That's Classified!
Inventing a New Patent Taxonomy

Stephen D. Billington[†] Alan J. Hanna [‡]

April 2020

Abstract

We investigate how patent classification influences the interpretation of patent statistics. Innovation researchers currently make use of various patent classification schemas, which are hard to replicate. Using machine learning techniques, we construct a transparent, replicable and adaptable patent taxonomy, and a new automated methodology for classifying patents. We then contrast our new schema with existing ones using a long-run historical patent dataset. We find quantitative analyses of patent characteristics are sensitive to the choice of classification; our interpretation of regression coefficients is schema-dependant. We suggest much of the innovation literature should be carefully interpreted in light of our findings.

Keywords: Innovation, Invention, Machine Learning, Patents, Patent Classification, Taxonomy, Economic History.

JEL Codes: K11, N24, N74, 031, 033.

[†]Corresponding author: Department of Accounting, Finance, and Economics, Ulster University. Email: s.billington@ulster.ac.uk.

[‡]Queen's Management School, Queen's University Belfast. Email: a.hanna@qub.ac.uk.

1 Introduction

Patent statistics are a widely used proxy for measuring and understanding technological change (Griliches, 1990).[1] Patents are particularly popular in the field of economic history, where alternative measures of inventive activity are few. Patentable inventions, however, have heterogeneous characteristics which, if not accurately controlled for, have the potential to influence any interpretation of patent statistics. For example, the propensity to patent varies by industry, suggesting the decision to obtain a patent can also vary by industry (Cohen et al., 2000).

Classification systems can be used to account for varying patent characteristics. Here, innovation scholars and social scientists can adopt one of two approaches: classification using a taxonomy of their own construction; or patent office classifications, such as the International Patent Classification (IPC), the United States Patent Classification (USPC), or the Cooperative Patent Classification (CPC) schemas.[2] The prevalence of both approaches in the literature raises the following questions: how comparable are existing studies that use different taxonomies and methods, and which, if any, of the existing taxonomies can and should be used in future studies?

The use of both manually constructed taxonomies as well as patent office schemas complicates our ability to interpret the results of patent studies. Manual classification is subjective, and there is no guarantee any two patent studies would classify the patents in the same way. Few, if any, taxonomies see repeated usage; academic schemas are often not fully discussed or described, hindering successful replicability as well as adaptability. By contrast, patent office schemas more often see repeated usage, but are prone to problems of scope, as they usually consist of a few broad categories encompassing thousands of narrowly defined subclasses. Not only are narrow subclasses too fine-grained for econometric usage (Benner and Waldfogel, 2008), but the broad classes suffer problems associated with the purpose of the schema and its associated class definitions. This problem was first identified by Schmookler (1966) who observed

[1] A patent is a temporary monopoly right granted to a particular novel and non-obvious invention or process; it provides the holder with the legal power to prevent replication or copying without express permission (Scotchmer, 1991, 2004).

[2] A similar observation is made of more modern patent research (Younge and Kuhn, 2016).

patents for a toothpaste tube and a manure spreader to fall into the same class, simply because they both had the same function of 'dispensing solids' (Schmookler, 1966, p. 20). Recently, innovation scholars have made similar comments (e.g., McNamee, 2013), and have gone so far as stating 'the best way forward is to devise identification systems that avoid entirely technology classification systems that were devised for the sole purpose of helping examiners locate prior art' (Thompson and Fox-Kean, 2005, p. 466).

Patents can be classified under "time-invariant" or "time-variant" schemas. Time-invariant schemas consist of broad classes, reflecting industry lines, which do not change over time. Time-variant schemas in comparison encompass fine-grained classes, reflecting time- or country-specific innovation; patent office schemas are time-variant. This second approach is useful for identifying specific types of inventions and emerging technologies (Boschma et al., 2014; Strumsky et al., 2012). Time-variant schemas can also have broad classes, but these are composed of technology subclasses related by technical function. By contrast, time-invariant taxonomies are useful for relating patenting to economic phenomena over time and space, and in the long-run.

Modern patent systems do not vary much, having largely homogenised over time. The long-run, however, encompasses numerous instances of patent reform. Such events act as natural experiments, which can provide important insights concerning the optimal design of patent institutions. The ability to contrast patents throughout history is important for developing a fuller understanding of how patent systems affect innovation, and how they have developed. Innovation historians therefore make extensive use of time-invariant schemas. Of course, a "one-size-fits-all" schema may not be useful or appropriate for answering all possible research questions. Patent researchers require a standardised schema that can be adapted to suit specific research questions while ensuring patents continue to be classified consistently. For this reason, we opt to develop an adaptable, time-invariant taxonomy.

This paper presents a new, time-invariant patent taxonomy for producing more consistent and comparable results within the innovation literature. Our taxonomy is built on the principle of transparency, so future investigators can understand its design

and application. In this way, investigators can either: reuse our schema, adapt it for their own needs, or even develop new schemas using our methods. We also propose a new methodology for automating patent classification to ensure patent data are grouped consistently. We adopt machine learning techniques that can classify patent data using any patent taxonomy. Machine learning techniques minimize the subjective element of classification, reducing the probability of patents being classified inconsistently. Establishing a consistent approach to patent classification will lead to increased comparability of innovation studies, which helps to strengthen our understanding of innovation and its relationship with patents. In turn, this can only benefit policymakers in designing appropriate measures to encourage innovation.

The first half of this paper is concerned with developing a new taxonomy, and an automated method for classifying patent data. We use text as data to derive our set of time-invariant patent classes. Because the literature abounds of alternative patent taxonomies, we can observe which classes appear frequently. Frequent classes in historical taxonomies reflect technology groups existing independent of time or geography, making them indicative of time-invariant classes. We then test the validity of our schema by applying machine learning techniques to multiple patent datasets. Patent data have historically contained rich textual information in their titles. Using these titles, we elicit a set of common word associations, or "topics". Topics capture related patents which reflect different technology groups, and can be used to observe whether we have omitted any potential classes; we derive topics from multiple patent datasets to check this. Finally, we use our machine learning techniques to automate patent classification.

The second half of our paper is focused on whether the choice of schema influences the results of examining patent characteristics. To test this, we examine the population of British patents granted between 1700 and 1850. There are several advantages to using this dataset. First, we can reproduce several taxonomies that have classified the data, such as Woodcroft (1860); Sullivan (1989, 1990); Nuvolari and Tartari (2011); Bottomley (2014a); Dowey (2017). Second, the British patent institution remains relatively unchanged during the period of observation, undergoing its first major reform

only after 1850 (Dutton, 1984). This allows us to better investigate the nature of invention over the long-run, as changes to the patent system are unlikely to complicate our understanding of innovation. Third, the data span the period of the Industrial Revolution, a phenomenon described by Clark (2007) as the most important in human history, by allowing humanity to transition from agricultural economies which could not sustain continuous innovation, into rapid-growth industrial economies which could. Any insights are useful to help address important questions about the origins of the wealth of nations and the role of innovation in industrialisation. Fourth, the breadth of the data are more manageable, making manual assignments and comparisons of classes simpler, and reducing the time needed to run our machine learning techniques.

We contribute to the field of innovation studies through the creation of a new, well-defined, time-invariant patent taxonomy. We thoroughly describe the development of our schema to ensure future users understand how it was constructed and how it can be adapted or adopted to compliment existing work. We also provide a new methodology for automating the classification of any patent dataset, based solely on the text contained in patent titles. This method classifies related patents in a similar manner, leading to more consistent classification with fewer errors. Our approach minimizes the subjective element of patent classification, and also decreases the time needed to classify large patent datasets, reducing the difficulty of engaging in any large-scale analysis of patenting.

We also contribute by documenting the existence of "classification divergence" – statistical significance, direction of association, and coefficient magnitude are all subject to the choice of classification used in a regression analysis of patent characteristics. To our knowledge, we are the first to identify this kind of sensitivity in the innovation literature. The implications of classification divergence could be severe for the innovation history literature, as well as the innovation literature more generally. Within the innovation history literature, divergence complicates our understanding of important historical events related to inventive activity, such as the Industrial Revolution. Similarly, the divergence makes it difficult for policymakers to develop measures to encourage innovation based on the findings of the existing literature.

Understanding the potential divergence in the literature requires understanding how schemas have been constructed, while having a consistent means of classifying patent data should reduce the potential divergence.

We also contribute to the growing trend in applying text analytics to examine patent data. With the development of more sophisticated text analysis techniques, the rich textual data contained in patent titles, abstracts, and descriptions can be more thoroughly exploited to advance our understanding of patent systems. Applications of textual analysis usually centre around quantifying the text contained in patent titles to develop 'similarity' measures: pairwise correlations of patents based on their text (Younge and Kuhn, 2016; Arts et al., 2018). Such approaches have strong applications to developing new measures of innovativeness (Kelly et al., 2018), identifying knowledge spillover effects (Feng, 2019; Blit and Packalen, 2019), understanding stock-return variability (Khimich and Bekkerman, 2016), identifying general or specific purpose technologies (Packalen and Bhattacharya, 2012), and measures of patent novelty (Balsmeier et al., 2018).

Our paper is closely related to this recent trend in using text analytics within the modern innovation literature, particularly Younge and Kuhn (2016); Arts et al. (2018); Feng (2019). In their articles, the authors develop measures of patent similarity using common keywords contained in patent specifications or abstracts – the detailed technical documents outlining what is new about a particular patented invention and how to use it. While these approaches are of great utility for the innovation literature, there are several drawbacks. First, the articles do not produce long-run classification schemas for use in historical analysis. Second, whether similarity captures related patents based on the patent's technical function or its intended usage is unclear, particularly as the authors rely on the highly technical patent specifications. Third, similarity measures say nothing about the comparability of existing studies. By contrast, we endeavour to classify patent data according to the industry of final use, rather than by similar technical functions. In doing so, we rely entirely on patent titles, which contain fewer references to technicality, and are more likely to help us identify a patent's relevant industry.

The paper proceeds as follows: Section 2 surveys the existing literature concerning patent classification. Section 3 outlines the machine learning techniques used in this present study. Section 4 describes the patent data used in this study. Section 5 details how we derived and validated our time-invariant patent taxonomy. Section 6 discusses the alternative patent taxonomies that we use in our regression analysis. Section 7 reports the results of contrasting patent taxonomies in our analysis of patent classes on patent characteristics. Section 8 interprets our findings and their implications for the study of innovation. Finally Section 9 concludes.

2 Patent Classification Literature

In 1830, John D. Craig, the US Superintendent of Patents, gave evidence to the US House of Representatives regarding the development of the US patent classification schema. In his evidence, Craig raised two points: the 'imperceptible shades of difference' of patent classes, and that 'a doubt frequently arose concerning the class to which some of the patents did properly belong' (cited in Bailey, 1946, p. 466). Craig was concerned with the overlapping characteristics of patented inventions. Accurately pinpointing a particular class for a particular patent is a difficult task.

It is precisely because assigning classes is difficult that a standardised schema and classification methodology is necessary. The likelihood of inconsistent patent classification increases without a standard approach. Pearce (1957, p. 1) discusses how the inconsistent classification of industrial statistics led to any comparisons of industrial data as 'difficult and often misleading', resulting in the creation of the Standard Industrial Classification (SIC) schema.

This problem persists in the innovation history literature, particularly as patent data are a popular proxy to study inventive behaviour over the long-run. Innovation historians desire a classification approach which classifies patent data according to the industry of final use, as this allows them to understand the effect of patenting on the wider economy. At present, different authors classify (often the same) patent data in different ways.

Patent classes are supposed to account for common patent characteristics that could influence how we interpret such data. If scholars do not adopt the same approach to identifying group-specific characteristics, then studies cannot be easily compared.

2.1 Patent Office Schemas

The development of patent office schemas has primarily been to aid patent examiners (WIPO, 1992). Examining patents usually requires multiple well-trained, professional patent examiners to engage in the time-consuming search for prior art – old or existing patents likely to influence or anticipate future ones. These assigned classes are subject to change, as patents are examined at several different stages throughout the patent application (Righi and Simcoe, 2019). Having thousands of well-defined classes and subclasses facilitates a more efficient search for prior art. Such classes make fine distinctions between seemingly similar types of inventions, allowing examiners to find the relevant art more readily.

Patent office schemas are most suitable for time-variant classification. This method primarily classifies patents according to their technical functions, rather then for understanding their effect on the wider economy – exactly how patent offices classify their data.[3] Such methods are extremely useful for identifying and examining emerging technologies (Strumsky et al., 2012), identifying cumulative innovation (Boschma et al., 2014; Rigby, 2015; Youn et al., 2015) and also for observing the increasing modularisation of technology (Arts and Veugelers, 2015). However, these methods are less useful for relating patenting and the real economy. Despite this, there have been growing attempts to utilise time-variant patent office schemas more widely, such as through the creation of 'concordances'.

Concordances between patent office schemas and industrial classification schemas have become a popular method to relate patenting to the wider economy (e.g. Verspagen et al., 1994; Kortum and Putnam, 1997; Johnson, 2002; Schmoch et al., 2003;

[3]Patent offices can also classify patents according to their use-based function alongside the technical function; the mixture of approaches hampers the applicability of these schemas in studying the real economy.

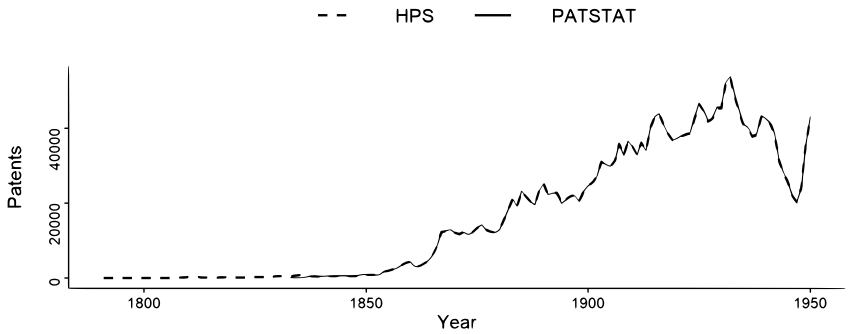
Costantini et al., 2015; Leydesdorff et al., 2017). Perhaps the most famous, well described, and widely used of these concordances is Schmoch (2008). Schmoch's concordance links 30 industrial classes to the 4-digit subclasses of the IPC. More recent developments expand such concordances further, by introducing statistical methods for classifying patents. Lybbert and Zolas (2014), for example, have pioneered a new approach of using probabilistic algorithms to match IPC classes to industrial schemas. By matching keywords contained within existing industrial schemas to keywords in patent titles, they attempt to reduce the subjective element of concordance mapping.

Recently, the United States Patent and Trademark Office (USPTO) has made considerable efforts to develop a concordance between the USPC system and the NBER patent classes constructed by Hall et al. (2001). The NBER patent classification system is a higher-level classification derived from the USPC; it comprises 36 sub-classes, aggregated into six main categories, which classify the 400 USPC patent classes, but this mapping only exists for patents granted since the 1960s.[4] In Marco et al. (2015), the authors develop an algorithm designed to map all patents granted in the US after 1840 to one of the six NBER classes, based on the patents USPC code and keywords, increasing the ability to contrast US patenting behaviour over the long-run. In addition, the algorithm is also used to classify patent applications which were not subsequently granted, which serves to enhance the utility of their approach by allowing researchers to examine successful and unsuccessful patent applications.

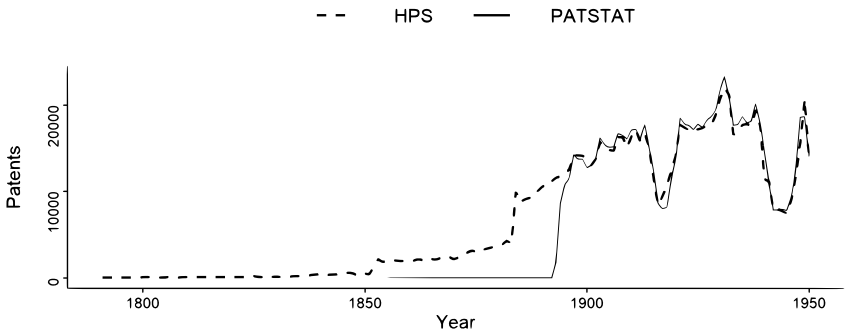
This sub-field, however, relies on existing patent office schemas applied to the data. For the economic historian concerned with historical patent data, the approach is not always feasible. Most historical patents do not have patent office classes assigned, and such classes cannot be easily assigned by academics themselves because of the highly-skilled and specialised nature of patent office classification. The exception here is the case of Marco et al. (2015), while their approach is useful for innovation historians, it is exclusive to US patents.

Figure 1 provides a comparison between the European Patent Office's (EPO)

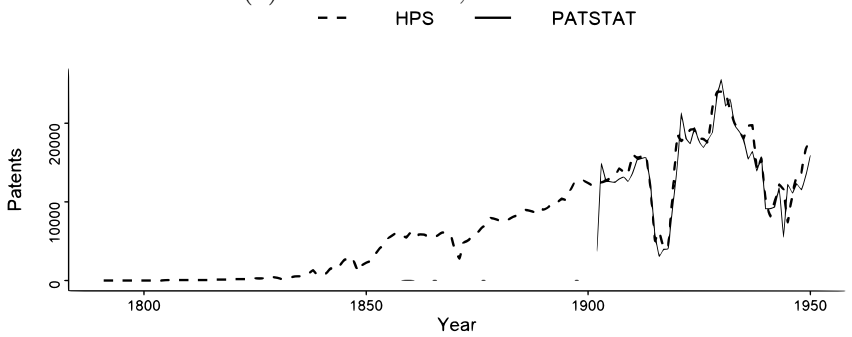
[4]Hall et al. (2001) acknowledge that an element of arbitrariness exists in their aggregation method, and recommends their schema be used with great care.



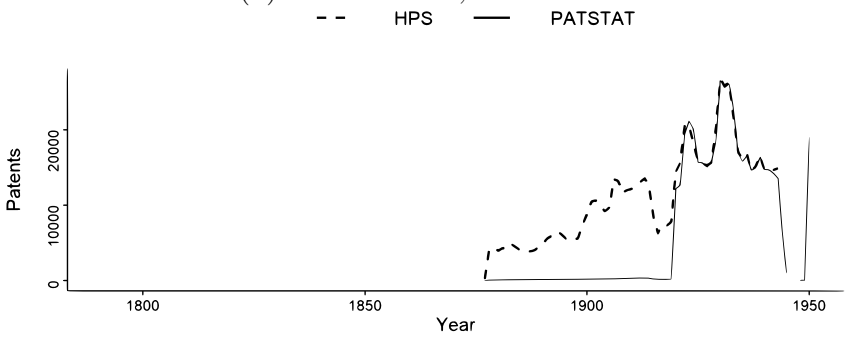
(a) *United States, 1791-1950*



(b) *Great Britain, 1791-1950*



(c) *France, 1791-1950*



(d) *Germany, 1877-1950*

Figure 1: *PATSTAT versus Historical Patent Counts, 1791-1950*

Notes: Comparison of the counts of patents granted in PATSTAT against the Historical Patent Counts data for the US, Great Britain, France, and Germany. Germany's series begins in 1877 since this is when Germany was established.

Source: PATSTAT Biblio Autumn Edition (2016) and Frederico (1964).

PATSTAT Biblio (Autumn 2016) database and an external count of patent grants pre-1950, for Britain, France, Germany and the United States.[5] The PATSTAT database claims to contain all patents ever granted in EPO countries, and is a popular data source for innovation studies. However, historical patent data are largely incomplete or missing in PATSTAT; the most commonly omitted information are patent office classes. As the figure shows, PATSTAT is not a suitable data source for historical patent data, and therefore patent office schemas cannot be used.[6]

Aside from the omitted data, there are more severe problems relating to the use of patent office schemas within academic studies. Patent office schemas classify patents based on two separate principles: "application-oriented" and "function-oriented". The former refers to 'a thing "in general", i.e., characterised by its intrinsic nature or function' (WIPO, 2016, p. 22); the latter refers to 'a thing "specifically adapted for" a particular use of purpose' and 'the incorporation of a thing into a larger system', where a thing refers to any technical subject matter. The difficulty is both principles are seemingly jointly applied within the EPO and other patent examination bodies. This is problematic for two reasons. First, the approach results in patent classes which are difficult to interpret and understand. Second, the use of function-oriented principles will inevitably lead to patents being grouped together by a particular function, and the function could apply to multiple industries. Since innovation scholars and social scientists frequently study the wider effects of patenting on the real economy, function-oriented classification hinders the usefulness of patent office schemas in academic enquiry.

Patent offices are becoming more aware of this hindrance, as patent examination bodies are currently adapting their patent classification systems to better capture their final economic use in new products which combine different technologies. One example of this is the EPO's work on the so-called "Internet of Things" (EPO, 2017); another is the work undertaken at the USPTO (Marco et al., 2015). While these adaptations are conceptually related to our own aim, they continue to rely on the function-oriented approach. In the

[5]These countries are chosen due to their popularity in the economic history literature.

[6]PATSTAT is useful for certain countries (such as Denmark and Switzerland). But for the vast majority of countries, there are substantial data missing.

EPO's case, for example, examiners produced a concordance between CPC classes and a 'cartography' for identifying "Fourth Industrial Revolution" (4IR) technologies. But identifying 4IR patent applications relies on an examination of a patent's CPC codes by patent examiners, who then recommend which field of the cartography the patent belongs to. For the Marco et al. (2015) approach, the NBER categories rely on patents classified according to the USPC, where patents can be classified based on a number of rationales (USPTO, 2005).

2.2 Classification in Economic History

The primary purpose of classification in innovation studies is to allow researchers to relate patent data to changes in the real economy. For economic historians studying innovation, this necessitates taxonomies which cover the long-run – schemas we term as time-invariant. Time-invariant schemas group together related inventions, independent of time or country or specific technical functions for the purpose of economic enquiry. In doing so, researchers are more capable of identifying and controlling for broad characteristics of different types of inventions, which simplifies their study, and prevents these characteristics from complicating insights drawn from patent data. For example, mechanical inventions are more likely to be patented than chemical inventions across time and countries, as machines are more susceptible to reverse engineering. The necessity of using time-invariant schemas are to control for such unchanging and broad characteristics, which requires a standardised set of patent classes.

