Technology Entry in the Presence of Patent Thickets

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March 2013

Abstract

We present an empirical analysis of the effects of patent thickets at the European Patent Office on entry into patenting by UK firms. Using a direct measure of patent thicket density, we provide evidence for the existence and growth of patent thickets in specific industries, notably in telecommunications, audiovisual technology, and computer technology. Our analysis indicates that the density of patent thickets is associated with reduced entry into patenting in the particular technology area (controlling for the level of patenting in that area). We find this effect to be particularly pronounced for electronics and telecommunications. It is also stronger for smaller than for large companies.

We are grateful to the Intellectual Property Office of the United Kingdom for research support and to the National Institute of Economic and Social Research for hospitality while this paper was being written. The views expressed here are those of the authors. They are not necessarily those of the UK Intellectual Property Office or NIESR.
The revision of this paper has benefitted from comments by participants in seminars at the UKIPO, the USPTO, and the University of California at Berkeley.

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1 Introduction

The past two decades have seen an enormous increase in patent filings worldwide (WIPO, 2011). There is widespread concern among researchers and policy makers that the level of patenting in certain sectors may be so high as to discourage rather than encourage innovation in the sector (Federal Trade Commission, 2011; Lemley and Shapiro, 2005; Bessen and Maskin, 2007). The principal argument for why such high levels of patenting may discourage innovation in some technologies is that companies may (inadvertently) block each other because of dense or overlapping patent rights, so-called patent thickets.

Patent thickets have been shown to consist of patents that protect components of modular and complex technologies. In this context, modular means that different sets of components can be assembled to yield a variety of technological products. Complex means that products consist of tens or hundreds of such modular components. Each component may end up being used in several products. Often there are partial or complete overlaps in the functionality of components and then the patents protecting the components may also overlap. If overlapping patents belong to different firms, then a patent thicket exists.

In a world of cumulative innovation where one product depends on hundreds of inventions owned by a large number of firms, there is good reason to think that the patent system may discourage innovation overall rather than encourage it, even as it may encourage innovation by a few large firms (Bessen and Maskin, 2007). This could happen because large numbers of patents are generated in the course of strategic patenting by large firms. These patent portfolios may create a sunk cost of entry that especially smaller firms would find hard to overcome. This is especially problematic if the portfolios consist of large numbers of patents that would not survive if challenged in court. The cost of entry consists of the cost of creating a patent portfolio that is sufficiently large to constitute a bargaining chip in negotiations over cross licensing, standards, patent pools, or in-court proceedings (Grindley and Teece, 1997; Hall and Ziedonis, 2001; Ziedonis, 2004). This cost is generally sunk because the majority of such patents are marginal – they do not in fact protect a technology that would find a buyer in a market for technology.[1] In addition, there is some evidence that patent offices flooded with patent filings by firms building large portfolios are unable to devote sufficient time to prior art search and therefore may issue patents of low quality in the sense that the invention does not satisfy statutory patentability requirements (Shapiro, 2000; Bessen and Maskin, 2007).

As a result, patent thickets have been a concern of antitrust agencies and regulators in the United States for over a decade (Federal Trade Commission, 2003; U.S. Department of Justice and Federal Trade Commission, 2007; Federal Trade Commission, 2011). In Europe interest in the phenomenon picked up with some delay (Arundel and Patel,

[1] Recently a few well-publicised purchases of patent portfolios have suggested that such patents may be valuable at resale for *defensive* purposes, that is, for augmenting the portfolios of other large firms.

2003; Harhoff, 2006; Harhoff *et al.*, 2007) and has taken a back seat to reforms of the European patent system such as the unified patent court.[2]

There is a large and growing academic literature on patent thickets, which we survey in Hall et al. (2012a). This literature is dedicated almost entirely to the empirical measurement of thickets, the analysis of their origins, and suggested legal remedies. There are relatively few empirical studies on the impact of patent thickets on firms.

In this paper we contribute to filling this gap in the literature by asking whether the need to acquire large numbers of patents in specific complex technologies is creating barriers to entry. In some technologies firms adopt the strategy of patenting heavily in order to defend themselves against patent assertion by other firms. The result can be a rather dense landscape of relatively unimportant patents that nevertheless may threaten other firms as technologies evolve in the future. Such patent thickets are barriers to entry, if they create important negative externalities for firms not in possession of large patent portfolios. Specifically, we examine whether patent thickets constitute a barrier to entry into patenting in particular technology areas. In so doing, we control for the overall level of patenting in the technology area and focus on the density of the thickets in the area. We are especially interested in investigating whether such thickets affect small and medium sized enterprises (SMEs) more than larger firms. To empirically measure thickets in a technology area, we use a novel indicator that captures both the complexity and the possibility of overlapping claims.

We find strong evidence for the existence and growth of patent thickets in electrical engineering, including telecommunications, audiovisual technology, and computer technology. Our empirical analysis of entry into technology areas affected by patent thickets shows that entry decreases as patent thickets become denser, controlling for overall patenting activity in a technology area. We find this effect to particularly pronounced in telecommunications and electronics. Moreover, this effect is stronger for smaller companies.

The remainder of this paper is organized as follows. Section 2 describes the origins of patent thickets. Section 3 discusses the limited available evidence on the effect of patent thickets. Section 4 describes the empirical measurement of technology entry and patent thickets. Section 5 contains a description of the data used in our analysis. Section 6 discusses our results and Section 7 provides some concluding remarks.

2 Determinants of patent thickets

In this section, we briefly review the factors that contribute to the growth of patent thickets. Some of these factors are specific to the United States, where patent thickets were first identified in the patent system. However, the importance of the US economy, especially as a market for high-technology firms from around the globe, has meant that

[2] One reason for reduced interest in Europe is the exclusion of software *per se* as patentable subject matter at the EPO. In the U.S., many of the problems identified with thickets are associated with software and internet-related patents.

patenting strategies of corporations from outside the United States have adapted to strategies used initially by US corporations.

As we review in detail in Hall et al. (2012a), the current literature has identified the following factors as contributing to the growth of patent thickets:

1. The strengthening of patent rights with the creation of the Court of Appeals of the Federal Circuit (CAFC) in the United States in 1984, the broadening of patentable subject matter and an increased tendency to resolve patent disputes using injunctions in some jurisdictions;
2. The cumulative nature of science and by extension of technology and as a result a shift towards complexity in many technologies;
3. Shifts in the degree of technological opportunity in various key technologies;
4. Strategic patenting by corporations and the assertion of patents by Patent Assertion Entities (PAEs);
5. Lack of resources and misaligned incentives at patent offices dealing with a flood of patent applications that resulted from the aforementioned factors;
6. Growth in trade of high technology products, leading to an increase in demand for patents by foreign firms and to the spread of patenting trends from Japan and the United States to other jurisdictions.

These factors have independent origins; nonetheless they interact to strengthen incentives for large and specialized firms to acquire as many patents as possible. For instance, incentives at the European Patent Office (EPO) appear to have made it cheaper in some complex technologies to acquire additional patents, than to oppose a rival's weak patent that might be used to limit the use of a specific technology. These additional patents could be used to bargain with the rival and can be applied for much more quickly than an opposition process could be brought to a definitive conclusion. Another example is documented by Hegde *et al.* (2009) who analyze continuations at the USPTO.[3] They cite Robert Barr, former patent counsel for Cisco Inc., who states that continuation applications are used by telecommunications firms to separate weak claims that are initially rejected by patent examiners from strong claims. The weaker claims are then pursued in separate patent applications, the continuation applications. The empirical analysis of different types of continuations in Hegde *et al.* (2009) lends support to this claim.

Incentives to patent extensively create a number of feedback loops – in other words the effects of growth in patent applications feed back to the factors that created incentives for patenting and strengthen these even more:

[3] "Continuation applications permit firms to restart the examination of their patent applications while retaining the filing date of a previous application that discloses the same invention. Inventors can use continuations to revise the claims submitted in their initial application or to pursue claims that have been disallowed after initial examination with new arguments and evidence," from Hegde *et al.* (2009), p. 1214.

1. Patent offices have found it hard to obtain resources necessary for careful delineation of patents in a period in which larger patent counts were regarded as essential to obtaining freedom to operate via the negotiation of cross licenses. This meant patents were sometimes incompletely examined for prior art, which facilitated the emergence of thickets. Firms intensified their patenting efforts as they understood both the weakness of the patent offices and the growing strength of rivals acquired by means of their growing patent portfolios. Microsoft and Google provide recent examples of this phenomenon.
2. The very large increases in patent applications have led to increasing backlogs of patent applications and long delays in the examination and issuing of patent applications. This in turn allows applicants to exploit uncertainty surrounding their (possibly) overly broad patent applications (Harhoff, 2006; Harhoff *et al.*, 2007; Federal Trade Commission, 2011). The growing awareness of this opportunity on the part of firms creates incentives for firms to file broad claims that create more uncertainty for rival applicants.
3. At least in the United States, the CAFC has handed out injunctions frequently against firms deemed to be infringing or potentially infringing in some jurisdictions. This forced and forces firms to patent and/or to acquire patent portfolios in order to be able to threaten would-be litigators with counter-suits or achieve early settlements. It has also created an environment in which firms specialized in the acquisition and legal enforcement of patents flourished because of the profitability of a hold-up strategy even if a patent was of dubious validity (Reitzig *et al.*, 2007; Farrell and Shapiro, 2008). So-called Non-practicing entities (NPE), PAEs or patent trolls have been shown to exploit this possibility for hold-up. There is also evidence of increasing litigiousness in specific technology areas which is generally attributed to the activity of PAEs (Berneman *et al.*, 2009; Federal Trade Commission, 2011).[4]

Although most of these changes began in the United States, they have had knock-on effects on patenting systems in the rest of the world, first in Japan, and then Europe and other East Asian countries.

3 Literature Review

This section briefly summarizes the sparse, existing literature on the effect of patent thickets on firm behavior.

Lerner (1995) finds a negative association between proxies for litigation costs of new biotech companies in the US and their likelihood to patent (between 1973 and 1992) in USPTO subclasses in which rival companies had already patented.[5] This effect is stronger if the companies that had patented previously in a given subclass had low

[4] Data by PatentFreedom indicate that the number of PAE lawsuits in the US has increased dramatically from 145 in 2001 to 2,923 in 2012. Electronics, telecom, and computer software are the industries with the highest number of PAE-related lawsuits (see https://www.patentfreedom.com/about-npes/litigations).

