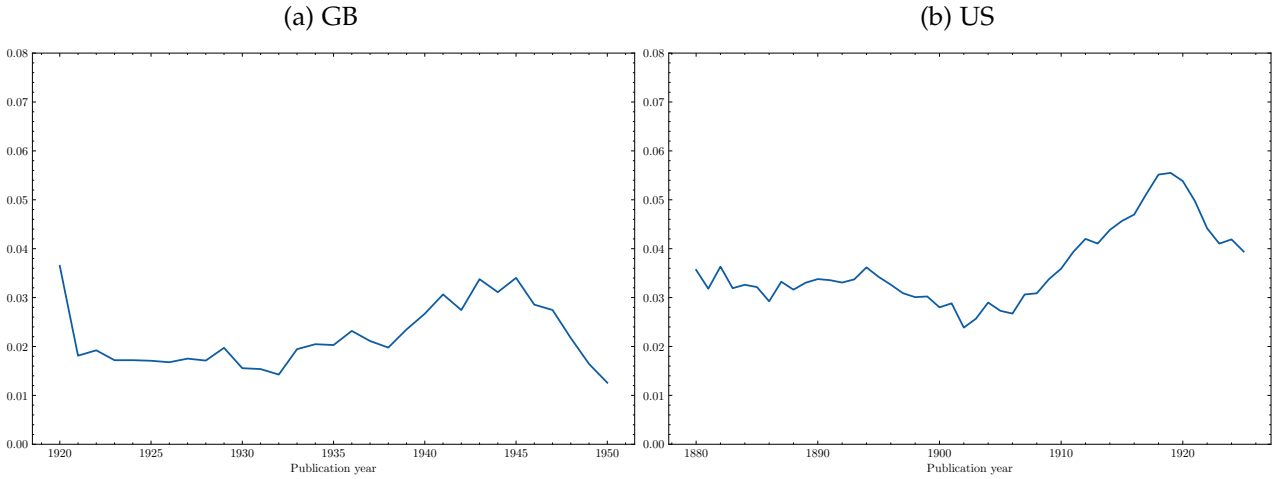
Finally, note that the citizenship entity can also be linked to assignees when a firm declares to be established under the commercial laws of a given country (see Appendix A.3) an information that is absent from other datasets.

3.4.2 Innovation by immigrants

Figure 7 reports the evolution of the composition of these immigrants by country of citizenship for the 10 most frequent nationalities respectively in the United Kingdom and the US. As expected, Europeans constituted the bulk of immigrant inventors (consistently between 70% and 90%) in the US.[22] The share of British and German inventors alone represented close to 60% of immigrant inventors in the late 19^{th} century and gradually decreased to reach 40% in the 1920s. In the United Kingdom the 1930s were marked by the massive migration of German inventors (most likely pushed out by the Nazis) who represented up to 40% of immigrant inventors in 1940 while they were almost absent before 1930. Following the *Anschluss* and the subsequent Poland invasion, the share of Austrian and Polish

[21] Although such rules have applied in some cases in earlier periods, see Appendix C.
[22] The list of the most represented citizenship is similar to the one shown in Diodato et al. (2022).

Figure 6: Share of immigrant inventors over time



Notes: The share of immigrant is computed as the ratio of the number of inventors who report a non-domestic citizenship different over the number of inventors reporting a domestic address. Time periods: 1920-1950 (GBR) and 1880-1925 (USA).

inventors rose up to close to 10%. Before this decade, American and Swiss immigrants represented up to around 40% of immigrant inventors.

Figure 7: Composition of immigrant inventors' citizenship

Notes: Each area represents the share of top 10 most frequent citizenship in the set of detected immigrant inventors in US (left-hand side) and British (right-hand side) patents. The remaining (blank) area represent the remaining citizenship. Time periods: 1920-1950 (GBR) and 1880-1925 (USA).

4 Conclusion

In this paper, we have presented a novel dataset constructed from an automated text analysis of patent documents published in the German (including East German), French, British

and US patent offices. The data cover as many years as possible and include most of the 20^{th} century, and part of the 19^{th} century. The information extracted from these publications offer a novel opportunity to acquire a better understanding of the long-term determinants of innovation and we presented three examples of future avenues using information on the geography of the patent, the occupation of the patentee and its citizenship.

Our work could be prolonged in different directions. One natural improvement would be to include more countries in the dataset. Patents have existed since the end of the 19^{th} century in many places that are important R&D actors: Japan, Sweden, Switzerland... The methodology presented in this paper has been designed with the goal of limiting future efforts to apply it to new patent corpus. We also hope that making the codebase open source will support a collective data design and continuous improvement momentum.

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Online Appendix

A Data Appendix

A.1 Selection of utility patents

Intellectual property offices publish many documents that are called "patents". For example, the USPTO publishes "plant patents", "defensive publications", "reissue patents". To select the patents that most closely match the idea of *patents of invention* and to avoid double counting, we select documents based on the kind codes. Our goal is to mimic as closely as possible the concept of "first publication of granted patent". We start with a list of kind code that corresponds to utility patents which we enumerate in Table A1. From this list, we make additional selections to remove non granted patents and to keep only first publications. Formally, we made the following selections:

- **United States:** We keep documents with kind code A (Granted patents prior to 2001), B1 (Granted patent published without an application), B2 (Granted patent published with an application, after 2001).
- **Germany:** We keep publications with kind code C (*"Patentschrift"*) or B (*"Auslegeschrift"*) without conditions. These corresponds to first publications of patents before 1970. After 1970, the publication process changed and a given patents could have several publication. We keep kind code A1 (*"Offenlegungsschrift"*) whenever a given patent (identified by the publication number without the kind code) has more than one publication. We then keep kind code C2 if the patent does not have a A1 publication but has more than one additional publication (on top of the C2). Finally, we keep all patents that have only one publication, except if this publication is a A1 document.
- **France:** We keep publications with kind code A and A5 without conditions (*"Brevet d'invention"*). We then keep kind code A1 (*"Demande de Brevet d'Invention"*) if there is only one publication for a given patent and if the publication year is earlier than 1971. Otherwise we keep publications with kind code A1 if there are more than one publication for the patent.
- **United Kingdom:** We keep documents with kind code A (Patent Application) if the publication number is lower than 2000000 or if the publication year is earlier than 1921. Otherwise, we keep A if there are more than one publication for the patent.

These rules are governed by the fact that the patent systems change over time. Typically in earlier years, all patent publications correspond to the one and only document that served as the final granted patent. In the most recent decades, patent offices published the patent applications along with other subsequent documents if the granting process was successful. Simply counting all patent applications would result in the inclusion of patents that have not been granted and to overestimate the number of patents in the most recent period. Note that we also release a version of the database where we did not make these restrictions and include all utilities patents, whose kind code are summarized in Table A1.

Table A1: Granted utility patents

Patent office	Time span (publication year)	Kind code(s)
DD	1950-1992	A, A1, A3, B
DE	1877-2013	A1, B, B3, C, C1, D1
FR	1902-2013	A, A1, A5*, B1*
GB	1893-2013	A, B*
US	1836-2013	A, B1*, B2*

Notes: The selected kind codes try to emulate the USPTO concept of "Granted Utility Patent". We restrict to the first publication or second publication without first publication kind codes in order to avoid double counting issues. We exclude patent *applications* and *revised* publications for the same reason. In the case of DD, we are limited by the availability of raw patent images and therefore include all types of publications. * indicates that the kind-code is considered only after 1980. This can be due to changes in the meaning of the kind-code or to its creation date.

A.2 Formats

The structure of a patent document can change over time as the patent office modernizes its publications and processes. We tracked these changes and adapted the statistical model that we used to each cases. Table A2 shows the different formats for each patent offices and the first and last patents of each format.

Table A2: Publication number and patent format

Patent office	Publication number (range)	Format number	Earliest Year
DD	DD1 - DD123499	1	1951
DD	DD123500 -	2	1977
DE	DE1C - DE977922C	1	1877
DE	DE1000001B -	2	1957
FR	FR317502A - FR1569050A	1	1902
FR	FR1569051A - FR1605567A and then from FR2000001A1	2	1969
GB	GB189317126A - GB2000001A	1	1894
GB	GB2000001A -	2	1979
US	US1A - US1583766A	1	1836
US	US1583767A - US1920166A	2	1924
US	US1920167A - US3554066A	3	1933
US	US3554067A -	4	1971

Notes: The structure of a patent document can change over time. We track these changes and adapt the statistical model to each case. The table shows the different formats for each patent office and the associated first and last patents of each format. The earliest year corresponds to the first year in which the corresponding format was implemented. For more details, see Annotation guidelines for the US, Germany, the UK and France.

A.3 Entities by country

In this Section, we detail the different types of entities matched for each country and what they usually means.

United States In the case of the US, the inventors and assignees are clearly separated entities. The inventor is the name of the person who conceived the invention while the

assignee is the entity (either a person, a firm, the government, a university...) who own the right of the patent. US patents also give information on the citizenship of patentees. In the case of inventors, this is the country of citizenship (e.g., "a citizen of the kingdom of Italy") and in the case of assignee the legal origin of the firm when applicable ("a company duly organized under the laws of New Jersey"). Finally, the entity location gives the address of the inventor and assignee, usually at the city level. For more details, see the Annotation guidelines for the US

Germany In the case of Germany, inventors are referred to as *"Erfinder"* and assignees as *"Anmelder"*. Both entities can represent physical people while assignees can also be companies. Most of the patents filed before the 1950s do not include any inventor. Although it is likely that in that case, the inventor and the assignee can be the same person, we only label the entity as inventor when the term *"Erfinder"* is explicitly mentioned. German patents also give some information on the occupation of inventors or assignees from the denomination of their academic title (e.g., *"Dr."*, *"Ing."* or *"Pr."*). Finally, the location is usually given by the city of the inventor or assignee. For more details, see the Annotation guidelines for Germany and the specific guidelines for East-Germany

France The case of France is similar to the case of Germany regarding inventors and assignees. Most of the patents have a *"déposant"* which we label as assignee while some patents also have an *"inventeur"* which we label as inventor. French patents do not give information on occupation or citizenship, except if extremely rare instances. The location is given at the county (*"département"* level in the case of a patentee located in France and at the country level for foreign inventors. For more details, see the Annotation guidelines for France

United Kingdom In the British case, the inventor and the assignees are not explicitly distinguishable. By convention, we denote each firm by an assignee and each person as an inventor. The British patents also include information on the occupation of the inventor, and in some case on the occupation of the assignee (e.g., "a clock manufacturing company"). Information on the citizenship of inventor and assignee are also provided like in the US. Finally, the location of the assignee and of the inventor is given as a full postal address. For more details, see the Annotation guidelines for British patents.

A.4 Data coverage

This Section presents the coverage of each entities as a share of patents for the five patent offices considered. Precisely:

- Figure A1 plots the yearly share of patents with at least one inventor
- Figure A2 the yearly share of patents with at least one assignee
- Figure A3 plots the yearly share of patents with at least one location
- Figure A4 the share of patentees that are matched with a location

- Figure A5 plots the yearly share of inventors with at least one entity occupations
- Figures A6 plots the yearly share of inventors with at least one entity citizenship
- Figure A7 shows the relative share of each level of geographical matching.
- Figure A8 reports the composition of the geocoding by source: either using commercial geocoding supplier: HERE or GMAPS or manually

Finally, Figures A9, A10 report the number and share of patent publications by source: either from PatentCity, from de Rassenfosse et al., 2019 or from the expansion (that is, we expand the entities and relationships to all patents of the same family when information is missing). Figures A11 and A12 compare the coverage of the PatentCity database with the coverage of the Claims database that we take as the universe of patents.