Schmookler (1966) was amongst the first scholars to highlight the fundamental flaw of using patent office classifications for studying the wider economy. Schmookler's observation that unrelated inventions can be grouped together by a patent office, because of a related functionality, meant social scientists and innovation historians would need to adopt new taxonomies directly related to industry. One of Schmookler's key innovations was to overtly classify patents based on their industry of final use.

In his seminal article, Griliches (1990) builds on Schmookler's efforts, and outlines three methods of classification: "Origin", "Production", and "Destination". Origin

groups patents by the industry that produced them, which is suitable for examining R&D expenditure since R&D occurs within a given industry. Production groups patents by the industry most likely to produce the invention, or use within the production of goods or services. Destination groups patents according to the industry most likely to make use of, or benefit from, the invention. Destination and Production overlap. The major difference is the use of an invention does not intrinsically imply its use is in production, but an invention used within production constitutes Destination. Destination is the most suitable method for studying patenting within the wider economy, as it is easier to determine the intended industry of final use of a patent.

Magee (1997) reiterates the points of Griliches (1990), highlighting the difficulties associated with focusing on the 'technical dimension' of patents (Magee, 1997, p. 7). Magee adapts the SIC to derive patent classes based on the likely destination of patented inventions. Basberg (1997, 2006) takes a similar approach, forgoing the historical Norwegian system of patent classification, and adapting their own patent classes based on industry lines. Basberg mixes broad and specific classes in their taxonomy, citing the difficulties of being able to assign patents from more 'narrow technological areas' (Basberg, 1997, p. 154). This mixed approach could create further inconsistencies, as each patent class may capture fundamentally different aspects of patented inventions. More recent work continues to classify patent data by industry of final use (Greasley and Oxley, 2010; Khan, 2014; Sáiz, 2014; Donges and Selgert, 2019), supporting the need for patent classes based on destination.

However, the development of a single standardised, replicable and adaptable taxonomy has received little attention in the literature. Most studies adopt a set of single-use classes as controls for their econometrics. What is unclear, however, is how authors have constructed their taxonomies, defined their classes, and assigned patents to those classes. Without this information, replicating existing taxonomies is difficult. This leads to two possible outcomes. Either future investigators apply existing taxonomies incorrectly – leading to further inconsistencies – or they construct additional taxonomies, further compounding the problem of incomparability.

Table 1 displays a set of 35 patent and invention taxonomies, which have been used within the economic history literature.[7] This set is representative of the economic history literature; the papers were compiled from a systematic search of "economic history" and "patent" keywords in the Econlit and EBSCO databases. We focused on papers observing patent data on the wider economy, and not specific industries, in an attempt to avoid very narrow research questions which may require very specific classification. Furthermore, we only included those studies which published or made reference to another published taxonomy in the paper. The table lists the number of classes in each paper's taxonomy, the country or countries of observation, the time-period examined, which of the three methods of classification were used (if any), and a brief description concerning the construction of the taxonomy and whether definitions were provided for patent classes.

The table highlights several things. First, the existing patent evidence is derived from a number of countries (14 in total) and a number of different time periods. This reasonably highlights the need for a time-invariant taxonomy to classify similar patents in the same way, independent of location or time. Second, the Destination method of classification is the most popular in the economic history literature. Most studies explicitly state their classification is based on the industry of final use, as this is the most relevant for understanding the relationship between patents and the real economy. We should therefore endeavour to construct a taxonomy based on this method. Third, there is great disparity in the number of classes per taxonomy. The largest taxonomy belongs to Woodcroft (1860) with 246 classes, although this taxonomy is much more likely to have been designed for reference purposes for prospective patentees. Even ignoring those patent examination-type classifications, the largest schema has 32 classes (belonging to Magee (1999)), the smallest has four (such as Sokoloff (1988); Nicholas (2008); Khan (2013b)) and the average is 14.

Perhaps one of the most important questions Table 1 raises is how do authors choose the number of classes in their taxonomy? A second important question is how do authors then classify their patent data once they have chosen the structure of their

[7]The set includes papers which make use of Exhibition invention classes, which are then matched up with patent classes. Exhibition classes operate similarly to patent ones, and are therefore included.

taxonomy? To understand this, each author would need to detail exactly how they derived their classes, how they defined them, and their method of assigning patents to them. The 'Description' column describes whether this type of information is provided in each study. In the majority of cases, a discussion concerning taxonomy construction is not provided, and in almost all cases patent class definitions are not reported. Some authors rely on restructuring existing taxonomies (such as Moser (2005); Brunt et al. (2012); Moser (2012)), although the original means of classification is not described. Others use concordances between patent schemas and industrial schemas (e.g. Nanda and Nicholas (2014)) or the IPC headings (e.g. Sáiz (2014)). In most cases, authors have constructed a new taxonomy without much additional information (e.g. Khan (2013b)). Future researchers therefore gain limited insights into how to design a taxonomy, how to classify patents consistently, or how to choose the number of classes for their taxonomy.

It is important to note the above discussion does not mean authors have randomly constructed schemas without any thought. On the contrary, we acknowledge the existing taxonomies are the result of a great deal of thought and effort. The authors of the aforementioned studies will, of course, have developed or used a particular schema as part of answering a particular research question. The major difficulty, however, is understanding how authors have classified their patent schemas. Without an understanding of how schemas are constructed or how classes are defined, the literature is at risk of classifying similar patents in a number of different and possibly inconsistent ways. Whether this inconsistency matters for our interpretation of patent data is explored later in this paper.

3 Text Analysis

Text analysis techniques create structured data from natural language documents. In the first instance, we apply these techniques to existing patent classification taxonomies to aid the development of our time-invariant schema. The text describing existing systems

Table 1: Classification Literature

Authors	Classes	Country	Time-period	Method	Brief Description
Woodcroft (1860)	**246**	**England**	**1617-1852**	**Destination**	**The author compiled a complete collection of all patents granted in England prior to 1852. The associated taxonomy was most likely to reduce search costs for previously granted patents, akin to schemas constructed by and for patent examiners. Each broad class has an associated list of keywords.**
Sokoloff (1988)	4	US	1790-1846	Destination	The author likely uses the NBER patent data schema, although it is not explicitly stated. If not, how the taxonomy was designed is unclear. Class definitions are not provided.
Sullivan (1990)	7	England	1711-1850	Destination	The author constructs their taxonomy to study six important industries. It is unclear how patents are classified, although this is based on Woodcroft's Subject-matter index. Class definitions are not provided.
Basberg (1997)	21	Norway	1839-1860	Destination	The author constructs their own schema based on a combination of broad and narrow classes. It is unclear how the taxonomy was constructed nor how patents are classified. Class definitions are not provided.
Magee (1999)	32	Australia	1858-1902	Destination	The author constructs their taxonomy based on the standard classification of manufacturing industries used in Australia in 1902. From this the author constructs 32 classes. Keywords are provided for certain classes. It is unclear how the author assigns patents to classes.
Cantwell (2000)	15	Britain, France, Germany, Sweden, Switzerland, US	1920-1995	Unclear	The author constructs their taxonomy based on the USPTO classification schema. It is unclear exactly how the author has derived their classes nor how patents are classified. Class definitions are not provided.
Davids (2000)	16	Dutch Republic	1580-1720	Unclear	The author constructs their own schema. It is unclear how the taxonomy is constructed nor how patents are classified. Class definitions are not provided.
Khan (2000)	23	US	1870-1895	Destination	The author constructs their own schema. It is unclear how the taxonomy is constructed nor how patents are classified. Class definitions are not provided.
Moser (2005)	7	England and US	1851, 1876	Unclear	The author uses exhibition data and constructs their taxonomy based on the 1851 Crystal Palace Exhibition classification scheme. It is unclear why the author chose 7 classes or how these class have been constructed. There is no explicit discussion concerning how US inventions have been classified according to the schema.
Basberg (2006)	18	Norway	1860-1914	Unclear	The author constructs their taxonomy from the official patent office classification scheme. It is unclear how their taxonomy has been designed nor how patents are classified. Class definitions are not provided.
Streb et al. (2006)	89	Germany	1877-1918	Production	The author's patent data has been classified according to the historical German Patent Office classification schema comprising 89 technological classes. This approach is more likely to capture patent functionality rather than application
Baten et al. (2007)	19	Germany	1895-1913	Origin	The author relies on classifying patents according to the Standard Industrial Classification (SIC) two-digit code of the firm who held the patent. This method captures the 'Origin' of patents. The research question focuses on industry spillover effects for innovation, so this is likely a reasonable approach.
Nicholas (2008)	4	US	1910-1939	Unclear	The author uses the NBER patent data, and likely constructs their 4 patent classes from this. However, it is not explicitly described how the classes have been constructed; one class is 'Other' which likely captures a number of different technologies. It is unclear why the author has chosen 4 classes instead of the 6 NBER classes, or even the NBER subclasses.
A Cradle of Invention (2009)	**15**	**England**	**1617-1852**	**Unclear**	**The compilers of the data constructed a simple taxonomy to make the database more useful. They assert that their schema is based on their interpretation and so may be flawed. Class definitions are provided.**

Continued on next page

Table 1 – continued from previous page

Authors	Classes	Country	Time-period	Method	Brief Description
Greasley and Oxley (2010)	8	New Zealand	1861-1939	Destination	The author's construct their taxonomy to match their commodity output groups. Their taxonomy is based on Magee (1999), but with fewer classes. It is unclear how patents are classified. Class definitions are provided.
Meisenzahl and Mokyr (2011)	12	England	1660-1830	Unclear	The author's construct their own schema. It is unclear how the taxonomy has been designed nor how patents are classified. Class definitions are not provided.
Nicholas (2011c)	30	Britain, Germany, Japan, US	1900-1940	Production	The author classifies their patents using 30 main categories of the International Patent Classification (IPC) taxonomy. As described in the text, the IPC method classifies patents based on functionality, and so may be classifying un-related technologies as similar.
Nicholas (2011a)	16	US	1921-1938	Origin	The author classifies their patents according to the two-digit SIC code for the firm who held the patent. This method captures a patent's origin.
Nuvolari and Tartari (2011)	**21**	**England**	**1617-1841**	**Destination**	**The author's construct their taxonomy based on a working paper version of Moser (2012). It is unclear how they derived their additional classes nor how patents are classified. Class definitions are not provided.**
Moser (2012)	10	England and US	1851, 1876, 1893, 1915	Unclear	The author uses exhibition data and constructs their taxonomy based on the 1851 Crystal Palace Exhibition classification scheme. It is unclear how the author derives their classes. Class definitions are not provided.
Brunt et al. (2012)	12	England	1839-1939	Destination	The author's examine prize data from the Royal Agricultural Society of England (RASE) compared with patent data from the British patent office. The author's construct a taxonomy of 12 classes with 130 subclasses based on the Subject-matter Index from Woodcroft (1860), which relies on generating a list of keywords for each patent class. This approach likely relies on a patent's 'destination' for classification.
Burhop and Wolf (2013)	10	Germany	1884-1913	Unclear	The author's report 10 active technology fields, although it is unclear whether there are more. It is also unclear how patents have been classified and according to what kind of taxonomy. Class defintions are not provided.
Khan (2013b)	4	US	1790-1930	Destination	The author reports 4 patent classes in their regression analysis. It is unclear where the classes are derived from, or if any other patent classes are controlled for in their regressions. Class definitions are not provided
Khan (2013a)	12	US	1837-1874	Destination	The author uses exhibition data and patent data. Their taxonomy classifies inventions which were exhibited at industrial fairs. Invention's were classified according to their Destination. It is unclear how the taxonomy was constructed and how inventions are classified. Class definitions are not provided.
Khan (2014)	12	US	1835-1870	Destination	The author uses both exhibition and patent data. They construct their own schema to classify both datasets. It is unclear how the taxonomy has been constructed nor how patents are classified. Class definitions are not provided.
Nanda and Nicholas (2014)	15	US	1921-1938	Origin	The author's classify their patents according to the two-digit SIC code for the firm who held the patent. This method captures a patent's origin.
Khan (2015a)	26/7	Britain, France, US	1754-1852	Unclear	The author surveys prize-giving institutions in Britain, France, and the US. The French exhibition classes for inventions are those classes produced for the Paris exhibition. For Britain, the invention data are classified according to the Royal Society of Arts (RSA) own designated technology categories. No US classification is described. It is unclear whether the inventions in France and Britain are comparable. Class definitions are not provided.
Sáiz (2014)	20	Spain	1820-1930	Destination	The author constructs their schema based on the IPC descriptions and the descriptions in the patent. It is unclear how they constructed their schema nor how patents are classified. Class definitions are not provided.

Continued on next page

Table 1 – continued from previous page

Authors	Classes	Country	Time-period	Method	Brief Description
Nuvolari and Vasta (2015)	14	Italy	1861-1913	Unclear	The author's construct their schema based on the International Standard Industrial Classification (ISIC). It is unclear how the classes have been constructed nor how the patents are classified. Class definitions are not provided.
Khan (2016)	10	France	1791-1855	Destination	The author's patent data are categorised into industry of final use. It is unclear how the taxonomy has been produced nor how patents are classified. Class definitions are not provided.
Lehmann-Hasemeyer and Streb (2016)	5	Germany	1892-1913	Origin	The author's classify their patents according to the industry of the firm who held them. It is not clear how the taxonomy is formed or how firms are classified. Class descriptions are not provided.
Akcigit et al. (2017)	63	US	1880-1940	Production	The author's use the United States Patent and Trademark Office (USPTO) classification schema and the NBER aggregate classes. Using the USPTO codes patents are matched to the two-digit and three-digit SIC codes. This methodology more likely captures functionality rather than application.
Comino et al. (2017)	17	Venetian Republic	1474-1550	Production	The author's use the technology classification assigned to those patents by another researcher. The author's manually classified their patents, although it is unclear how patents have been assigned. Class definitions are not provided.
Khan (2017)	6	England	1750-1850	Unclear	The author classifies their exhibition data based on the categories used by the RSA to administer prizes to inventions. It is unclear how these classifies are defined or assigned. Class definitions are not provided.
Donges and Selgert (2019)	29	Germany	1843-1877	Production	The author's construct their schema based on the classification scheme of the Imperial Patent Office in 1877. They construct 30 technology groups to match patent data to industrial data, creating a table describing how their classes are defined. The author's assign their schema based on the patent's technical description.

Notes: The table shows a sample of 35 widely disseminated patent taxonomies. 'Classes' shows the number of reported patent classes in each study. 'Country' refers to the country or countries observed in the study. 'Time-period' dorefers to the period being studied. 'Method' indicates how the taxonomy has been constructed, this column takes one of four values: 'Destination', 'Origin', 'Production' or 'Unclear'. For a method to be recorded it must be either explicitly stated or based on classifying patents according to the firm's own industry (the origin approach). The patent taxonomies highlighted in bold are those used in this study to examine whether the choice of patent classification affects the results from a regression of patent characteristics.

Sources: see Column 1

is parsed, stemmed and stripped of stop words for analysis.[8] We subsequently use further techniques to validate the schema, and to assign patents to the appropriate class.

Historically, patent applications contained short, descriptive titles, which are required to detail the nature of the invention a patent covers. Under the European Patent Convention, for example, applications are checked by patent examiners to verify the accuracy of their titles (EPO, 2017). In instances where the title does not match the invention, an examiner can amend the title as they see fit. But, patent titles can no longer reveal the actual invention, historically they were more descriptive. In the case of the historical British patent system, patents could be annulled if the invention was not properly described in the title, which led to the adoption of a standardised approach to writing titles (Dutton, 1984; MacLeod, 2002; Bottomley, 2014b). Therefore, historical patent titles provide a rich source of textual data that can be used to classify patents according to their industry of final use.

This study relies exclusively on patent titles, rather than the more commonly used abstracts of patent specifications (see Magerman et al. (2015); Ruckman and McCarthy (2016); Younge and Kuhn (2016); Arts et al. (2018), for examples). We do so for two reasons. First, many historical patents do not possess digitally available abstract or technical specification data. In some cases, the data do not exist. Using abstracts and specifications would therefore discriminate heavily against historical patent data. Second, we wish to avoid a classification system based on the technical subject matter of the patent. Abstracts and specifications describe how their patented invention is to be worked, and what is new compared to the prior art, so they can be easily replicated by those "trained in the art". This requires considerable technical detail. Historically, patent titles concisely state what the patent application is, making them more reflective of potential industries of final usage.

When working with patent data, topic modelling is an increasingly popular methodology to approach classification (Wu et al., 2010; Kaplan and Vakili, 2012; Venugopalan and Rai, 2015; Ruckman and McCarthy, 2016; Wu et al., 2016; Chen

[8]see Appendix A for a description of these terms.

et al., 2017; Suominen et al., 2017). This exploits the tendency of patent titles from particular industries to consist of distinctive keywords. Two commonly used approaches are Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF).

Both attempt to model documents as combinations of topics, where topics are defined by the prevalence of particular words. LDA, introduced by Blei et al. (2003), assumes a generative process for documents and estimates the distributions. NMF (see Appendix A) uses a linear-algebra fitting technique. In preliminary investigations we found that topics suggested by LDA were more difficult to interpret.

For example, when using 80 topics the 10 most prominent words appearing in the first topic of each model were:

NMF: steam, engine, rotary, rotatory, marine, navigable, condense, power, vapour, part

LDA: igniting, wove, progress, circle, lantern, mache, decorating, multiplying, insects, check

The NMF topic suggests it has grouped patents for steam engines or other mechanical inventions. By contrast, the LDA topic does not seem to have derived a singular technology group, as it consists of a number of non-similar keywords.

One reason for this relative interpretability of topics may be related to the specialist language necessary to describe inventions. Investigations by O'Callaghan et al. (2015) find that NMF can produce more coherent topics with associated generality and suggest that it may be more suitable for such non-mainstream domains. A second reason may be related to the relatively low average number (5.6) of non-trivial words used in the patent dataset titles. In experiments conducted over 'short text' datasets (with average word count ranging from 3.4 to 14.3) Chen et al. (2019) found that NMF was inclined to produce better topics than LDA. We also found that LDA produced more extreme topics: those that were dominant in either a very small or very large number of documents. Topics which were dominant in only a small number of documents proved particularly ambiguous and were not suggestive of a generalizable patent class. For these reasons, our preferred method of topic derivation is NMF, using the implementation from scikit-learn

(Pedregosa et al., 2011). For further details of our approach please refer to Appendix A.

4 Patent Data

The patent data used in this study are the EPO's PATSTAT database – to help validate the construction of our patent taxonomy – and the entire population of British patents granted up to 1852 – to test for classification-specific econometric results. Designing and constructing any new time-invariant patent taxonomy requires robustness testing to ensure the taxonomy is capable of consistently classifying any and all historical patent data. PATSTAT is useful for robustness testing, because it contains the vast majority of all patents ever granted for Europe, the United States, and Japan. In addition, understanding whether the choice of patent taxonomy influences the results of any econometric analysis undertaken on patent data requires a dataset which has been classified according to multiple alternative taxonomies. The British patent data is useful for this comparative analysis, because it has been classified several times in the economic history literature.

4.1 PATSTAT

PATSTAT is the EPO's comprehensive patent database. It is alleged to contain all patents ever granted, although its records are incomplete as shown in section 2.1. Despite this, PATSTAT is still an incredibly useful dataset because it contains a wealth of bibliographic patent data. PATSTAT contains over 100 million patents from 90 different patenting authorities, with a large number of patents dating back to the nineteenth century. However, PATSTAT's historical coverage is much more complete from the early twentieth century.

The data contained in PATSTAT are digitised patent records, which can be found on Espacenet - a complete online collection of patent records from all member states of the EPO. The patent records are recorded in their national language, and as such the digitised records maintain the original language. All patents held in PATSTAT contain

their original patent title, and for the majority of patents the original specification is also digitised. PATSTAT also records the language patent titles are transcribed in, which is particularly useful for patents granted in countries which have multiple languages, such as Switzerland.

Because patents are recorded in their original language this provides a useful opportunity to extract a number of patent datasets covering a variety languages. As our goal is to construct a new patent taxonomy and methodology capable of classifying any and all patents according to a standard set of classes, having access to different national patent datasets allows us to test the versatility of our methods. If our method cannot classify patents in different languages in a consistent manner, then it cannot be considered a standardised or time-invariant taxonomy. For the remainder of this paper, we will be working with datasets from PATSTAT in their original language, and impose no translations during our methodology.

4.2 British Patent Data

While PATSTAT is used for checking the versatility of our machine learning methodology, we use the historical British patent data to test whether the choice of classification influences the results of econometric analyses. This dataset contains all patents granted in Britain until the Patent Law Reform Act of 1852. Following the Reform Act, Bennet Woodcroft, then Superintendent of the Patent Office, meticulously collated all records for patents granted prior to the Act. In doing so, Woodcroft produced four tomes, each of which provides a wealth of information concerning all British patents granted. Of these, the tome 'Titles of Patents of Inventions', published in 1854, compiled the patent titles of all British patents, who they were granted to, the patentee's occupation(s), and their listed residence. Given this wealth of information, this tome has been digitised and compiled into a structured patent dataset on multiple occasions.

We focus on this patent dataset for four reasons. First, the dataset has been used extensively within the historical innovation literature (Dutton, 1984; Sullivan, 1989,

1990; MacLeod, 2002; Nuvolari and Tartari, 2011; Meisenzahl and Mokyr, 2011; Bottomley, 2014a; Dowey, 2017; Khan, 2018). Second, prior studies have classified the patent data. Nuvolari and Tartari (2011), *A Cradle of Inventions: British Patents from 1617 to 1894*, and Woodcroft (1860) have assigned obtainable alternative schemas to the data, allowing for comparisons with our own. Third, the dataset covers the traditional period of the Industrial Revolution (dated approximately 1760-1830). Any insights from this era are vital to our understanding of this phenomenon, which transformed low-growth agriculturally-focused economies into high-growth industrialised ones, birthing the modern age. Fourth, Britain's patent system remains relatively unchanged over the period we analyse. Our results are therefore unlikely to be driven by any institutional changes.