[5] Litigation costs are proxied by the number of lawsuits a firm was involved in and paid-in capital.

litigation costs. While the analysis does not analyze directly the effect of patent thickets on technology entry, it shows that first-time patenting in a given technology is affected by the presence of other companies' patents.

In an analysis of determinants of patenting in Europe, Graevenitz *et al.* (2012) show that large and small firms react to patent thickets differently. They find that increases in patent thicket density increase patent applications of owners of large patent portfolios but decrease patent applications by owners of smaller patent portfolios in technology areas covering complex technologies like telecommunications. In discrete technologies, such as pharmaceuticals, where thicket density is significantly lower, large and small firms react to variation in thicket density in the same way. These findings are noteworthy because they are consistent with a process in complex technologies through which holders of large patent portfolios increasingly dominate these technologies, making it more difficult for firms holding smaller portfolios to establish a foothold.

Cockburn *et al.* (2010) present evidence from a representative survey of innovating firms in Germany. They have information on the introduction of new products into the market and find significant differences between firms that rely on licenses and those that do not. The ability of firms that must license-in patents to introduce a larger share of innovative products is reduced, if the references in their patents are to a more fragmented set of firms. In contrast, they find a positive effect of fragmentation on innovative performance of firms that do not rely on licenses. These results support the view that effects of patent thickets on R&D investments and competition are not evenly spread amongst firms. In particular, those firms that are not easily held up benefit, whilst those that must license-in technologies, are at a disadvantage. This paper is one of the few to provide direct evidence of effects of thickets on product market competition.

Additional evidence of heterogeneous effects is provided by, Cockburn and MacGarvie (2011). In their paper, which is perhaps most closely related to our analysis, the authors study entry in relatively narrow software markets over the period 1990-2004. They construct counts of patents relevant to a given product market based on a text-search algorithm and IPCs that assigns patents to markets. While this measure certainly captures something related to thickets, it does not measure directly the degree of overlap in these patents. Cockburn and MacGarvie find substantial effects: a 1% increase in the number of existing patents is associated with a .8% drop in the number of product market entrants. They also find that firms that hold relevant patents before entry are substantially more likely to eventually enter a market. Concerns over endogeneity of patent counts are somewhat mitigated by fact that the authors exploit arguably exogenous variation in patent eligibility of software over time. These findings demonstrate that the presence of large numbers of patents affect entry and by extension competition in software markets.

4 Measurement of entry and patent thickets

This section describes the empirical measurement of entry into a technology field and that of patent thickets within a given technology.

4.1 Methodology to identify entry of firms

We are concerned with the ability of firms to compete in particular technology spaces. Therefore we define entry in terms of the patenting behavior of firms rather than as market entry. In the case of entry, this approach has the advantage of providing us with a pool of all potential entrants, that is, we also observe those firms that could have entered a given technology, but chose not to do so. If we were to consider product market entry, we would only observe the set of firms that entered the market but not the entire pool of potential entrants, which makes a study of entry notoriously difficult (Bresnahan and Reiss, 1991; Berry, 1992).

In addition, linking the analysis of market entry in a specific market context to patenting activity requires linking patents to products and product markets. We are not aware of any research that contains this kind of analysis at the level of an entire patent system.[6] For this reason we limit our analysis to entry into patenting activity, which is a reasonable proxy for a firm's ability and desire to compete in a certain technology area.

4.2 Methodology for the measurement of patent thickets

The main problem that patent thickets create for firms are the costs of adequate patent search, the ability to identify all relevant technology, and the consequent threat of hold-up *ex post*, even if adequate due diligence has been done. This problem is most likely to arise for firms producing and selling products that use a complex technology, for instance the producer of a mobile phone. Such a firm cannot effectively ensure that its products do not infringe on patents granted to another firm, because there are usually very many relevant patents (Shapiro, 2000), because the claims in these patents are not always precise (Hall and Harhoff, 2004; Lemley and Shapiro, 2007; Bessen and Meurer, 2008) and because it is increasingly in the strategic interest of some applicants to hide their applications within the system for as long as the rules allow (Hegde *et al.*, 2009), leading to uncertainty over exactly which patents and claims will be granted in the end. In addition, complex technologies are associated with the ICT sector, where there is a prevalence of patents on standards, access to which is essential for firms that wish to compete in the sector.

The early literature on patent thickets identified the costs and hold-up potential associated with thickets using qualitative techniques such as interviews (Hall and Ziedonis, 2001). Other studies relied on counts of relevant patents (Cockburn and MacGarvie, 2010). While high levels of patent applications can be a signal for the presence of patent thickets, there are many other possible explanations for increased patent applications such as greater technological opportunity. Also, in principle, an active technology area could have a large number of patents, each clearly delineating the invention concerned and none with overlapping claims or claims with uncertain breadth or scope. In this kind of setting, thickets do not exist.

Ziedonis (2004) introduced the first measure of hold-up potential into the literature. This measure uses citations from a focal firm's patents to prior art owned by other

[6] The most comprehensive mapping of patents' IPC subclasses to economic activities is provided by Lybbert and Zolas (2012). Their mapping is based on a data mining approach as well as probabilistic matching of keywords contained in patents and industry and trade classifications.

firms. It then measures the fragmentation of these citations to prior art. The more rival firms are cited by the focal firm, the higher the degree of fragmentation. While the measure captures hold-up potential in the sense that the firm faces many rival firms with similar technological competencies, it does not identify technology areas with a potential 'web of overlapping patent rights'. As we have noted above, patent thickets affect firms' costs in several ways and hold-up may not be the most significant of these in all jurisdictions. Where hold-up is less important as an immediate threat based on injunctions, the costs of disentangling overlapping property rights may still be significant. Thus an identification of the web of overlapping patent rights as a web or network is useful.

Building directly on the concept of thickets as overlapping patent rights, Graevenitz *et al.* (2012; 2011) define a measure of patent thickets by focusing on "particularly relevant" references to prior art as indicated in patent examiners' European search reports at the EPO. According to the EPO's Guidelines for Examination,[7] such particularly relevant references – also known as X and Y citations – point to prior art that jeopardizes the novelty or inventive step of the claimed invention.[8] If the referenced relevant prior art is owned by another company, the presence of such references indicates that at the application stage there is overlap between the patent claims of two firms. Graevenitz *et al.* (2012; 2011) use these critical references to define the concept of "firm triples" to identify patent thickets. A *triple* is defined as a group of three firms in which each firm has critical prior art limiting claims on recent patent *applications* of each of the other two firms. Clearly such a group of firms is potentially caught in the most basic type of a patent thicket created by potentially overlapping patent portfolios. While two firms holding mutually limiting or blocking patents may resolve the threat of hold-up by contract, this is no longer as simple for firms in a triple. Here the relative value of any two firms' patents depends on the actions of a third firm, making bargaining more difficult. Where multiple triples arise within the same network of firms it is highly likely that these will overlap creating ever more complex bargaining problems that require recourse to patent pools or standards for their resolution.

It might be argued that the EPO identifies critical references in order to allow examiners to redraw claims in a patent document so as to reduce or eliminate the overlap that is identified. If this were completely successful the triples measure would not correlate with real patent thickets or any of their effects. This view is to place extreme faith in the ability of the EPO to remedy overlapping claims. In our view the EPO is unlikely to identify all potentially overlapping claims nor are examiners likely to remove all threats arising from them. This becomes apparent in studies showing that critical references are highly significant predictors of post grant opposition at EPO (Harhoff and Reitzig, 2004). We also note that 37 per cent of granted patents have search reports that contain

[7] http://www.epo.org/law-practice/legal-texts/html/guidelines/e/index.htm

[8] According to 9.2.1 of the EPO's Guidelines for Examination: "Category "Y" is applicable where a document is such that a claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other documents of the same category, such combination being obvious to a person skilled in the art. However, if a document (a so-called "primary document") explicitly refers to another document as providing more detailed information on certain features (see G-IV, 5.1) and the combination of these documents is considered particularly relevant, the primary document should be indicated by the letter "X", i.e. not "Y" […]."

at least one X and/or Y reference, compared to 50 per cent of applications that are not eventually granted, so that although such a reference reduces the probability of grant, it does not do so by much.[9] Thus the triples measure identifies groups of firms who are likely bound together by further overlapping patents covering similar technologies used by them.

Graevenitz *et al.* (2011) show that counts of triples by technical area are significantly higher for technologies classified as complex than for areas classified as discrete by Cohen *et al.* (2000). Graevenitz *et al.* (2012) provide a model of patenting efforts in complex and discrete technologies that provides counter-intuitive predictions for effects of technological opportunity on patenting in complex technologies. They show that their predictions are supported empirically, when they use the triples measure as a proxy for complexity of technologies. Also, Harhoff *et al.* (2012) show that post-grant opposition is affected by patent thickets in ways predicted by Farrell and Merges (2004). This study shows that patent applications of firms in the midst of patent thickets are less likely to be opposed than applications of firms on the fringes of thickets. This finding is hard to rationalize, in the absence of patent thickets. In sum, these studies, which all compare patenting behavior across technology areas and time, indicate that the measure successfully proxies changes in the density of thickets.

5 Data

5.1 Firm-level data

Our analysis relies on an updated version of the Oxford-Firm-Level-Database, which combines information on patents (UK and EPO) with firm-level information obtained from Bureau van Dijk's Financial Analysis Made Easy (FAME) database (for more details see Helmers *et al.* (2011) from which the data description in this section draws).

The integrated database consists of two components: a firm-level data set and IP data. The firm-level data is the FAME database that covers the entire population of registered UK firms.[10] The original version of the database, which formed the basis for the update carried out by the UKIPO, relied on two versions of the FAME database: FAME October 2005 and March 2009. The main motivation for using two different versions of FAME is that FAME keeps details of `inactive' firms (see below) for a period of four years. If only the 2009 version of FAME were used, intellectual property could not be allocated to any firm that has exited the market before 2005, which would bias the matching results. FAME is available since 2000, which defines the earliest year for which the integrated data set can consistently be constructed. The update undertaken by the UK Intellectual

[9] We compared the claims of a few applications marked with X/Y citations with the claims of the granted patents. We found that often all claims of the original application remain in the granted patent although claims narrow in the grant process as a result of the prior art presented by examiners. It is unlikely that a narrowing of the claims removes any potential overlap with the conflicting prior art cited in the search report.