Figure A1: Share of patents with at least one inventor

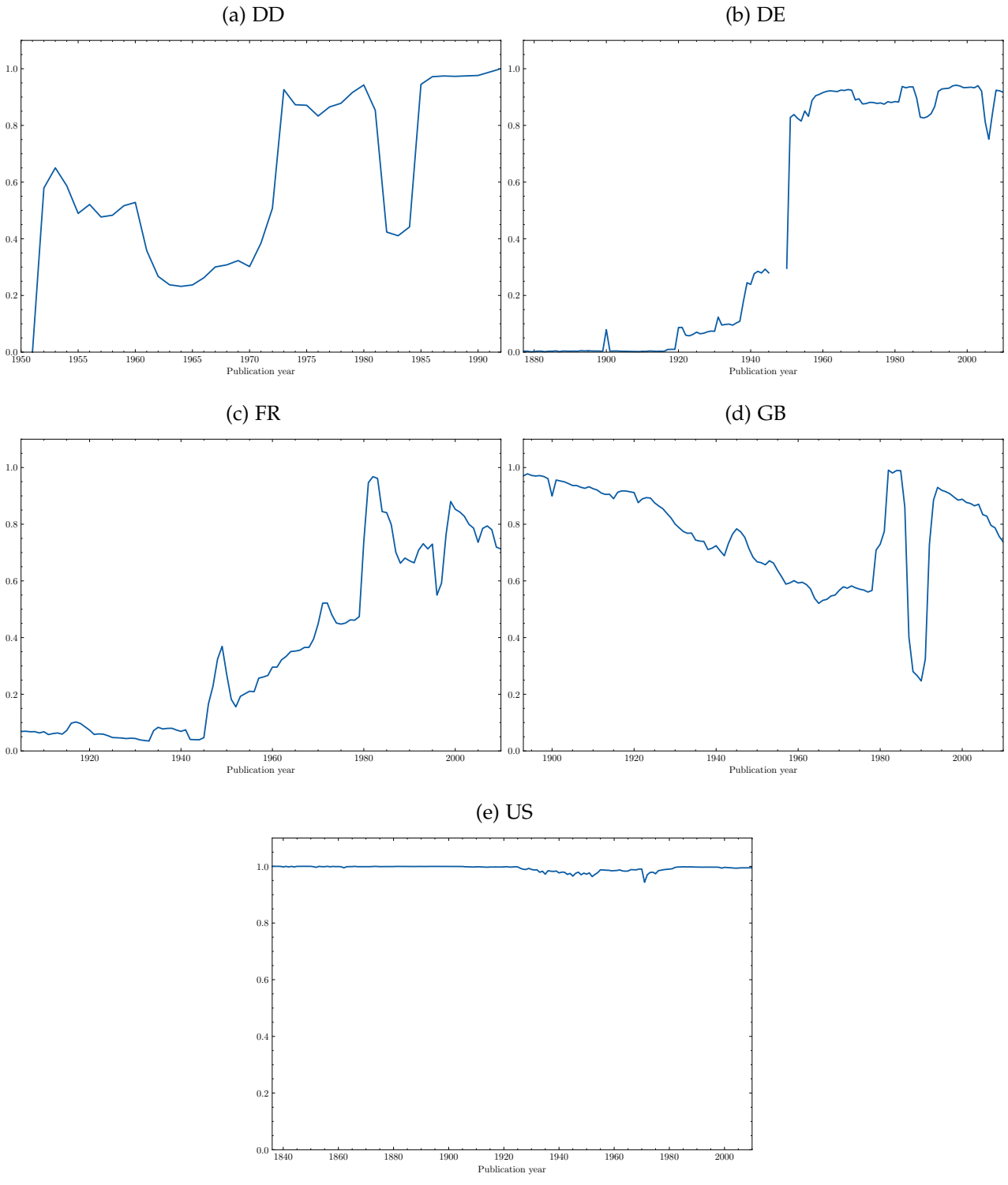


Figure A2: Share of patents with at least one assignee

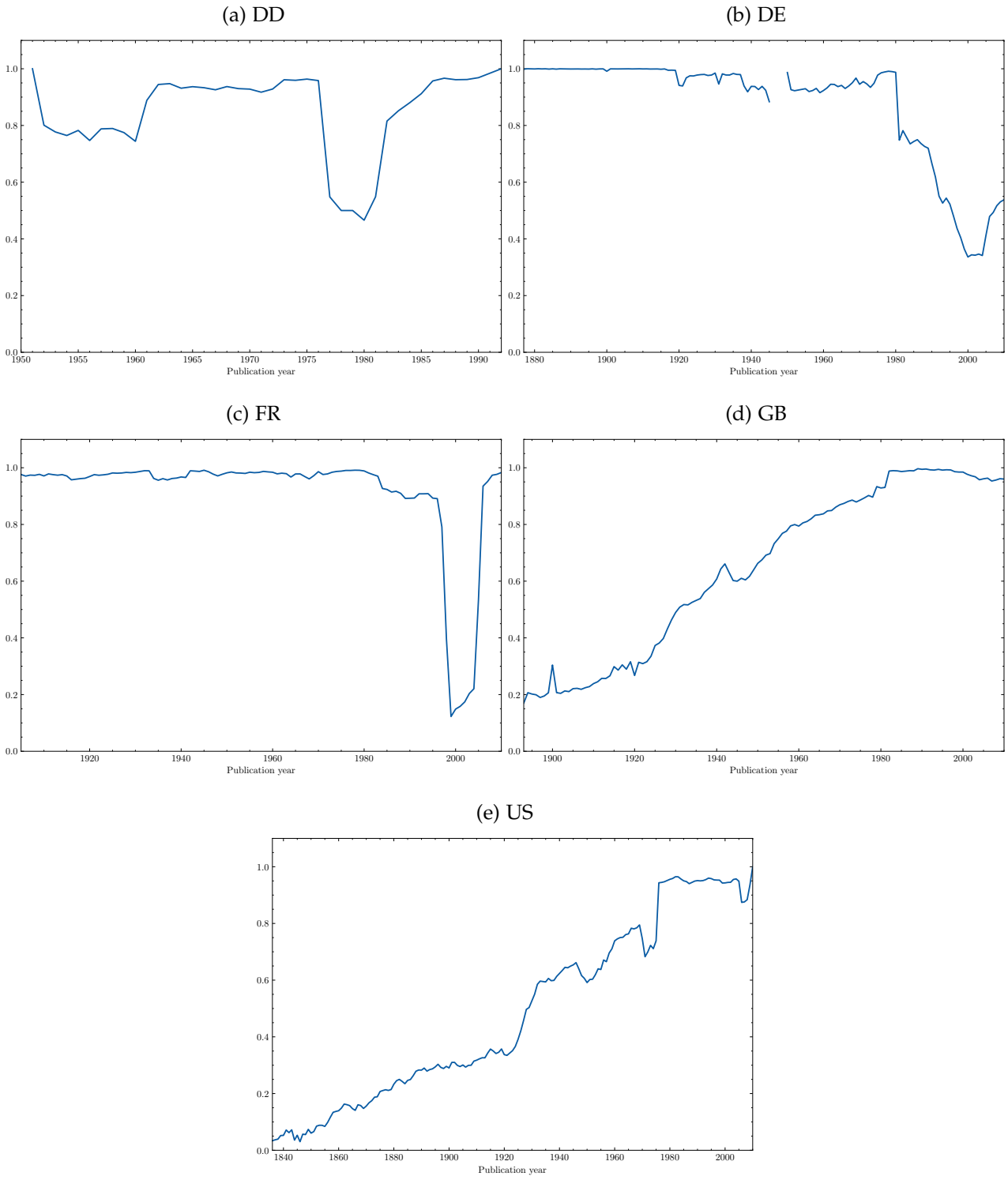


Figure A3: Share of patents with at least one location

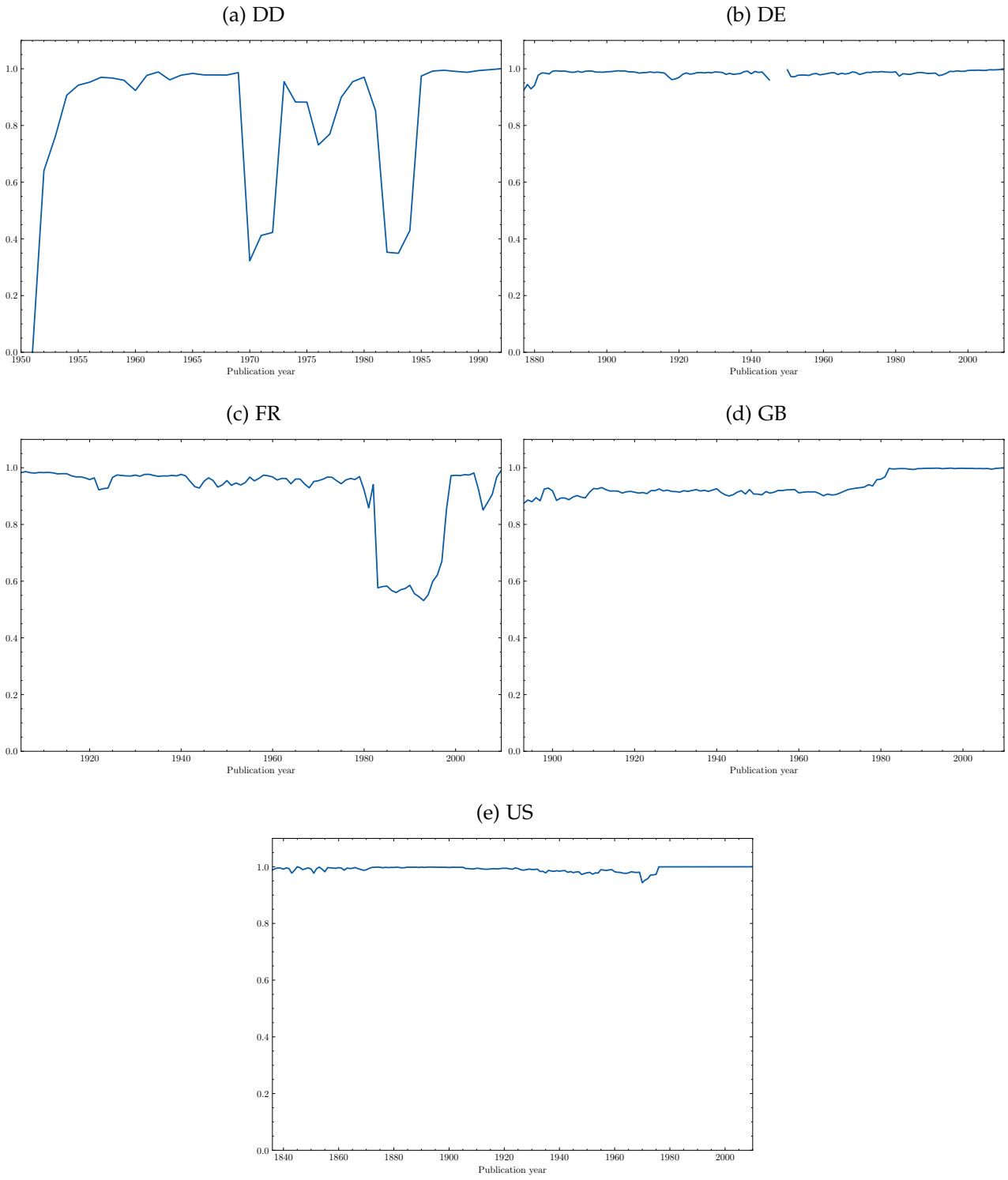


Figure A4: Share of patentees with a detected location

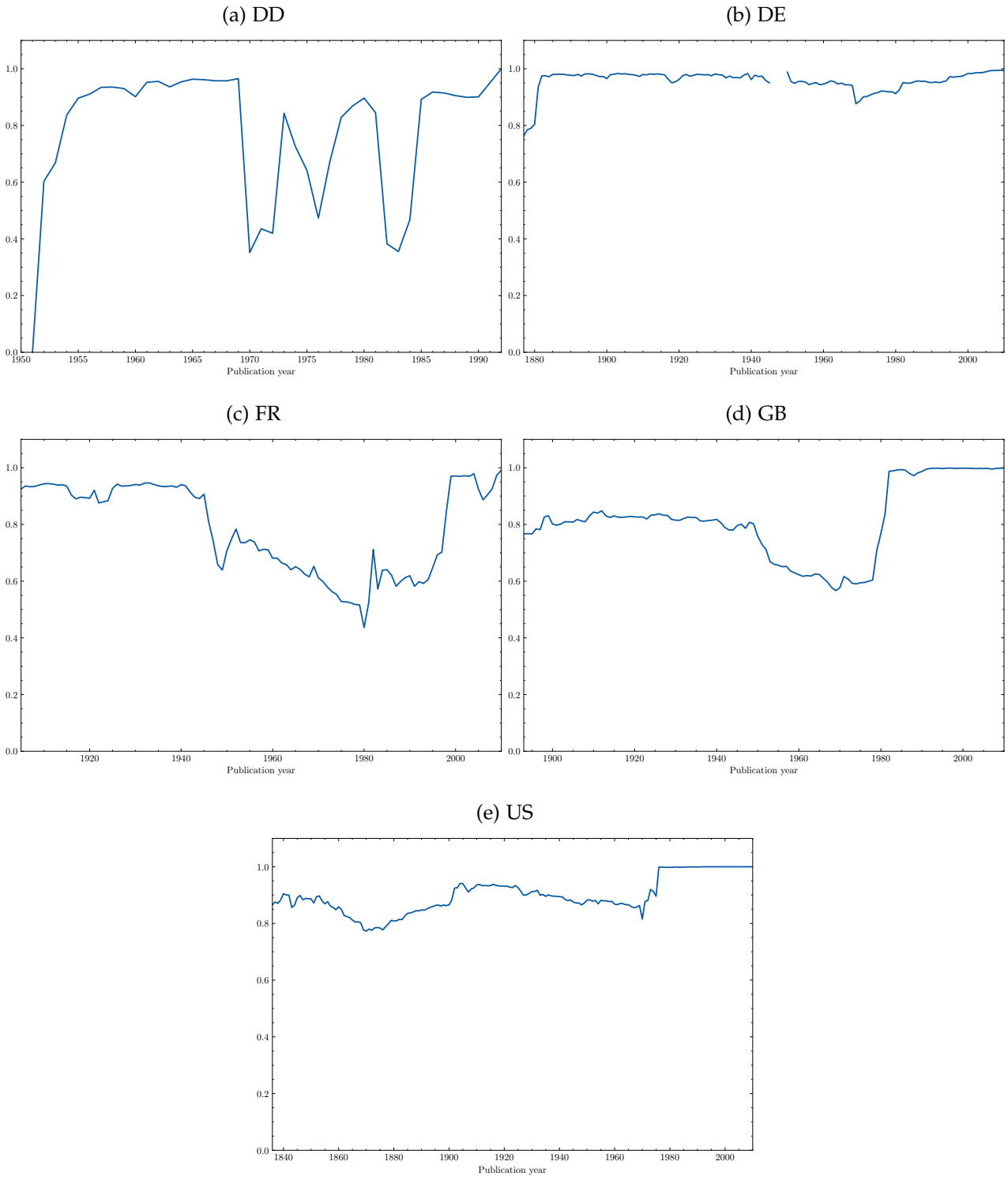
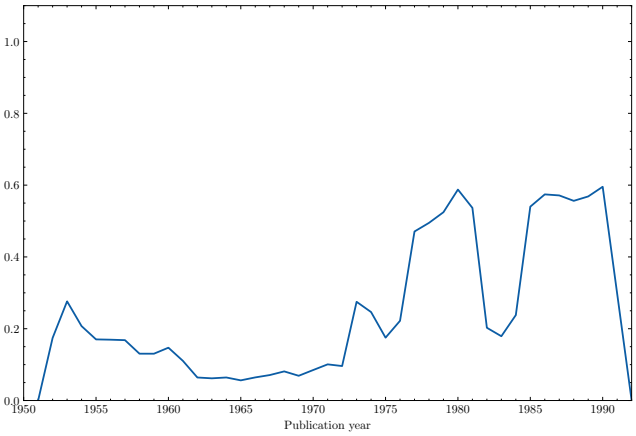
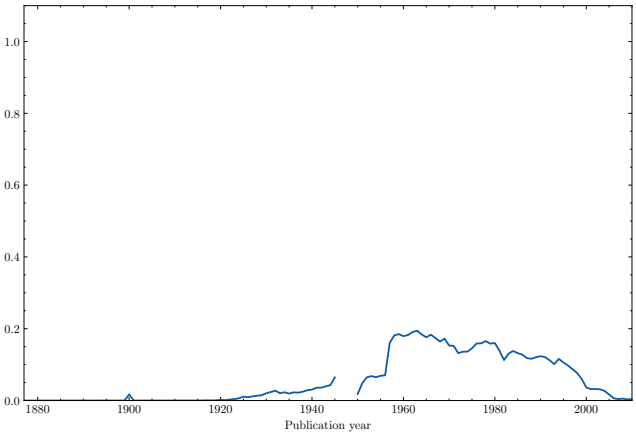