To understand whether the choice of classification influences the results from an econometric analysis of patent data, we need to be able to accurately replicate prior taxonomies. Any degree of inaccuracy severely hinders the conclusions that can be drawn from this exercise. To this end, we are capable of replicating three previously used taxonomies: Nuvolari and Tartari (2011); *A Cradle of Inventions: British Patents from 1617 to 1894* which has been used in Dowey (2017); and Woodcroft (1860) which has been used by Sullivan (1989, 1990); Brunt et al. (2012).

For the Nuvolari and Tartari (2011) schema, the authors kindly provided their classified patent data, allowing us to match their patent classes to our data. Their classification covers patents granted from 1617-1850.[9] According to their paper, the authors constructed their taxonomy based on a working paper version of Moser (2012), which relies on a taxonomy derived from the 1851 Crystal Palace Exhibition schema. The Crystal Palace schema comprises 30 technology groups, and was designed to encompass all possible inventions and submissions supplied to the 1851 Exhibition. Unfortunately, exactly how either of the aforementioned taxonomies were constructed is unclear, as is how any patent data have been classified.

A Cradle of Inventions: British Patents from 1617 to 1894 is a CD-ROM containing

[9]While their paper only covers patents granted until 1841, the dataset which they supplied had classified all patents up to 1850.

the entire population of British patents with the COI taxonomy assigned. Again, we were able to match up our schema to that from *A Cradle of Invention*. According to the insert provided with the CD, the taxonomy has been constructed as a simple means of aiding users to find relevant patent information. The insert states that the authors do not claim infallibility of the classification system, and that it is predicated on their interpretation of patent titles. In addition, class definitions are provided, which help us understand how patents may be classified, although the overall design of the taxonomy remains unclear.

Finally, Woodcroft (1860) is assigned based on a unique British patent identifier constructed by Woodcroft. When Woodcroft collated the British patent records, he assigned a unique number for each patent, for the purposes of linking patents through each of his four tomes. Each unique identifier is listed against at least one of the 246 classes in Woodcroft (1860), and so we were again able to match this data to ours. We can therefore be certain that each taxonomy has been accurately replicated. However, we are much less certain about how Woodcroft designed his taxonomy, but considering his role as Superintendent of the Patent Office, his goal may have been similar to those of patent examiners: group technologies based on functionality to help future inventors locate prior art. Woodcroft's schema is the largest by a considerable margin, which suggests the taxonomy was primarily for reference purposes.

5 The Taxonomy

In this section, we begin the design, validation, and description of our new, time-invariant patent taxonomy. This taxonomy should be used to classify patent data based solely on the text contained in patent titles. It should also be used to classify patents according to their Destination (Griliches, 1990). This allows us to identify the relevant classification based on the information provided in patent titles. Finally, it should contain a set of broad, time-invariant classes, which means those classes should be independent of both time and country of origin of the patent rights.

To construct and validate our taxonomy, we take a two-step text analysis approach.

In the first step, we attempt to identify a set of commonly occurring patent classes using parsing and stemming techniques described in section 3. We do this by constructing a corpus of unique words derived from the titles of patent classes contained in the taxonomies reported in Table 1. The sample is representative of the literature; it covers historical taxonomies from various time periods, as well as studies from different regions. This allows us to begin identifying which types of words frequently appear in the economic history literature by manually grouping together synonyms and other related terms.[10] Types of words which commonly appear in historical patent taxonomies are more likely to reflect broad technology groups rather than niche ones, making them more likely to reflect time-invariant classes.

In the second step, we apply the NMF method, described in Appendix 9, to a number of different patent datasets, from different countries and different time periods, to help validate our taxonomy. This robustness check helps to ensure that we have not omitted any classes nor that we have included any niche classes which are not representative of the literature. This allows us to be more confident that we have identified a set of broad, time-invariant patent classes. In addition, we use the NMF method to help construct definitions for our final classes. The words contained in the topics are used to assign each topic to a particular patent class, and so the words contained in those topics are useful for constructing the description of said class.

The taxonomy itself, however, does not immediately dictate the classification approach; the definitions of our patent classes will determine whether our schema classifies patents according to technical function or industry of final use. The taxonomy will instead derive a set of broad, adaptable classes which should capture the broad characteristics of patented technologies. The definitions for our classes will come from the words generated in the topics produced from the NMF approach. These words should more closely reflect industry lines rather than technical functions as historical patent titles are supposed to briefly describe the new invention. This means the title is

[10]Human judgement has the advantage here because we need to be able to identify related words and synonyms. A text analysis technique may not be able to do so, because splitting patent class into unique words strips them of their context or definitions. Accordingly, the text analytic techniques would not be able to identify related terms.

short and devoid of technical description, making it easier to identify the relevant industry of final use.

5.1 Constructing the Taxonomy

To derive our base set of classes, or "word-groups", we first undertake a counting exercise on the existing historical taxonomies contained in Table 1.[11] The counting exercise compiles all patent classes from each taxonomy into a single corpus of unique words. Stop words are removed, and the corpus is stemmed to avoid duplicate terms appearing separately. Each unique word is first tallied, and then manually grouped with other related words. This is achieved by treating each unique word as a patent class of its own, and then identifying which broader group of inventions each class should belong to. For example, the word 'agriculture' would be grouped with the related terms 'seeds', 'land', and 'cultivate', since each term is related to the agricultural industry. Within each word-group, the title is usually derived from the term with the highest tally.[12] This acts as a reference point, as it provides a noisy estimate of the most commonly occurring classes throughout the literature.

We have deliberately included both patent office and non-patent office schemas in our methodology. Patent office schemas classify patents based on function-oriented characteristics, while non-patent office schemas use application-oriented characteristics; technology-based versus use-based classification. The class definitions, rather than the schema itself, dictates whether patents are classified according to their technical functions or industry of final use. Patent office classes and subclasses usually consist of multiple words which identify specific technical functions, while non-patent office schemas rely on a single broad class title to convey the likely industry of final use. Our approach decomposes every patent title into unique words, stripping them of their class definitions, and thereby removing any particular technology or use-based focus. The decomposition of patent titles also removes the influence of highly technical terms as

[11] We use the term word-groups to distinguish from a finalised set of patent classes, as word-groups reflect possible classes which still require verification.

[12] In the previous example, 'agriculture' would have the highest unique tally of all related terms, and thus the word-group is titled 'Agriculture'.

these cannot be readily grouped with other word-groups, reducing the likelihood of our taxonomy being biased by function-oriented characteristics.

The result of this counting exercise is reported in Table 2. Our initial count produced 1,105 unique words, the majority of which appeared only once or twice. The first half of the table shows the unique words with the highest initial tallies. This tally on its own, however, is not informative because it does not yet account for synonyms or related text.

The second column of Table 2 shows the results of our manual grouping. As a provisional check, both authors conducted this exercise independently, twice. Each exercise resulted in a similar set of 24 word-groups. 'NA' reflects unique words too vague or too technical to assign to any word-groups.[13] 'Aggregate Count' represents the total tally of all related words within each word-group. This count acts as an indicator of how frequently a particular word-group appears. Word-groups with lower tallies are less likely to reflect broad patent classes. 'Heat', for example, has the lowest count, as terms related to 'Heat' did not often appear as part of any class within our sample; 'Heat' may not be a suitable patent class.

5.2 Taxonomy Validation

We next conduct a series of robustness checks to verify whether our initial set of word-groups can be considered representative patent classes. These checks include: inviting a senior international patent examiner to undertake our counting exercise just described; ascertaining the frequency of each word-group, verbatim, in our sample of patent taxonomies; and checking whether different patent datasets can be readily classified using our set of word-groups.

As our first robustness exercise, we invited a patent examiner, with over 30 years of experience of classifying patents and revising official patent classification schemas, to conduct our counting exercise. There are several advantages to soliciting an independent review from a patent examiner. First, they are experts in patent classification; it is their job. Second, they are constantly developing and updating

[13] To ensure 'NA' did not reflect its own word-group, we ran another exercise on the words not assigned to other groups. Neither author could readily identify any further sets of word-groups.

Table 2: Counting Exercise Results

Raw Count		Author's Count		Patent Examiner	
Word-group	Frequency	Word-group	Frequency	Word-group	Frequency
product	47	NA	237	NA	398
metal	38	Hardware	226	Engineering Tools	304
machin	31	Chemicals	218	Manufacturing	288
engin	29	Instruments	211	Transport	151
textil	29	Agriculture	182	Light Industry	150
instrument	28	Textiles	176	Household	143
agricultur	26	Transportation	145	Agriculture	113
chemic	25	Construction	124	Construction	109
equip	25	Goods/Services	117	Organisation	98
mine	24	Machinery	111	Textiles	95
transport	23	Paper	99	Foodstuffs	77
food	23	Power	95	Energy Production	72
electr	22	Manufacturing	79	Construction (resources)	60
machineri	21	Metal	73	Wearables	59
paper	20	Food	70	Chemistry	58
manufactur	19	Health	64	Furniture	52
construct	19	Mining	50	Engineering Components	52
print	18	Utility	47	Metallurgy	51
gas	17	Apparel	43	Mining	49
servic	17	Military	43	Engineering Electrical	48
ship	16	Electricity	40	Medical	47
furnitur	16	Gas	35	Weapons	37
glass	15	Light	22	Engineering Civil	19
		Water	19	Telecoms	18
		Communications	17	Machines	6
		Heat	16	Electrical	5

Notes: The 'Raw Count' columns represent our results from the initial frequency counts for words scoring 15 or greater. 'Author's Count' displays the word-groups from our manual assignment. 'Patent Examiner' displays the word-groups from our experienced patent examiner's second manual assignment attempt. 'NA' denotes words too vague to be grouped into word-groups.

Source: See Table 1.

classification methodologies, such as their recent work on classifying technologies relating to the Internet of Things. Third, they are trained to classify patents according to both function-oriented and application-oriented characteristics. Fourth, they understand the terminology contained in patent titles. The examiner was made aware of the purpose of our schema, and instructions were provided for them to complete the exercise. The examiner was not shown the results of our initial counting exercise, and was given only the necessary information so as not to bias their attempt. This examiner undertook our exercise twice, on separate dates.

The examiner first produced a set of 14 word-groups, 11 of which were a match to ours. However, some of the examiner's classes were too broad, and they were asked to repeat the exercise a second time, with a focus on deriving a larger number of word-groups. The result of this final attempt is shown in the third column of Table 2.

In their final attempt, the examiner also derived 24 word-groups, of which 17 word-groups are similar to ours. By comparing the descriptions provided by the patent examiner with the terms included in each of our word-groups, we could subsume the examiner's remaining word-groups into at least one of ours: 'Construction' and 'Construction (resources)' relates to Construction; 'Electrical' relates to Electricity; 'Energy Production' relates to Engines; 'Light Industry' relates to multiple word-groups; 'Metallurgy' relates to Metal; 'Engineering Civil' relates to Construction; 'Engineering Components' and 'Engineering Tools' are both related to Hardware and Instruments; 'Engineering Electrical' is related to Electricity; 'Furniture' and 'Household' relate to Goods/Services; 'Organisation' relates to Goods/Services and Paper; and 'Wearables' relates to Apparel. Therefore, the first robustness check provides strong support for our initial set of word-groups as reasonable patent classes.

We next check how often our word-groups appeared as a distinct class in the sample literature, highlighting whether we derived a schema representative of the literature and whether our word-group titles are sufficiently broad. We check each word-group against each taxonomy, and then tabulate how often they appear. The results are reported in Table 3. For example, 29 out of the 35 sample taxonomies list Machinery as a distinct

Table 3: Results from Matching Word-groups to the Literature

Word-groups	Total	Percentage
Machinery	29	82.86
Textiles	29	82.86
Chemicals	27	77.14
Metal	26	74.29
Agriculture	26	74.29
Instruments	23	65.71
Food	23	65.71
Paper	21	60.00
Construction	19	54.29
Mining	17	48.57
Electricity	16	45.71
Transportation	15	42.86
Health	15	42.86
Goods	12	34.29
Apparel	11	31.43
Military	11	31.43
Manufacturing	11	31.43
Engines	10	28.57
Utility	10	28.57
Hardware	7	20.00
Communications	7	20.00
Gas	4	11.43
Water	4	11.43
Heat	3	8.57
Light	3	8.57

Notes: The table shows how often each word-group appears, verbatim, in our sample of 35 taxonomies from Table 1. 'Percentage' indicate the percentage of taxonomies each word-group appeared in. Word-groups with higher scores are considered more robust and representative of the literature.

Source: Authors' calculations using data from Table 1.

class, while Heat appears only three times.

As our last verification check, we examine the ability of our word-groups to classify different patent datasets, using the machine learning methodology described in Section 3 and Appendix 9. Specifically, we derive a set of topics from a number of patent datasets gathered from PATSTAT, and then match these topics to our list of word-groups. Despite PATSTAT's incompleteness, it is a useful source for examining late-nineteenth and twentieth-century patents from France, Germany, Great Britain, and the US – those countries which are often studied in regard to patents and

Table 4: *Data Used for Topic Analysis*

Country	**Years**	**Source**
England ('EN')	1617-1852	*A Cradle of Inventions (2009)*
France ('FR')	1855-1938	PATSTAT Biblio
Germany ('DE')	1877-1933	PATSTAT Biblio
Great Britain ('GB')	1899-1913	PATSTAT Biblio
United States ('US')	1790-1900	PATSTAT Biblio

Notes: For France and Germany we took a random sample of patents. For Great Britain and the US, we included all patents available until the specified end date. This means many patents were missing for older periods. However, since we care about deriving word-groups, this omission is not serious as we are still capable of observing patent titles.

Source: See Source column.

innovation, and amongst the richest and most developed in recent history. Table 4 shows the data used to verify our word-groups.

We base the strength of our proposed schema on whether it can suitably classify each topic. In particular, we are concerned with the spanning nature of the proposed classes: we wish to assign at least one word-group per topic, and are less concerned with instances where ambiguity arises. Large patent datasets will inevitably contain pioneering and niche inventions which are more difficult to classify. Such outlier patents are unlikely to undermine an entire classification schema. Nevertheless, if significant numbers of patents appear as distinct, unclassifiable topics, then our schema is likely to be undermined.

To check the robustness of our word-groups, we apply the NMF topic analysis method to the patent datasets described in Table 4. For France and Germany, we draw a random sample from each decade. By taking samples, we can ensure each patent dataset is of a similar manageable size, and we can use the same number of topics.

To justify including additional classes, we should observe topics which cannot be mapped to existing word-groups. Should such a distinct class exist, then we should observe significant numbers of patents and a distinct language describing the associated patents. By extracting more topics from each dataset than word-groups within the proposed schema, we attempt to identify any omitted classes.

The results of this exercise are shown in Table 5. Each column represents one of our patent datasets from Table 4, and their values indicate how many topics could be

Table 5: Topic Analysis Results using PATSTAT Datasets

Word-group	EN	FR	DE	GB	US
Agriculture	7	3	1	3	5
Apparel	2	2	2	3	2
Chemicals	15	17	10	5	2
Communications	0	1	0	2	4
Construction	4	2	3	3	2
Electricity	1	6	3	6	5
Engines	8	4	6	6	6
Food	1	3	4	1	0
Gas	1	1	2	2	1
Goods	3	6	5	7	5
Hardware	17	17	20	25	28
Health	1	2	0	1	3
Heat	1	0	0	2	2
Instruments	9	6	12	11	11
Light	3	1	0	2	1
Machinery	4	3	5	8	13
Manufacturing	1	1	0	1	3
Metal	4	4	4	2	5
Military	2	3	0	2	1
Mining	2	1	2	1	0
Paper	5	3	1	6	3
Textiles	18	2	0	4	5
Transportation	7	9	2	8	8
Utility	2	5	3	8	5
Water	2	1	0	1	1

Note: The table shows how many topics could be classified according to our set of 24 word-groups. For France and Germany, their total will not add up to 120 due to spurious word associations. This is a result of the difficulties of stemming French and German patent titles.

assigned to a particular word-group: for example, seven topics out of 120 were assigned to 'Agriculture' for the England data. For France and Germany there were more unclassifiable topics due to spurious word associations. For most word-groups, we were able to classify multiple topics across each dataset. Few word-groups were not well represented, such as 'Heat' and 'Light', suggesting these may be unsuitable patent classes.

Our topic analysis confirms the proposed schema is sufficient to capture patents from a number of diverse datasets.[14] We could readily assign each topic to at least one of our

[14]To prepare the patents for analysis, patent titles were stripped of non-printing characters and stop words. Suitable substitutions are applied to reduce all text to a standard character set. Once the topics are generated, they are translated into English.

Table 6: *Patent Class Methodology Scores*

Word-group	Tally	Patent Examiner	Literature Validation	Topic Datasets					Frequency	Outcome
				EN	US	GB	FR	DE		
Chemicals	218	1	27	15	2	5	17	10	0	–
Metal	73	1	26	4	5	2	4	4	0	–
Construction	124	1	19	4	2	3	2	3	0	–
Transportation	145	1	15	7	8	8	9	2	0	–
Goods/Services	117	1	12	3	5	7	6	5	0	–
Machinery	111	0	29	4	13	8	3	5	1	–
Textiles	176	1	29	18	5	4	2	0	1	–
Agriculture	182	1	26	7	5	3	3	1	1	–
Instruments	211	0	23	9	11	11	6	12	1	–
Engines	95	0	10	8	6	6	4	6	1	–
Hardware	226	1	7	17	28	25	17	20	1	–
Paper	99	0	21	5	3	6	3	1	2	–
Electricity	40	1	16	1	5	6	6	3	2	–
Apparel	43	0	11	2	2	3	2	2	2	–
Utility	47	0	10	2	5	8	5	3	2	–
Food	70	1	23	1	0	1	3	4	3	–
Health	64	1	15	1	3	1	2	0	3	–
Military	43	1	11	2	1	2	3	0	3	–
Mining	50	1	17	2	0	1	1	2	4	–
Manufacturing	79	1	11	1	3	1	1	0	4	–
Communications	17	1	7	0	4	2	1	0	5	Reassigned to Electricity
Gas	35	0	4	1	1	2	1	2	6	Reassigned to Chemicals and Utility
Heat	16	0	3	1	2	2	0	0	6	Reassigned to Utility
Light	22	0	3	3	1	2	1	0	6	Reassigned to Utility
Water	19	0	4	2	1	1	1	0	7	Reassigned to Utility

Notes: 'Tally' refers to our initial derivation of unique word-groups. 'Patent Examiner' refers to our patent examiner's derivation of word-groups, we score a value of 1 if the examiner's word-group matched ours. 'Literature Validation' refers to counting the number of taxonomies in which each of our 24 word-groups appear. 'Topic Datasets' shows how often each of our word-groups classified topics in each of our five patent datasets. 'Frequency' is a simple count indicating how likely a word-group reflects a patent class: the higher the score, the less likely the group should be kept. Word-groups can only have a maximum Frequency of eight, as there are seven distinct exercises. For a word-group to receive a score from any given exercise, we defined "cut-off" points. The cut-off points are defined as follows: 'Tally' below 50; 'Patent Examiner' score of zero; 'Literature Validation' below 10; 'Topic Datasets' score of zero or one.

word-groups, supporting the word-groups as time-invariant classes. Similarly, the French and German datasets were able to be classified with our proposed word-groups, further supporting the use of our methods for any patent dataset, irrespective of the language.

5.3 Finalising the Taxonomy

To determine whether our proposed schema constitutes a time-invariant taxonomy, we compile the results from each of our exercises into Table 6. The table is sorted by the column 'Frequency' which is a simple score indicating the likelihood of a particular word-group reasonably reflecting a patent class. To derive scores for the Frequency column, "cut-off points" are constructed for each exercise. Cut-off points are subjectively determined, and are intended only to help guide the construction of our patent schema; these are described in the table notes. When reviewing the results of our exercises, we place less weight on the Frequency score if word-groups received scores only from the final exercise.

'Outcome' records our final decisions regarding the word-groups. Based on our review, we merge the following classes: 'Communications' into 'Electricity'; 'Gas' into 'Chemicals' or 'Utility'; 'Heat', 'Light' and 'Water' into 'Utility'. For the word-groups 'Mining' and 'Manufacturing', which had high Frequency scores, we kept these due to their scores in the first three exercises; both word-groups received the entirety of their score from the 'Topic Datasets' exercise. Additionally, we amend the titles of certain word-groups to broaden their scope as patent classes: 'Goods/Services' is renamed 'Commodities' and 'Engines' is renamed 'Power'. Our final schema then comprises 20 time-invariant classes.

Finally, we use the topic analysis techniques to help construct class descriptions. Descriptions should ensure patents are classified by industry of final use, rather than technical function. Inadequate descriptions can lead to a subjective interpretation of how to apply our taxonomy. Such difficulties would deter adoption of the schema, and undermine results derived from its application. Topics represent word clusters tending to appear in combination with one another. Where a topic directly relates to a class the words comprising the topic act as descriptors. This uncovers the vocabulary used to

connect a patent's description with its intended classification, from which we derive our class definitions. Descriptions also grant the schema adaptability; classes can be further aggregated or disaggregated to aid future users apply an appropriate taxonomy that suits their research question. Table 7 presents our schema definitions.