[10] FAME downloads data from Companies House records where all limited companies in the UK are registered.

Property Office (UKIPO) used the April 2011 version of FAME. However, since there are significant reporting delays by companies, even using the FAME 2011 version means that the latest year for which firm-level data can be used reliably is 2009.

FAME contains basic information on all firms, such as name, registered address, firm type, industry code, as well as entry and exit dates. Availability of financial information varies substantially across firms. In the UK, the smallest firms are legally required to report only very basic balance sheet information (shareholders' funds and total assets). The largest firms provide a much broader range of profit and loss information, as well as detailed balance sheet data including overseas turnover. Lack of these kinds of data for small and medium-sized firms means that our study focuses on total assets as a measure of firm size and growth.

The patent data come from the EPO Worldwide Patent Statistical Database (PATSTAT). Data on UK and EPO patent publications by British entities were downloaded from PATSTAT version April 2011. Due to the average 18 months delay between the filing and publication date of a patent, using the April 2011 version means that the patent data are presumably only complete up to the third quarter in 2009. This effectively means that we can use the patent data only up to 2009 under the caveat that it might be somewhat incomplete for 2009. Patent data are allocated to firms by the year in which a firm applied for the patent.

Since patent records do not include any kind of registered number of a company, it is not possible to merge data sets using a unique firm identifier; instead, applicant names in the IP documents and firm names in FAME have to be matched. Both a firm's current and previous name(s), were used for matching in order to account for changes in firm names. Matching on the basis of company names requires names in both data sets to be `standardized' prior to the matching process in order to ensure that small (but often systematic) differences in the way names are recorded in the two data sets do not impede the correct matching. For more details on the matching see Helmers *et al.* (2011).

5.2 Patent thickets

[I think we need a more detailed description of how thickets were constructed, e.g. what version of Patstat, the fact that only EP patents are used, something about the search reports, what the time window for a triple is etc.]

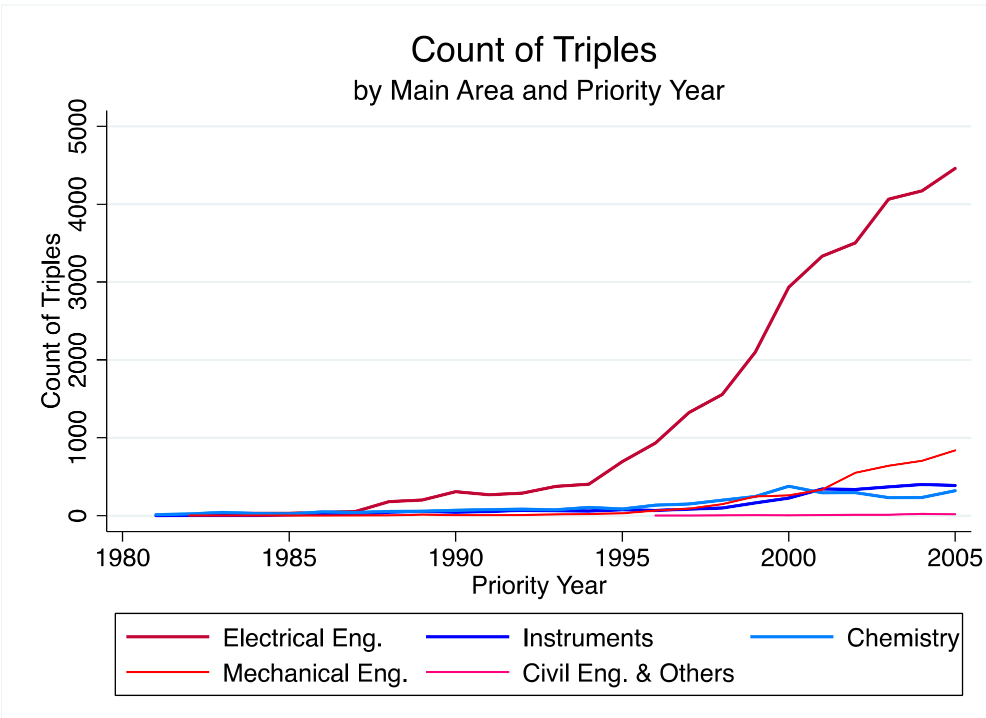
6 Effects of Patent Thickets on Entry

In this section we use the triples measure described above to provide a descriptive analysis of patent thickets in European patent data. We then examine the impact of the presence of patent thickets on companies in the UK by looking at the probability of entry into patenting in a particular technology sector as a function of EPO patent thickets in that sector.

6.1 A descriptive analysis of patent thickets

In Figure 1 below we segment patent applications at the EPO into five main technology areas based on the 2008 version of the ISI-OST-INPI technology classification (Schmoch, 2009). We then plot the number of triples for each of these technology areas between 1978 and 2005. Figure 1 clearly shows that the count of triples in Electrical Engineering far outstrips the counts of triples in any of the other main technology areas. This is commensurate with the earlier finding of Hall (2005) that the increase in patent applications at USPTO after 1984 was primarily due to firms operating in Information and Communications Technologies (ICT). At the EPO these firms patent primarily in the main technology area of Electrical Engineering.

Figure 1



Graevenitz *et al.* (2012) show that the increases in triples are not affected by differential rates of patenting in the five main technology areas. We have checked that this remains true also when normalizing by the total weighted patent applications at the EPO (compare Table 1 below).

The ISI-OST-INPI technology classification (Schmoch, 2009) also allows us to further segment each main technology area into constituent technology areas. Below we document the evolution of the number of triples in three main technology areas by technology area, these are: Electrical Engineering (Figure 2), Instruments (Figure 3) and Chemistry (Figure 4). Table A-1 in the appendix provides additional descriptive statistics for the triples counts by technology area.

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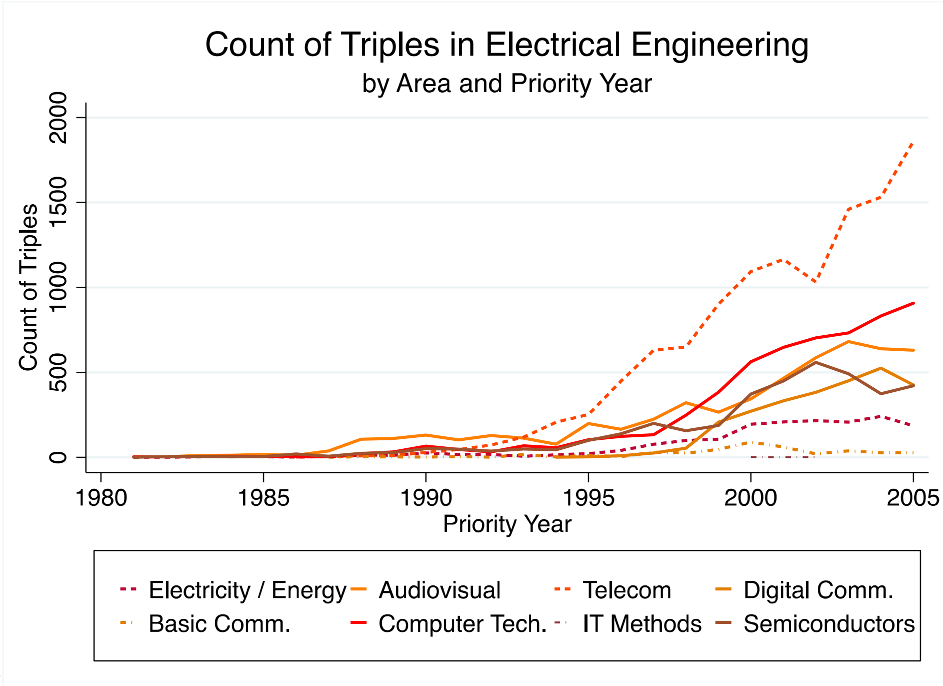


Figure 2

These three figures largely confirm, what Figure 1 already indicated. The increases in triples counts are very high in almost all technology areas within the main area Electrical Engineering, while they are significantly lower in almost all technology areas within the main areas Instruments and Chemistry.

Some noteworthy detail emerges, however:

- In Electrical Engineering triple counts are particularly high in the areas of Telecommunications, Audiovisual Technology, and Computer Technology.
- In Instruments there is a five-fold increase in the level of the triples count between 1995 and 2000 in Optics. We found that the initial growth in triples was driven mainly by patenting of the following firms: Canon, Matsushita, Seiko, and Epson. Subsequently the high level of triples is due to Sony, Ricoh and Samsung.
- In Chemistry we would not expect patent thickets to play a major role, with the possible exception of Biotechnology where it has been repeatedly argued that they may exist. Figure 4 indicates that if at all a patent thicket may be growing in the area of Organic Chemistry where triples counts doubled between 2000 and 2005.