Figure A5: Share of inventors with a detected occupation

(a) DD



(b) DE



(c) GB

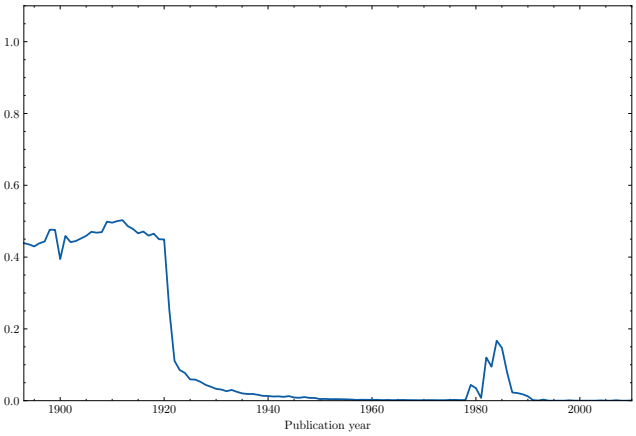
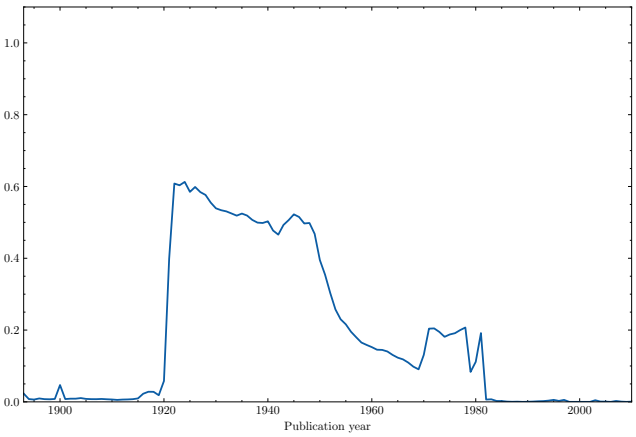


Figure A6: Share of inventors with a detected citizenship

(a) GB



(b) US

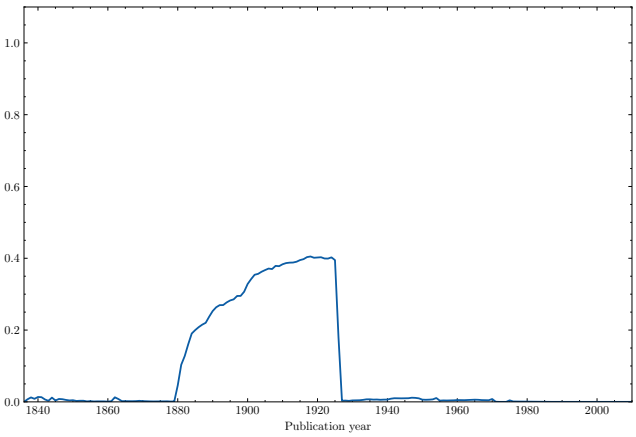
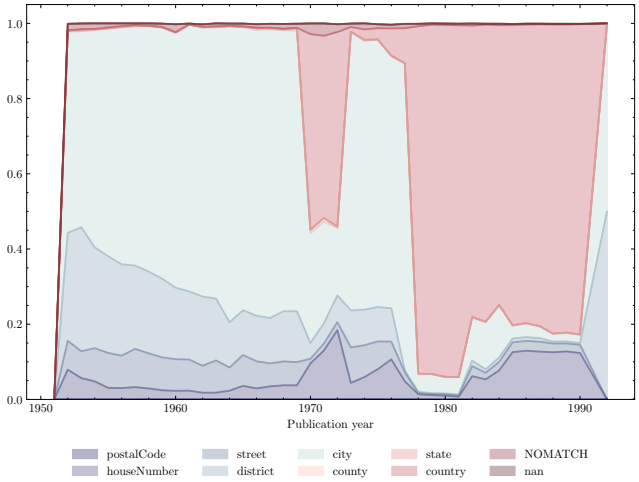
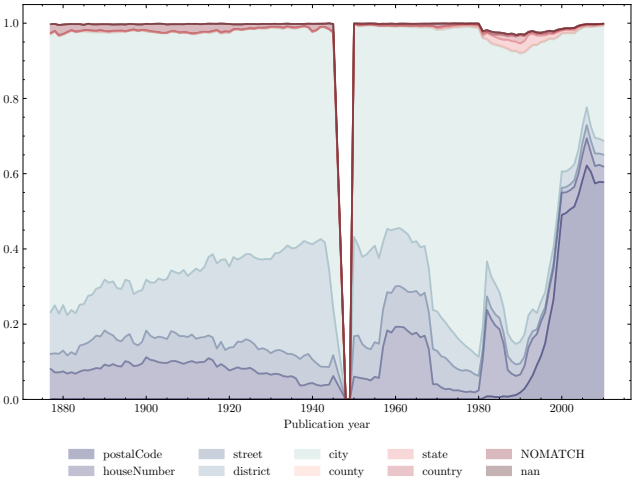


Figure A7: Composition of the most detailed level of geocoding

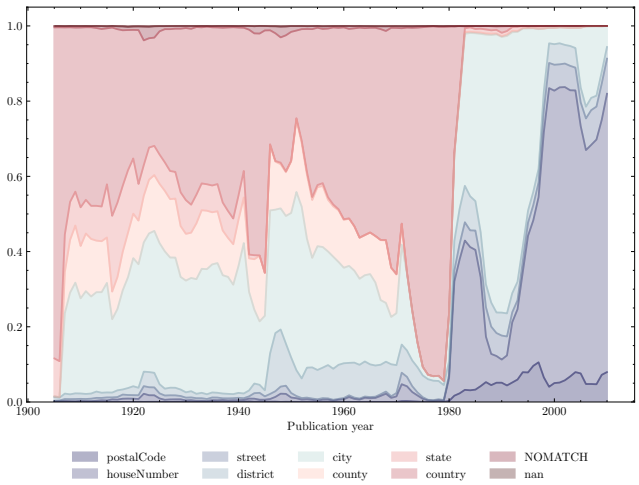
(a) DD



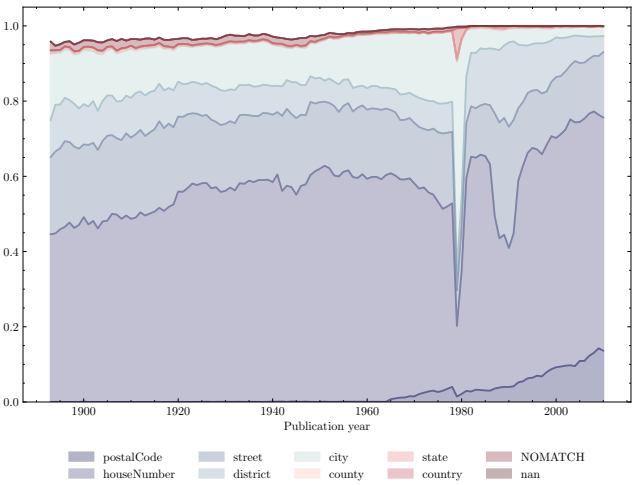
(b) DE



(c) FR



(d) GB



(e) US

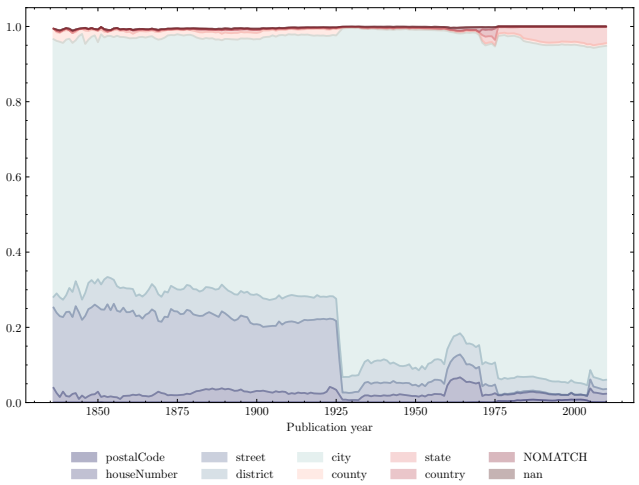
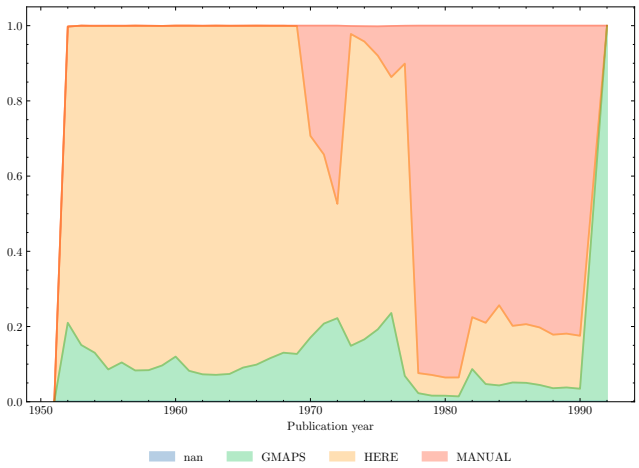
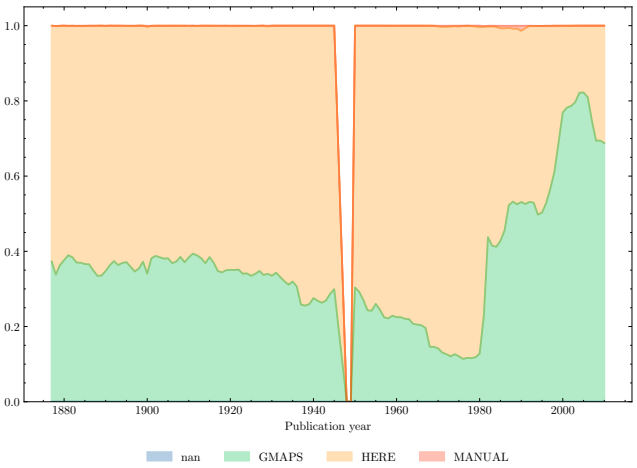