Table 7: Patent Class Definitions

Number	Classification	Inventions Pertaining To:
(1)	Agriculture	The growth of crops and raising of livestock; fishing, forestry and hunting; horticulture; unspecified use of land
(2)	Apparel	Articles to be worn; articles of clothing for humans and animals; jewellery, broaches, and the like
(3)	Chemicals	The development of new chemicals, the applications of chemicals, or products developed by chemicals processes; organic and inorganic chemistry; gases; nuclear
(4)	Commodities	Consumable, durable, and non-durable goods which are not explicitly for industrial usage, with a focus on inventions to be sold in the market for private use; intangible services; recreational items
(5)	Construction	Building; tools for building; civil engineering; construction and building related accessories; building of infrastructure; construction of items of a physical nature
(6)	Electricity	The creation, management, and application of electricity; of electrical appliances, components, and instruments; aspects of electricity which do not overlap with other utilities; combinations of electricity with galvanism, magnetism and the like
(7)	Food	The production, treatment, and management of foodstuffs and beverages for consumption; tobacco
(8)	Hardware	Devices, objects, items or articles that provide a productivity-enhancing or labour-saving function requiring little or no manual interaction; Machine tools; Non-mechanical objects
(9)	Health	Improving the quality of life; life-saving medicines or apparatus; protection from ailments
(10)	Instruments	Measuring, gauging, weighing; general devices or objects which reduce the effort required to perform certain tasks; devices or objects which aid in productivity of labour; a tool or implement especially for precision work
(11)	Machinery	Machines which operate on mechanical power, and to their maintenance; processes conducted by machines
(12)	Manufacturing	The production of goods or items; large scale and small scale
(13)	Metal	Metallurgy; extracting metals from their ores; the application of chemical processes to metals, whether by producing, refining, galvanising or other such methods
(14)	Military	Weapons, armaments, armour, and other types of offensive or defensive articles
(15)	Mining	The construction of mines, their excavation, management, flood management, and extraction of natural resources; the raising and lowering of heavy bodies
(16)	Paper	The use of paper; methods which improve paper; the process of printing; paper and cardboard production, and to other such related items; physical record keeping; bills, cheques
(17)	Power	Generating, regulating, and applying energy for power, speed, or such related uses
(18)	Textiles	The creation of fabrics from processes of weaving, spinning, knitting, felting, etc, and their bleaching or dyeing, and treatment
(19)	Transportation	Facilitating speedy, or easier, travel across distances; transport infrastructure; packaging and storage of items for easier transport
(20)	Utility	The management of public systems, such as sewerage; the creation, management, and application of gas, heat, light, and water; the regulation of water, light, heat, gas, and electricity as public goods; and to inventions which encompass combinations of water, light, heat, gas, and electricity; fireproofing structures

Notes: Definitions are constructed using the word associations derived from the topic analysis methodology. Some classes could be further divided using these definitions, or further aggregated.

6 Application of Taxonomy

The use of alternative patent taxonomies within the literature is problematic: the results posited may be contingent on the choice of classification. How can we compare the results derived using different taxonomies, especially when we do not know how to replicate them?

To prepare the dataset for comparison, we assign each alternative taxonomy as described in section 4.2. We assign our schema using our machine learning methodology. After deriving our 120 topics, we assigned one class per topic.[15] Our method creates each topic and assigns patents to them simultaneously. We then assign the topic's associated class. By assigning the top two topic scores to each patent, we can account for any potential overlap across technology groups. We denote these as "Topic-One" and "Topic-Two". In some instances, a patent has the same class assigned twice. We consider these patents to have little overlapping characteristics. We also manually classified the entire dataset, and compared our assignments with the machine's. Both authors did so independently. Either of our manually assigned classes matched either of the assigned topics in 93 per cent of cases.[16] The remaining seven per cent did not match because of too few unique words.

Table 8 presents a comparison of the schemas used in this study. Several classes appear across most of the taxonomies: Agriculture, Apparel, Chemicals, Engines/Power, Medical/Health, Metal, Military, Mining, Paper, and Textiles. For these commonly occurring classes, however, the number of assigned patents are not identical across taxonomies. The COI schema, for example, assigns 1,676 patents to Textiles, while our own Topic-One assigns 2,280; approximately 600 patents have been classified inconsistently across schemas. Food patents exhibit a similar inconsistency across existing schemas. COI lists 323 patents as Food, while NT lists 754 instead, and our Topic-One schema lists only 50. The majority of patents also receive a different

[15]Where a topic was inconsistent in its word associations, it should be labelled 'Unclear' and then the patents assigned to it should be manually reviewed. In our analysis, no topics were labelled Unclear.

[16]We invited the senior patent examiner to manually classify a random sample of 250 patents according to our schema. We then checked their classification against the machine's and found a 70 per cent match.

Table 8: Comparison of Class Assignments

Cradle of Invention				Nuvolari				Topic-One				Topic-Two				Woodcroft			
Class	**Count**	**Percent**	**HHI**	**Class**	**Count**	**Percent**	**HHI**	**Class**	**Count**	**Percent**	**HHI**	**Class**	**Count**	**Percent**	**HHI**	**Class**	**Count**	**Percent**	**HHI**
AGR	442	3.21	0.001	Agriculture	455	3.30	0.001	Agriculture	597	4.33	0.002	Agriculture	493	3.58	0.001	Agriculture	483	3.55	0.001
BEV	278	2.02	0.000	Carriages	844	6.13	0.004	Apparel	105	0.76	0.000	Apparel	109	0.79	0.000	Apparel	179	1.31	0.000
CLO	279	2.02	0.000	Chemicals	1,152	8.36	0.007	Chemicals	1,189	8.63	0.007	Chemicals	990	7.19	0.005	Chemicals	151	1.11	0.000
COM	80	0.58	0.000	Clothing	344	2.50	0.001	Commodities	482	3.50	0.001	Commodities	217	1.57	0.000	Engines	1,018	7.47	0.006
DOM	1,642	11.92	0.014	Construction	641	4.65	0.002	Construction	564	4.09	0.002	Construction	778	5.65	0.003	Medical	237	1.74	0.000
FOO	323	2.34	0.001	Engines	1,714	12.44	0.015	Electricity	97	0.70	0.000	Electricity	60	0.44	0.000	Metal	432	3.17	0.001
IND	5,875	42.64	0.182	Food	754	5.47	0.003	Food	50	0.36	0.000	Food	77	0.56	0.000	Military	142	1.04	0.000
INS	458	3.32	0.001	Furniture	690	5.01	0.003	Hardware	1421	10.31	0.011	Hardware	1,689	12.26	0.015	Mining	40	0.29	0.000
MED	248	1.80	0.000	Glass	141	1.02	0.000	Health	85	0.62	0.000	Health	141	1.02	0.000	Paper	151	1.11	0.000
MIL	203	1.47	0.000	Hardware	879	6.38	0.004	Instruments	1153	8.37	0.007	Instruments	782	5.68	0.003	Textiles	1,323	9.71	0.009
MIN	207	1.50	0.000	Instruments	623	4.52	0.002	Machinery	666	4.83	0.002	Machinery	1,126	8.17	0.007				
MIS	15	0.11	0.000	Leather	224	1.63	0.000	Manufacture	459	3.33	0.001	Manufacture	1,075	7.80	0.006				
PAP	530	3.85	0.001	Manufacturing	736	5.34	0.003	Metal	517	3.75	0.001	Metal	484	3.51	0.001				
TEX	1,676	12.16	0.015	Medicines	287	2.08	0.000	Military	206	1.50	0.000	Military	116	0.84	0.000				
TRA	1,522	11.05	0.012	Metallurgy	719	5.22	0.003	Mining	166	1.20	0.000	Mining	253	1.84	0.000				
				Military	256	1.86	0.000	Paper	501	3.64	0.001	Paper	410	2.98	0.001				
				Mining	85	0.62	0.000	Power	1263	9.17	0.008	Power	1,464	10.63	0.011				
				Paper	504	3.66	0.001	Textiles	2,280	16.55	0.027	Textiles	1,863	13.52	0.018				
				Pottery	290	2.10	0.000	Transportation	1,080	7.84	0.006	Transportation	844	6.13	0.004				
				Ships	616	4.47	0.002	Utility	897	6.51	0.004	Utility	807	5.86	0.003				
				Textiles	1,824	13.24	0.018												
HHI			**0.229**				**0.070**				**0.083**				**0.080**				**0.026**

Notes: The table displays the Herfindahl-Hirschman Concentration ratios for each taxonomy. Count represents the total number of patents related to each class. This is then represented as a percentage. The individual class HHI scores are represented. The bottom row displays the HHI ratio for each taxonomy as a whole. For the 'Woodcroft' schema, we have included only those classes found in other schemas instead of the entire 146 classes. The HHI for Woodcroft is still calculated using the whole taxonomy.

Sources: Authors' calculations using data from *A Cradle of Inventions (2009)*, Nuvolari and Tartari (2011); Woodcroft (1860). All taxonomies cover 1700-1850.

Topic-Two assignment, suggesting the characteristics of many patented inventions overlap multiple technology groups. This suggests that patents should have more than one assigned classification.

We calculate Herfindahl-Hirschman (HHI) scores for each schema. HHI scores show how concentrated a particular taxonomy is. A higher score indicates a more skewed distribution of patents within a particular schema. For example, COI has the highest associated HHI score at 0.229, while Woodcroft has the lowest at 0.026. Examining the COI schema shows 'Industry' accounts for 42 per cent of all British patents. No other schema has such a 'catch-all' class.

7 Comparison of Taxonomies

The existing, alternative schemas do not consistently classify patent data as schemas have different classes and presumably different approaches to classifying patents. Consequently, studies using different schemas are likely to produce different results. To test for any potential divergences, we observe each schema in relation to six commonly examined patent characteristics relating to the nature of invention: the citations of patented inventions, the occupational status of patentees, the stock of patents held by patentees, the number of named inventors per patent, whether a patentee is considered an insider, and whether a patent is for a capital-saving invention. Because each taxonomy does not have the exact same patent classes, we examine only those classes common to at least three schemas: Agriculture, Chemicals, Clothing (or Apparel), Engines (or Power), Food, Instruments, Medicines (or Health), Metal, Military, Mining, Paper, and Textiles.

While we could focus on those classes common to all schemas, doing so would remove additional useful information concerning the existence and degree of classification divergence. For all ensuing regressions, we include all patent classes in each schema, but report only the common classes to clarify our analysis. In addition, all regressions are run on observations common to all patent schemas.

To determine whether classification divergence exists, we contrast the results from a series of regression models described below. First, we contrast results between taxonomies for a given patent characteristic: how does a common patent class coefficient's magnitude, sign, or significance change from one taxonomy to another? Second, we contrast whether the differences between taxonomies are the same across patent characteristics: if we observe a particular class's divergence for one patent characteristic, do we observe the same class divergence for the other characteristics?

The interpretation that follows centres around comparisons of coefficient magnitude, statistical significance, and the direction of association across taxonomies for the same patent class. When examining coefficients, the size of any difference relative to the coefficients being compared will provide an indication of magnitude divergence. Changes in statistical significance across taxonomies highlights strong inconsistencies in the subject matter being classified. We consider this to be particularly strong if coefficients fluctuate from no statistical significance, to significance at the one per cent level. The direction of association will also help us understand the inconsistency of classification. Where coefficients all have the same sign, this highlights a degree of consistency, but where they differ it further emphasises the degree of classification inconsistency.

Given the taxonomies examined in this study are very similar, observing any differences is even more concerning. For a similar set of taxonomies, we would expect to observe no differences if patents are classified in the same manner. But, observing any divergence between similar taxonomies, no matter how small, suggests similarity is strictly not enough to ensure consistency, and that divergences between less similar taxonomies are likely to be considerably larger and perhaps more serious.[17]

Unfortunately, we are unable to estimate the degree of divergence within the existing literature, nor exactly how existing results would change had our methodology been employed. Such an endeavour is beyond the scope of this study. The purpose of our comparative analysis is to identify whether classification divergence exists between a set

[17]As a further examination of similarities between the alternative schemas, Appendix B reports a series of regression plots showing correlations between the alternative schemas for the patent characteristics we examine in this section.

of similar patent taxonomies. If it does, then wider divergence would also be expected between dissimilar taxonomies.

7.1 The Citations of Patented Inventions

First, we examine how the choice of taxonomy affects an analysis of the citations of patented inventions. In the innovation literature, patent citations are a popular metric used to proxy for patent quality or value (Hall et al., 2001, 2005; Lach and Schankerman, 2008; Bernstein, 2015; Kogan et al., 2017). In place of citations, the historical British literature has adopted the Woodcroft Reference Index (WRI), as pioneered by Nuvolari and Tartari (2011). This index lists how many contemporary scientific and trade journals referenced a particular patent within our dataset. The references are used to proxy for the technical and economic significance of a particular patented invention: more references signals a higher quality patent. Because the number of references artificially increases over time, we adopt the approach of Hall et al. (2005); Nuvolari and Tartari (2011), by weighting the total sum of references on a patent by the average number of references on all patents within a given time period; the time periods we use are those used in Nuvolari and Tartari (2011).[18] To ensure comparability, all regressions also use the same time periods as time controls.

The quality indicator is a count variable with a skewed distribution; many patents have few references, and few patents have many references. The negative binomial model accounts for skewness by relaxing the assumption that the mean and the variance are equal (Greene, 2008).[19] Under this model, our dependent variable is the weighted number of references for a given patent. Our control variables constitute: whether the patentee had a prior patent; the patentee's occupation; whether the patentee's occupation directly relates to the class of their invention; their nationality; and time controls. The explanatory variables are the classes associated with each schema. We represent patent classes with dummy variables, where Agriculture is the chosen baseline

[18]These time periods are as follows: 1700-1721; 1722-1741; 1742-1761; 1762-1781; 1782-1801; 1802-1811; 1812-1821; 1822-1831; 1832-1841; 1842-1850.

[19]We also test the relationship using the poisson model. The results from poisson are equivalent to the negative binomial approach.

category.

Table 9 provides the results of our approach. Column 1 uses the Woodcroft schema; column 2 the NT schema; column 3 the COI taxonomy; column 4 the Topic-One taxonomy; column 5 the Topic-Two taxonomy; and column 6 controls for Topic-One and Topic-Two simultaneously (henceforth known as "CombinedTopics"). We argue that future investigators who employ our schema and methodology run three separate econometric specifications, using Topic-One, Topic-Two, and then both schemas together as a robustness check.

At first glance, the table posits consistencies for several classes. Metallurgy and Textiles patents are the most consistent across taxonomies, perhaps reflecting better defined technology and industry boundaries compared to other patent classes. Despite the consistency, both classes still display divergence. For Metallurgy, coefficient magnitude fluctuates considerably – Metal patents are in the range of 10 to 20 per cent more valuable than Agricultural ones, dependent on taxonomy. Similarly, under the COI schema only, Textiles patents are not statistically different from Agricultural ones.

After examining the remaining classes, we find that classification divergences exist. This divergence affects all aspects related to interpreting regression coefficients. The magnitude of coefficients fluctuates when comparing Mining inventions, for example. The COI schema suggests Mining patents are likely to have 20 per cent more references per patent compared to Agricultural patents. One reasonable interpretation is that capital-intensive inventions are of a greater quality.[20] Topic-One, however, suggests Mining patents have nine per cent fewer references. Capital-intensive inventions, then, are of a lower quality compared to Agricultural ones.

Statistical significance also exhibits inconsistency. Chemicals patents, for example, show a statistically significant association under the NT, Topic-Two and Woodcroft schemas. For Topic-One and CombinedTopics, however, Chemicals patents are not statistically distinguishable from Agricultural patents, in terms of their respective

[20]Based on their titles, Mining patents were likely to be highly mechanised during this period. Such inventions are considered to be capital-intensive, as suggested by Khan (2005), because more capital than labour is required for their development.

Table 9: Negative Binomial: Dependent Variable is the Weighted Number of References per Patent

VARIABLES	(1) Woodcroft	(2) NT	(3) COI	(4) Topic-One	(5) Topic-Two	(6) CombinedTopics
Chemicals	0.090***	0.105***	-	0.017	0.071***	0.018
	(0.029)	(0.023)	-	(0.020)	(0.020)	(0.012)
Clothing	-0.058	-0.098***	-0.046	-0.151***	0.033	-0.055*
	(0.038)	(0.034)	(0.039)	(0.028)	(0.039)	(0.032)
Engines	0.009	0.045	-	0.002	0.038	0.010
	(0.052)	(0.040)	-	(0.038)	(0.033)	(0.025)
Food	-	0.021	0.026	0.115	0.134***	0.122
	-	(0.022)	(0.027)	(0.164)	(0.051)	(0.087)
Instruments	-	0.041*	-0.014	-0.039**	0.017	-0.036***
	-	(0.023)	(0.025)	(0.019)	(0.023)	(0.012)
Medicines	-0.104***	-0.069***	-0.031	-0.067**	-0.092	-0.098***
	(0.027)	(0.025)	(0.029)	(0.028)	(0.057)	(0.028)
Metallurgy	0.186***	0.145***	-	0.098***	0.107***	0.092***
	(0.030)	(0.030)	-	(0.033)	(0.038)	(0.029)
Military	-0.051*	-0.019	-0.034	-0.067*	-0.010	-0.043**
	(0.028)	(0.033)	(0.038)	(0.035)	(0.026)	(0.019)
Mining	0.092	0.182***	0.202***	-0.090**	0.004	-0.055*
	(0.103)	(0.060)	(0.056)	(0.036)	(0.051)	(0.030)
Paper	0.210***	0.077*	0.060	0.023	0.033	0.021
	(0.058)	(0.040)	(0.043)	(0.030)	(0.028)	(0.021)
Textiles	-0.111***	-0.066*	-0.039	-0.071***	-0.058***	-0.071***
	(0.042)	(0.039)	(0.031)	(0.021)	(0.022)	(0.013)
Constant	-0.031	-0.101	-0.084	-0.041	-0.058	-0.034
	(0.071)	(0.073)	(0.065)	(0.059)	(0.052)	(0.052)
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	12,937	12,937	12,937	12,937	12,937	12,937
Pseudo R-Squared	0.00667	0.00371	0.00287	0.00292	0.00271	0.00325

Notes: The table shows how the quality of patented inventions varies by technology group. The dependent variable is the weighted number of references per patent. In each column, the omitted variable is the Agriculture class. Coefficients are interpreted as the difference in the logs of expected counts of the predictor variable. To translate into a unit change, the coefficients need to be exponentiated. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations using data from *A Cradle of Inventions (2009)* and Nuvolari and Tartari (2011); Woodcroft (1860). All datasets cover 1700-1850.

number of references. Such a result is likely to lead investigators to consider Chemical patents as being no different from Agricultural patents. Similar observations are found when interpreting Clothing, Food, Instruments, Medicines, Military, Paper, and Textile related patents.

The direction of association of coefficients is also subject to divergence. Three classes exhibit inconsistency regarding the direction of association: Clothing, Instruments, and Mining. Mining and Instruments are perhaps the most divergent classes, as not only does their direction of association fluctuate across taxonomies, but so too does their statistical significance – both positive and negative statistically significant associations are shown. Depending on which schema had been adopted, investigators could find completely contradictory results.

7.2 Patentee Occupational Status

To ascertain whether classification divergence is unique to examining the citations of patented inventions, we next examine patentee's occupations against patent classes. The innovation literature has examined the role of independent inventors and the types of industries they are likely to select into, or the types of inventions they are likely to produce (Schmookler, 1966; Khan and Sokoloff, 2004; Nicholas, 2010, 2011b; Khan, 2018). Our data allow us to conduct a similar examination. The patent data record the patentee's occupation alongside their name. This allows us to match occupations to a statistical measure of potential skills using the HISCLASS schema of Van Leeuwen and Maas (2011). This metric groups occupations based on their skills, whether they are manual or non-manual labour, and the degree of supervision required. For simplicity, we break the HISCLASS codes into manual versus non-manual occupations, following Klemp and Weisdorf (2012). Non-manual occupations are likely to be higher-skilled than their manual counterparts (Van Leeuwen and Maas, 2011).

We represent non-manual occupations using a dummy indicator variable. Consequently, a probit regression model is necessary to derive the probability of patent classes being associated with non-manual occupations. Our control variables constitute:

whether the inventor had a prior patent; their nationality; and time controls. The explanatory variables are patent classes, with the baseline class being Agriculture.

Table 10 reports our results. Classification divergence still exists, however it is less severe for this particular characteristic. This may be due to the skewed distribution of non-manual occupations: approximately 75 per cent of occupations in the data are classified as non-manual. Despite this, there exists variation because of class divergence.

Paper patents show a significant range in terms of coefficient size, for example. Under the COI schema, an average Paper patent is approximately 8.3 per cent more likely to be associated with a non-manual occupation, when compared to an Agriculture patent. The size of the result could be considered small, suggesting inventors of Paper patents were similarly skilled as inventors of Agriculture patents. However, the Woodcroft schema suggests non-manual occupations were, on average, 34 per cent more likely to produce Paper patents. While the conclusion remains similar, the contrast between coefficient sizes can lead to differing interpretations regarding the importance of human capital or skills when producing paper inventions.

Statistical significance also varies across taxonomies. The majority of patent classes report fluctuations between significance and non-significance. For example, Food patents are statistically significant at the one per cent level under the NT and COI schemas. The remaining schemas, however, are not statistically significant at conventional levels. Chemicals, Engines, Medicines, and Mining patents are the only ones to show no variation in statistical significance. This is in clear contrast to their variation observed against patent citations, suggesting divergences do not appear consistently when examining various patent characteristics.

The direction of association shows more stability compared with the previous set of results. Only Food, Instruments, and Paper patents show any variation in direction across taxonomies. The NT schema suggests Instruments patents were more likely to be associated with non-manual occupations compared to Agricultural patents. The remaining schemas, however, suggest the opposite: skilled individuals were less likely to produce instruments patents.

Table 10: Probit: Dependent Variable is a Dummy representing a Non-Manual Occupation

VARIABLES	(1) Woodcroft	(2) NT	(3) COI	(4) Topic-One	(5) Topic-Two	(6) CombinedTopics
Chemicals	0.381***	0.189***	-	0.153***	0.099***	0.119***
	(0.065)	(0.045)	-	(0.046)	(0.023)	(0.015)
Clothing	0.061	0.051	0.011	0.102**	0.016	0.054*
	(0.046)	(0.040)	(0.041)	(0.040)	(0.035)	(0.031)
Engines	0.214***	0.183***	-	0.166***	0.081***	0.110***
	(0.037)	(0.040)	-	(0.043)	(0.028)	(0.019)
Food	-	0.118***	0.166***	-0.067	0.040	-0.015
	-	(0.042)	(0.050)	(0.103)	(0.052)	(0.032)
Instruments	-	0.044	-0.026	-0.017	-0.015	-0.036
	-	(0.055)	(0.059)	(0.058)	(0.041)	(0.026)
Medicines	0.271***	0.242***	0.237***	0.219***	0.133***	0.179***
	(0.040)	(0.036)	(0.043)	(0.038)	(0.030)	(0.027)
Metal	0.178***	0.164***	-	0.137***	0.069	0.086***
	(0.058)	(0.052)	-	(0.051)	(0.043)	(0.030)
Military	-0.064	-0.028	-0.048	-0.114*	-0.126**	-0.105***
	(0.051)	(0.064)	(0.064)	(0.067)	(0.053)	(0.034)
Mining	0.261***	0.210***	0.206***	0.148***	0.110***	0.104***
	(0.081)	(0.066)	(0.060)	(0.046)	(0.038)	(0.022)
Paper	0.341***	0.130***	0.083**	0.064	-0.028	0.016
	(0.052)	(0.043)	(0.040)	(0.046)	(0.026)	(0.012)
Textiles	-0.042	-0.033	-0.006	-0.050	-0.063	-0.046*
	(0.056)	(0.075)	(0.067)	(0.055)	(0.054)	(0.028)
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	12,741	12,741	12,741	12,741	12,741	12,741
Pseudo R-Squared	0.132	0.0906	0.0728	0.0833	0.0698	0.0859

Notes: The table shows how the association between non-manual occupations and technology groups. The dependent variable is a dummy variable, where a value of 1 indicates a non-manual occupation. In each column, the omitted variable is the "Agriculture" class. Coefficients are interpreted as marginal effects at the means. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations using data from *A Cradle of Inventions (2009)* and Nuvolari and Tartari (2011); Woodcroft (1860). All datasets cover the period 1700-1850.