Figure 3

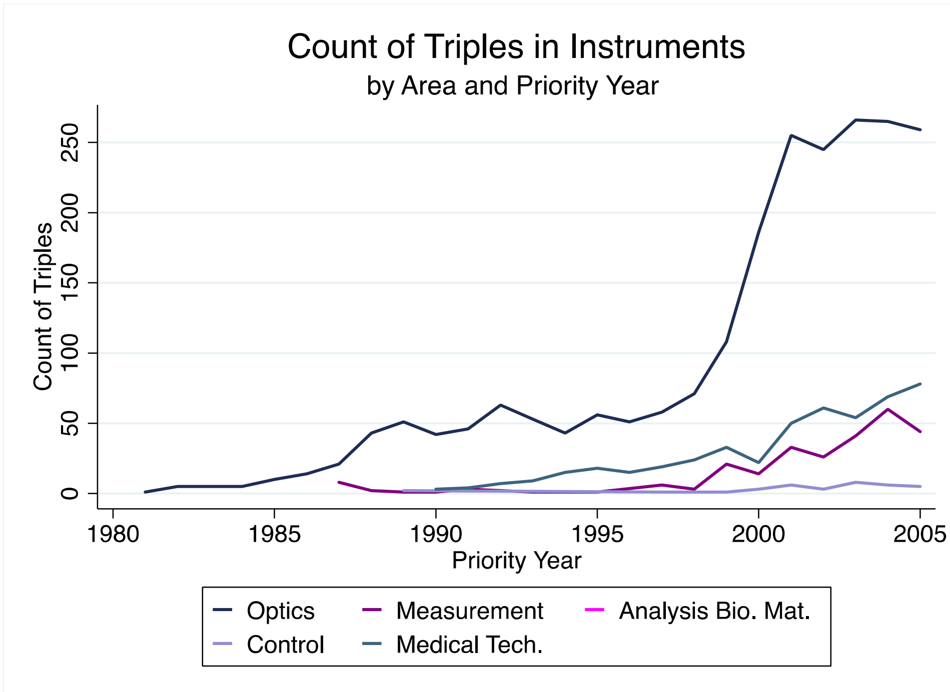
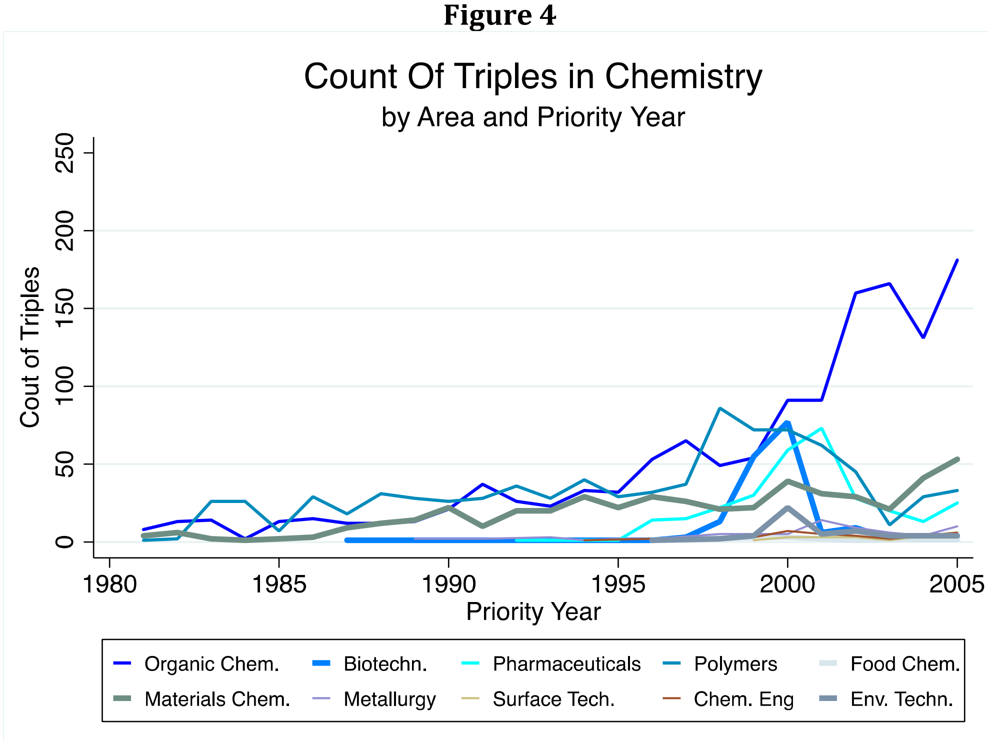
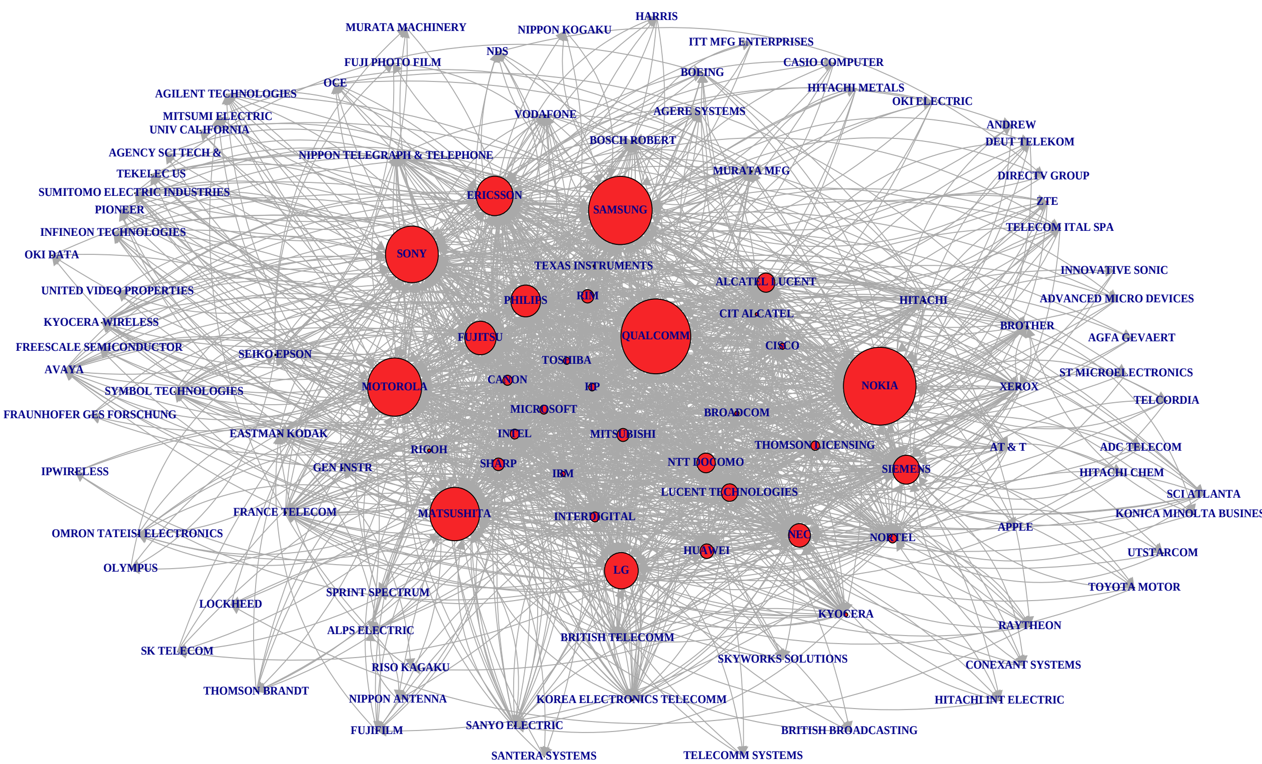


Figure 4



While these figures provide an indication of how dense patent thickets are in different technology areas, they do not show the structure of thickets and the firms involved in it. Figure 5 below shows the network of critical references, which contributed to one or more triples, in the technology area telecommunications in the year 2005. The nodes in this figure represent individual firms. The size of the node represents the number of limiting citations to the firm's prior art. This can be interpreted as the importance of the firm's patents for the commercialization of telecommunications technology by rival firms. Most of the firms in Figure 5 that own many patents which served as X and Y references are also frequently involved in patent litigation.[11] This is an additional indication that the measure of thicket density based on critical references is able to capture patent thickets that lead to disputes.

Figure 5 – Network of Critical References in the Technology Area Telecommunications in 2005



6.2 Patent thickets and entry

One of the functions of the patent system is to allow inventors to exclude others from practicing their invention. The implication of this fact is that in technology areas where there are large numbers of patents, it might be more difficult for new firms to enter because the technology space is effectively covered by patents held by existing firms. By itself, this is not necessarily a phenomenon requiring some kind of policy intervention, as it is to be expected if the patent system is doing its job. However, in sectors where

[11] A discussion of patent litigation maps related to smartphones can be found here: http://www.techdirt.com/blog/wireless/articles/20101007/22591311328/meet-the-patent-thicket-who-s-suing-who-for-smartphone-patents.shtml.

firms must draw on technologies for which their competitors hold patents in order to produce, it is possible that the presence of many overlapping patents held by incumbent firms could discourage the entry of new firms with novel ideas, because such entry requires negotiating access to a prohibitively large number of other technologies in order to incorporate their invention(s) in a product. Many researchers have identified sectors based on complex technologies and standards as sectors of this kind (Shapiro, 2000; Hall and Ziedonis, 2001; Arora *et al.*, 2008).

In order to capture the idea that some sectors may be characterized by collections of patents held by different firms, but at least some of which are jointly required for production, we use the previously described measure of patent thickets developed by Graevenitz *et al.* (2012, 2011). This measure identifies technology areas where there is active patenting by existing firms that have strategic relationships with one another. As shown above, such technology areas are those where products are also complex and draw on technologies held by multiple firms. We analyze whether UK firms are discouraged from entering such technology areas. Therefore we examine the influence of this measure on the probability that a UK firm enters a technology sector, where entry is defined as the priority year of the first patent in the relevant technology sector that is applied for at the EPO or the UKIPO. The sample we use for estimation includes all the firms with at least one patent application at the IPO in the UK or the EPO during the 2001-2009 period. We normalize the thicket measure by the number of patents in a technology area, to control for the fact that the first order effect of active patenting in a sector is more patenting.

The information for UK firms is drawn from the FAME database described in Section 5. Because this database includes all firms, it is very large, and includes mostly non-patenting firms. We do two things to deal with this: 1) we delete all firms in the industrial sectors with little patenting (amounting to less than 2 per cent of all patenting);[12] and 2) we choose a one per cent sample of non-patenting firms to compare to our patenting firms.[13] The latter selection results in about equal numbers of patenting and non-patenting firms for estimation. In principle, this approach will result in an endogenous (choice-based) sample, but because we analyze at the firm-34 technology class level rather than at the firm-level, we do not expect this to introduce a large amount of bias to the estimates. In addition, we delete all firms for which we have no size measure (the assets variable is missing).[14] The resulting sample is the set of FAME firms with non-missing assets in manufacturing, oil and gas extraction and quarrying, construction, utilities, trade, and selected business services including financial services.

[12] The excluded sectors where patenting was negligible include agriculture, other mining, education services, and hotels and restaurants.

[13] Because each firm can in principle generate 34 sectors*8 years = 272 observations, we are unable to include the full FAME dataset in our estimation. In practice, we found including the non-patentees made little difference to our estimates.

[14] Earlier estimations included these firms along with a dummy for missing assets, and we found that the results were almost identical with and without the firms that were missing data. In the interests of computing time and space, we therefore removed them.

The technology sectors that we use are based on the 2008 version of the ISI-OST-INPI technology classification (denoted TF34 classes). The list is shown in Table 1, along with the number of EPO and UKIPO patents applied for by UK firms in the FAME database with priority dates between 2002 and 2009. A comparison of the frequency distribution across the technology classes in the two patent offices clearly shows that firms prefer to apply for chemical patents at the EPO whereas in other technologies except instruments they prefer to apply at the UKIPO (see the bottom panel in Table 1).