Figure A8: Composition of geocoding by geocoding source

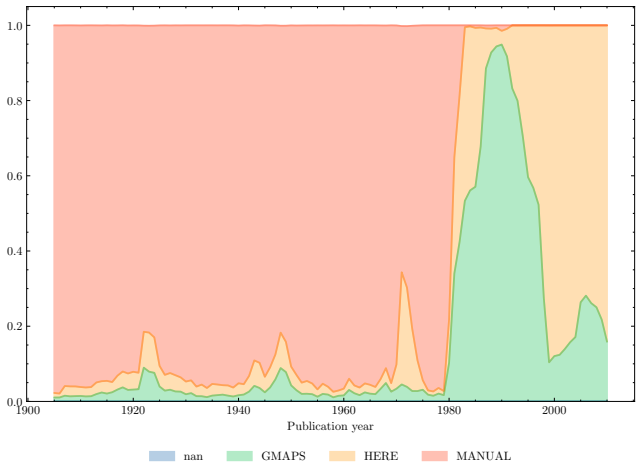
(a) DD



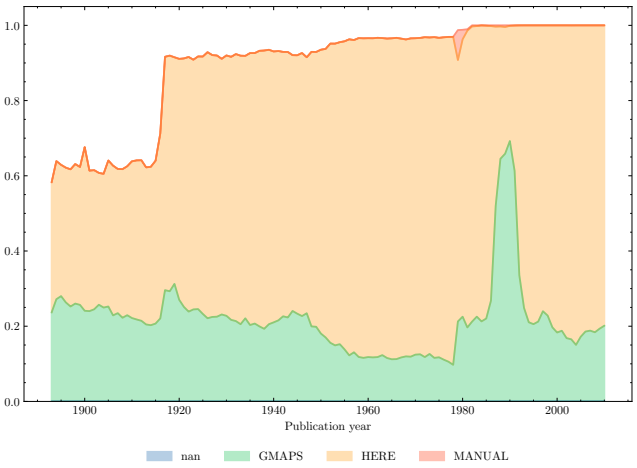
(b) DE



(c) FR



(d) GB



(e) US

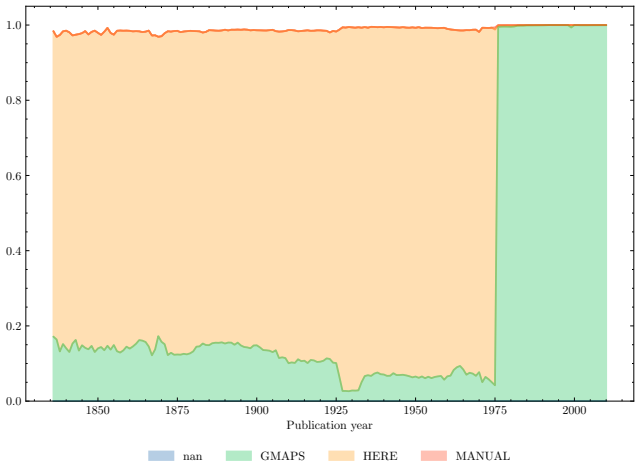
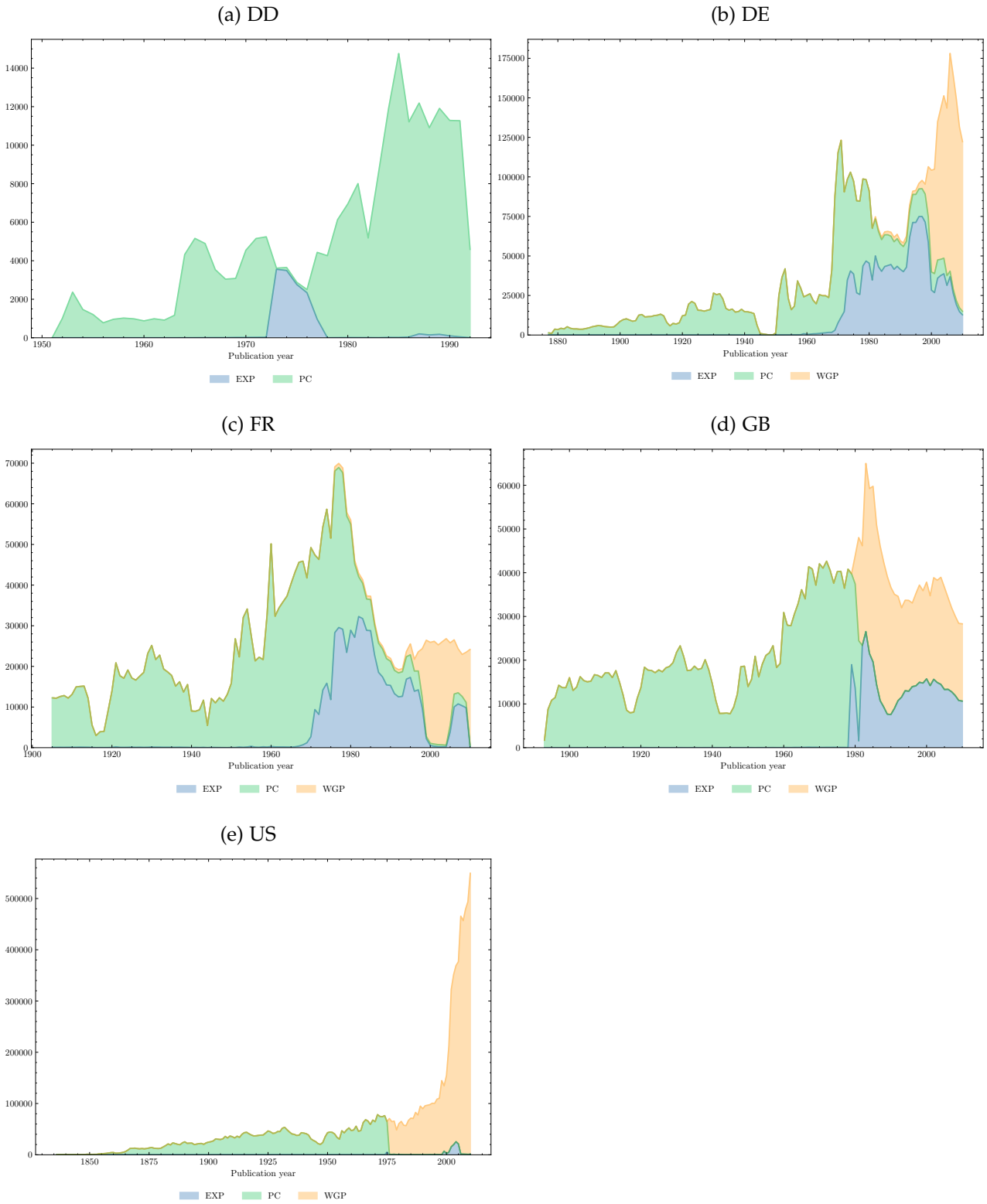
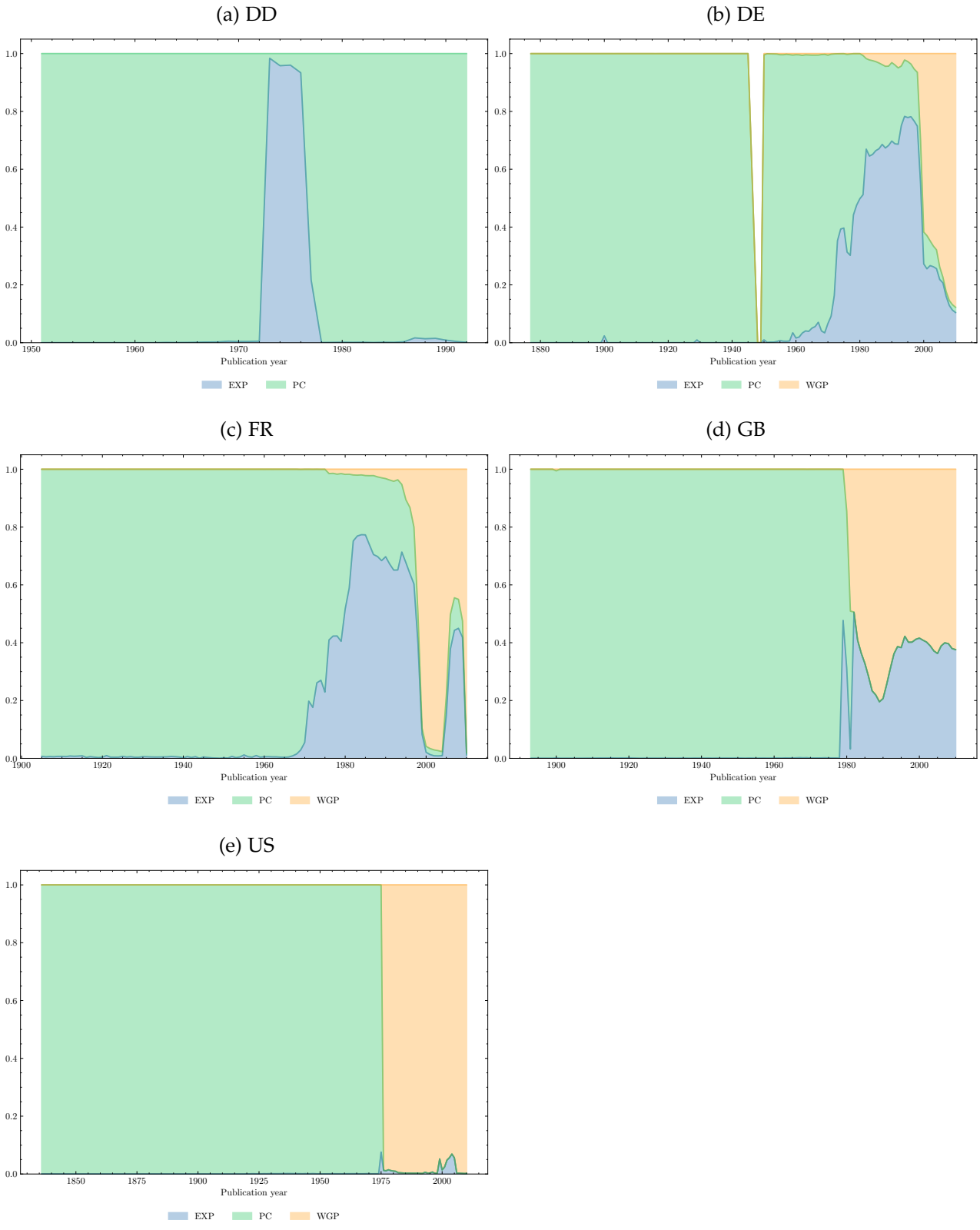


Figure A9: Database composition by source (number of patents)



Notes: PC refers to PatentCity data, WGP refers to de Rassenfosse et al. (2019) data and EXP refers to data collected from family expansion from patents included in either PC or WGP.

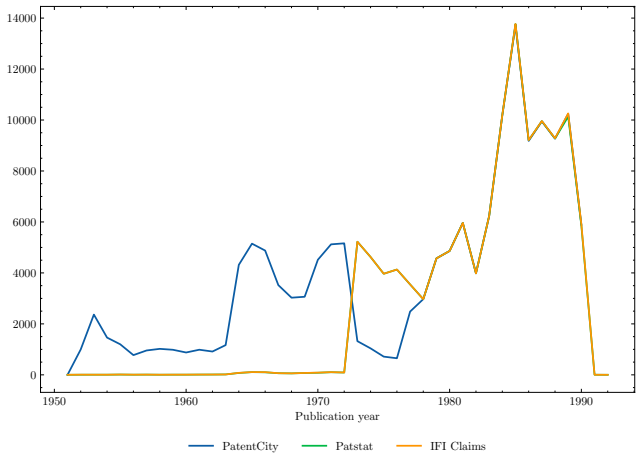
Figure A10: Database composition by source (in share)



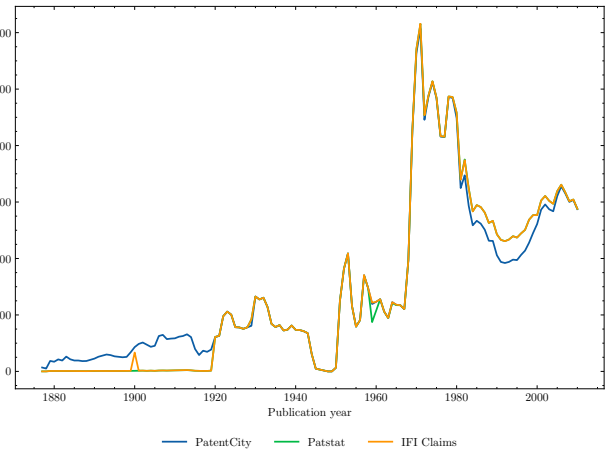
Notes: PC refers to PatentCity data, WGP refers to de Rassenfosse et al. (2019) data and EXP refers to data collected from family expansion from patents included in either PC or WGP.