7.3 Patent Stock

The third variable of interest is the stock of patents granted to patentees. This measures how many patents an individual has held in total each time they obtain a new patent. Patent stock is often used to control for other patent characteristics, and has been studied in Dutton (1984); MacLeod (2002); Khan and Sokoff (2001); Khan (2015b). Patent stock is useful for observing the behaviour of professional inventors or patentees, who are likely to view patents more favourably or as a greater necessity than other inventors who do not exploit the patent system. These inventors can be more commonly thought of as "Economic men" (Dutton, 1984, p. 104-117), who respond to demand-side conditions. Observing what they patent can inform us about inventor perceptions of profitable avenues of invention.

Patent stock is represented by a simple count variable with a skewed distribution, as few individuals hold many patents while many hold few. Therefore, we use a negative binomial model, as when observing patent citations. The control variables constitute: inventor occupations; their nationality; and time controls. The explanatory variables are patent classes, with the baseline class being Agriculture. Table 11 reports our results.

Once again, we find evidence of classification divergence. Patent stock shows a relatively greater degree of divergence compared to our previous results. In terms of coefficient magnitude, there is substantial variation. Under the Woodcroft schema, inventors who held Mining patents, for example, are 60 per cent more likely to have had a greater stock of patents, suggesting inventors of Mining patents may have either deemed patents as necessary or earned enough profits from their patent stock to purchase additional patents. By contrast the COI schema suggests these inventors were only four per cent more likely to have held other patents, while the Topic-Two schema shows a magnitude less than one per cent.

Statistical significance also fluctuates across taxonomies. There is no single class to show consistently significant or non-significant results, which stands in contrast to the previous tables. For example, under the NT schema, Clothing patents are not statistically significantly different to Agriculture patents, while the Topic-One schema's

Table 11: Negative Binomial: Dependent Variable is Patent Stock

VARIABLES	(1) Woodcroft	(2) NT	(3) COI	(4) Topic-One	(5) Topic-Two	(6) CombinedTopics
Chemicals	-0.242	0.245	-	0.078	0.351***	-0.002
	(0.187)	(0.150)	-	(0.099)	(0.092)	(0.066)
Clothing	-0.429***	0.200	-0.302*	-0.369*	0.109	-0.399***
	(0.136)	(0.273)	(0.161)	(0.201)	(0.285)	(0.129)
Engines	0.085	0.244	-	0.188*	0.298**	0.072
	(0.175)	(0.191)	-	(0.096)	(0.126)	(0.073)
Food	-	0.233	-0.138	-0.029	-0.036	-0.265
	-	(0.166)	(0.128)	(0.247)	(0.206)	(0.182)
Instruments	-	0.216*	0.175	0.105	0.251**	-0.022
	-	(0.116)	(0.153)	(0.071)	(0.106)	(0.047)
Medicines	-0.476***	-0.282**	-0.495***	-0.381	0.004	-0.336
	(0.137)	(0.117)	(0.127)	(0.324)	(0.338)	(0.298)
Metallurgy	0.093	0.355**	-	0.205*	0.374***	0.149
	(0.187)	(0.166)	-	(0.118)	(0.107)	(0.118)
Military	0.151	0.455**	0.173	0.378***	0.290*	0.132
	(0.152)	(0.188)	(0.148)	(0.113)	(0.148)	(0.119)
Mining	0.606	0.367	0.075	0.238	-0.011	-0.176***
	(0.415)	(0.235)	(0.195)	(0.161)	(0.119)	(0.057)
Paper	-0.078	0.310*	0.244	0.206*	0.221*	0.032
	(0.302)	(0.164)	(0.162)	(0.115)	(0.114)	(0.091)
Textiles	0.404*	0.561**	0.347*	0.448**	0.475***	0.291**
	(0.234)	(0.218)	(0.205)	(0.189)	(0.128)	(0.146)
Constant	-0.480	-0.805*	-0.605	-0.650*	-0.777**	-0.590
	(0.430)	(0.451)	(0.389)	(0.363)	(0.374)	(0.369)
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	13,347	13,347	13,347	13,347	13,347	13,347
R-squared	0.091	0.066	0.062	0.064	0.063	0.064

Notes: The table shows how the patent stock held by patentees at a given time varies by technology group. The dependent variable is the number of patents held by an inventor at the time of their latest patent grant. In each column, the omitted variable is the "Agriculture" class. Coefficients are interpreted as the difference in the logs of expected counts of the predictor variable. To translate this into a unit change, the coefficients need to be exponentiated. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations using data from *A Cradle of Inventions (2009)* and Nuvolari and Tartari (2011); Woodcroft (1860). All datasets cover 1700-1850.

result is significant at the ten per cent level, the COI's at the five per cent significance, and Woodcroft's at the one per cent significance. It would be difficult to conclude Clothing patents were different to Agricultural ones, given the results.

The direction of association also varies. Compared with prior results, fewer classes are consistently positive or negative across schemas. For example, Military is consistently positive, while Clothing exhibits positive and negative associations. This suggests classification divergences are not consistent when examining different variables of interest.

7.4 The Number of Inventors per Patent

The fourth characteristic we examine is the number of listed inventors per patent. Woodcroft included all named inventors when compiling patents granted prior to 1852. There are two plausible reasons why multiple inventors are listed: because either they helped develop the invention or they contributed to the cost of the patent. Inventor's had no claim over a patent right unless their name was also on that patent. Individuals who contributed to the development of an invention, either through their labour or their resources, would presumably have wished to retain a legal form of ownership over that invention. However, having an additional named inventor increased the cost of a patent by an undisclosed amount (Carpmael, 1842). Despite this, many patents have more than one named inventor. This suggests the additional cost was either outweighed by the benefit of retaining ownership or was sufficiently small so that inventors could effectively split the cost of the patent.

Obtaining a patent in England during our period of observation was expensive, with an average cost of approximately £100 in 1840 prices (Dutton, 1984). Given the high costs, either inventors had to be significantly wealthy or have access to additional funds, which could have been supplied by co-inventors or potential financiers. As part of the condition to extend financial resources to the prospective patentee, financiers may have requested their names be attached to the patent right. James Watt's famous patent, for example, was originally financed by his friends before Matthew Boulton became his

financial partner (Bottomley, 2014a), but in Watt's case his friends were not listed on the patent.

The types of technologies which were likely to entail additional named inventors may reflect the cost of making that invention, or the prospective profitability of that invention once patented. Should additional named inventors be financiers, then correlations between technology groups and the number of named inventors may provide insights into the technologies perceived as profitable during our period of observation.

Table 12 reports our results, which show that classification divergence continues to exist. The divergence here is much milder compared to our prior results. Coefficient magnitude exhibits divergence. The largest fluctuations are observed in relation to Clothing, Medicines, Mining, and Textiles. For example, compared to Agricultural patents, Textiles patents are associated with about 12.5 per cent more named inventors under the Woodcroft schema. By contrast, the COI schema suggests that only seven per cent more named inventors are associated with Textile patents, while 'CombinedTopics' suggests only five per cent more. In several cases, coefficients are at least twice the size under one schema compared to another. Comparing two negative coefficients, for example, Clothing patents range from -0.077 up to -0.002, the latter being approximately 38 times larger in absolute terms.

Few classes exhibit any statistically significant coefficients across alternative taxonomies. The Medicines and Textiles classes exhibit the most consistent statistically significant coefficients, although evidence of divergence remains. Under the Woodcroft schema, Medicines patents are significant at the ten per cent level of significance, while both NT and Topic-One are significant at the one per cent level, and the Topic-Two and CombinedTopics schemas exhibit no statistical significance.

Direction of association also diverges considerably. For the majority of the common classes, the direction of association is consistently fluctuating. Only Instruments, Military, and Textiles patents report a consistently positive or negative correlation across taxonomies.

Table 12: Negative Binomial: The Dependent Variable is the Number of Inventors per Patent

VARIABLES	(1) Woodcroft	(2) NT	(3) COI	(4) Topic-One	(5) Topic-Two	(6) CombinedTopics
Chemicals	0.059	-0.019	-	0.033	0.022	-0.010
	(0.082)	(0.044)	-	(0.034)	(0.022)	(0.022)
Clothing	0.055	-0.003	-0.044	-0.002	-0.043	-0.077***
	(0.056)	(0.041)	(0.043)	(0.049)	(0.031)	(0.027)
Engines	0.001	-0.005	-	0.008	0.017	-0.022*
	(0.039)	(0.041)	-	(0.032)	(0.021)	(0.013)
Food	-	-0.029	-0.037	-0.061	0.074	-0.026
	-	(0.039)	(0.039)	(0.058)	(0.079)	(0.053)
Instruments	-	-0.041	-0.033	-0.002	-0.014	-0.054***
	-	(0.040)	(0.041)	(0.034)	(0.020)	(0.013)
Medicines	-0.077*	-0.110***	-0.089**	-0.115***	0.018	-0.063
	(0.041)	(0.040)	(0.039)	(0.034)	(0.067)	(0.048)
Metal	0.049	0.011	-	0.070	0.073*	0.037
	(0.053)	(0.041)	-	(0.048)	(0.039)	(0.033)
Military	-0.087*	-0.095**	-0.080	-0.060*	-0.076*	-0.105***
	(0.052)	(0.043)	(0.049)	(0.035)	(0.044)	(0.023)
Mining	-0.083	0.048	-0.008	0.030	0.015	-0.014
	(0.069)	(0.080)	(0.054)	(0.047)	(0.036)	(0.022)
Paper	-0.018	-0.028	-0.005	0.012	-0.031	-0.052**
	(0.044)	(0.050)	(0.048)	(0.035)	(0.034)	(0.022)
Textiles	0.125***	0.112**	0.070	0.099**	0.095***	0.051**
	(0.041)	(0.046)	(0.045)	(0.044)	(0.029)	(0.025)
Constant	0.018	0.007	0.009	-0.015	-0.022	0.028
	(0.070)	(0.056)	(0.068)	(0.067)	(0.056)	(0.065)
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	13,347	13,347	13,347	13,347	13,347	13,347
Pseudo R-Squared	0.00512	0.00347	0.00268	0.00290	0.00260	0.00299

Notes: The table shows whether the number of inventors listed per patent varies by technology group. The dependent variable is an ordinal variable indicating how many inventors were listed on a given patent. In each column, the omitted variable is the "Agriculture" class. Coefficients are interpreted as the difference in the logs of expected counts of the predictor variable. To translate this into a unit change, the coefficients need to be exponentiated. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations using data from *A Cradle of Inventions (2009)* and Nuvolari and Tartari (2011); Woodcroft (1860). All datasets cover 1700-1850.

7.5 Insiders versus Outsiders

Our next patent characteristic indicates whether the patentee is an 'insider': an inventor is an insider if their invention relates to their occupation. Physicians patenting medicinal inventions or engineers patenting engineering related inventions are considered insiders. Following the approach of Nuvolari and Tartari (2011), we construct a dummy variable to indicate whether a patentee's occupation matched the subject matter of their invention. In some cases, the occupation or subject matter is too vague to indicate whether the patentee was an insider. Because of this, we do not directly interpret a value of zero as reflecting an 'outsider'.

Whether an invention is developed by an insider has implications for how we understand the nature of invention. Jewkes et al. (1969) are amongst the earliest to argue that radical innovations are produced by outsiders, because such individuals are more willing to challenge accepted ideas. Insiders, by contrast, are too engrained into the technology to observe opportunities for radical advancement. O'Brien et al. (1996) have suggested that outsiders were responsible for significant advancements in textiles technology during the Industrial Revolution, while insiders were responsible for incremental improvements. Mokyr (2009) echoes this argument and considers outsiders responsible for "macro-inventions" – inventions responsible for opening up new technologies – and insiders responsible for "micro-inventions" – inventions which improved on existing technologies.

The results in Table 13 exhibit a relatively strong degree of divergence compared to the prior results. Coefficient magnitude displays considerable divergence. Clothing patents report the most extreme divergence. Under the Woodcroft schema, Clothing patents are 44-45 per cent more likely to be associated with an Insider than an Agricultural patent. But, the CombinedTopics schema suggests that Clothing patents are only eight per cent more likely. Our interpretation of the importance of insiders is then inconsistent; Woodcroft's schema suggests insiders are extremely important to Clothing innovation, while CombinedTopics suggests they are only marginally more important. Even in less extreme cases, such as Mining or Engine patents, there is significant divergence in terms

Table 13: Probit: The Dependent Variable is a Dummy representing an Insider

VARIABLES	(1) Woodcroft	(2) NT	(3) COI	(4) Topic-One	(5) Topic-Two	(6) CombinedTopics
Chemicals	0.028	-0.039	-	-0.017	0.001	-0.112***
	(0.046)	(0.030)	-	(0.025)	(0.027)	(0.015)
Clothing	0.448***	0.228***	0.253***	0.237***	0.213***	0.082*
	(0.043)	(0.039)	(0.049)	(0.062)	(0.048)	(0.048)
Engines	-0.018	-0.002	-	0.044	-0.018	-0.080
	(0.030)	(0.034)	-	(0.094)	(0.097)	(0.051)
Food	-	-0.075***	-0.018	-0.071	-0.055	-0.124***
	-	(0.029)	(0.042)	(0.059)	(0.034)	(0.037)
Instruments	-	-0.035	0.012	0.041	0.007	-0.030
	-	(0.051)	(0.061)	(0.048)	(0.035)	(0.036)
Medicines	0.097	0.062	0.146**	0.139***	0.117***	0.057*
	(0.070)	(0.069)	(0.065)	(0.045)	(0.039)	(0.034)
Metal	0.133**	0.146***	-	0.139*	0.034	0.013
	(0.063)	(0.053)	-	(0.072)	(0.069)	(0.055)
Military	0.111*	0.070	0.101*	0.082**	-0.014	-0.013
	(0.057)	(0.061)	(0.059)	(0.039)	(0.039)	(0.030)
Mining	0.058	0.110*	0.141**	0.197***	0.145***	0.085***
	(0.084)	(0.056)	(0.060)	(0.038)	(0.031)	(0.027)
Paper	0.348***	0.177***	0.173***	0.035	0.029	-0.028
	(0.065)	(0.040)	(0.039)	(0.036)	(0.026)	(0.028)
Textiles	0.393***	0.318***	0.306***	0.271***	0.245***	0.174***
	(0.040)	(0.035)	(0.038)	(0.040)	(0.049)	(0.034)
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	12,908	12,908	12,908	12,908	12,908	12,908
Pseudo R-Squared	0.225	0.196	0.180	0.182	0.179	0.191

Notes: The table shows whether a patent belonged to an insider as opposed to an outsider, and whether this varies by technology group. In each column, the omitted variable is the "Agriculture" class. Coefficients are interpreted as marginal effects at the means. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations using data from *A Cradle of Inventions (2009)* and Nuvolari and Tartari (2011); Woodcroft (1860). All datasets cover 1700-1850.

of coefficient magnitude.

Statistical significance fluctuates considerably across taxonomies for several classes, most notably Food, Mining, and Paper patents. For those patent classes, significance ranges from statistical significance at the one per cent level to no statistically significant association at all. This is most profound for Paper patents, where exactly half of the examined taxonomies report no significant association while the other half report an association at the one per cent level. By contrast, Clothing and Textile patents exhibit consistent levels of statistical significance.

The direction of association of coefficients is also subject to divergence, albeit to a much lesser degree. Military patents, for example, are inversely correlated with insiders under the Topic-Two and CombinedTopics schema, when compared to Agricultural patents. Conversely, the remaining taxonomies yield a positive correlation instead. Chemicals, Engines, and Instruments patents exhibit a similar division in terms of positive versus negative correlations.

7.6 Capital Saving Patents

Our final characteristic indicates whether a patent is explicitly for a capital-saving invention. Invention during the Industrial Revolution has been viewed as a response to relative factor prices. According to Allen (2009), Britain had relatively high labour costs and cheap capital. The relative factor prices, Allen proposes, led to a rise in labour-saving invention and thus caused the Industrial Revolution.[21] This argument has been contested by Mokyr (2009), who points out that a significant number of inventions were not labour-saving. In her seminal work, MacLeod (2002) notes that the vast majority of patented inventions granted in Britain prior to 1800 were for capital-saving inventions.

Understanding which types of technologies are likely to benefit from capital-saving invention helps us understand the nature of invention. Do people choose to invent, and

[21]Labour-saving inventions are those which intend to reduce the amount of labour involved in the production process. Conversely, capital-saving inventions are intended to cheapen the cost of using capital.

then also patent, because certain productive activities have expensive capital inputs? Considering the rise in capital-related invention during the Industrial Revolution, examining patent records is an important means to observe this type of inventive behaviour. Consequently, understanding how interpretations from such data can be directed by the choice of taxonomy is equally important.

Following the methodology of MacLeod (2002), we construct a dummy variable for those patents which explicitly reference a form of capital-saving embodied in their invention.[22] A value of zero represents patents which did not have a stated capital-saving aim, while labour-saving inventions are controlled for in the analysis.[23]

The results are reported in Table 14, which exhibits classification divergence. When examining capital-saving patents, divergence is significantly more extreme than prior results. This is likely because we have fewer available observations. Capital-saving statements cease post-1830, and so they are dropped from our analysis. This may inhibit the comparability of divergence with the other taxonomies, but we are still able to contrast across schemas for this metric.

Coefficient magnitude is subject to divergence. For some classes, such as Metal, Mining, Paper, or Textiles patents, this divergence seems relatively small, while other classes, such as Chemicals, Clothing, and Medicines, exhibit a greater degree of divergence. Observing Medicines, for example, the Topic-Two schema suggests that Medicinal patents are on average three per cent less likely to be capital-saving than Agricultural patents. However, under the Woodcroft schema, the coefficient estimate for Medicinal patents is instead 29 per cent – a considerable difference in magnitude.

Statistical significance fluctuates across taxonomies. For most of the common classes, no statistical significance and statistical significance at the one per cent level are reported. For example, Clothing patents are statistically significant at either the one per cent or five per cent level under the Woodcroft, NT, COI, and CombinedTopics schemas. For Topic-

[22]Macleod constructs a list of stated aims derived from the patent titles of patents granted prior to 1800. This includes: saving time; saving fuel; saving on raw materials; increasing output; increasing power; reliability of equipment; regularity of output; saving on running costs in general; and saving on fixed capital. We follow this approach and only classify a patent as capital-saving if it states any of the aforementioned aims in its title.

[23]We do not analyse labour-saving patents because they are too few.

Two the association is not statistically significant at any conventional level. Only Textile patents remain consistent, exhibiting no statistically significant associations across any of the alternative taxonomies.

The direction of association is also inconsistent across taxonomies. For Chemicals, Clothing, Food, Mining, and Paper, both positive and negative associations are reported. In several of these classes there is an almost even divide between the direction of association. For example, the Woodcroft and NT schemas report a positive association between Chemical patents and capital-saving aims. By contrast, the Topic-One, Topic-Two, and CombinedTopics schemas report the opposite.

Table 14: Probit: Dependent Variable is a Dummy representing a Capital-saving Patent

VARIABLES	(1) Woodcroft	(2) NT	(3) COI	(4) Topic-One	(5) Topic-Two	(6) CombinedTopics
Chemicals	0.099*	0.093***	-	-0.055**	-0.127***	-0.165***
	(0.056)	(0.031)	-	(0.027)	(0.036)	(0.032)
Clothing	-0.191***	-0.073**	-0.102***	0.059**	0.050	0.062***
	(0.028)	(0.032)	(0.026)	(0.028)	(0.032)	(0.019)
Engines	0.021	0.063**	-	0.077**	0.004	0.039***
	(0.048)	(0.026)	-	(0.038)	(0.033)	(0.014)
Food	-	0.071	-0.025	0.286*	-0.001	0.106**
	-	(0.049)	(0.028)	(0.152)	(0.067)	(0.051)
Instruments	-	0.066*	0.024	0.034	-0.001	0.021
	-	(0.038)	(0.042)	(0.029)	(0.028)	(0.015)
Medicines	-0.289***	-0.087***	-0.143***	-0.092***	-0.035	-0.076***
	(0.033)	(0.033)	(0.028)	(0.017)	(0.042)	(0.029)
Metal	0.059	0.071*	-	0.081**	0.036	0.067***
	(0.036)	(0.038)	-	(0.032)	(0.034)	(0.021)
Military	0.061*	0.034	0.006	0.009	0.032	0.011
	(0.036)	(0.030)	(0.033)	(0.029)	(0.041)	(0.027)
Mining	0.072	0.118	-0.055	0.088**	0.076	0.069***
	(0.071)	(0.118)	(0.054)	(0.039)	(0.052)	(0.017)
Paper	0.013	-0.020	-0.070**	-0.032	-0.015	-0.032
	(0.068)	(0.033)	(0.031)	(0.025)	(0.040)	(0.020)
Textiles	-0.009	-0.013	-0.024	-0.011	-0.030	-0.010
	(0.038)	(0.028)	(0.028)	(0.026)	(0.033)	(0.019)
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	5,379	5,379	5,379	5,379	5,379	5,379
Pseudo R-Squared	0.158	0.119	0.109	0.103	0.103	0.110

Notes: The table shows whether a capital-saving patent varies by technology group. The dependent variable is a dummy variable indicating whether a patent explicitly stated its purpose was to save capital, following the approach of MacLeod (2002). There are fewer observations in this instance because capital or labour saving statements cease post-1830 and so are dropped from the analysis. In each column, the omitted variable is the "Agriculture" class. Coefficients are interpreted as marginal effects at the means. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations using data from *A Cradle of Inventions (2009)* and Nuvolari and Tartari (2011); Woodcroft (1860). All datasets cover 1700-1830.