Table 1

Patenting by Fame firms on Patstat (priority years 2002-2009)

Technology categories	*Weighted by #owners & #classes** *GB pats*	*EP pats*	*Total*	*Sector shares* *GB pats*	*EP pats*	*Total # of EPO patents*	*Number of EPO triples@*	*Triples per 1000 patents*
Elec. machinery, energy	1,741	1,251	2,992	6.5%	4.2%	54,560	1,590	29.1
Audiovisual technology	822	644	1,465	3.1%	2.2%	32,935	3,708	112.6
Telecommunications	1,425	1,434	2,859	5.3%	4.9%	58,402	10,176	174.2
Digital communication	696	816	1,512	2.6%	2.8%	34,759	3,129	90.0
Basic comm processes	347	159	506	1.3%	0.5%	9,709	149	15.3
Computer technology	1,916	1,560	3,476	7.1%	5.3%	58,231	5,251	90.2
IT methods for mgt	327	275	601	1.2%	0.9%	8,499	8	0.9
Semiconductors	316	313	629	1.2%	1.1%	23,555	2,485	105.5
Optics	472	574	1,046	1.8%	1.9%	27,504	1,818	66.1
Measurement	1,504	1,716	3,220	5.6%	5.8%	42,544	278	6.5
Analysis bio materials	175	506	681	0.6%	1.7%	10,815	0	0.0
Control	754	657	1,411	2.8%	2.2%	17,022	52	3.1
Medical technology	1,258	1,887	3,144	4.7%	6.4%	61,448	492	8.0
Organic fine chemistry	231	1,840	2,071	0.9%	6.2%	38,544	941	24.4
Biotechnology	242	1,076	1,317	0.9%	3.6%	29,926	27	0.9
Pharmaceuticals	357	2,241	2,598	1.3%	7.6%	48,661	100	2.1
Macromolecular chem	141	300	441	0.5%	1.0%	20,234	175	8.6
Food chemistry	125	520	645	0.5%	1.8%	9,248	9	1.0
Basic materials chemistry	372	1,174	1,546	1.4%	4.0%	26,212	260	9.9
Materials metallurgy	201	347	548	0.7%	1.2%	16,024	53	3.3
Surface tech coating	372	363	735	1.4%	1.2%	16,492	25	1.5
Chemical engineering	631	854	1,485	2.3%	2.9%	23,179	26	1.1
Environmental tech	384	449	833	1.4%	1.5%	12,054	42	3.5
Handling	1,245	984	2,229	4.6%	3.3%	29,114	56	1.9
Machine tools	508	402	909	1.9%	1.4%	23,146	95	4.1
Engines,pumps,turbine	1,021	1,149	2,170	3.8%	3.9%	31,491	1,673	53.1
Textile and paper mach	288	339	627	1.1%	1.1%	22,460	429	19.1
Other spec machines	892	722	1,614	3.3%	2.4%	28,581	27	0.9
Thermal process and app	501	305	806	1.9%	1.0%	14,664	47	3.2
Mechanical elements	1,437	988	2,424	5.3%	3.4%	31,590	220	7.0
Transport	1,289	1,111	2,400	4.8%	3.8%	47,497	2,381	50.1
Furniture, games	1,309	766	2,075	4.9%	2.6%	19,048	17	0.9
Other consumer goods	768	572	1,341	2.9%	1.9%	18,888	114	6.0
Civil engineering	2,864	1,191	4,055	10.6%	4.0%	27,954	68	2.4
Total	**26,927**	**29,483**	**56,409**			**974,988**	**35,921**	**36.8**
Electrical engineering	7,589	6,451	14,040	28.2%	21.9%	280,648	26,496	94.4
Instruments	4,162	5,339	9,502	15.5%	18.1%	159,332	2,640	16.6
Chemistry	3,055	9,164	12,219	11.3%	31.1%	240,574	1,658	6.9
Mechanical engineering	7,179	6,000	13,179	26.7%	20.4%	228,543	4,928	21.6
Other Fields	4,942	2,529	7,470	18.4%	8.6%	65,891	199	3.0

* Weighting by owners is innocuous, since they all get added back into the same class cell.
Weighting by classes means that a patent in multiple TF34 sectors is downweighted in each of the sectors.
@ Triples based on all EPO patenting, priority years 2002-2009 (see text for definition and further explanation).

A complication is that each firm can enter into any one of the 34 technology sectors, and many of the firms enter more than one, as one might have expected. More than half the firms patent in more than one sector, and 10 per cent patent in more than four. Our solution to this problem is to treat each entry possibility separately for each firm. That is, we have about 29,000 firms, each of which can potentially enter into each one of the 34 technology sectors, yielding about one million observations at risk. We cluster the standard errors by firm, so the model is effectively a firm random effects model for entry into the 34 sectors.

In order to isolate the possible impact of triples on entry into patenting, it is important to control for other characteristics that affect the probability that a firm chooses to patent in a particular technology sector. First, it is well known that firm size and industry are important predictors of whether a firm patents at all (Bound *et al.* 1984 for US data). Hall *et al.* (2012b) show this for UK patenting during the period studied here. In our entry regressions, we include the logarithm of the firm's reported assets and a set of two-digit industry dummies to control for these characteristics.[15] Second, we would expect that technology sectors with many triples are also sectors with many patents, and it is therefore more likely that a firm will patent in that sector, other things equal. To control for this effect, we include the logarithm of the aggregate EPO patent applications in the technology sector during the year, and we normalize the count of triples by aggregate patenting in the same sector, so that the triples variable represents the intensity with which firms potentially hold blocking patents on each other *relative* to aggregate patenting activity in the technology.

We use hazard models to estimate the probability of entry into a technology. The models express the probability that a firm enters into patenting in a certain sector conditional on not having entered yet as a function of the firm's characteristics and the time since the firm was "at risk," which is the time since the founding of the firm. Obviously in some cases, our data do not go back as far as the founding date of the firm, and in these cases the data are "left-censored." When we do not observe the entry of the firm into a particular technology sector by the last year (2009), the data is referred to as "right-censored."

In Appendix B, we discuss the choice of the survival models that we use for analysis, how to interpret the results, and present some robustness checks. Overall, we estimate two classes of failure or survival models: 1) *proportional hazard*, where the hazard of failure over time has the same shape for all firms, but the overall level is proportional to an index that depends on firm characteristics; and 2) *accelerated failure time*, where the survival rate is accelerated or decelerated by the characteristics of the firm. We transform (2) to a hazard rate model for comparison with (1), using the usual identity between the probability of survival to time t and the probability of failure at t given survival to t-1. Our preferred model is the log-logistic model stratified by two-digit industry, which is an accelerated failure time (AFT) model that provides the most flexibility. The survival function for this model is the following:

[15] The choice of assets as a size measure reflects the fact that it is the only size variable available for the majority of the firms in the FAME dataset.

$$S(t) = \left[1 + (\lambda_i t)^{1/\gamma_j}\right]^{-1} \quad \text{with} \quad \lambda_i = \exp(-X_i\beta)$$

where i denotes a firm, j denotes a technology sector, and t denotes the time since entry into the sample. Note that we allow the parameter γ to vary freely across industries. That is, for this model, both the mean and the variance of the survival distribution are specific to the 2-digit industry. The elasticity of the hazard with respect to a characteristic x depends on time and on the industry-specific parameter γ, yielding a more flexible model than the proportional hazard class of models. The hazard rate is given by the following expression:

$$h(t) = \frac{-d \log S(t)}{dt} = \frac{\lambda_i^{1/\gamma_j} t^{-1+1/\gamma_j}}{\gamma_j \left(1 + (\lambda_i t)^{1/\gamma_j}\right)}$$

From this we can derive the elasticity of the hazard rate with respect to a regressor x:

$$\frac{\partial \log h_{ij}(t)}{\partial x_i} = \frac{-\beta}{1 + (\lambda_i t)^{1/\gamma_j}}$$

The implication of the above formula is that the elasticity will vary across firms, over time, and also across industries. However, for our data the probability of entry is small so that λ is very small and γ is near unity, which means that the coefficients shown in the table are approximately equal to the central tendency of the elasticities.[16] Later on, we will show the actual distributions of the implied elasticities, which do vary, especially across industry.

As indicated earlier, our data for estimation are for the 2002-2009 period, but many firms have been at risk of patenting for many years prior to that. The oldest firm in our dataset was founded in 1856 and the average founding year was 1992. Because the EPO was only founded in 1978, we chose to use that year as the earliest date any of our firms is at risk of entering into patenting. That is, we defined the initial year as the maximum of the founding year and 1978. Table B-2 in the appendix estimates our model using 1900 instead of 1978 as the earliest at risk year and finds essentially no difference in the estimates. We conclude that the precise assumption of the initial period is innocuous. Our assumption amounts to assuming that the shape of the hazard for firms founded between 1856 and 1978 but otherwise identical is the same during the 2002-2009 period.

Appendix Table B-1 shows exploratory regressions made using various survival models. None of the choices made large differences to the coefficients of interest, so that we focus here on the results from our preferred specification, the log-logistic accelerated failure time model, estimated with stratification by two-digit industry. The effect of the stratification is that we allow firms in each of the industries to have different means and standard deviations of the time until entry into patenting. That is, each industry has its

[16] All the tables show the negative of the estimated coefficients β for consistency between the PH and AFT models.

own “failure” time distribution, where failure is defined as entry into patenting in a technology area, but this distribution is also modified by the firm’s size, aggregate patenting in the technology, and the triples density.

Our estimation sample has about 29,000 firms and one million firm-TF34 sector combinations. During the 2002-2009 period there are 12,991 entries into patenting for the first time in a technology sector by these firms. Table A-2 shows the distribution of the number of entries per firm: 3,507 enter one class, and the remainder enters more than one. Table A-3 shows the FAME population of UK firms in our industries, together with the shares in each industry that have applied for a UK or EP patent during the 2001-2009 period. These shares range from over 10 per cent in pharmaceuticals and R&D services to less than 0.1 per cent in construction, oil and gas services, real estate, law, and accounting.