Figure A11: Database coverage by office and publication year (in absolute values)

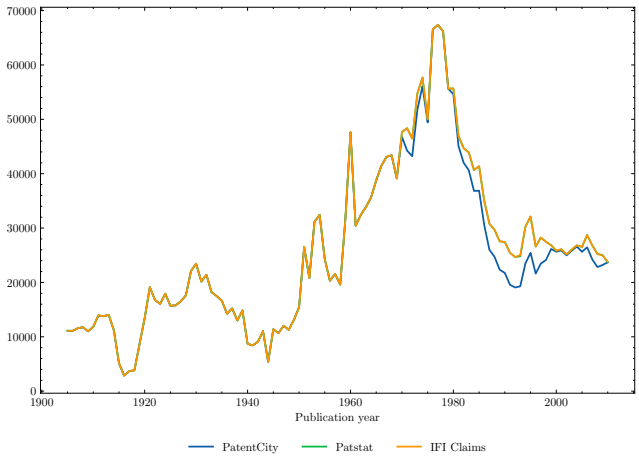
(a) DD



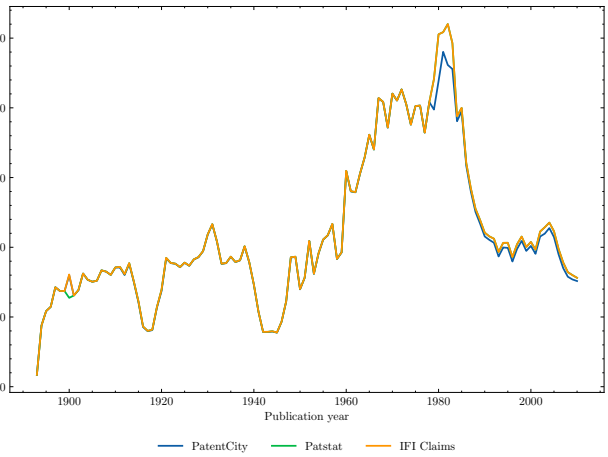
(b) DE



(c) FR



(d) GB



(e) US

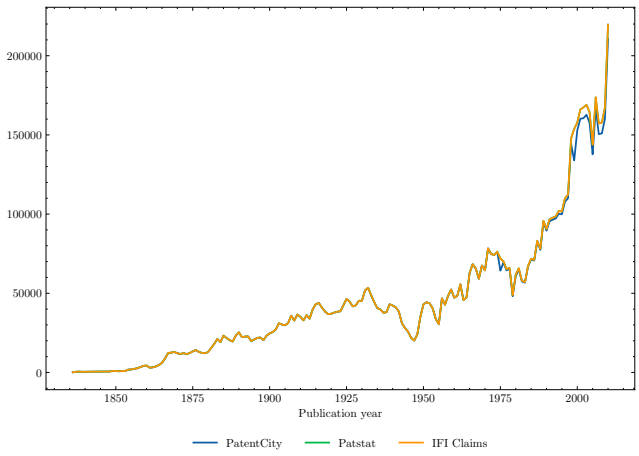
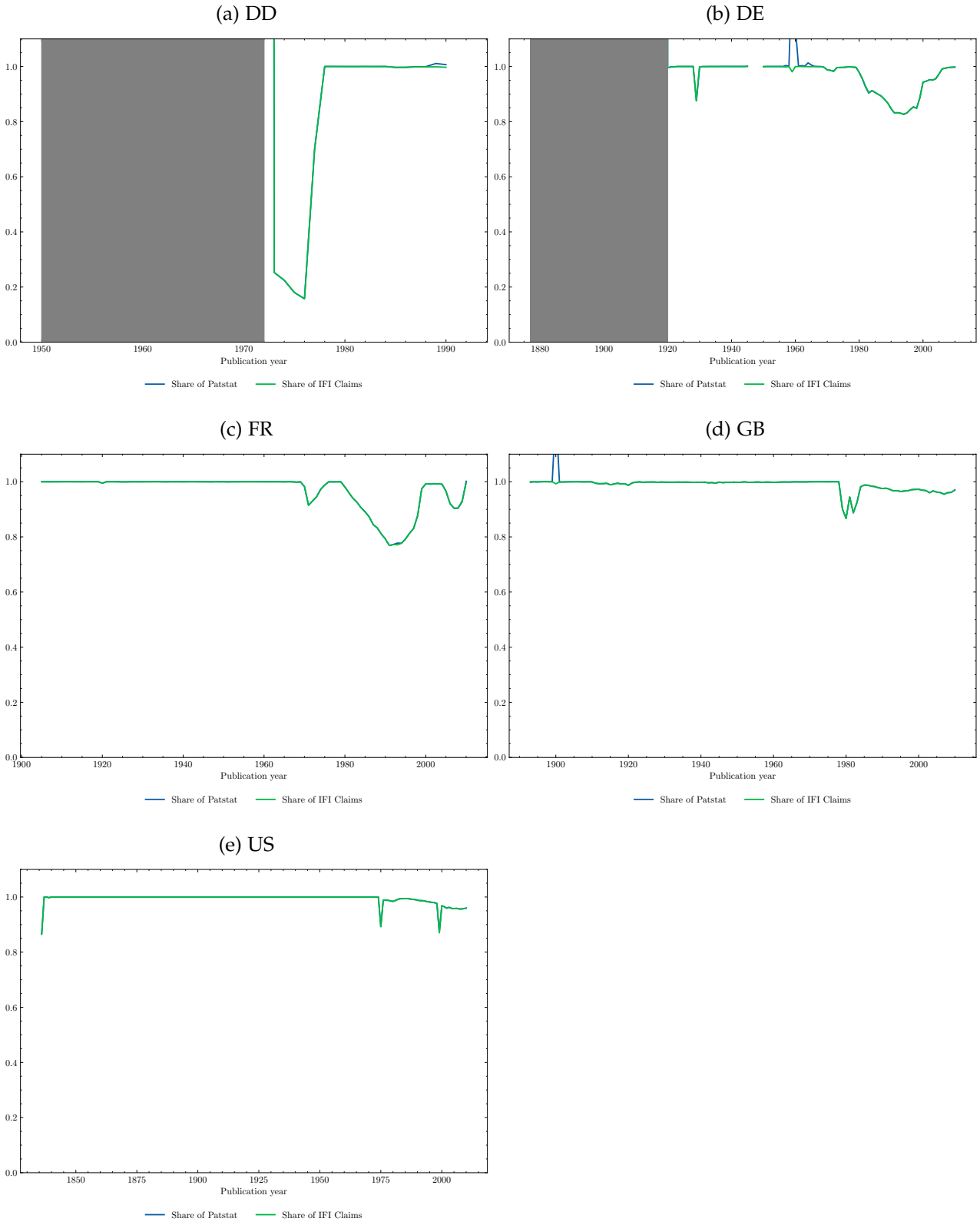


Figure A12: Database coverage by office and publication year (in share of the Claims database coverage



Notes: We report the share of patents which are reported in our database at the office-publication year level as compared to the coverage of the IFI Claims database (publicly available as part of the Google patents public dataset). Shaded areas correspond to office and publication years where patents reported in the IFI Claims database miss dates, meaning that we miss a proper denominator.

A.5 Population data and geographical adjustments

We construct population data at the regional level using official sources for the most recent period from as long as possible: respectively De-Statis for Germany, the Insee for France, the ONS for the United Kingdom and the Census Bureau's Population Estimates for the US. We summarize the source and construction below.

United States We start from the Census' population estimate at the county level 1969-2020 which we backdate using the census estimates every ten years since 1790. We aggregate the data at the current county boundaries using the crosswalk provided by Eckert et al. (2020).

Germany We begin with the official estimates provided by De-Statis, which are available yearly starting from 1977. To estimate population figures for earlier years, we use Census estimates from 1871, 1900, 1905, 1910, 1925, 1939, 1950, 1961, 1964, and 1974. In order to account for changes in territorial boundaries, we group the 401 NUTS 3 regions into 288 units by merging the most populous city-regions (*Stadtkreise*) with the surrounding regions using the procedure described in Wyrwich (2020).

France The Insee provides yearly estimates of population at the city level as well as for the years 1876, 1881, 1886, 1891, 1896, 1901, 1906, 1911, 1921, 1926, 1931, 1936, 1954, 1962, 1968, 1975, 1982, 1990 and 1999. We aggregate these at the NUTS 3 (*département*) level. To account for changes in the Paris area, we merged current départements 91, 78 and 95 into one (which broadly correspond to the former *Seine-et-Oise* region before 1968) and current départements 92, 93, 94 with Paris to form the former *Seine* département.

United Kingdom The ONS provides yearly estimates of population by local authorities since 1981 which can be aggregated at the NUTS 3 level using the crosswalk provided in the repository of the project. Unfortunately, we were not able to construct historical estimates at the NUTS 3 level due to the very high number of boundary changes and only report estimates aggregated at the NUTS 2 level (Northern Ireland, counties in England, groups of districts in Greater London, groups of unitary authorities in Wales, groups of council areas in Scotland). We use the census in years 1871, 1881, 1891, 1901, 1911, 1921, 1931, 1939, 1951, 1961, 1966 and 1971 which we retrieved from Vision of Britain (VoB) population data, except for London where we use data directly available from the London Census and for Northern Ireland where we used information from NISRA. Not all NUTS 2 regions were available through VoB and we proceed to the following assumptions:

- Tweeddale was constructed by aggregating Peebles and Selkirkshire
- Roxburgh Ettrick and Lauderdale was constructed using Roxburghshire + Selkirkshire + one fourthe of Berwickshire and one fourth of Midlothian
- Cheshire was obtained by aggregating Halton, Warrington, Cheshire east, Cheshire West and Chester

- Mid Glamorgan was constructed by taking half of Caerphilly to which we added Bridgend, Merthyr Tydfil and Rhondda Cynon Taff
- South Glamorgan was constructed as the sum of Vale of Glamorgan and Cardiff
- Clwyd was taken as the aggregation of Flintshire, Wrexham and Denbighshire
- Dyfed was constructed using Carmarthenshire, Ceredigion and Pembrokeshire
- Gwent was constructed from Blaenau Gwent, half of Caerphilly, Monmouthshire, Newport and Torfaen
- Vale of Glamorgan was assimilated to Glamorganshire

A.6 Additional annotation guidelines

Tables A3 and A4 present additional representative examples of the rules we used to label the patents. See Section 2 and the detailed guidelines for East Germany, Germany, France, the United Kingdom and the United States.

A.7 Structure of the dataset

The dataset is publicly available both as a csv file and in SQL. The unit of observation is the patent, identifiable from the DOCDB publication number. Each patent is associated with a set of patentees (inventors or assignees) which have nested attributes: name, citizenship, location and occupation. The structure of the dataset is presented in Table A5.

Table A3: Entity annotation guidelines

Patent office	Entity	Content	Example
DD	ASG	Assignee full name	Inhaber: Rhône Poulenc S.A , Paris (Frankreich).
	INV	Inventor full name (*Erfinder*)	Erfinder: Dr. Karl Jellinek , WD
	LOC	Location of the assignee/inventor	Erfinder: Jean Auguste Phelisse, Lyon (Frankreich).
	OCC	Occupation of the assignee/inventor (academic title)	Dr. Elisabeth Kob, WD.
DE	ASG	Assignee full name	ANTON KLEBER in SAARBRUCKEN
	INV	Inventor full name (*Erfinder*)	Frutz Doring , Berlin-Frohnau ist als Erfinder genannt worden
	LOC	Location of the assignee/inventor	Demag Akt-Ges. in Duisburg.
	OCC	Occupation of the assignee/inventor (academic title)	Dipl-Ing Georg Werner Gaze, Ingolstadt
	CLAS	Technological class (German system)	KLASSE 49h GRUPPE 27 D 16736VI/49h
FR	ASG	Assignee full name	M. Robert John Jocelyn SWAN résidant en Angleterre
	INV	Inventor full name	(Demande de brevet déposée aux Etats-Unis d'Amérique au nom de M. Ladislas Charles MATSCH)
	LOC	Location of the assignee/inventor	M. Louis LEGRAND résidant en France.
	CLAS	Technological class (French system)	XII Instruments de précision 3 POIDS ET MESURES, INSTRUMENTS DE MATHEMMATIQUES
GB	PERS	Person full name	Maxim Hanson Hersey , Lighting Engineer
	ORG	Firm full name	We, The Convex Incandescent Mantle Company Limited , Manufacturers
	CIT	The origin of the firm or citizenship of the person	a subject of the king of Great Britain and Ireland ,
	LOC	Location of the person/firm	Maxim Hanson Hersey, Lighting Engineer, of 145, Bethune Road, Amhurst Park, London N..
	OCC	Occupation of the person	Maxim Hanson Hersey, Lighting Engineer .
US	INV	Inventor full name	Be it known that I, JAMES M. GARDINER , ...
	ASG	Assignee full name	ASSIGNOR OF ONE-HALF TO SMITH FULMER
	LOC	Location of the assignee/inventor	residing at Mikkalo, in the county of Gilliam and State of Oregon
	CIT	Citizenship of inventor	JOHN SCHLATTER, a citizen of United States

Notes: Colored text corresponds to the entities that we seek to extract: red for inventors, purple for assignees, olive for locations, brown for citizenship and blue for occupations. Full annotation guidelines available at https://cverluise.github.io/patentcity/ (section Guides).

Table A4: Relation annotation guidelines

Patent office	Relation	Content	E.g
DD	LOCATION	Links an ASG/INV to a LOC	Rhône Poulenc S.A ⟶ LOCATION ⟶ Paris (Frankreich)
	OCCUPATION	Links an ASG/INV to an OCC	Dr ⟵ OCCUPATION ⟵ Elisabeth Kob
DE	LOCATION	Links an ASG/INV to a LOC	MARIUS ALBERT de DION ⟶ LOCATION ⟶ PUTEAUX (Seine, Frankr.)
	OCCUPATION	Links an ASG/INV to an OCC	Dr. ⟵ OCCUPATION ⟵ KARL HENKEL
FR	LOCATION	Links an ASG/INV to a LOC	M.Frederic PERDRIZET ⟶ LOCATION ⟶ France (Gironde)
GB	CITIZENSHIP	Links an ORG/PERS to its CIT	Maxim Hanson Hersey ⟶ CITIZENSHIP ⟶ subject of the king of Great Britain and Ireland
	LOCATION	Links an ASG/INV to a LOC	Maxim Hanson Hersey ⟶ LOCATION ⟶ 145, Bethune Road, Amhurst Park, London N.
	OCCUPATION	Links an ASG/INV to an OCC	Maxim Hanson Hersey ⟶ OCCUPATION ⟶ Lighting Engineer
US	CITIZENSHIP	Links an INV/ASG to its CIT	WILLIAM H. BAKER ⟶ CITIZENSHIP ⟶ citizen of the United States
	LOCATION	Links an ASG/INV to a LOC	SEDWARD WILLIAM YOUNG ⟶ LOCATION ⟶ Tytherley, Wimborne, Dorset, England

Notes: Examples of relations between extracted entities for each patent office. Colored text corresponds to the entities extracted: red for personal inventors, purple for assignees, olive for locations, brown for citizenship and blue for occupations.