8 Discussion

To our knowledge, the present study is the first to show classification divergence exists in the field of innovation studies. Prior studies have not explicitly addressed the potential consequences of their choice of taxonomy. This is a serious concern, as statistical significance, direction of influence, and coefficient magnitude are sensitive to the chosen schema. In addition, classification divergence is not consistent: the degree of divergence can vary dependent on what patent characteristics are being investigated. Depending on which schemas are used, and which patent characteristics are examined, investigators could find conflicting results.

The extent of classification divergence within the literature is uncertain. Without a complete understanding of how authors construct their taxonomies, for what purpose, and the method they use for classifying patents, we cannot determine how significant the divergence might be. Most academic studies do not provide such detail. Therefore, prior research articles which do not expressly describe their taxonomy should be interpreted with caution. The results of our findings have implications for the field of innovation history, as well as economic policymaking more generally.

8.1 Implications for Innovation History

Innovation historians examine patent data to better understand inventive behaviour and the nature of invention, typically during periods of rapid technological change. Patents are usually the only available source of time-series invention data available to innovation historians. As such, patent data are popularly used throughout the innovation history literature. This gives rise to a significant number of alternative taxonomies which cannot be accurately replicated. Given the results observed in this study, the number of alternative schemas serves to complicate our interpretation of patent studies. At present, the literature has not identified the existence of classification divergence, and therefore does not acknowledge this consideration in classification construction.

The existence of classification divergence within the innovation history literature is

concerning because it calls into question our collective understanding of patent systems as a means to foster innovation. Given the recent re-evaluation of the importance of Britain's patent system in encouraging the Industrial Revolution (Bottomley, 2014b, 2019), and the increasing use of patent indicators to measure inventive behaviour and technological change more generally (Khan, 2013a; Nuvolari and Vasta, 2015; Dowey, 2017; Murfitt, 2017; Donges and Selgert, 2019; Lane, 2019, for example,), the implications of classification divergence are significant.

Historians of innovation have long sought to explain the causes of the British Industrial Revolution. Invention is considered one of the most important contributors to British industrialisation (Crafts, 2011), but the exact cause for Britain's uptake in inventive activity is debated. The competing views centre around how best to explain the decision to invent. The views are described as "demand-side" versus "supply-side", or "incentives" versus "capabilities" respectively. Demand-side arguments favour economic incentives, suggesting inventors choose to invent and patent because it is profitable to do so; the most prominent argument favouring this viewpoint is Allen (2009) who views the Industrial Revolution as a result of induced innovation. By contrast, the supply-side viewpoint contends that inventors invent because they possess the specialist skills or knowledge to do so (Mokyr, 2009; McCloskey, 2011).

One popular incentives argument favouring the patent system relates to how easy it is to reverse engineer particular technologies. Inventors whose inventions can be easily copied are likely to rely more heavily on patents for protection (Cohen et al., 2000). For example, machine inventions are more prone to reverse engineering than Chemical related inventions (Moser, 2005); inventors who invent Machine inventions may then need patent protection to encourage them to invent.

The British Industrial Revolution is commonly associated with a wave of new machine inventions (such as steam engines, spinning wheels, furnaces, etc). Since machine inventions are more likely to be patented, being able to accurately identify and classify them is important. But, the existence and use of alternative schemas suggests these class-specific characteristics might not be consistently controlled for. This

inconsistency may unintentionally confound our understanding of the role of the patent system during the Industrial Revolution, as well as the relationship between patenting and innovation more generally. Given that our results are based on an examination of a number of important patent characteristics, the implications of classification divergence may be more severe for innovation history. How can we hope to understand the nature of inventive behaviour when those variables the economic historian investigates are sensitive to classification choice?

To highlight the severity of classification divergence, we can use our results to contrast how our understanding of the nature of invention may be subject to the choice of schema. Considering the Industrial Revolution represents a shift away from agricultural economies toward mechanised ones, we compare Mining patents against Agricultural patents. Mining was an important industry during the British Industrial Revolution, and responsible for a number of important technological advancements (Nuvolari, 2004; Allen, 2009; Mokyr, 2009; de Pleijt et al., 2019). Indeed, James Watt's famous separate condenser significantly improved the efficiency of steam engines: one of the key technologies of the Industrial Revolution, and a mining invention.

Considering first the results from the Woodcroft schema, they reasonably suggest the following: Mining patents were at least of the same economic value as Agricultural patents (Table 9); Mining patents were significantly more likely to be acquired by more skilled inventors (Table 10); holders of Mining patents did not patent any more than holders of Agricultural patents (Table 11); Mining patents had equal or fewer named inventors per patent (Table 12); Mining patents were not any more likely to be produced by Insiders (Table 13); and Mining patents were not any more likely to be regarded as capital-saving (Table 14).

Together, the evidence suggests Mining innovations were likely driven by more skilled inventors who may have been capable of financing their inventions and patents, and who presumably invented because of their capabilities rather than any incentive mechanisms.[24]

[24]The final point is derived from the lack of statistically significant results for either the quality metric, the patent stock metric, or the capital-saving metric, any of which would provide some support for the incentives argument.

Now, we examine Mining patents under the Topic-One schema. Compared to Agricultural patents the results reasonably suggest: Mining patents were less economically valuable than Agricultural patents (Table 9); Mining patents were more likely to be acquired by more skilled inventors (Table 10); holders of Mining patents did not patent any more than holders of Agricultural patents (Table 11); Mining patents had equal or more named inventors per patent (Table 12); Mining patents were significantly more likely to be held by Insiders (Table 13); and Mining patents were more likely to be capital-saving (Table 14).

The evidence suggests Mining innovation was still driven by skilled inventors, but their patents were typically less economically valuable than Agricultural ones. Similarly, Mining patents had more named patentees, suggesting those inventors were not as rich or needed more financial assistance to produce and finance their inventions and patents. Mining patentees were also individuals from within the industry and their patents were intended to reduce capital costs.

A possible interpretation of the Topic-One evidence is that incentives were more important than capabilities for encouraging inventor behaviour; insiders recognised the need to reduce factor costs, but these inventions would not have been of a significant economic value, presumably because they were likely to be micro-inventions rather than macro-inventions. By contrast, the Woodcroft evidence is closer in-line with the capabilities argument, as patentee's potential skills is the only statistically significant metric.

Our simple example serves to highlight how classification divergence can lead to conflicting interpretations regarding the nature of invention during periods of intense innovation and industrialisation. The same patent data when examined according to alternative schemas resulted in support for both of the prevailing competing explanations of Britain's Industrial Revolution. Having a single, consistent, reusable and transparent taxonomy and classification procedure can significantly reduce this inconsistency within the literature.

8.2 Implications for Economic Policymaking

While the results of our study are based on historical evidence, we argue they have implications for current innovation studies and economic policymaking. To our knowledge, there is no commonly accepted patent taxonomy used throughout the innovation literature. Based on our evidence, the innovation literature may also be subject to classification divergence.

Innovation scholars are interested in understanding the process of innovation and how best to encourage it. Although patents are not the only metric available that captures innovative activity, it is still a popular one (Griliches, 1990). From a survey of US manufacturing firms, Cohen et al. (2000) find that patents are more useful for possible rent-seeking motives, such as preventing competitors from patenting related inventions, or to force competitors into negotiations with the patent holders. Such strategic patenting has become an important explanation for the modern day patenting behaviour of firms (Kingston, 2001; Arundel and Patel, 2003; Blind et al., 2006; Boldrin and Levine, 2008).

Cohen et al. (2000) find that certain strategic patenting approaches are used in relation to particular types of technologies, which the authors refer to as "discrete" or "complex" products. Discrete products are categorised by inventions which comprise few patentable elements, such as chemicals and metals, while complex products comprise many patentable elements, such as electronics and transportation. Cohen et al. (2000) argue that patent blocking is one of the strategies available to firms, although the motivation differs dependent upon whether firms operate in discrete or complex product industries. Firms patenting discrete products are more likely to obtain patents to slow competitor innovation, while firms patenting complex products do so to enhance their positions when negotiating patent licenses. Another possible strategy is to use patents solely for the purpose of litigating or to defend against possible patent litigation from competitors. Lanjouw and Schankerman (2001) find that litigation rates vary across patent technology groups, while more recent evidence suggests certain firms purchase patents solely for purposes of enforcing them against infringers, thereby appropriating their profits (Fischer and Henkel, 2012; Galasso and Schankerman, 2015).

The decision to acquire a patent is therefore related to the technology of the invention in question. Indeed, patenting incentives in the modern innovation literature are likely more numerous and complex than those identified in innovation history. Such complexity makes accurately identifying relevant technology groups in a consistent manner important. To understand and encourage innovative behaviour, scholars and policymakers need to understand the nature of innovation and what role patents play within it. If scholars do not classify their patent data in a consistent or transparent manner, then the comparability of existing studies may be called into question.

As an example, suppose a policymaker is tasked with designing measures to encourage innovation in high-value technologies, and adopts an evidence-based approach. Utilising the COI taxonomy in their analysis, they observe capital-intensive inventions, such as Mining, were on average more valuable, and more likely to be produced by higher skilled inventors who hold a larger stock of patents. This result is consistent with the technologies which drove the Industrial Revolution. However, utilising the Topic-One schema, they may conclude that capital-intensive inventions are not of great value, are still produced by highly skilled individuals, but these individuals hold fewer patents.

Of course we are not suggesting that such decisions should be made on the basis of single sources of evidence, or single episodes from history. However, it does highlight the potential implications classification divergence has for prescribing policy, which may result in the misdirection or suboptimal allocation of important resources, or in extreme cases, inadvertently hinder rather than encourage innovation.

Finally, existing taxonomies are difficult to replicate, and may lead to the development of new taxonomies, which further compounds the inconsistency problem. The collective body of evidence on the economics of patents then becomes increasingly difficult to interpret.

Our recommendations for future patent investigations are as follows. Firstly, creators of any new taxonomies should describe how they design them, ensuring potential divergences can be identified and the methods are replicable. Descriptions need to accompany patent classes to ensure a consistent classification of patent data throughout

the literature. Secondly, mitigating potential divergences requires adopting a universal schema. While the classification procedure may also depend on the research question being investigated, there still needs to be a consistent classification of the same technologies. The taxonomy produced here is a useful starting point, and adaptable for future studies. Thirdly, subjectivity can be reduced by employing machine learning techniques to improve the consistency of patent classification. Finally, topic analysis provides a means to both identify appropriate classes and omitted classes, and to perform the classification of patent datasets in useful ways for economic analysis of innovation.

9 Conclusion

Our goal has been: to document methods of taxonomy construction; to design and develop a new and adaptable time-invariant patent taxonomy in a clear and transparent manner; to develop a new method for classifying all patent data consistently; and to show that classification divergence exists. We recommend our methodology and taxonomy be used in future studies. We acknowledge, however, that our schema may not be applicable to every study. In such cases, future investigators should describe either how they adapt our schema or any new taxonomies they produce. The machine learning techniques herein described are adaptable and adoptable for any future researchers.

The implications of classification divergence are likely to be profound for the patents and innovation literature. Classification divergence exists, at least, in the long-run British patent data studied here. Whether divergence exists in other datasets necessitates a re-examination of the existing literature for clarification. In the case where tcdivergence is small, interpreting the literature is less problematic, and deriving appropriate policy measures would remain possible. However, in the extreme case, where all studies are subject to divergence, the external validity of studies must be questioned. Given the results shown here, the extreme case seems more likely.

If studies are not comparable, then appropriate policy measures cannot be readily

prepared. We recommend existing studies, where possible, be re-examined using our schema and methodology. This is not to say our schema is "right", as there can be no objective measure of this. Our schema is, however, transparent making it straightforward for any subsequent studies to make use of it, or draw from it, as they see fit, while our methodology is consistent and replicable. Human error and human effort is substantially minimised using our machine learning approach. Related patents will always be identified, and will always be grouped together. Compared to humans, the machine is more consistent.

References

A Cradle of Inventions: British Patents from 1617 to 1894 (2009). *Stevenage, UK: Metal Finishing Information Services Ltd.*

Akcigit, U., J. Grigsby, and T. Nicholas (2017). The rise of American ingenuity: Innovation and inventors of the Golden Age. *National Bureau of Economic Research Working Paper Series No. 23047*.

Allen, R. C. (2009). *The British Industrial Revolution in global perspective*. Cambridge: Cambridge University Press.

Arts, S., B. Cassiman, and J. C. Gomez (2018, jan). Text matching to measure patent similarity. *Strategic Management Journal 39*(1), 62–84.

Arts, S. and R. Veugelers (2015). Technology familiarity, recombinant novelty, and breakthrough invention. *Industrial and Corporate Change 24*(6), 1215–1246.

Arundel, A. and P. Patel (2003). Strategic patenting. In *Background report for the Trend Chart Policy Benchmarking Workshop" New Trends in IPR Policy*.

Bailey, M. F. (1946). History of classification of patents. *Journal of the Patent Office Society 28*(7), 463–507.

Balsmeier, B., M. Assaf, T. Chesebro, G. Fierro, K. Johnson, S. Johnson, G.-C. Li,

S. Lück, D. O'Reagan, B. Yeh, and Others (2018). Machine learning and natural language processing on the patent corpus: Data, tools, and new measures. *Journal of Economics & Management Strategy 27*(3), 535–553.

Basberg, B. L. (1997, may). Creating a patent system in the European periphery: The case of Norway, 1839-1860. *Scandinavian Economic History Review 45*(2), 142–158.

Basberg, B. L. (2006, apr). Patenting and early industrialization in Norway, 1860-1914. Was there a linkage? *Scandinavian Economic History Review 54*(1), 4–21.

Baten, J., A. Spadavecchia, J. Streb, and S. Yin (2007). What made southwest German firms innovative around 1900? Assessing the importance of intra- and inter-industry externalities. *Oxford Economic Papers 59*(suppl 1), i105–i126.

Benner, M. and J. Waldfogel (2008, oct). Close to you? Bias and precision in patent-based measures of technological proximity. *Research Policy 37*(9), 1556–1567.

Bernstein, S. (2015, aug). Does going public affect innovation? *The Journal of Finance 70*(4), 1365–1403.

Blei, D. M., A. Y. Ng, and M. I. Jordan (2003). Latent dirichlet allocation. *Journal of machine Learning research 3*(Jan), 993–1022.

Blind, K., J. Edler, R. Frietsch, and U. Schmoch (2006). Motives to patent: Empirical evidence from Germany. *Research Policy 35*(5), 655–672.

Blit, J. and M. Packalen (2019). A Machine Learning Analysis of the Geographic Localization of Knowledge Flows. *Northwestern University Working Paper*.

Boldrin, M. and D. K. Levine (2008). *Against intellectual monopoly*. New York: Cambridge University Press.

Boschma, R., P.-A. Balland, and D. F. Kogler (2014, may). Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change 24*(1), 223–250.

Bottomley, S. (2014a). Patenting in England, Scotland and Ireland during the Industrial Revolution, 1700-1852. *Explorations in Economic History 54*, 48–63.

Bottomley, S. (2014b). *The British patent system during the Industrial Revolution 1700-1852: From privilege to property*. Cambridge University Press.

Bottomley, S. (2019). The returns to invention during the British Industrial Revolution. *Economic History Review 72*(2), 510–530.

Brunt, L., J. Lerner, and T. Nicholas (2012). Inducement prizes and innovation. *Journal of Industrial Economics 60*(4), 657–696.

Burhop, C. and N. Wolf (2013). The German market for patents during the "Second Industrialization", 1884-1913: A gravity approach. *Business History Review 87*(1), 69–93.

Cantwell, J. (2000, aug). Technological lock-in of large firms since the interwar period. *European Review of Economic History 4*(2), 147–174.

Carpmael, W. (1842). *The law of patents for inventions, familiarly explained for the use of inventors and patentees*. London: Simpkin, Marshall, and Co., Stationer's-Hall Court; and Weale, High Holborn.

Chen, H., G. Zhang, D. Zhu, and J. Lu (2017, jun). Topic-based technological forecasting based on patent data: A case study of Australian patents from 2000 to 2014. *Technological Forecasting and Social Change 119*, 39–52.

Chen, Y., H. Zhang, R. Liu, Z. Ye, and J. Lin (2019). Experimental explorations on short text topic mining between lda and nmf based schemes. *Knowledge-Based Systems 163*, 1–13.

Clark, G. (2007). *A farewell to alms: A brief economic history of the world*. Princeton University Press.

Cohen, W. M., R. R. Nelson, and J. P. Walsh (2000). Protecting their intellectual assets:

Appropriability conditions and why US manufacturing firms patent (or not). *National Bureau of Economic Research No. 7552*.

Comino, S., A. Galasso, and C. Graziano (2017). The diffusion of new institutions: Evidence from Renaissance Venice's patent system. *National Bureau of Economic Research Working Paper Series No. 24118*.

Costantini, V., F. Crespi, and Y. Curci (2015, may). A keyword selection method for mapping technological knowledge in specific sectors through patent data: the case of biofuels sector. *Economics of Innovation and New Technology 24*(4), 282–308.

Crafts, N. F. R. (2011). Explaining the first Industrial Revolution: Two views. *European Review of Economic History 15*(1), 153–168.

Davids, K. (2000, jan). Patents and patentees in the Dutch republic between c.1580 and 1720. *History and Technology 16*(3), 263–283.

de Pleijt, A., A. Nuvolari, and J. Weisdorf (2019, mar). Human Capital Formation During the First Industrial Revolution: Evidence from the use of Steam Engines. *Journal of the European Economic Association 17*, 1–61.

Donges, A. and F. Selgert (2019, feb). Technology transfer via foreign patents in Germany, 1843-1877. *The Economic History Review 72*(1), 182–208.

Dowey, J. (2017). *Mind over matter: Access to knowledge and the British Industrial Revolution*. Ph. D. thesis, The London School of Economics and Political Science.

Dutton, H. I. (1984). *The patent system and inventive activity during the Industrial Revolution, 1750-1852*. Manchester University Press.

EPO (2017). *Patents and the fourth Industrial Revolution*. Munich.

Feng, F. S. (2019). The proximity of ideas: an analysis of patent text using machine learning. *NYU Stern Working Paper*.

Fischer, T. and J. Henkel (2012). Patent trolls on markets for technology – An empirical analysis of NPEs' patent acquisitions. *Research Policy 41*(9), 1519–1533.

Frederico, J. P. (1964). Historical patent statistics. *Journal of the Patent Office Society 46*(3), 89–172.

Galasso, A. and M. Schankerman (2015). Patents and cumulative innovation: Causal evidence from the courts. *The Quarterly Journal of Economics 130*(1), 317–369.

Greasley, D. and L. Oxley (2010). Knowledge, natural resource abundance and economic development: Lessons from New Zealand 1861-1939. *Explorations in Economic History 47*(4), 443–459.

Greene, W. (2008, jun). Functional forms for the negative binomial model for count data. *Economics Letters 99*(3), 585–590.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature 28*(4), 1661–1707.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001). The NBER patent citation data file: Lessons, insights and methodological tools. *National Bureau of Economic Research Working Paper Series No. 8498*.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2005). Market value and patent citations. *The RAND Journal of Economics 36*(1), 16–38.

Hutchins, L. N., S. M. Murphy, P. Singh, and J. H. Graber (2008). Position-dependent motif characterization using non-negative matrix factorization. *Bioinformatics 24*(23), 2684–2690.

Jewkes, J., D. Sawers, and R. Stillerman (1969). *The Sources of Invention* (2nd ed.). Macmillan, London.

Johnson, D. K. N. (2002). The OECD Technology Concordance (OTC): Patents by industry of manufacture and sector of use. *OECD Science, Technology and Industry Working Papers No. 2002/0*.

Kaplan, S. and K. Vakili (2012). Identifying breakthroughs: using topic modeling to

distinguish the cognitive from the economic. In *Academy of Management Proceedings*, Volume 2012, pp. 1–1.

Kelly, B., D. Papanikolaou, A. Seru, and M. Taddy (2018). Measuring technological innovation over the long run. *National Bureau of Economic Research Working Paper Series No. 25266*.

Khan, B. Z. (2000). "Not for Ornament": Patenting activity by nineteenth-century women inventors. *The Journal of Interdisciplinary History 31*(2), 159–195.

Khan, B. Z. (2005). *The democratization of invention: Patents and copyrights in American economic development, 1790-1920*. Cambridge University Press.

Khan, B. Z. (2013a). Going for gold. Industrial fairs and innovation in the nineteenth-century United States. *Revue économique 64*(1), 89–113.

Khan, B. Z. (2013b). Selling ideas: An international perspective on patenting and markets for technological innovations, 1790-1930. *Business History Review 87*(1), 39–68.

Khan, B. Z. (2014). Inventing in the shadow of the patent system: Evidence from 19th-Century patents and prizes for technological innovations. *National Bureau of Economic Research Working Paper Series No. 20731*.

Khan, B. Z. (2015a). Inventing prizes: A historical perspective on innovation awards and technology policy. *Business History Review 89*(4), 631–660.

Khan, B. Z. (2015b). The impact of war on resource allocation: "Creative Destruction," patenting, and the American Civil War. *Journal of Interdisciplinary History 46*(3), 315–353.

Khan, B. Z. (2016, mar). Invisible women: Entrepreneurship, innovation, and family firms in nineteenth-century France. *The Journal of Economic History 76*(1), 163–195.

Khan, B. Z. (2017, jan). Prestige and profit: The Royal Society of Arts and incentives for innovation, 1750-1850. *National Bureau of Economic Research Working Paper Series No. 23042*.

Khan, B. Z. (2018, may). Human capital, knowledge and economic development: Evidence from the British Industrial Revolution, 1750–1930. *Cliometrica 12*(2), 313–341.

Khan, B. Z. and K. L. Sokoff (2001). The early development of intellectual property institutions in the United States. *Journal of Economic Perspectives 15*(3), 233–246.