Our estimates of the model for entry into patenting are shown in Table 2 below. The first column is for estimates that have not been corrected for the fact that we sampled non-patenting firms rather than including the entire population, and the next three columns are weighted estimates that do adjust for the sampling strategy. Correcting for sampling made little difference to the coefficients of interest, although it reduces the firm size coefficient quite a bit, because non-patenters tend to be smaller firms.[17]

[17] The sampling weights effectively downweight the non-patenters, so the fact that they are smaller has less impact on the prediction.

Table 2

Hazard of entry into patenting in a TF34 Class

998,219 firm-TF34 observations with 12,991 entries (29,435 firms)

	Accelerated failure time - Log Logistic			
Variable	*Unweighted*	*Weighted by sampling probability*		
Log (triples density	-0.121***	-0.123***	-0.112***	-0.114***
in class)	(0.007)	(0.007)	(0.007)	(0.007)
Log (patents in class)	0.678***	0.696***	0.647***	0.675***
	(0.020)	(0.020)	(0.018)	(0.020)
Log assets	0.156***	0.048***	0.041***	0.044***
	(0.006)	(0.006)	(0.005)	(0.005)
Log (pats applied for			0.428***	0.426***
by firm previously)			(0.023)	(0.023)
D (no prior pat apps)			1.486***	1.482***
			(0.038)	(0.038)
Log (triples density)				0.002
* Log assets				(0.002)
Log (patents)				-0.023***
* Log assets				(0.006)
Industry dummies	***stratified#***	***stratified#***	***stratified#***	***stratified#***
Year dummies	***yes***	***yes***	***yes***	***yes***
Log likelihood	-59,813.9	-51,369.1	-49,559.0	-49,552.3
Degrees of freedom	35	43	45	47
Chi-squared	2178.2	1982.1	3251.3	3309.3

Coefficients for the hazard of entry into a patenting class are shown.

Standard errors are clustered on firm. *** (**) denote significance at the 1% (5%) level.

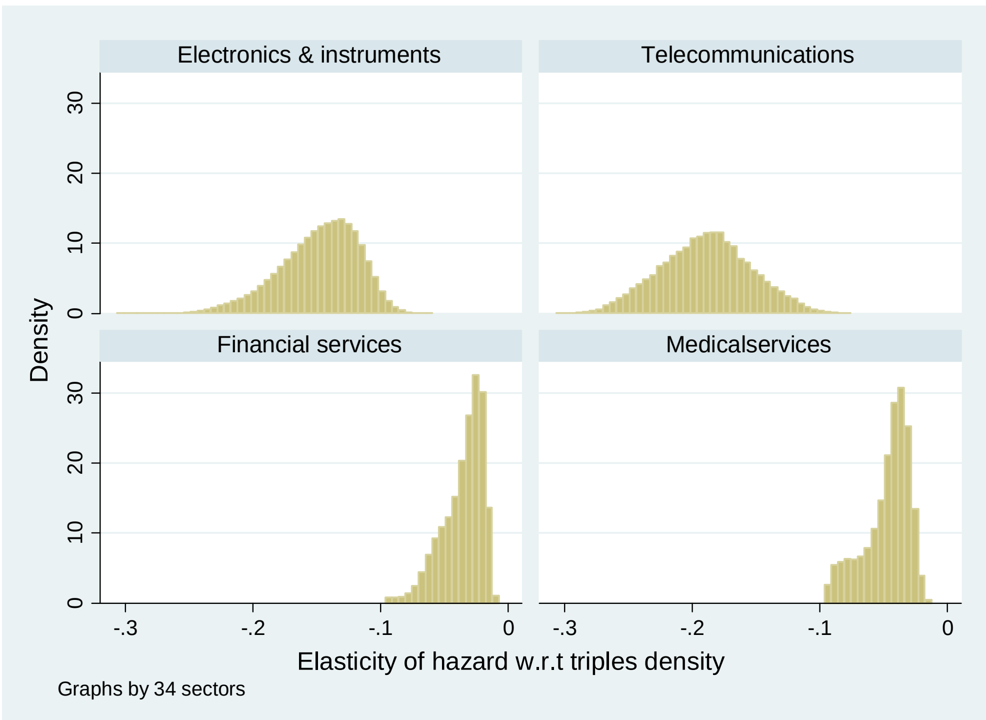
Time period is 2002-2009 and minimum entry year is 1978. Sample is all UK firms with nonmissing assets.

Estimates are stratified by industry - each industry has its own baseline hazard.

Focusing on our variables of interest and on the weighted estimates, we see that aggregate patenting in a technology class is a strong predictor of whether a firm enters that class. A doubling of patenting is associated with approximately a 65-70 per cent higher probability of entry (standard error 2.0%). However, when we include the triples density in the class, we find that it depresses entry. Doubling the intensity of triples in a class is associated with a highly significant approximately 11-12 per cent lower hazard of entry into that class (standard error 0.7%).

Figure 6 shows the distribution of actual elasticity with respect to triples density for four industries, chosen because they are at the two extreme ends of the hazard distribution. The figure shows two things: first, the elasticity of the hazard with respect to triples density is higher in absolute value in the ICT sectors electronics and telecommunications than it is in the two services sector. Second, the dispersion is also higher for the ICT sectors.

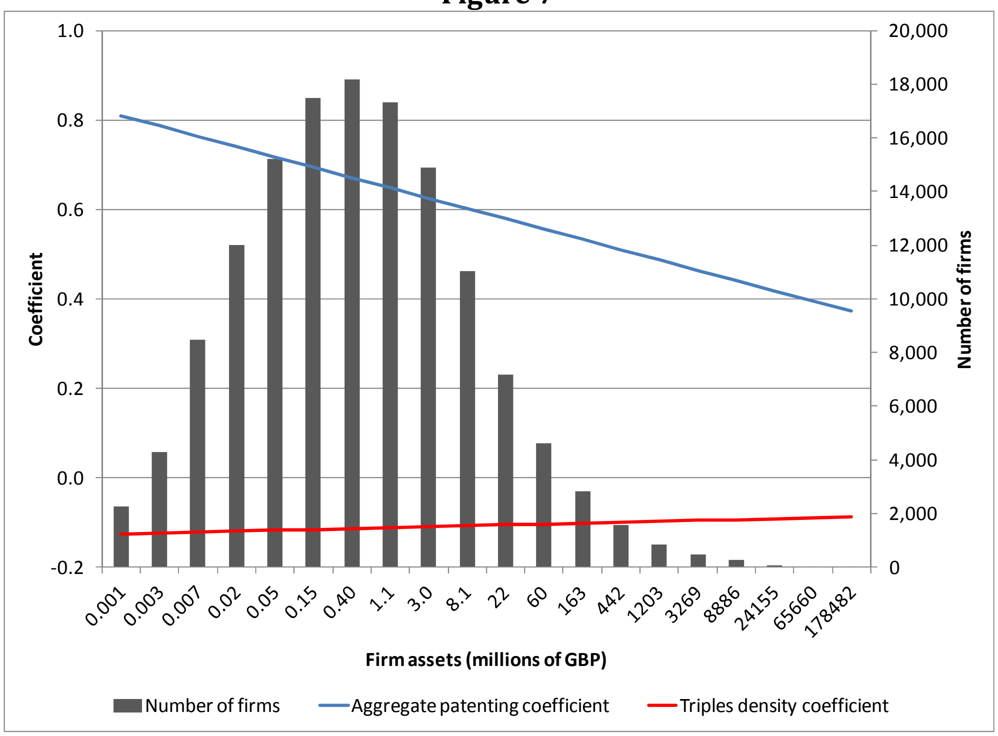
Figure 6



There are fixed costs to patenting, and a firm may be more likely to enter into patenting in a new area if it already patents in another area. To test this idea, in the third colum of Table 2, we add the logarithm of past patenting by the firm, along with a dummy for those firms that have not patented before. Firms with a greater prior patenting history are indeed more likely to enter a new technology area – doubling a firm's past patents leads to an almost 50% higher hazard of entry. However, it is also true that firms with no prior patenting history are much more likely to enter any given technology area, other things equal.

In the last column we interact the log of assets with the log of patents and the log of triples density to see whether these effects vary by firm size.[18] They do, and in the expected way, although not significantly in the case of triples. The impact on larger firms from aggregate patenting weakens and the impact of triples strengthens slightly. That is, the impact of both aggregate patenting (positive) and triples density (negative) on SMEs is stronger than it is for larger firms. We show this graphically in Figure 7, which overlays the coefficients of aggregate patenting and triples density as a function of firm size on the actual size distribution of our firms. From the graph one can see that the impact of aggregate patenting in a sector is higher and more variable than the impact of the triples density. Firms in the lower range of the size distribution (assets less than GBP 10,000) are much more likely to enter a sector with high aggregate patenting if they enter at all, but their hazard of entry falls 15 per cent if the triples density doubles in that sector. On the other hand, for the few firms in the upper range of the size distribution (assets greater than 100 billion pounds), the hazard of entry falls only 7 per cent if the triples density doubles.