Table A5: Database schema

Name	Description	Type	Nb non null
publication_number	Publication number.	STR	18,626,068
publication_date	Publication date (yyyymmdd).	INT	18,625,367
family_id	Family ID (DOCDB).	STR	18,625,353
country_code	Country code of the patent office.	STR	18,626,068
pubnum	Publication number.	STR	18,626,068
kind_code	Kind code.	STR	18,626,068
origin	Indicates the origin of the patentee data (PC: patentcity, WGP25: Worldwide Geocoding of Patent - slot 25, WGP45: Worldwide Geocoding of Patent - slot 45, EXP: expansion).	STR	18,626,068
patentee	Patentee	REC	18,626,068
__.is_inv	True if the patentee is an inventor, else False.	BOOL	45,537,241
__.is_asg	True if the patentee is an assignee, else False.	BOOL	45,537,241
__.name_text	Name.	STR	43,402,865
__.person_id	Person ID (PATSTAT).	INT	23,763,520
__.name_start	Name start.	INT	19,639,345
__.name_end	Name end.	INT	19,639,345
__.occ_text	Occupation text.	STR	1,354,930
__.occ_start	Occupation start.	INT	1,354,930
__.occ_end	Occupation end.	INT	1,354,930
__.cit_text	Citizenship text.	STR	3,996,958
__.cit_code	Citizenship code.	STR	3,861,775
__.cit_start	Citizenship start.	INT	3,996,958
__.cit_end	Citizenship end.	INT	3,996,958
__.loc_text	Location text.	STR	42,232,737
__.loc_start	Location start.	INT	16,334,841
__.loc_end	Location end.	INT	16,334,841
__.loc_addressLines	Formatted address lines built out of the parsed address components.	STR	16,003,816
__.loc_locationLabel	Assembled address value for displaying purposes.	STR	41,901,699
__.loc_country	ISO 3166-alpha-3 country code.	STR	41,898,330
__.loc_state	First subdivision level(s) below the country. Where commonly used, this is a state code (for instance, CA for California).	STR	41,428,298

Continued on next page

__.loc_county	Second subdivision level(s) below the country. Use of this field is optional if a second subdivision level is not available.	STR	34,200,971
__.loc_city	Locality of the address.	STR	40,391,684
__.loc_district	Subdivision level below the city. Use of this field is optional if a second subdivision level is not available.	STR	18,276,320
__.loc_subdistrict	Subdivision level below the district. Used only for India.	STR	16,003,816
__.loc_postalCode	Postal code.	STR	23,837,493
__.loc_street	Street name.	STR	18,145,660
__.loc_building	Building name.	STR	16,130,485
__.loc_houseNumber	House number.	STR	17,710,245
__.loc_longitude	Longitude.	FLOA	41,517,796
__.loc_latitude	Latitude.	FLOA	41,517,796
__.loc_relevance	Indicates the relevance of the results found; the higher the score the more relevant the alternative. The score is a normalized value between 0 and 1.	FLOA	12,203,353
__.loc_matchType	Quality of the location match. pointAddress: Location matches exactly as point address. interpolated: Location was interpolated.	STR	41,268,017
__.loc_matchCode	Code indicating how well the result matches the request. Enumeration [exact, ambiguous, upHierarchy, ambiguousUpHierarchy].	STR	16,003,816
__.loc_matchLevel	The most detailed address field that matched the input record.	STR	41,643,215
__.loc_matchQualityCountry	MatchQuality provides detailed information about the match quality of a result at attribute level. Match quality is a value between 0.0 and 1.0. 1.0 represents a 100% match. Here, matchQuality is defined at country level.	FLOA	2,658,311
__.loc_matchQualityState	Same at state level.	FLOA	6,553,671
__.loc_matchQualityCounty	Same at county level.	FLOA	1,547,347
__.loc_matchQualityCity	Same at city level.	FLOA	11,331,772
__.loc_matchQualityDistrict	Same at district level.	FLOA	1,361,402

Continued on next page

__.loc_matchQualityPostalCode	Same at postalCode level.	FLOA	147,862
__.loc_matchQualityStreet	Same at street level.	FLOA	2,452,802
__.loc_matchQualityHouseNumber	Same at houseNumber level.	FLOA	1,034,844
__.loc_matchQualityBuilding	Same at building level.	FLOA	410
__.loc_key	Key used for statistical area mapping (internal use).	STR	31,137,221
__.loc_statisticalArea1	Name of the high level Statistical Area.	STR	31,061,188
__.loc_statisticalArea1Code	Code of the high level Statistical Area.	STR	31,061,188
__.loc_statisticalArea2	Name of the mid level Statistical Area.	STR	31,061,165
__.loc_statisticalArea2Code	Code of the mid level Statistical Area.	STR	19,738,673
__.loc_statisticalArea3	Name of the low level Statistical Area.	STR	31,055,300
__.loc_statisticalArea3Code	Code of the low level Statistical Area.	STR	31,067,057
__.loc_recId	Identifier of the input address in the response.	STR	42,232,737
__.loc_seqLength	Number of results for the corresponding input record.	INT	12,244,380
__.loc_seqNumber	Consecutively numbers the different results for the corresponding input record starting with 1.	INT	29,657,332
__.loc_source	Geocoding source (in [HERE, GMAPS, MANUAL]).	STR	41,901,712
__.is_duplicate	True if a patentee with the 'same' name has been detected in the same patent. Only one of the two is marked as duplicate.	BOOL	3,985,815

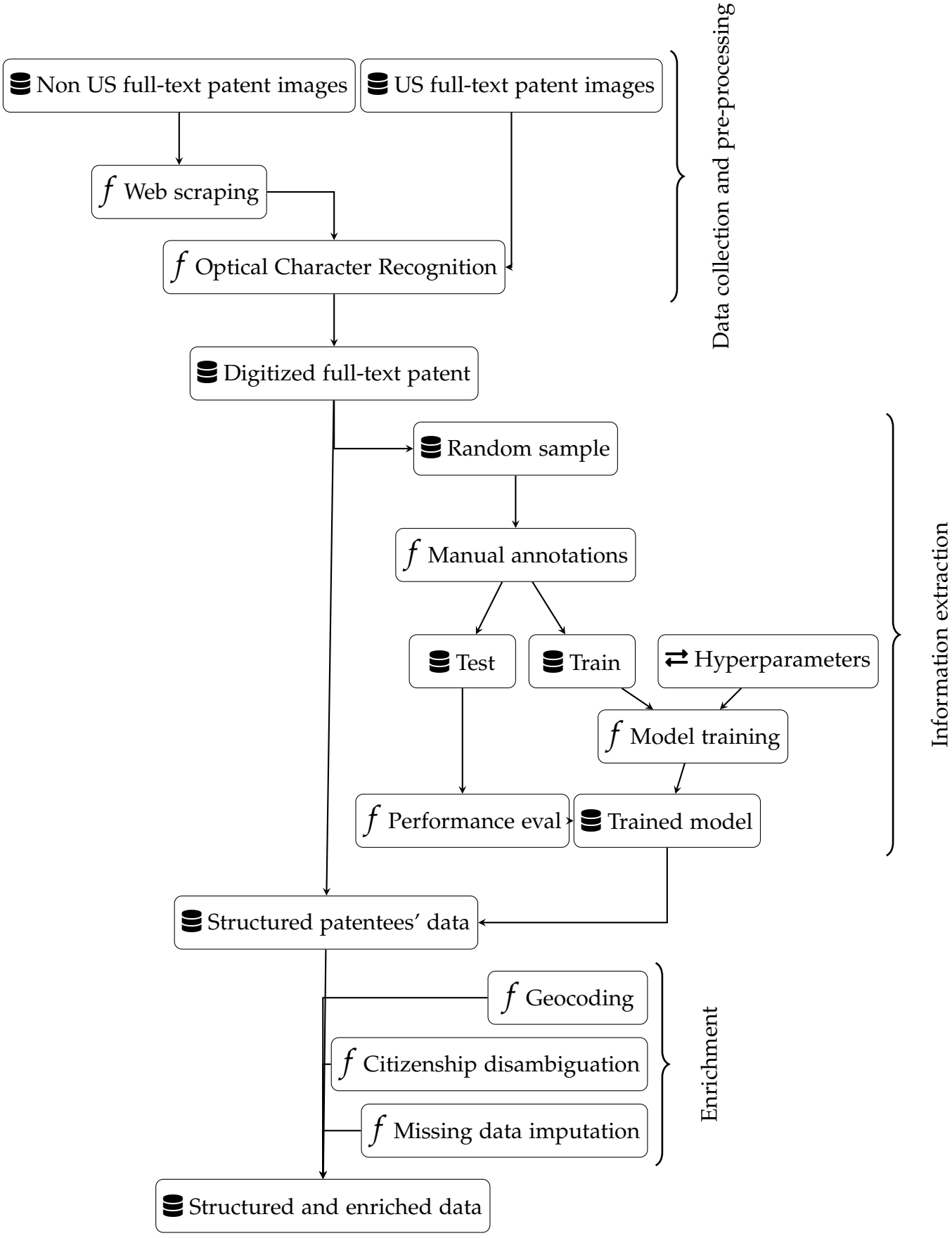
Notes: Variable names prefixed by a «__.» are nested variables. For example, «__.is_inv» is nested in the «patentee» variable.

A.8 Pipeline

We summarize the full pipeline from the raw documents to the structured and enriched database in Figure A13.

A13.