Khan, B. Z. and K. L. Sokoloff (2004). Institutions and democratic invention in 19th-Century America: Evidence from 'great inventors,' 1790-1930. *National Bureau of Economic Research Working Paper Series No. 10966*.

Khimich, N. V. and R. Bekkerman (2016). Technological Similarity and Stock Return Cross-Predictability: Evidence from Patents' Big Data. *Available at SSRN 3147218*.

Kingston, W. (2001). Innovation needs patents reform. *Research Policy 30*(3), 403–423.

Klemp, M. and J. Weisdorf (2012). The lasting damage to mortality of early-life adversity: Evidence from the English famine of the late 1720s. *European Review of Economic History 16*(3), 233–246.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman (2017, may). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics 132*(2), 665–712.

Kortum, S. and J. Putnam (1997). Assigning patents to industries: Tests of the Yale Technology Concordance. *Economic Systems Research 9*(2), 161–176.

Lach, S. and M. Schankerman (2008, jun). Incentives and invention in Universities. *The RAND Journal of Economics 39*(2), 403–433.

Lane, J. (2019, may). Secrets for sale? Innovation and the nature of knowledge in an early industrial district: The potteries, 1750-1851. *Enterprise & Society*, 1–46.

Lanjouw, J. O. and M. Schankerman (2001, mar). Characteristics of Patent Litigation: A Window on Competition. *The RAND Journal of Economics 32*(1), 129–151.

Lehmann-Hasemeyer, S. and J. Streb (2016). The Berlin Stock Exchange in Imperial

Germany: A market for new technology? *American Economic Review 106*(11), 3558–3576.

Leydesdorff, L., D. F. Kogler, and B. Yan (2017). Mapping patent classifications: portfolio and statistical analysis, and the comparison of strengths and weaknesses. *Scientometrics 112*(3), 1573–1591.

Lybbert, T. J. and N. J. Zolas (2014). Getting patents and economic data to speak to each other: An 'Algorithmic Links with Probabilities' approach for joint analyses of patenting and economic activity. *Research Policy 43*(3), 530–542.

MacLeod, C. (2002). *Inventing the Industrial Revolution: The English patent system, 1660-1800*. Cambridge University Press.

Magee, G. B. (1997). *Patents, R&D and invention in nineteenth-century Australia*. Dept. of Economic History, RSSS, Australian National University Canberra.

Magee, G. B. (1999, oct). Technological development and foreign patenting: Evidence from 19th-century Australia. *Explorations in Economic History 36*(4), 344–359.

Magerman, T., B. V. Looy, and K. Debackere (2015, nov). Does involvement in patenting jeopardize one's academic footprint? An analysis of patent-paper pairs in biotechnology. *Research Policy 44*(9), 1702–1713.

Marco, A. C., M. Carley, S. Jackson, and A. Myers (2015). The USPTO Historical Patent Data Files Two Centuries of Innovation.

McCloskey, D. (2011). *Bourgeois dignity*. Chicago University Press.

McNamee, R. C. (2013). Can't see the forest for the leaves: Similarity and distance measures for hierarchical taxonomies with a patent classification example. *Research Policy 42*(4), 855–873.

Meisenzahl, R. and J. Mokyr (2011). The rate and direction of invention in the British Industrial Revolution: Incentives and institutions. *National Bureau of Economic Research Working Paper Series No. 16993*.

Mimno, D., H. M. Wallach, E. Talley, M. Leenders, and A. McCallum (2011). Optimizing semantic coherence in topic models. In *Proceedings of the conference on empirical methods in natural language processing*, pp. 262–272. Association for Computational Linguistics.

Mokyr, J. (2009). *The enlightened economy: An economic history of Britain 1700-1850*. Yale University Press.

Moser, P. (2005). How do patent laws influence innovation? Evidence from nineteenth-century World's Fairs. *The American Economic Review 95*(4), 1214–1236.

Moser, P. (2012). Innovation without patents: Evidence from World's Fairs. *The Journal of Law & Economics 55*(1), 43–74.

Murfitt, S. E. (2017). *The English patent system and early railway technology 1800-1852*. Ph. D. thesis, University of York.

Nanda, R. and T. Nicholas (2014). Did bank distress stifle innovation during the Great Depression? *Journal of Financial Economics 114*(2), 273–292.

Nicholas, T. (2008). Does innovation cause stock market runups? Evidence from the Great Crash. *The American Economic Review 98*(4), 1370–1396.

Nicholas, T. (2010). The role of independent invention in U.S. technological development, 1880-1930. *The Journal of Economic History 70*(1), 57–82.

Nicholas, T. (2011a). Did R&D firms used to patent? Evidence from the first innovation surveys. *Journal of Economic History 71*(4), 1032–1059.

Nicholas, T. (2011b). Independent invention during the rise of the corporate economy in Britain and Japan. *Economic History Review 64*(3), 995–1023.

Nicholas, T. (2011c). The origins of Japanese technological modernization. *Explorations in Economic History 48*(2), 272–291.

Nuvolari, A. (2004). Collective invention during the British Industrial Revolution: The case of the Cornish pumping engine. *Cambridge Journal of Economics 28*(3), 347–363.

Nuvolari, A. and V. Tartari (2011). Bennet Woodcroft and the value of English patents, 1617-1841. *Explorations in Economic History 48*(1), 97–115.

Nuvolari, A. and M. Vasta (2015). Independent invention in Italy during the Liberal Age, 1861-1913. *Economic History Review 68*(3), 858–886.

O'Brien, P. K., T. Griffiths, and P. A. Hunt (1996). *Technological change during the first industrial revolution: the paradigm case of textiles, 1688-1851*. Routledge.

O'Callaghan, D., D. Greene, J. Carthy, and P. Cunningham (2015, aug). An analysis of the coherence of descriptors in topic modeling. *Expert Systems with Applications 42*(13), 5645–5657.

Packalen, M. and J. Bhattacharya (2012). Words in patents: Research inputs and the value of innovativeness in invention. *National Bureau of Economic Research Working Paper Series No. 18494*.

Pearce, E. (1957). History of the Standard Industrial Classification. Technical report, Executive Office of the President. Office of Statistical Standards, Washington.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research 12*, 2825–2830.

Rigby, D. L. (2015, nov). Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes. *Regional Studies 49*(11), 1922–1937.

Righi, C. and T. Simcoe (2019). Patent examiner specialization. *Research Policy 48*(1), 137–148.

Ruckman, K. and I. McCarthy (2016, nov). Why do some patents get licensed while others do not? *Industrial and Corporate Change 26*(4), 667–688.

Sáiz, P. (2014). Did patents of introduction encourage technology transfer? Long-term evidence from the Spanish innovation system. *Cliometrica 8*(1), 49–78.

Schmoch, U. (2008). Concept of a technology classification for country comparisons. *Final report to the World Intellectual Property Organisation*.

Schmoch, U., F. Laville, P. Patel, and R. Frietsch (2003). Linking technology areas to industrial sectors. *Final Report to the European Commission, DG Research*.

Schmookler, J. (1966). *Invention and economic growth*. Harvard University Press.

Scotchmer, S. (1991). Standing on the shoulders of giants: Cumulative Research and the patent law. *The Journal of Economic Perspectives 5*(1), 29–41.

Scotchmer, S. (2004). *Innovation and incentives*. MIT Press.

Sokoloff, K. L. (1988). Inventive activity in early industrial America: Evidence from patent records, 1790-1846. *The Journal of Economic History 48*(4), 813–850.

Stevens, K., P. Kegelmeyer, D. Andrzejewski, and D. Buttler (2012). Exploring topic coherence over many models and many topics. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pp. 952–961. Association for Computational Linguistics.

Streb, J., J. Baten, and S. Yin (2006). Technological and geographical knowledge spillover in the German empire 1877-1918. *Economic History Review 59*(2), 347–373.

Strumsky, D., J. Lobo, and S. van der Leeuw (2012, apr). Using patent technology codes to study technological change. *Economics of Innovation and New Technology 21*(3), 267–286.

Sullivan, R. J. (1989, oct). England's 'Age of Invention': The acceleration of patents and patentable invention during the Industrial Revolution. *Explorations in Economic History 26*(4), 424–452.

Sullivan, R. J. (1990). The revolution of ideas: Widespread patenting and invention during the English Industrial Revolution. *The Journal of Economic History 50*(2), 349–362.

Suominen, A., H. Toivanen, and M. Seppänen (2017, feb). Firms' knowledge profiles:

Mapping patent data with unsupervised learning. *Technological Forecasting and Social Change 115*, 131–142.

Thompson, P. and M. Fox-Kean (2005). Patent citations and the geography of knowledge spillovers: A reassessment: Reply. *The American Economic Review 95*(1), 465–466.

USPTO (2005). Handbook of Classification.

Van Leeuwen, M. H. and I. Maas (2011). *HISCLASS: A historical international social class scheme*. Leuven University Press.

Venugopalan, S. and V. Rai (2015, may). Topic based classification and pattern identification in patents. *Technological Forecasting and Social Change 94*, 236–250.

Verspagen, B., T. Van Moergastel, and M. Slabbers (1994). MERIT concordance table: IPC-ISIC (rev. 2). *MERIT Research Memorandum February*.

WIPO (1992). The International Patent Classification (IPC). *Journal of the Patent and Trademark Office Society 74*(7), 481–483.

WIPO (2016). Guide to the International Patent Classification.

Woodcroft, B. (1860). *Subject-matter index of patents of invention, from March 2, 1617 (14 James I.) to October 1, 1852 (16 Victoria)*. London: Queen's Printing Office.

Wu, C.-H., Y. Ken, and T. Huang (2010, sep). Patent classification system using a new hybrid genetic algorithm support vector machine. *Applied Soft Computing 10*(4), 1164–1177.

Wu, J.-L., P.-C. Chang, C.-C. Tsao, and C.-Y. Fan (2016, apr). A patent quality analysis and classification system using self-organizing maps with support vector machine. *Applied Soft Computing 41*, 305–316.

Youn, H., D. Strumsky, L. M. A. Bettencourt, and J. Lobo (2015). Invention as a combinatorial process: evidence from US patents. *Journal of The Royal Society Interface 12*(106), 20150272.

Younge, K. A. and J. M. Kuhn (2016). Patent-to-patent similarity: A vector space model. *SSRN Working Paper No. 270923*.

Acknowledgements

Billington thanks Chris Colvin and Christopher Coyle for their detailed feedback and guidance in developing this paper, and Alessandro Nuvolari for hosting him on a visit to the Sant'Anna School of Advanced Studies, Pisa, in March 2018. Thanks to: a senior patent examiner for assisting in the construction of our patent classification schema, Owen Sims for his assistance with database software, Gerben Bakker, Graham Brownlow, Alan de Bromhead, Nola Hewitt-Dundas, David Jordan, and John Turner for their helpful comments. Thanks also to seminar participants at Queen's University Belfast (June, 2017). Finally, the authors would like to acknowledge the valuable feedback received from the anonymous reviewers. The authors will make their code available upon request.

Appendix A – Description of Machine Learning Methodology

The dataset, or "corpus", is represented as a matrix composed of word frequencies for each article (row) and word (column). Frequencies can be simple term counts, but following O'Callaghan et al. (2015) we adopt a log-based term frequency—inverse document frequency (TF-–IDF) representation, which helps to counter the influence of words that appear more frequently throughout the corpus. "Stop words" are entirely removed from the corpus. The term stop words is used to describe words which are most commonly used in a particular language (for example the conjunctions like 'and', 'if', or 'when', and prepositions like 'to', 'with' or 'in'). Such words are unhelpful in understanding the content of the corpus and are therefore ignored. Stop words were sourced from http://www.ranks.nl/stopwords. The corpus is then stemmed to ensure words with the same base are not counted separately. [25] We recommend that stemming and other text manipulation be undertaken with great care and only by those fluent in the language. For example, text analysis of Dutch patents is complicated by the prevalence of compound words. We further recommend that translation, where necessary, only be performed after the application of machine learning techniques where any single word mistranslation is likely to appear incongruous and therefore easy to detect.

To understand how the NMF approach works, suppose we have a corpus – a collection of patents in this instance – containing m patent titles, each composed of a set of n unique words. This corpus is represented by the matrix C, where $c_{i,j}$ represents, for each document i, the number of occurrences of word j. NMF attempts to factorize the matrix by approximating it as the product of two smaller non-negative matrices. This is represented as:

$$AT \approx C \tag{1}$$

[25] For example, 'cultivate' and 'cultivating' have the same base 'cultivat' but different stems, and would be observed as unique words without stemming.

where matrix T represents how often each word occurs within each topic. The weights in matrix A reveal the extent to which a patent relates to each topic. Word associations define their topics, which allows them to be interpreted by the investigator for further classification.

The number of topics is calibrated manually. When using topic scores to classify patents, the number of topics influences where each patent is assigned.[26] Initially, we generated topics in multiples of 20, and manually examined the results. Fewer topics were associated with less consistent word associations, while additional topics alleviated this inconsistency. To find the appropriate balance between the number of topics and consistency of word associations, we rely on three separate measures: the Residual Sum of Squares (RSS); Entropy scores; and Coherence scores. These are displayed in Figure A1. Future investigators, when working with datasets of a significantly different size, should recreate this process to determine their optimal number of topics.

The RSS measures the quality of the approximation to the original document term frequency matrix, where a higher score suggests a less accurate representation. This metric decreases with each additional topic. In the case where there is a hidden number of groups, we may observe an improvement in the score once the number of topics reaches the number of these groups, with diminishing returns thereafter (Hutchins et al., 2008). Figure A1a shows the RSS scores to be decreasing in the number of topics, but at a marginal rate of decline. The slope of the curve becomes relatively flat between 50 and 150 topics, suggesting our optimal number of topics lies within this range.

Entropy is a measure of unpredictability. Information theory shows that changes in entropy proxy as a measure of information gain. Following Stevens et al. (2012), for topic model M partitioning data into t groups, where t is the number of topics, entropy can be measured as:

$$H(M) = \sum_{i=1}^{t} -P(i)logP(i) \tag{2}$$

Entropy therefore measures the amount of information gained from adding an additional topic. Figure A1b shows a negative association between the number of topics

[26] We generate the optimal number of topics from our British dataset, described in Section 6.

and information gain. A lower score suggests little information gain from adding an extra topic. The figure shows, for each additional topic, the new information received is diminishing. Between 10 and 60 topics is when the greatest information gain occurs. This steadily falls between 50 and 100, getting flatter as the number of topics passes 100. Information gain is relatively constant after 130 topics. Based on this measure, the optimal number of topics likely lies between 100 and 130, but closer to the upper bound.

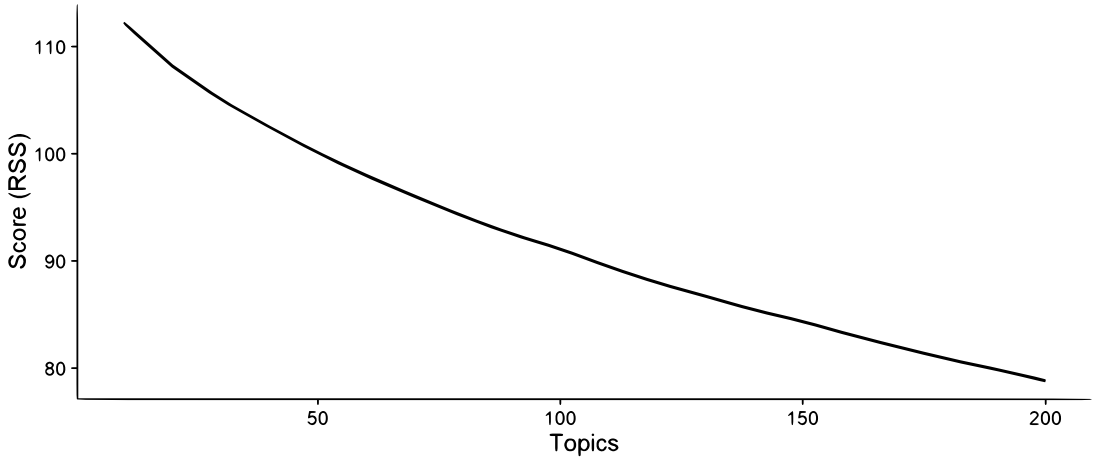
Finally, we use Coherence-based scores. We can think of topics that make meaningful connections between words as being coherent. Measures of coherence are based on 'pairs of topic descriptor terms that co-occur frequently or are close to each other within a semantic space are likely to contribute to higher levels of coherence' (O'Callaghan et al., 2015, p. 1). Stevens et al. (2012) consider measures of topic coherence which align with judgements by human investigators. One such measure is the "UMass" measure of Mimno et al. (2011). For topic T represented by the top n words t_i, the measure is defined as:

$$C(T) = \sum_{i=2}^{n} \sum_{j=1}^{i-1} log \frac{D(t_i, t_j) + 1}{D(t_j)} \tag{3}$$

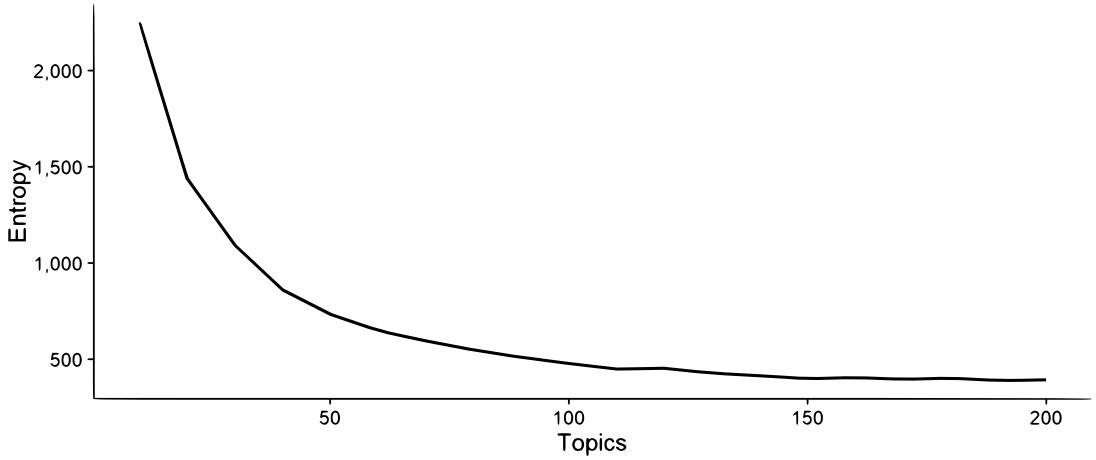
where $D(t_i)$ is the number of documents featuring word t_i, and $D(t_i, t_j)$ is the number of documents featuring both words t_i and t_j. For any given number of topics, we can then calculate the average topic coherence score.

Figure A1c displays the coherence scores. The overall trend suggests additional topics lead to less coherent associations. The figure shows a sharp decline in coherence between 10 and 30 topics. The scores steadily fall until 150 topics, where the slope becomes flatter. There is also a small increase in Coherence between 120 and 140 topics. This measure suggests the optimal number of topics falls between 120 and 150.

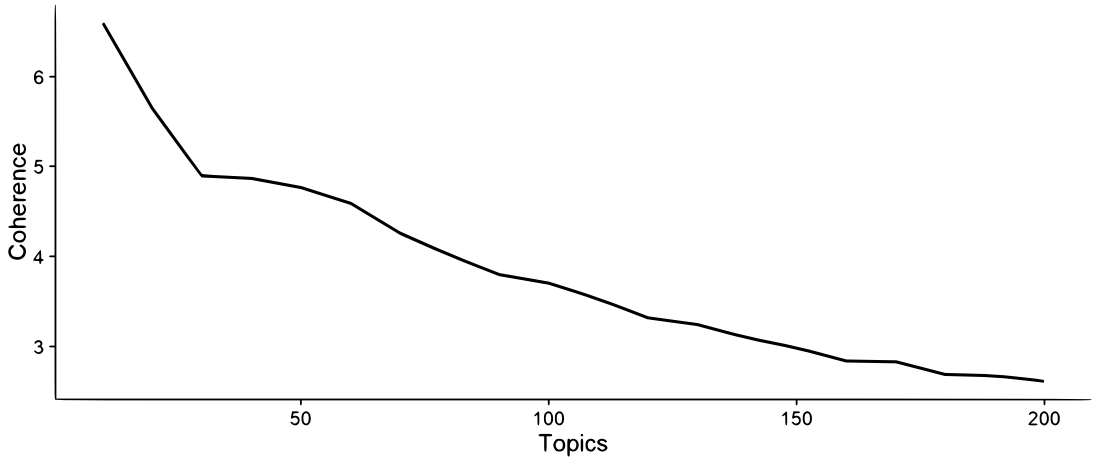
Based on the three metrics, we argue our optimal number of topics is 120. Each score indicates the range of 100-150 contains the optimal amount. We interpret the scores to point to 120 as an optimal number, however choosing 110 or 130 is unlikely to cause a substantial deviation in results. Thus, when we discuss or make use of topic analysis we will always use 120 topics. This does not mean we will have 120 distinct patent classes.



(a) *Residual Sum of Squares Scores Per Topic*



(b) *Entropy Scores Per Topic*



(c) *Coherence Scores Per Topic*

Figure A1: Measures for the Optimal Number of Topics

Source: Author's calculations using *A Cradle of Inventions: British Patents from 1617 to 1894* (2009)

On the contrary, topics are a means to derive common word associations that we will then classify according to our final patent schema.

Appendix B – Regression Plots for Common Patent Classes

The evidence presented in section 7 supports our assertion that classification divergence exists, at the very least, in the innovation history literature. The results indicate that the choice of taxonomy can influence the size, significance, and direction of association of coefficients in a regression analysis of patent characteristics. However, this approach relies on contrasting the results of alternative patent schemas independently – no two schemas are directly examined in relation to each other.

To complement our results, this section directly contrasts patent classes from alternative schemas against each other. This approach allows us to understand whether the alternative schemas are correlated, which could highlight how similarly they classify patents. Observing correlations between taxonomies may be useful for predicting how much classification divergence we should expect in any regression analysis of patent characteristics. If correlations can reasonably predict how a particular taxonomy may yield diverging results compared to another, then this would be useful for identifying the amount of divergence in the literature. However, such an endeavour would require access to other alternative schemas not discussed here, which is beyond the scope of our paper.