Figure 7

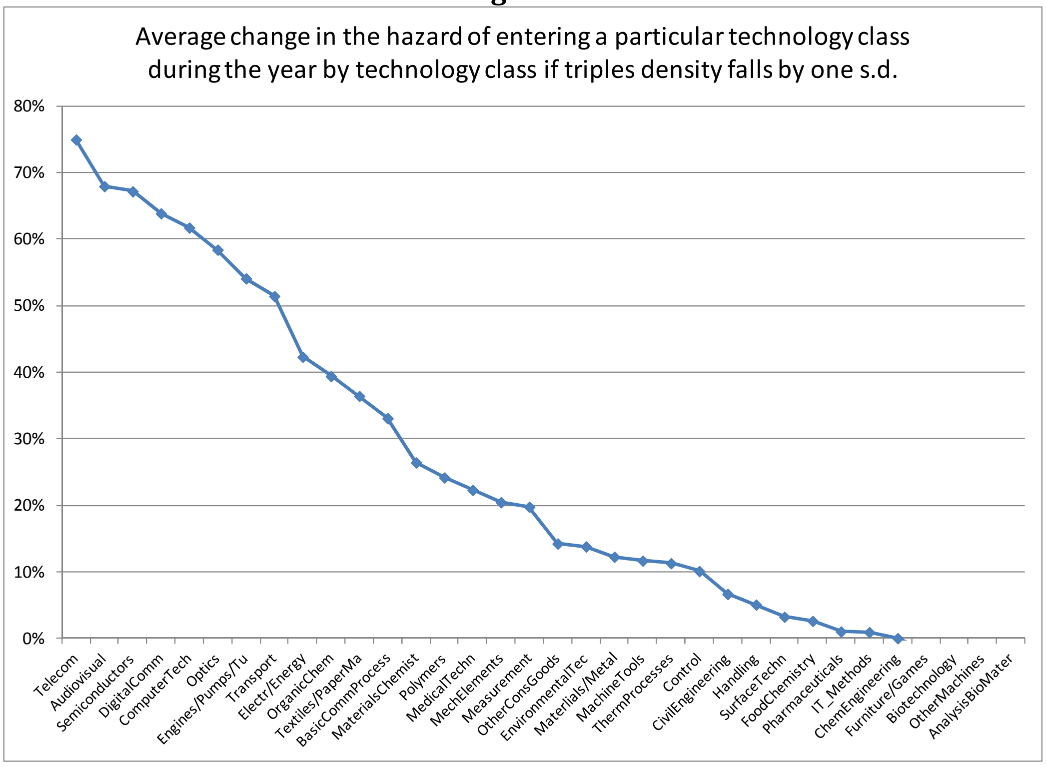


We also simulated the effect of reducing the log of the triples density by one standard deviation. Because the triples density has a wide range (0.0002 to 0.2407), a one standard deviation reduction in the log is quite large and corresponds to reducing the density fivefold). Figure 8 shows the corresponding increase in entry hazard by technology class. It is clear that entry into patenting increases greatly in those technologies where there are a large number of triples per patent: Telecommunications,

[18] Note that all the variables have been centered at their means, so that the coefficients on the non-interacted variables are coefficients at the mean of the data and can be compared across the columns directly.

Computer technology, Audio-visual technology, Digital communications, Semiconductors, etc.

Figure 8



6.3 Robustness

Table B-3 in the appendices explores some variations of the sample used in estimating the specification in the last column of Table 2. The first change (column 2) was to drop all the technology-industry combinations where Lybbert and Zolas (2012) find no patenting in their data and where there was no entry by any UK firm from the relevant industry into that technology category. This removes about 40 per cent of the sample. The results become slightly stronger, and the standard errors slightly larger (as we would expect).

Next we removed all the firms with assets greater than one billion pounds, to check whether very large firms were responsible for our findings. This removed about 8,000 of the 29,000 firms. Column 3 of Table B-3 shows that the results do not change much; if anything they become stronger, albeit with slightly larger standard errors. Finally we removed the telecommunications technology sector from the estimation, because it is such a large triples outlier. Once again, there was little change to the estimates. However, in this case the interaction between size and triples density once again becomes significant. That is, the negative effect of triples on entry weakens as firms become larger.

7 Conclusion

Patent thickets are defined as a dense web of patents with overlapping claims that are held by several (competing) companies. Such thickets can arise for a multitude of reasons; they are mainly driven by an increase in the number of patent filings (and its consequences for patent quality) as well as increased technological complexity and interdependence. In this paper, we investigate the effect of patent thickets on firm behavior. Specifically, we analyse whether patent thickets represent a barrier to entry into particular technologies for UK companies.

There is a lack of empirical evidence on the effect of thickets on firm behavior, both in terms of performance and innovative activity. Nevertheless, there is a substantial body of research investigating the factors that lead to the emergence and growth of thickets. The available empirical evidence provides strong evidence for the existence and growth of patent thickets, especially in ICT-related technologies.

To analyse the possible impact of thickets on UK firms, we measure entry as a firm's decision to patent for the first time in a given technology area rather than entry into product markets. This choice is partly driven by the lack of precise data on entry into product markets, but can be defended by the argument that competition in patent-intensive sectors will per force require some effort to patent in the relevant sector. Focusing on entry into patenting also has the advantage of providing us with the complete set of potential entrants, i.e., any registered firm in our database that has not previously patented. If instead we had studied entry into the product market, potential entrants would have become observable only after entry into the market. The absence of information on those firms that chose not to enter would complicate our analysis considerably.

Using the triples measure, our descriptive evidence shows strong increases in the density of thickets in almost all technologies related to Electrical Engineering, especially in Telecommunication, Audiovisual- and Computer-technology. Our data show that patent thickets are significantly less dense in all other technology areas, although we also find some evidence of an increase in the area of Optical instruments.

We study the probability of entry into patenting in a particular technology sector as a function of patent thickets in that sector, conditional on aggregate patenting in that technology. Our results suggest a substantial and statistically significant negative association between the density of thickets and the propensity to patent for the first time in a given technology area.

Patent thickets also create substantial transactions costs for the large incumbents caught up in the thickets (Hall and Ziedonis, 2001; Federal Trade Commission, 2003; Somaya, 2003). These costs are not the focus of our analysis in this study, because they do not affect entry directly. Nonetheless, one might surmise that such costs affect the decision to continue operating in a specific technology. If the transactions costs associated with thickets make it difficult for SMEs to survive in the marketplace, then patent thickets affect existing SMEs, even if they do not represent a barrier to entry. This effect of patent thickets on SMEs is not addressed in this study, but will be pursued in future research.

As we find thickets to affect entry negatively, there is a strong indication that thickets represent some kind of barrier to entry in those technology areas in which they are present. However, we must emphasize that the simple finding of a barrier to entry created by patent thickets is not proof positive that reducing that barrier and increasing entry would lead to welfare improvements in the innovation/competition space. Rather it is the existence of evidence that the presence of thickets reduces entry combined with the large existing literature that shows that currently patent systems do not work as well as they should. This literature documents quality issues with patents in technology areas affected by patent thickets, a large decline in the relationship between R&D spending and patenting in some sectors and a substantial increase in resources devoted to patent litigation leading to the partial or complete revocation of patents in areas identified as prone to thickets. All of this may lead one to the conclusion that the operation of the patent system could use some improvement.

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Appendix A

Table A-1: Descriptive Statistics on Triples by Technology Area 1981-2009

	Area	*Total Triples*	*Average per year*	*Median per year*	*Min.*	*Max.*
1	Electronics / energy	2,472	181	208	1	245
2	Audiovisual	6,561	423	466	3	682
3	Telecom	15,815	1161	1165	2	1860
4	Digital communication	4,035	397	426	1	525
5	Basic Comm. processes	455	44	38	1	90
6	Computer technology	7,818	625	703	3	908
7	IT Methods	10	2	2	1	3
8	Semiconductors	4,423	335	374	1	559
9	Optics	3,000	197	255	1	277
10	Measurement	373	35	36	1	60
11	Control	66	8	6	1	15
12	Medical technology	711	53	58	3	78
13	Organic chemistry	1,618	104	91	2	181
14	Biotechnology	185	50	55	1	77
15	Pharmaceuticals	316	40	30	1	73
16	Polymers	891	44	36	1	86
17	Food chemistry	17	2	2	1	3
18	Materials chemistry	604	30	29	1	53
19	Materials / metals	94	8	8	1	14
20	Surface technology	32	3	3	1	4
21	Chemical engineering	46	5	5	1	7
22	Environmental technology	76	10	7	1	22
23	Handling	96	9	10	1	14
24	Machinetools	104	14	17	1	20
25	Engines/pumps/turbines	2,212	203	225	1	305
26	Textiles/paper machines	672	57	53	1	99
27	Other machines	37	6	4	1	11
28	Thermal processes	51	6	6	1	9
29	Mechanical elements	244	28	27	1	43
30	Transport	2,770	295	314	1	441
31	Furniture/games	21	3	3	1	6
32	Other consumer goods	114	20	18	1	30
33	Civil engineering	90	9	9	1	16
	Total	**56,029**	**567**	**441**	**1**	**1860**

Table A-2: Number of TF34 sectors entered between 2002 and 2009

Number of sectors	*Number of firms*	*Number of entries*
1	3,507	3,507
2	1,901	3,802
3	781	2,343
4	313	1,252
5	158	790
6	72	432
7	42	294
8	20	160
9	10	90
10	6	60
11	10	110
12	4	48
14	2	28
15 or more	4	75
Total	**6,830**	**12,991**

8 Table A-3

FAME Population of UK firms, by industry

Industry	*2-digit SIC (2007 UK classification)*	*Number of firms*	*Number of patenters*	*Share patenting 2001-2009*	*Number of patents*
Oil & gas extraction	06	57,686	48	0.08%	231
Quarrying	08	48,182	87	0.18%	126
Oil & gas services	09	84,619	115	0.14%	727
Food mfg	10	10,110	106	1.05%	444
Beverage mfg	11	1,881	24	1.28%	70
Tobacco	12	72	3	4.17%	29
Textiles	13	5,625	96	1.71%	313
Apparel	14	7,029	38	0.54%	96
Leather	15	1,234	11	0.89%	22
Wood	16	8,004	58	0.72%	150
Paper	17	3,170	110	3.47%	551
Printing	18	18,663	109	0.58%	590
Oil,coke refining	19	355	5	1.41%	59
Chemicals	20	5,032	333	6.62%	6274
Pharmacueticals	21	1,306	132	10.11%	2324
Rubber & plastics	22	7,658	497	6.49%	2096
Stone, Clay, & glass	23	5,100	134	2.63%	621
Basic metals	24	4,160	84	2.02%	428
Fabricated metals	25	33,321	857	2.57%	3608
Electronics & instruments	26	13,539	888	6.56%	6757
Electrical machinery	27	2,852	228	7.99%	1132
Machinery	28	12,026	718	5.97%	4930
Motor vehicles	29	2,942	139	4.72%	1419
Other transport	30	4,542	120	2.64%	1194
Furniture	31	6,324	73	1.15%	168
Other manufacturing	32	22,366	1,016	4.54%	5673
Repairs	33	5,911	174	2.94%	1704
Utilities	35	3,848	37	0.96%	121
Water distribution	36	1,003	29	2.89%	112
Sewers	37	861	8	0.93%	9
Recycling	38	6,001	37	0.62%	69
Construction	41	201,216	186	0.09%	855
Site preparation	42	6,223	28	0.45%	31
Construction trades	43	182,441	393	0.22%	1161
Auto trade	45	50,491	77	0.15%	378
Wholesale trade, except autos	46	134,296	996	0.74%	4486
Retail trade	47	152,133	252	0.17%	699
Land transport	49	53,264	57	0.11%	173
Water transport	50	3,838	8	0.21%	20