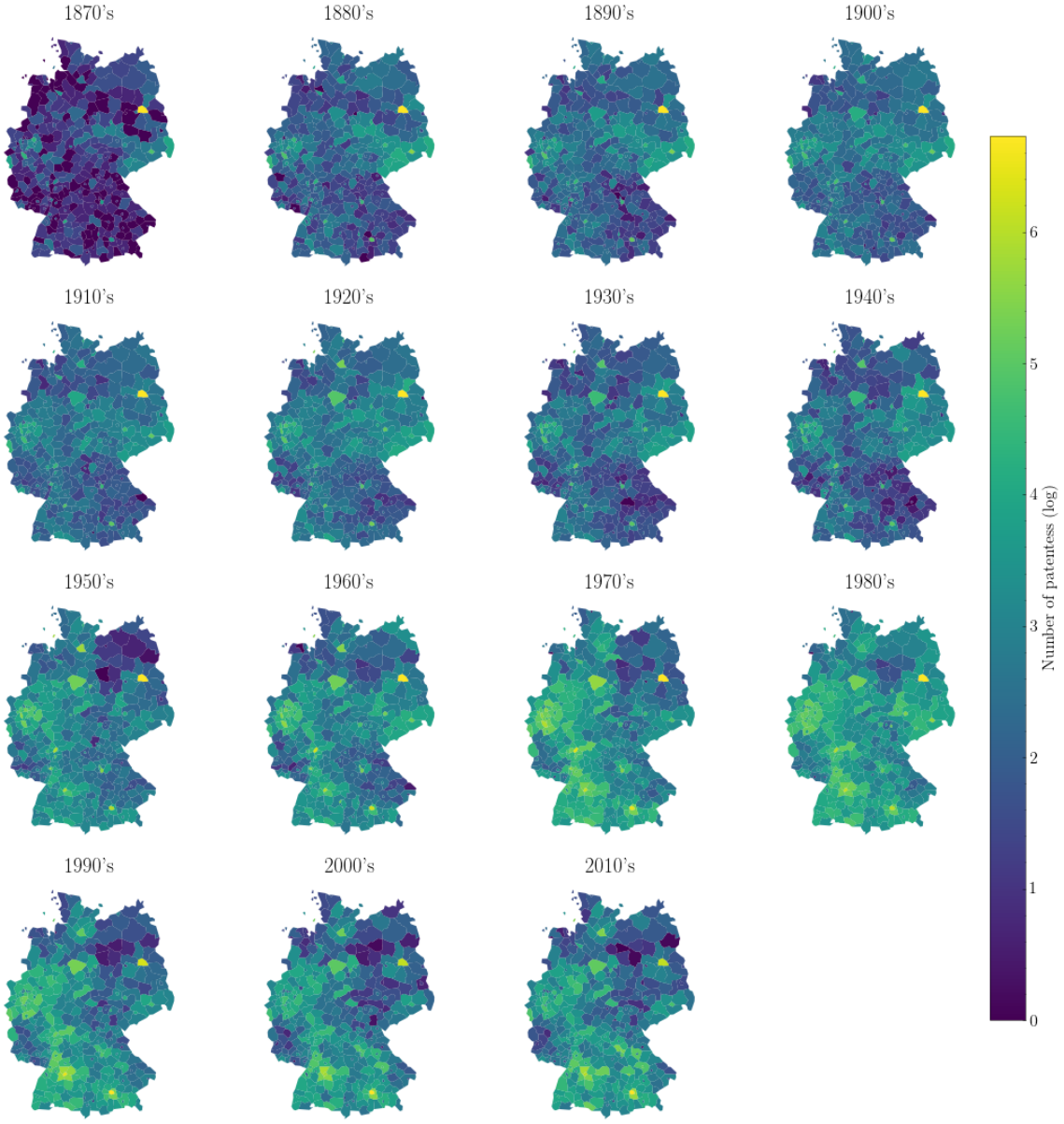
Figure A13: Workflow pipeline



B Additional Maps

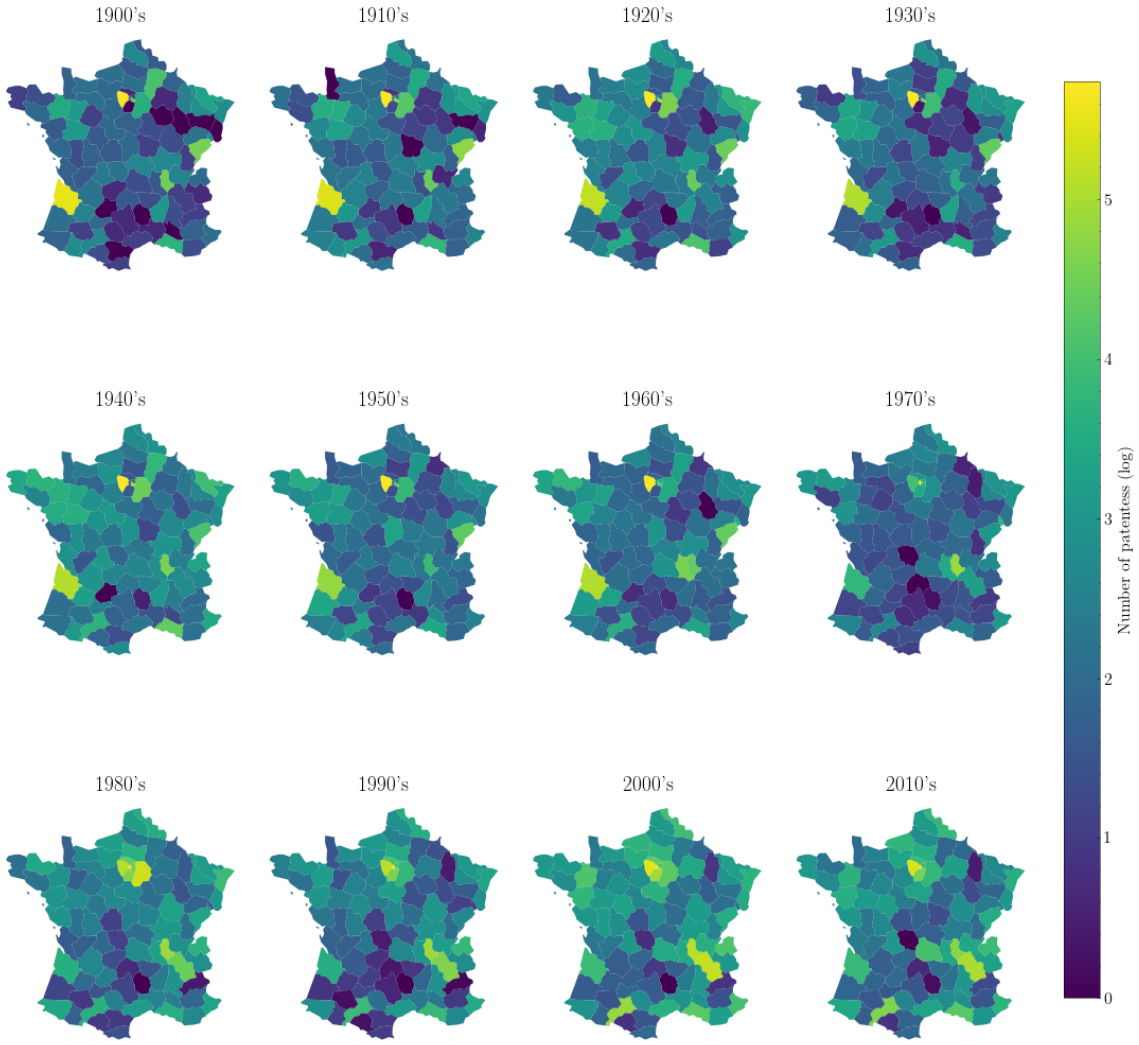
Figures B1, B2, B3 and B4 map the number of patentees by regions NUTS 3 (commuting zones in the US) by decade.

Figure B1: Patentees by regions and decade - Germany



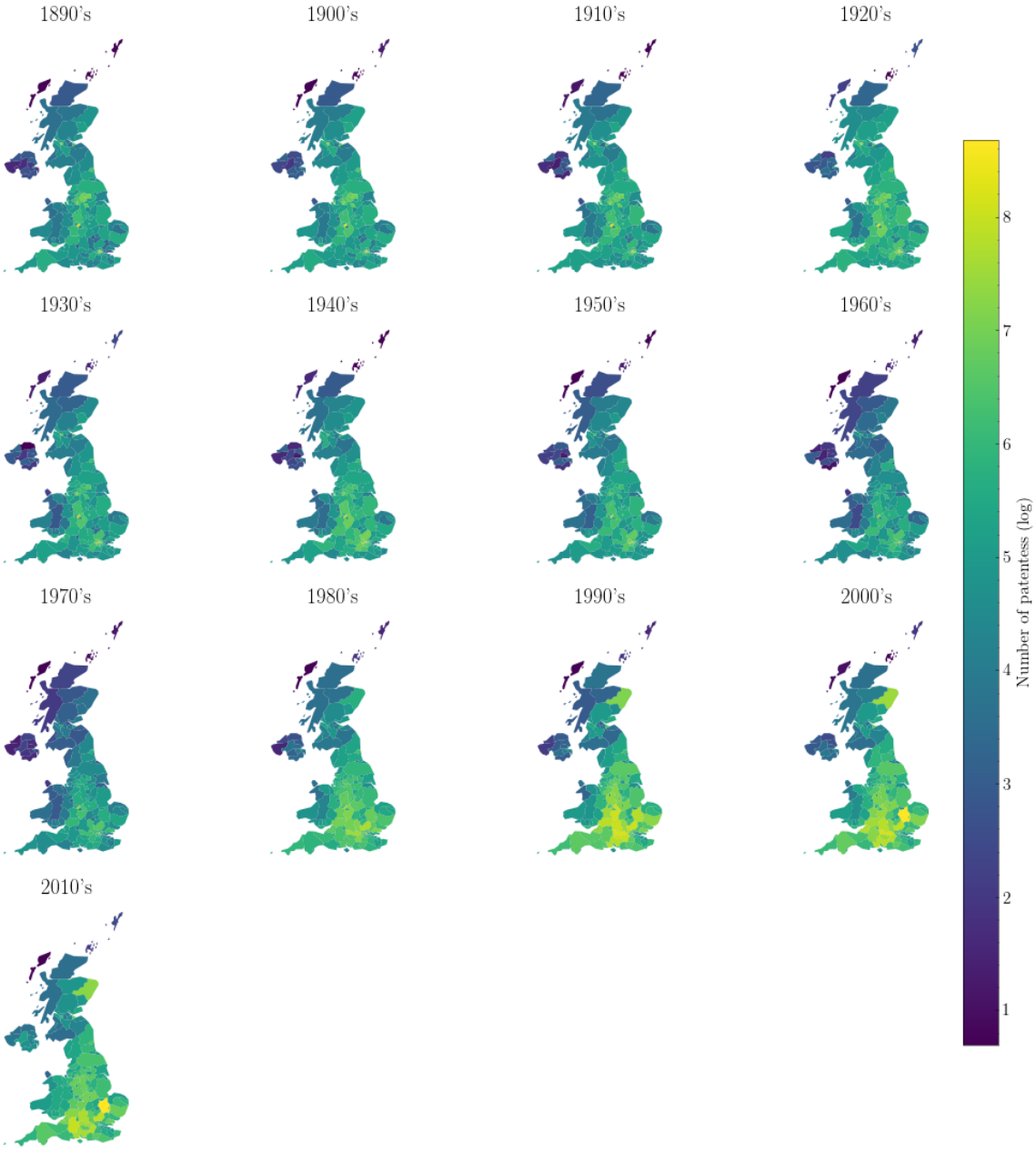
Notes: this Figure maps the total number of patentees (whether assignees or inventors), in log, for each county in Germany (*Kreise*) for each decade. The number of patentees is taken as a total over the full set of domestic patentees that are located at least at the county level.

Figure B2: Patentees by regions and decade - France



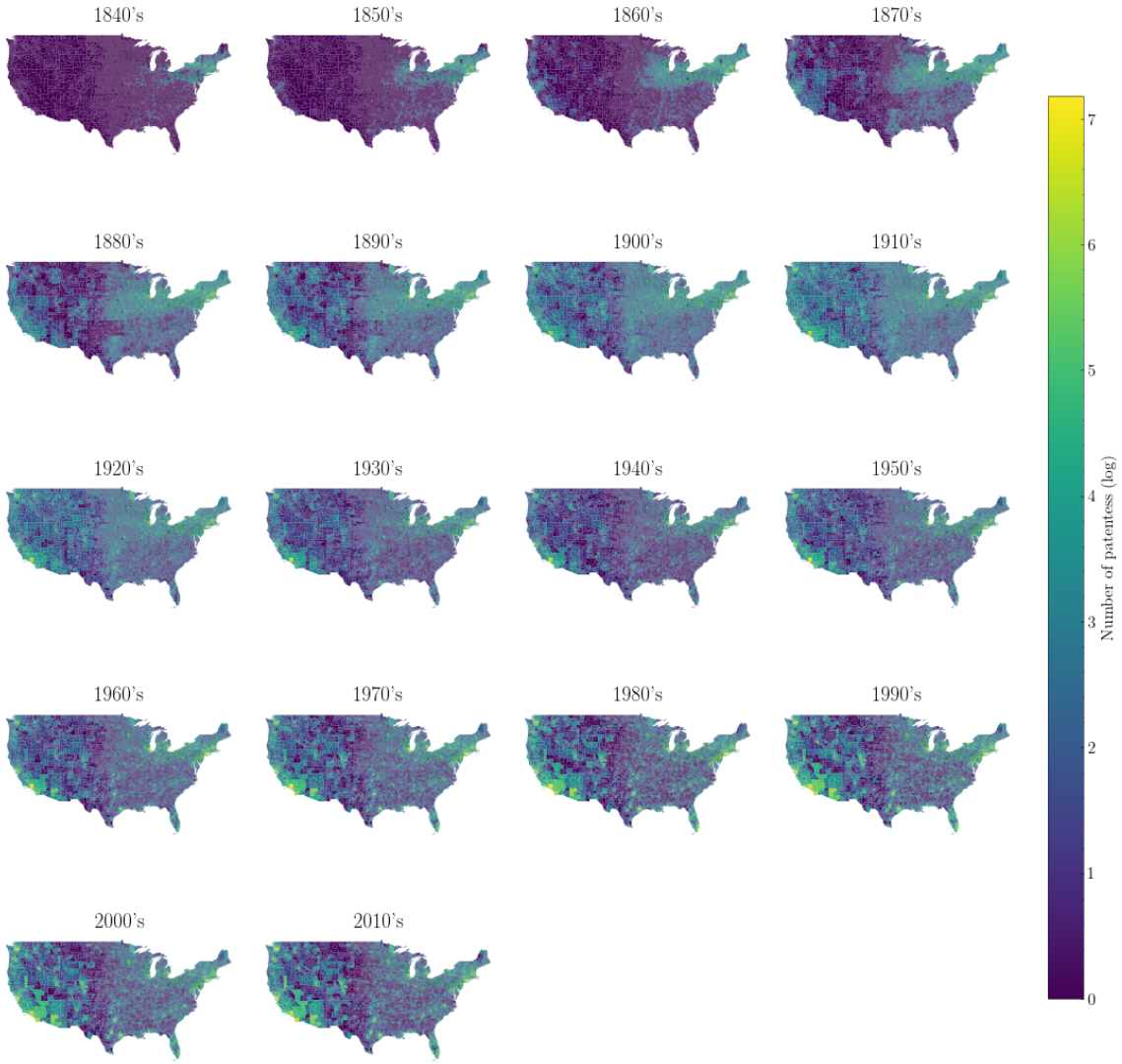
Notes: this Figure maps the total number of patentees (whether assignees or inventors), in log, for each county in France (*département*) for each decade. The number of patentees is taken as a total over the full set of domestic patentees that are located at least at the county level.

Figure B3: Patentees by regions and decade - United Kingdom



Notes: this Figure maps the total number of patentees (whether assignees or inventors), in log, for each county in the UK (NUTS 3 regions) for each decade. The number of patentees is taken as a total over the full set of domestic patentees that are located at least at the county level.

Figure B4: Patentees by regions and decade - United States



Notes: this Figure maps the total number of patentees (whether assignees or inventors), in log, for each county in the USA for each decade. The number of patentees is taken as a total over the full set of domestic patentees that are located at least at the county level.