To identify the degree of correlation between taxonomies, we report regression plots which contrast the existing alternative patent schemas. Our model, described in equation 4, sets the Nuvolari-Tartari (NT) as our baseline schema which we then regress against each of the alternative schemas used in section 7.[27] We run regressions for all six previously-presented patent characteristic metrics. Only results for patent quality and capital-saving metrics are reported; the remaining metrics show similar results and have been omitted for sake of brevity.

We present a series of plots of regression coefficients for each of the 12 common patent classes previously analysed. For a class to be considered 'common', it has to appear in

[27]We chose the NT schema to be our baseline since it contains all the common classes we wish to observe. We obtain similar results if we change the chosen baseline schema.

at least three out of four of the comparable patent schemas. OLS regressions are used to estimate the degree of correlation between the alternative schemas for each common patent class and each patent characteristic. The regression equation is as follows:

$$NT_{ci} * Metric_i = \alpha_i + \beta S_{ci} * Metric_i + \mu_i \tag{4}$$

$Metric$ represents each of the six patent characteristics individually interacted with the NT common classes, denoted c, for each patent i that has an NT classification 7. These characteristics are: the weighted number of citations per patent; the social class of an inventor's occupation; the inventor's current patent stock; the number of inventors listed per patent; whether an inventor is considered an 'insider'; and whether the patented invention is capital-saving.

The variable S denotes each of the other alternative schemas: COI, Woodcroft, Topic-One, Topic-Two, and CombinedTopics. Each alternative schema's classes, c, are also interacted with each of the six patent metrics separately, for all patents i which are classified according to those schemas. Each interacted alternative schema is then regressed against the interacted NT schema for each of the six characteristic metrics. This approach allows us to observe the degree of correlation between patent schemas by focusing exclusively on whether each schema is capturing the same patents as the NT schema.

In each regression plot, a coefficient score of one suggests that classes from the NT schema and the comparison schema classify the same patents in the exact same way. By contrast, a score of zero suggests no correlation, which implies that neither schema is classifying the same patent into the same technology group. The confidence intervals for each patent schema's coefficient are also reported, which helps us to understand whether a correlation is spurious. We also include a reference line at a value of 0.5 for ease of interpretation.

It is important to note that the regression coefficients reported in Section 7 are for dummy variables; they are interpreted compared to the omitted category of Agricultural patents within each schema. Here the regression coefficients are interpreted against the

baseline of the NT schema, rather than a single patent class within each schema. This creates difficulties in comparing the results from both methods, and we therefore make cautious comparisons between the main regression analyses and the regression plots.

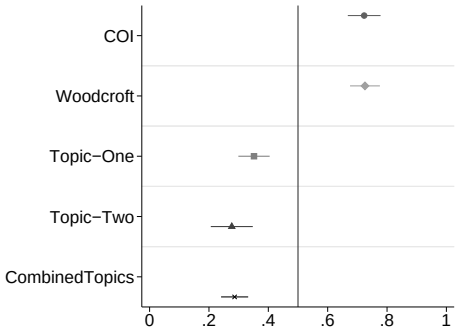
Appendix B.1 – The Citations of Patented Inventions

In Table 9, classification divergence considerably influenced coefficient size, significance, and direction of association when observing the patent quality measure. Therefore, when examining patent citation measures, our interpretation of those measures is at risk of being influenced by the choice of schema.

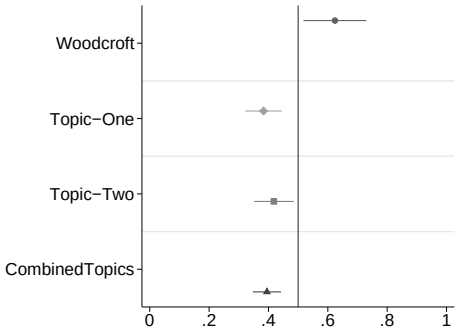
To understand how correlated the alternative schemas are, and whether the degree of divergence is predictable, Figure B1 exhibits the regression plots from the OLS regression model for our patent quality measure: the weighted number of references per patent in the Woodcroft Reference Index. Each sub-figure represents the correlations between the alternative schema and the NT for each of the common classes. In each sub-figure, regressions are run separately and then reported collectively on the same plot.

Observing sub-figure B1a, for example, shows both the COI and Woodcroft schemas are strongly correlated with the NT schema. By contrast, the Topic-One, Topic-Two, and CombinedTopics schemas are much less correlated with NT. To understand whether regression plots can be useful for predicting possible divergence, we contrast the plots for another patent class where the COI or Woodcroft schemas are also strongly correlated with NT. Medicine patents, for example, show a similar degree of correlation between our alternative schemas and NT compared to Agricultural patents: COI and Woodcroft are strongly correlated with NT in both instances. Therefore, we would expect very similar results for NT, COI, and Woodcroft in a regression analysis on patent quality. Referring to the results in Table 9, we do not observe such similarity. The Woodcroft coefficient is larger than the NT coefficient, while the COI coefficient is instead smaller. Furthermore, the Topic-One schema's coefficient is more similar in size to the NT coefficient, despite the lack of correlation observed in the regression plots.

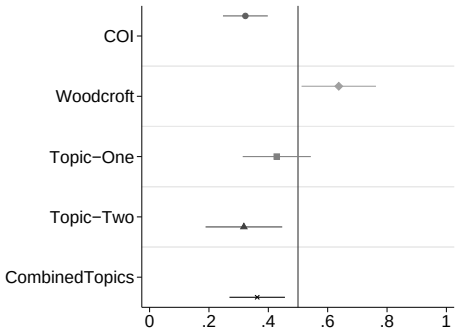
For the majority sub-figures, the COI and Woodcroft schemas are strongly correlated



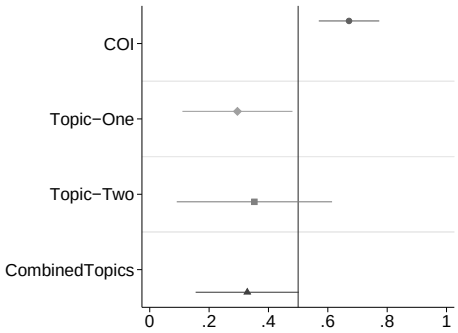
(a) Agricultural patents



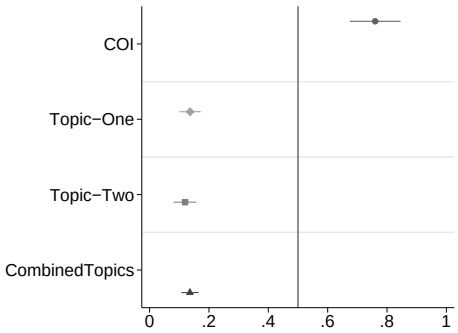
(b) Chemical patents



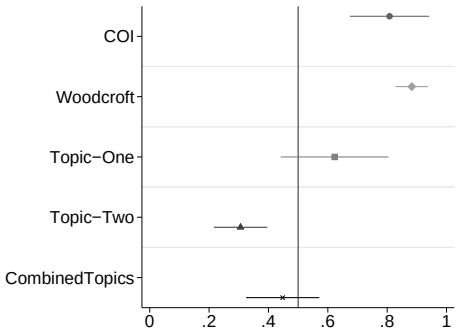
(c) Clothing patents



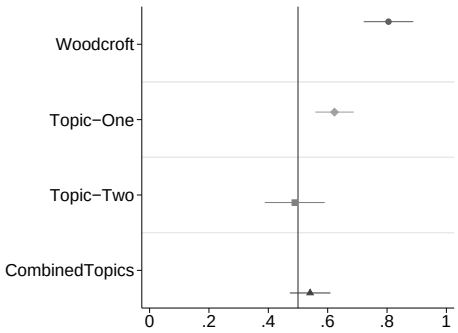
(d) Food patents



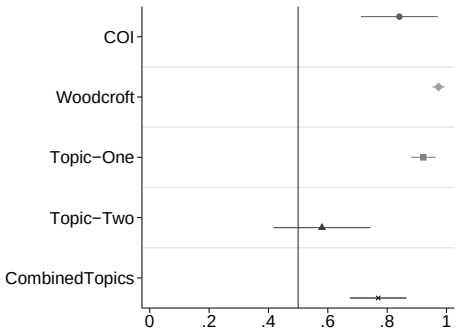
(e) Instrument patents



(f) Medicine patents

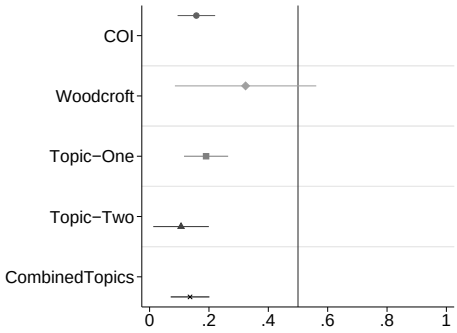


(g) Metal patents

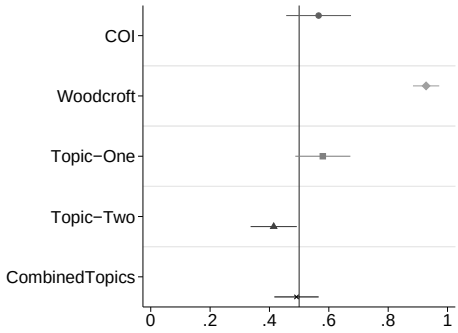


(h) Military patents

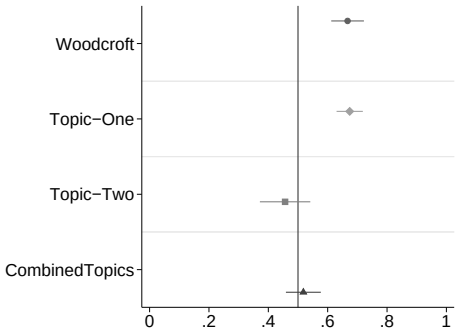
with the NT schema, while the Topic-One, Topic-Two, and CombinedTopics schemas generally are not. This difference in correlations does not appear to predict classification divergence in our main results. For Chemicals, Metallurgy, and Textiles patents, the



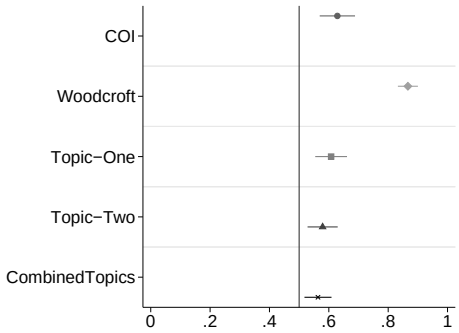
(i) Mining patents



(j) Paper patents



(k) Power patents



(l) Textile patents

Figure B1: Regression plots for the citations of patented inventions

Notes: The plots depict the results from OLS regressions of the Nuvolari-Tartari (NT) schema against the Cradle of Invention (COI), Woodcroft, Topic-One, Topic-Two, and CombinedTopics schemas. The variable of interest is the Woodcroft Reference Index. Each plot represents one of the 12 common patent classes analysed in section 7. A value of zero indicates no correlation between schemas. A value of one should indicate complete correlation between schemas, suggesting both taxonomies classify patents in the same way. The confidence intervals for coefficients reflect the fluctuations in terms of significance, and the position of coefficients represents the fluctuations in terms of size.

Topic-Two schema is not correlated with the NT schema compared to Woodcroft and COI, but Topic-Two coefficients in Table 9 are similar to the NT coefficients. This suggests that the regression plot measures are not reliable predictors for degree of classification divergence.

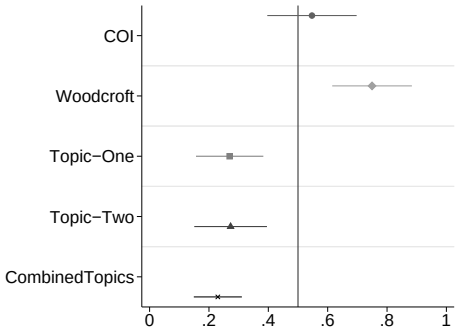
Appendix B.2 – Capital Saving Patents

The second metric we examine indicates whether a patent is intended to save on capital. The absolute divergence results for this metric are presented in Table 14. The degree of divergence for capital-saving patents is much more extreme compared to patent quality.

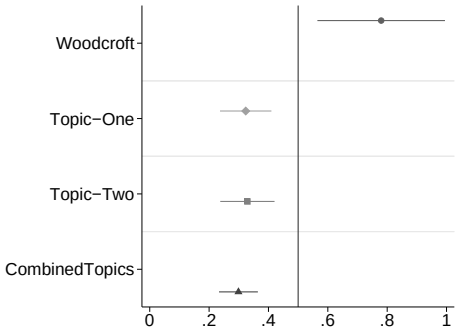
Figure B2 reports the regression plots for the capital-saving variable. Compared to

the patent quality regression plots, there is a stark difference when observing capital-saving patents. While the general trend remains similar to the patent quality metric, the confidence intervals associated with capital-saving coefficients for all of the common classes are much larger. This may be because of the nature of the variable; 'capital-saving' is a dummy variable, which means the interaction terms with each patent class are also dummies, while patent quality is a continuous numerical variable. Consequently, standard errors may be much larger as we are dealing only with values of zero and one. In addition, the capital-saving metric is the only metric which reports both complete and zero correlation coefficients For Clothing patents, in sub-figure B2c, the Topic-Two schema reports no correlation with the NT schema, which suggests that they have captured completely different patents. While Medicine patents, B2f, report a coefficient of zero for Topic-One, and a coefficient of one for Woodcroft. This indicates significant disparities between schemas, as Woodcroft and NT seem to classify the same patents, while Topic-One does not capture any similarity at all.

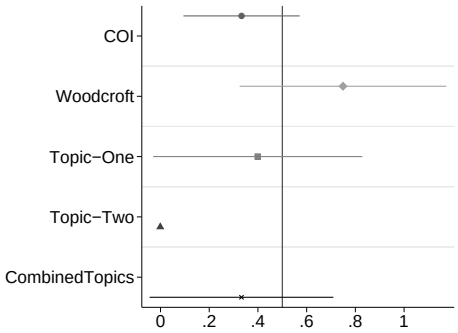
Comparing these results with the regressions in Table 14 may highlight whether the regression plots could predict the likely degree of classification divergence. Similar to patent quality, the COI and Woodcroft schemas are correlated with NT, so we may expect their results to be similar when compared the machine learning schemas. For example, the Woodcroft schema is strongly correlated with NT for both Agricultural and Chemical patents, therefore we may expect to see similar results for Chemical patents in Table 14 for both of those schemas. Indeed, this is what we observe, as both Woodcroft and NT report similarly sized coefficients, albeit with some difference in statistical significance. The regression plots for Metal patents, in sub-figure B2g also show the Woodcroft schema is more correlated with the NT schema than any of our schemas. But, in Table 14 the Topic-One schema reports a result much closer to the NT schema's, even though they are less correlated in our regression plots. Overall, this suggests that the regression plot method cannot reliably be used to predict classification divergence outcomes.



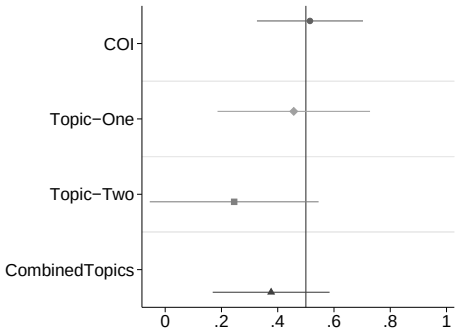
(a) Agricultural patents



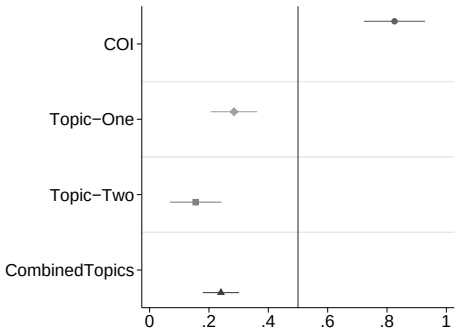
(b) Chemical patents



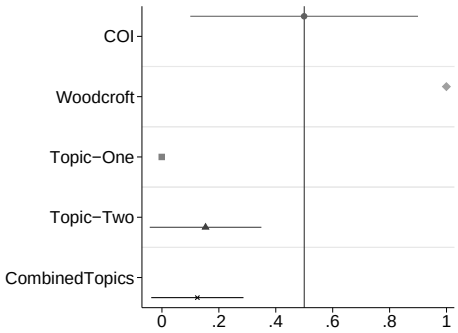
(c) Clothing patents



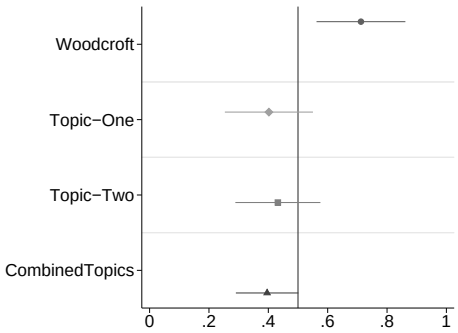
(d) Food patents



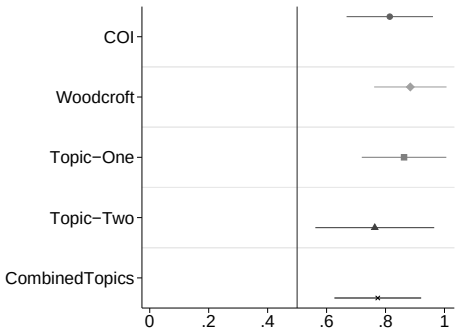
(e) Instrument patents



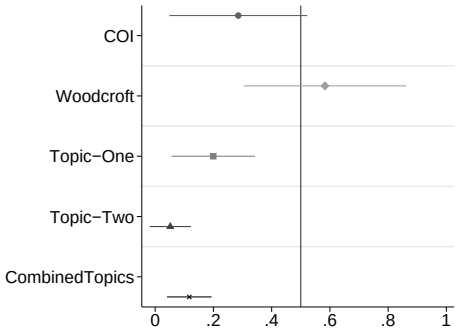
(f) Medicine patents



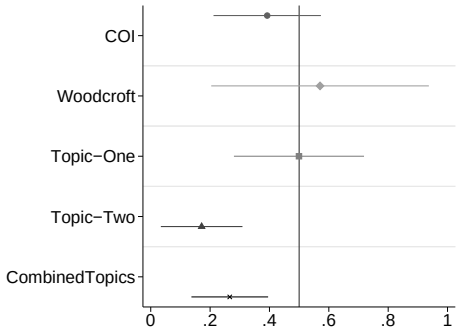
(g) Metal patents



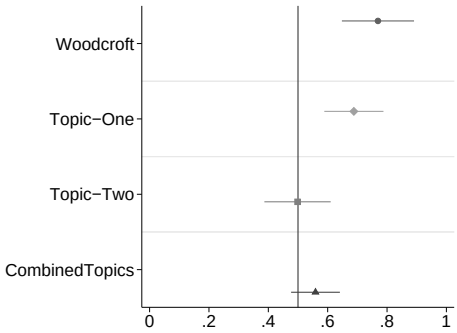
(h) Military patents



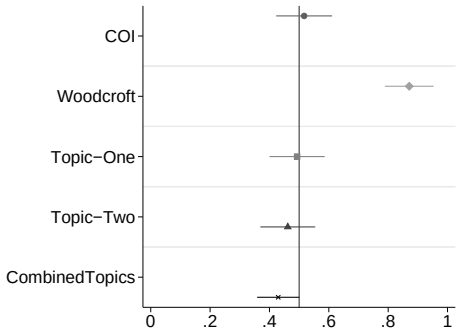
(i) Mining patents



(j) Paper patents



(k) Power patents



(l) Textile patents

Figure B2: Regression plots for capital saving patents

Notes: The plots depict the results from OLS regressions of the Nuvolari-Tartari (NT) schema against the Cradle of Invention (COI), Woodcroft, Topic-One, Topic-Two, and CombinedTopics schemas. The variable of interest is a dummy variable indicating whether a patent is capital-saving. Each plot represents one of the 12 common patent classes analysed in section 7. A value of zero indicates no correlation between schemas. A value of one should indicate complete correlation between schemas, suggesting both taxonomies classify patents in the same way. The confidence intervals for coefficients reflect the fluctuations in terms of significance, and the position of coefficients represents the fluctuations in terms of size.

Appendix B.3 – Discussion

The regression plots describe the degree of correlation between the NT schema and each of the alternative patent taxonomies. By creating a series of interaction terms between each of our six patent metrics and each of the alternative taxonomies, we could then regress each interacted taxonomy against the interacted NT schema for each metric. Regressing each interacted schema independently allows us to identify how correlated those patent schemas are, which is useful for understanding how similarly they classify patents.

Across all six metrics, the degree of correlation is very similar. Generally, the COI and Woodcroft schemas are found to be more strongly correlated with the NT schema than Topic-One, Topic-Two, or CombinedTopics. This may indicate that our machine

learning classifies patents in a considerably different way compared with those schemas which rely more extensively on manual classification. This is not to say our methodology is 'correct', but rather to point out that the differences could be categorised as machine versus human judgement. Because of the strong similarities in terms of coefficient size, we opted to report the results only for the patent quality and capital-saving metrics. The major difference arising from observing the capital-saving metric is the size of the confidence intervals for all coefficients, which were significantly larger than those observed in relation to the patent quality metric.

The variation observed in section 7 coupled with the strong similarities for the regression plots suggest that we cannot use taxonomy correlations to predict the likely degree of classification divergence. The capital-saving metric, for example, reports the greatest degree of classification divergence in our main results. But, capital-saving regression plots are strongly similar to patent quality regression plots, apart from the differences to confidence intervals. The larger confidence intervals are unlikely to explain the divergence in terms of coefficient size or direction of association.

Overall, we find that the regression plot method is not a reliable means for predicting classification divergence outcomes. For all six metrics, there are too many dissimilarities for this method to predict any outcomes with confidence. As shown for the patent quality and capital-saving metrics, there are instances where schemas that are correlated produce similar divergence results, but there are also instances where the opposite is true, Consequently, the regression plot results are useful for a general understanding of how patent taxonomies are correlated, but they provide no predictive power for identifying possible outcomes in relation to classification divergence.