Air transport	51	3,533	8	0.23%	138
Cargo handling & travel agencies	52	17,576	37	0.21%	111
Post & telecomm	53	4,313	7	0.16%	53
Publishing	58	65,015	209	0.32%	608
Telecommunications	61	17,393	161	0.93%	2682
Computer consulting	62	191,290	996	0.52%	4367
Data processing, hosting	63	9,714	54	0.56%	77
Banks and other financial services	64	44,921	75	0.17%	131
Insurance	65	13,581	15	0.11%	50
Securities	66	11,461	21	0.18%	204
Real estate	68	130,182	84	0.06%	266
Law and accounting	69	49,404	27	0.05%	189
Management consulting	70	205,811	618	0.30%	4124
Engineering services	71	48,517	272	0.56%	1626
R&D services	72	10,291	1,168	11.35%	11214
Advertising	73	25,454	78	0.31%	250
Non-trading companies	74	20,529	304	1.48%	4727
Other business activities	82	625,553	2,066	0.33%	9898
Medical services	86	44,865	161	0.36%	923
Other personal services	96	123,321	428	0.35%	1385
Dormant	99	2,464	23	0.93%	1259
Unknown		428,208	0	0.00%	408
Total		**3,262,720**	**15,123**	**0.46%**	**94,540**

Appendix B: Estimating survival models

This appendix gives some further information about the various survival models we estimated and the robustness checks that were performed. We estimated two general classes of failure or survival models: 1) *proportional hazard*, where the hazard of failure over time has the same shape for all firms, but the overall level is proportional to an index that depends on firm characteristics; and 2) *accelerated failure time*, where the survival rate is accelerated or decelerated by the characteristics of the firm. We transform (2) to a hazard rate model for comparison with (1), using the usual identity between the probability of survival to time *t* and the probability of failure at *t* given survival to *t-1*.

The first model has the following form:

$$Pr\left(i \text{ first patents in } j \text{ at } t \mid i \text{ has no patents in } j \,\forall s < t,\ X_i\right)$$

$$h(X_i, t) \;=\; h\left(t\right) exp(X_i, \beta)$$

where *i* denotes a firm, *j* denotes a technology sector, and *t* denotes the time since entry into the sample. *h(t)* is the baseline hazard, which is either a non-parametric or a parametric function of time since entry into the sample. The impact of any characteristic *x* on the hazard can be computed as follows:

$$\frac{\partial h\left(X_i, t\right)}{\partial x_i} = h\left(t\right) exp\left(X_i, \beta\right)\beta \quad \text{or} \quad \frac{\partial h\left(X_i, t\right)}{\partial x_i}\frac{1}{\left(X_i, t\right)} = \beta$$

Thus if *x* is measured in logs, β measures the elasticity of the hazard rate with respect to *x*. Note that this quantity does not depend on the baseline hazard *h(t)*, but is the same for any *t*. We use two choices for *h(t)*: the semi-parametric Cox estimate and the Weibull distribution pt^{p-1}. By allowing the Cox *h(t)* or *p* to vary freely across the industrial sectors, we can allow the shape of the hazard function to be different for different industries while retaining the proportionality assumption.

In order to allow even more flexibility across the different industrial sectors, we also use two accelerated failure time models, the log-normal model and the log-logistic model. These have the following basic form:

$$\text{log-normal:} \quad S(t) = 1 - \Phi\left[\frac{\log(\lambda_i t)}{\sigma_j}\right]$$

$$\text{log-logistic:} \quad S(t) = \left[1 + (\lambda_i t)^{1/\gamma_j}\right]^{-1}$$

where *S(t)* is the survival function and $\lambda_i = exp(X_i\beta)$. We allow the parameters σ (log-normal) or γ (log-logistic) to vary freely across industries (*j*). That is, for these models, both the mean and the variance of the survival distribution are specific to the 2-digit industry. In the case of these two models, the elasticity of the hazard with respect to a characteristic *x* depends on time and on the industry-specific parameter (σ or γ), yielding a more flexible model. For example, the hazard rate for the log-logistic model is given by the following expression:

$$h(t) = \frac{-d \log S(t)}{dt} = \frac{\lambda_i^{1/\gamma_j} t^{-1+1/\gamma_j}}{\gamma_j \left(1 + (\lambda_i t)^{1/\gamma_j}\right)}$$

From this we can derive the elasticity of the hazard rate with respect to a regressor *x*:[19]

$$\frac{\partial \log h_{ij}(t)}{\partial x_i} = \frac{-\beta}{(1 + \lambda_i t)^{1/\gamma_j}}$$

One implication of this model is therefore that both the hazard and the elasticity of the hazard with respect to the regressors depend on *t*, the time since the firm was at risk of patenting. We sample the firms during a single decade, the 2000s, but some of the firms have been in existence since the 19th century. This fact creates a bit of a problem for estimation, because there is no reason to think that the patenting environment has remained stable during that period. We explored variations in the assumed first date at risk in Tables B-1(1978) and B-2 (1900), finding that the choice made little difference. Accordingly, we have used a minimum at risk year of 1978 for estimation in the main table in the text.

[19] We assume that *x* is in logarithms, as is true for our key variables, so this can be interepreted as an elasticity.

Table B-1

Hazard of entry into patenting in a TF34 Class - Comparing models

998,219 firm-TF34 observations with 12,991 entries (29,435 firms)

	Proportional hazard		*AFT*
Variable	*Cox PH*	*Weibull*	*Log logistic*
Log (triples density	-0.112***	-0.112***	-0.123***
in class)	(0.006)	(0.006)	(0.007)
Log (patents in class)	0.644***	0.645***	0.696***
	(0.019)	(0.017)	(0.020)
Log assets	0.068***	0.045***	0.048***
	(0.004)	(0.005)	(0.006)
Industry dummies	***stratified#***	***stratified#***	***stratified#***
Year dummies	***yes***	***yes***	***yes***
Log likelihood	-102,255.9	-51,393.4	-51,369.1
Degrees of freedom	10	35	35
Chi-squared	2848.1	2415.9	1982.1

All estimates are weighted estimates, weighted by sampling probability. For the Cox and Weibull models, coefficients shown are elasticities of the hazard w.r.t. the variable. For the log-logistic, -beta is shown.

*** (**) denote significance at the 1% (5%) level.

Time period is 2002-2009 and minimum entry year is 1978. Sample is all UK firms with nonmissing assets.

AFT - Accelerated Failure Time models

Estimates are stratified by industry - each industry has its own baseline hazard.

Table B-2

Hazard of entry into patenting in a TF34 Class - Comparing models

Origin time is max(founding year, 1900)

998,219 firm-TF34 observations with 12,991 entries (29,435 firms)

	Proportional hazard			*AFT*	
Variable	*Cox PH*	*Weibull*		*Log logistic*	
Log (triples density	-0.112***	-0.112***	-0.122***	-0.110***	-0.113***
in class)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Log (patents in class)	0.644***	0.645***	0.693***	0.645***	0.669***
	(0.019)	(0.017)	(0.020)	(0.018)	(0.020)
Log assets	0.068***	0.046***	0.047***	0.042***	0.044***
	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)
Log (pats applied for				0.427***	0.426***
by firm previously)				(0.023)	(0.022)
D (no prior pat apps				1.494***	1.492***
				(0.038)	(0.038)
Log (triples density)					0.003
* Log assets					(0.002)
Log (patents)					-0.021***
* Log assets					(0.006)
Industry dummies	***stratified#***	***stratified#***	***stratified#***	***stratified#***	***stratified#***
Year dummies	***yes***	***yes***	***yes***	***yes***	***yes***
Log likelihood	-102,255.9	-49,961.7	-49,975.2	-48,138.2	-48,132.9
Degrees of freedom	10	43	43	45	47
Chi-squared	2848.1	2418.5	2034.6	3047.2	3455.3

All estimates are weighted estimates, weighted by sampling probability. For the Cox and Weibull models, coefficients shown are elasticities of the hazard w.r.t. the variable. For the log-logistic, -beta is shown.

*** (**) denote significance at the 1% (5%) level.

Time period is 2002-2009. Sample is all UK firms with nonmissing assets

AFT - Accelerated Failure Time models

Estimates are stratified by industry - each industry has its own baseline hazard.

Table B-3

Hazard of entry into patenting in a TF34 Class - Robustness

Variable	*(1)*	*(2)*	*(3)*	*(4)*
Log (triples density	-0.114***	-0.125***	-0.135***	-0.126***
in class)	(0.007)	(0.008)	(0.011)	(0.008)
Log (patents in class)	0.675***	0.845***	0.871***	0.845***
	(0.020)	(0.024)	(0.034)	(0.024)
Log assets	0.044***	0.043***	0.023**	0.043***
	(0.005)	(0.005)	(0.011)	(0.005)
Log (lagged firm-level	0.426***	0.431***	0.513***	0.432***
patent stock)	(0.023)	(0.025)	(0.056)	(0.025)
D (firm has no patents yet)	1.482***	1.456***	1.775***	1.452***
	(0.038)	(0.038)	(0.063)	(0.038)
Log (triples density)	0.002	0.010***	0.008	0.011***
* Log assets	(0.002)	(0.003)	(0.006)	(0.003)
Log (patents)	-0.023***	0.040***	0.043**	-0.040***
* Log assets	(0.006)	(0.007)	(0.018)	(0.008)
Year dummies	yes	yes	yes	yes
Observations	998,219	608,251	444,939	589,422
Firms	29,435	29,435	21,539	29,435
Entries	12,991	12,991	5,280	12,852
Entry rate	1.30%	2.14%	1.19%	2.18%
Log likelihood	-49,552.3	-39,600.6	-18,501.3	-38,336.4
Degrees of freedom	47	47	47	47
Chi-squared	3309.3	7141.8	3893.9	6984.0

All estimates are weighted estimates, weighted by sampling probability. Coefficients shown are negative of the estimates (larger coefficient increases entry probability).

*** (**) denote significance at the 1% (5%) level.

Time period is 2002-2009. Sample in (1) is all UK firms with nonmissing assets.

Log-logistic model stratified by industry.

(1) Estimates from Table 4, for comparison.

(2) Observations for tech sectors of firms whose industry has no such patenting (Lybbert-Kolas) and where there is no entry by any UK firm in that industry are dropped.

(3) Firms with assets>1 billion GBP removed.

(4) The Telecom tech sector is removed.