C Brief history of the patent systems

This Appendix briefly summarizes the major changes in the patent systems of the five patent offices considered in this article, focusing on the period ranging from the 19^{th} century to 1980. Much more details can be found in Khan and Sokoloff (2001); Van Dulken (1999); Khan and Sokoloff (2004); Moser (2005); Bert (1960); Hipp et al. (2022); Davenport (1979); Dobyns (2016) and reference therein.

United States

- July 1790: The USPTO granted its first patent. A patent is defined as "any useful art, manufacture, engine, machine, or device or any improvement thereon not before known or used". The fee for obtaining a patent was set at $3.70 and its terms was set to 14 years (with a possibility of a 7 year extension).
- 1793: Significant changes were made to the patent law. Applications were no longer examined for novelty but were granted as long as the fees were paid. The fees were raised to about $30 to which some small additional costs should be added for each page of the patent description.
- 1802: The patent office became an independent bureau within the Department of State.
- July 1836: The examination system and novelty criteria were reestablished. A search process for prior art was implemented, and appeals were permitted. The fees were higher for foreigners, with British citizens paying $500 and others paying $300. This is generally view as the establishment of the modern patent system in the US.
- December 1836: A fire destroyed all patent records and drawings. Around 2,800 of these have been recovered, mainly from the inventors' copy. These are now known as the X-patents. Fees were about $30.
- 1861: The term of a patent grant was extended from 14 to 17 years (and stayed at 17 until 1994). The fees for obtaining a patent were raised to $35 ($15 at the time of application and $20 when granted). All discrimination against foreign applicants are eliminated, except for countries discriminated against the United States
- 1870: The 1870 Patent act consolidated the previous acts and strengthened the authority of the patent office. The USPTO started to register trademarks
- 1887: The United States becomes a member of the Paris Convention which guaranteed the protection of US inventions abroad and conversely
- 1921: To help European countries following WWI, the Nolan Act provided foreign inventors some benefits regarding time of application and fees
- 1922: The fees for filling a patent increased from $15 to $20. The total fees were about $40 dollars.

- 1930: Application fees are raised to $25 and remain relatively stable in real terms until the end of the 1960s (De Rassenfosse and van Pottelsberghe de la Potterie, 2013)
- 1952: Modernization of the patent law. Inventors were required to not only describe their invention but also the grounds for its infringement. In addition, for a patent to be granted, the invention had to be novel, useful, and non-obvious.
- 1967: Fees increase from 60 to 239 dollars
- 1968: The Patent Cooperation Treaty (PCT) is signed. This treaty provides a unique procedure to file a patent application in all member states.
- 1980: The Patent and Trademark Law Amendments Act, also known as the Bayh-Dole Act was enacted and authorizes contractors to retain ownership of inventions resulting from research funded by the federal government.

France

- 1791: The first patent legislation was enacted in France. Applications can be filed through a registration system without any examination. The inventor could chose a period of 5, 10 or 15 years. The price of a patent ranged from 300 to 1500 francs.
- 1844: The initial act was amended in 1800 and 1844. The fees remained in the same order of magnitude as before: 500 francs for a 5 year protection and 500 additional francs of each additional 5 years up to 15. The fees were payable annually. The law of 1844 changed the nature of the patent right. The patent is granted on the sole basis of the applicant's declarations and under his sole responsibility but could be voided if the patentee failed to implement its innovation within 2 years. Scientific discoveries or theoretical concepts can be patented under the condition that there is a clear industrial application.
- 1883: The Paris convention is signed. Foreign inventors enjoyed a 12 month priority period after their domestic application to apply for their patent in France. The country commit to create a centralized service of intellectual property and to edit a list of granted patents.
- 1901: The national patent office: "Office National de la Propriété Intellectuelle" (ONPI) is created. Until this year, the search for prior arts by inventors was very difficult as the specifications of patents were solely accessible in handwritten form in the office where they were initially deposited. The ONPI centralized all the journals and publications.
- 1902: All the patents are published *in extenso* which are typed and no longer hand-written and sold at the unique cost of 1 franc. Inventors could chose to delay the publication of their patent for up to one year.
- 1910: The total fees are still around 100 francs per year and paid annually
- 1919: The maximum term of a patent is set to 20 years

- 1951: The ONPI is replaced by the "Institut Nationale de la Propriété Industrielle" (INPI) , entirely self-financed and placed under the supervision of the Ministry of the Economy and Finance
- 1953: The legal obligation to implement one's patent within 2 years is removed
- 1968: Modernization of the intellectual property law with the implementation of an examination system for all applications. The application is made public 18 months after its filing.
- 1978: Alignment of the French patent legislation with the European legislation following the creation of the European Patent Convention.

Germany

- 1877: Creation of the Imperial Patent Office (*Kaiserliches Patentam*) in Berlin. Before this date each of all the 25 small states that came together to form the nation of Germany in 1871 was responsible for its own intellectual property law. The cost of a patent was high in order to filter trivial inventions: 30 marks during the initial year, 50 and 100 marks for the next two years and 50 additional marks per years for up to 15 years (in 1871 the average wage in the manufacturing sector was about 10 marks per week). German patent system included a mandatory examination by an official patent examiner. This is the first patent system in the world to do so.
- 1891: The Patent Act of 1891 enhanced the efficiency of the patent office through changes in its organization including the separation of the application division and appeal division, as well as in the administrative procedure. As a part of these changes, this Act introduced a "preliminary examiner" who was tasked with addressing any issues in an application before it went to the application stage. Utility models (*gebrauchsmuster*) are introduced promoted by the chemical industry which allows inventors to protect their products and not only the process that produced it. Utility models are viewed as a weaker version of examined patents and could be obtained through a registration system.
- 1903: The German Empire acceded to the Paris Convention
- 1919: The Imperial Patent Office is replaced by the *Reichspatentamt* (Patent Office of the German Reich).
- 1923: Maximum term is extended from 15 to 18 years.
- 1936: The Patent Act of 1936 reorganized the role of the patent office. Patent litigation and cancellation requests were centralized in the patent office and no longer in ordinary courts. In order to help small inexperienced inventor, the patent act introduced a "grace period" of six months which allows an inventor to fill for a patent even if its invention is already known to the public from less than 6 months. The Act also introduced the principle that the right to an invention belongs to the inventor
- 1945: The patent office is destroyed and remained inactive until 1950.

- 1949: The Office for Inventions and Patents (*Amt für Erfindungs- und Patentwesen*) opened in Soviet occupied Berlin. Meanwhile the Federal German Republic patent office moved from its destroyed Berlin's premises to Munich. The regulations concerning the protection of intellectual property rights were very similar in both of the German states but the main difference rest on the exploitation of the patent. In West Germany, the patent holder enjoyed full rights to exploit their patent. Conversely in East Germany, most patents were in fact economic patents (*Wirtschaftspatente*) and state-owned enterprises were authorized to use them. The inventor was only recognized as the intellectual source and remunerated in case the patent proved useful. Only a small shares of patents were provided exclusive rights to the applicant (*Ausschließungspatente*).
- 1968: Implementation of a publication of the new applications 18 months after the filing date.
- 1970: The Patent Cooperation Treaty is signed and implemented.
- 1977: The European Patent Convention came into effect
- 1980: The new Patent Act modernized and harmonized the intellectual property laws in Germany.
- 1990: Following the unification of Germany, the East German patent office was merged to the DPMA. Former Federal German Republic patents validity was extended to the whole German territory while former East German patents continued to be only effective in the former East German territories.

United Kingdom

- 1449: The first English "patent" was granted in 1449. During the 15^{th} century, exclusive rights for trades and manufacturers, such as patents for inventions, were bestowed by The Crown through the grant of monopolies.
- 1624: England's first patent law, the Statute of Monopolies was established. The patent system then developed progressively. The term of a patent is 14 years.
- 1852: Modern patent law was established. The separate patent systems of Scotland and Ireland were abolished and a office was set in Chancery Lane. The Patent Office mandated a written account of the invention to be submitted and implemented the practice of publication of patent documents. Until this time, the cost of a patent was about £100 (and up to £350 for extended coverage to Scotland and Ireland) which is view as very high (almost the yearly wage of a skilled worker). This high cost was accompanied with very lengthy administrative procedures which reflected the general distrust of monopolies that prevailed in England (MacLeod et al., 2003). As a result, only 14,359 patents were granted between 1617 and 1852 (Van Dulken, 1999). The 1852 patent law reduced the cost of a patent dramatically to £25 but subsequent fees have to be incurred to renew the patent: £50 after 3 years and £100 after 7 years up to a maximum term of fourteen years. The cost of a patent in Britain was still considerably higher than in the US or in other European countries.

- 1883: The Patents, Designs and Trademark bill introduced a new simplification in the patent application procedure (for example, applications could be mailed rather than presented in person) and a further reduction in the cost of patents to £4 (£1 a the time of application and £3 at the time of granting). Additionally, the first renewal payment of £50 was postponed by one year (after 4 years). An option to smooth the renewal fees and pay every year was also introduced.
- 1884: The United Kingdom signed the Paris Convention
- 1902: Official examination for prior art by an examiner became mandatory before granting a patent. An additional £1 was charged for this service. The fees gradually increased to reach £85 in 1977. Total renewal fee costs also increased gradually to £824 in 1977.
- 1907: Patents applications can be rejected on the basis that they are considered "frivulous" or not novel enough.
- 1919: the term of a patent is extended to 16 years
- 1932: the rules under which a patent may be revoked are clarified and a patent appeal court is established.
- After World War Two there were various efforts to internationalize the patent system and increasing cooperation. The Patent Cooperation Treaty was signed in 1970 and the European Patent Convention in 1977 which opened the way to EPO patents.
- 1977: the Patent Act of 1977 is viewed as one of the main changes in the British patent system. It established a 20 year term, a two-stage review process which implies a publication after a 18-month period, in line with other European patent offices. The requirements in terms of novelty were raised to match international standards.

D Model Cards

Details on the performance of the model are given in the website of the project. Specifically:

- Model cards for DD
- Model cards for DE
- Model cards for FR
- Model cards for GB
- Model cards for US

Model performance are also summarized in Tables D1, D2, D3, D4 and D5, respectively for East Germany, Germany, France, the United Kingdom and the United States.

Table D1: Models' performance by format in DD

Format	Metric	ALL	ASG	INV	LOC	OCC
	p	0.99	0.99	0.96	0.99	0.99
1	r	0.99	0.99	0.96	0.99	1
	f	0.99	0.99	0.96	0.99	0.99
	p	0.95	0.94	0.95	0.98	0.94
2	r	0.94	0.87	0.97	0.95	0.94
	f	0.95	0.91	0.96	0.96	0.94

Notes: Reported performance metrics were computed on the test set - unseen during training. The "Format" column indicates the different models used for the office. For the German office, there was a major shift in the patent information display in 1881 forcing us to train two different models. Performance metrics are reported as follows: precision/recall/F1-score.

Table D2: Models' performance by format in DE

Format	Metric	ALL	ASG	CLAS	INV	LOC	OCC
	p	0.99	0.98	0.99	0.99	1	0.97
1	r	0.99	0.99	1	0.96	1	0.98
	f	0.99	0.98	1	0.98	1	0.97
	p	0.99	0.99	0.99	0.98	0.99	0.97
2	r	0.98	0.98	1	0.99	0.98	0.97
	f	0.98	0.98	0.99	0.99	0.98	0.97

Notes: Reported performance metrics were computed on the test set - unseen during training. The "Format" column indicates the different models used for the office. Performance metrics are reported as follows: precision/recall/F1-score.

Table D3: Models' performance by format in FR

Format	Metric	ALL	ASG	CLAS	INV	LOC
	p	0.97	0.99	0.93	0.99	0.99
1	r	0.97	0.99	0.93	1	0.99
	f	0.97	0.99	0.93	0.99	0.99
	p	0.98	0.98	-	0.99	0.99
2	r	0.98	0.98	-	0.98	0.99
	f	0.98	0.98	-	0.98	0.99

Notes: Reported performance metrics were computed on the test set - unseen during training. The "Format" column indicates the different models used for the office. Performance metrics are reported as follows: precision/recall/F1-score.

Table D4: Models' performance by format in GB

Format	Metric	ALL	ASG	CIT	INV	LOC	OCC
	p	0.93	0.93	0.96	0.95	0.92	0.9
1	r	0.94	0.92	0.96	0.96	0.92	0.86
	f	0.94	0.93	0.96	0.96	0.92	0.88

Notes: Reported performance metrics were computed on the test set - unseen during training. For GB, only one model is used. Performance metrics are reported as follows: precision/recall/F1-score.

Table D5: Models' performance by format in US

Format	Metric	ALL	ASG	CIT	INV	LOC
	p	0.98	0.94	0.98	1	0.98
1	r	0.99	0.96	0.98	0.99	0.99
	f	0.99	0.95	0.98	0.99	0.99
	p	0.98	0.96	0.98	1	0.98
2	r	0.99	0.96	0.97	1	0.99
	f	0.98	0.96	0.98	1	0.99
	p	0.97	0.96	0.97	0.99	0.97
3	r	0.97	0.96	0.97	0.98	0.98
	f	0.97	0.96	0.97	0.98	0.98
	p	0.99	0.99	-	1	0.99
4	r	0.99	0.98	-	1	0.99
	f	0.99	0.98	-	1	0.99

Notes: Reported performance metrics were computed on the test set - unseen during training. The "Format" column indicates the different models used for the office. Performance metrics are reported as follows: precision/recall/F1-score.