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ABSTRACT

We analyze the effect of patent thickets on entry into technology areas by firms in the UK. We present a model that describes incentives to enter technology areas characterized by varying technological opportunity, complexity of technology, and the potential for hold up in patent thickets. We show empirically that our measure of patent thickets is associated with a reduction of first time patenting in a given technology area controlling for the level of technological complexity and opportunity. Technological areas characterized by more technological complexity and opportunity, in contrast, see more entry. Our evidence indicates that patent thickets raise entry costs, which leads to less entry into technologies regardless of a firm's size.

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1 Introduction

The past two decades have seen an enormous increase in patent filings worldwide (Fink *et al.*, 2013). There are signs that the level of patenting in certain sectors has become so high as to discourage innovation (Federal Trade Commission, 2011; Bessen and Meurer, 2008; Jaffe and Lerner, 2004; Federal Trade Commission, 2003). The main reason is that companies inadvertently block each other's innovations because of multiple overlapping patent rights in so-called "patent thickets" (Shapiro, 2001). Patent thickets arise where individual products draw on innovations protected by hundreds or even thousands of patents, often with fuzzy boundaries. These patents belong to many independent and usually competing firms. Patent thickets can lead to hold-up of innovations, increases in the complexity of negotiations over licenses, increases in litigation, and they create incentives to add more and weaker patents to the patent system (Allison *et al.*, 2015). This increases transaction costs, reduces profits that derive from the commercialization of innovation, and ultimately may reduce incentives to innovate.

There is a growing theoretical (Bessen and Maskin, 2009; Clark and Konrad, 2008; Farrell and Shapiro, 2008; Fershtman and Kamien, 1992) and legal literature on patent thickets (Chien and Lemley, 2012; Bessen *et al.*, 2011). Related work analyzes firms' attempts to form patent pools to reduce hold-up (Joshi and Nerkar, 2011; Lerner *et al.*, 2007; Lerner and Tirole, 2004) and the particular challenges posed in this context by standard essential patents (Lerner and Tirole, 2013).

The existing empirical evidence on patent thickets is largely concerned with showing that they exist and measuring their density (Graevenitz *et al.*, 2011; Ziedonis, 2004). There is less evidence on the effects patent thickets have for firms. Cockburn and MacGarvie (2011) demonstrate that patenting levels affect product market entry in the software industry. They show that a 1 per cent increase in the number of existing patents is associated with a 0.8 per cent drop in the number of product market entrants. This result echoes earlier findings by Lerner (1995) who showed for a small sample of U.S. biotech companies that first-time patenting in a given technology is affected by the presence of other companies' patents. Bessen and Meurer (2013) suggest that patent thickets also lead to increased litigation related to hold-up. Patent thickets have remained a concern of antitrust agencies and regulators in the United States for over a decade (Federal Trade Commission, 2011, 2003; USDoJ and FTC, 2007). Reforms that address some of the factors contributing to the growth of patent thickets have recently been introduced in the U.S. (America Invents Act (AIA) of 2011) [1] and by the European Patent Office (EPO).

[1] For further information see http://www.gpo.gov/fdsys/pkg/BILLS-112hr1249enr/pdf/BILLS-112hr1249enr.pdf

In spite of the available theoretical and empirical evidence, it is frequently argued that patent thickets are a feature of rapidly developing technologies in which technological opportunities abound (Teece *et al.*, 2014). Thickets are thus seen as a reflection of fast technological progress that is paired with increased technological complexity (Lewis and Mott, 2013). This suggests that a trade-off between technological opportunity and growth on the one hand and increased transaction costs due to the emergence of patent thickets on the other may exist. The challenge in assessing this trade-off is to develop a framework that captures the main incentives that lead to patent thickets as well as the most important effects of thickets.

This paper contributes to the literature by analyzing the effect of patent thickets on entry into new technology areas. Our focus on entry into patenting captures the positive effects of greater technological opportunity and negative effects of greater transaction costs imposed by a complex patent landscape characterized by thickets. We are able to quantify both effects empirically.

The paper makes two contributions: first, we extend the theoretical model of patenting in complex technologies introduced by Graevenitz *et al.* (2013) to free entry and the interaction between incumbents and entrants. Our model shows that technological complexity and technological opportunity increase entry in the context of patent thickets, while potential for hold-up in patent thickets reduces entry. Whereas complexity and opportunity are shown to have countervailing effects on patenting incentives in Graevenitz *et al.* (2013), we find that both factors increase the incentives to enter. However, hold-up potential clearly reduces entry incentives. These findings reflect the fact that patent thickets arise due to increased technological opportunity and complexity but create a potential for hold-up.

The second contribution of the paper consists of an empirical test of these predictions using firm-level data on UK firms and their patenting in the UK and Europe. We exploit patent data at both the EPO and the USPTO in order to construct measures of technological opportunity, technological complexity and hold-up potential and relate these to entry into new technology areas by UK firms.

Our empirical analysis confirms that entry increases in technology areas characterized by greater technological opportunity and complexity. However, we also show that the hold-up potential of patent thickets has negative and substantive effects on entry into patenting. While we cannot quantify the overall net welfare effect, our results do suggest that thickets raise entry costs for large and small firms alike. To the extent that more original and radical rather than incremental ideas come from new entrants rather than incumbents, this is likely to have negative long-run consequences on innovation and product market competition.

The remainder of this paper is organized as follows. Section 2 presents a model of entry into patenting in a technology area and derives several testable predictions. Section 3 describes the data, and the empirical measurement of the key concepts in the model. Section 4 discusses our results and Section 5 provides concluding remarks.

2 Theoretical Model

This section summarizes the main results of a two-stage model of entry into patenting and of subsequent patenting decisions. The model shows how complexity of a technology, technological opportunity and the expectation of hold-up affect firms' decisions to enter a technology area. The incentives to patent in such a setting are analyzed by Graevenitz *et al.* (2013). We generalize their model to analyze entry into technology areas by incumbents and new entrants.

Patent systems provide protection of innovations in technologies that vary significantly in their complexity and for which the degree of technological opportunity changes with the underlying science base. We model varying complexity and opportunity across technology areas as follows: each technology area is divided into technological opportunities. Firms invest in R&D per opportunity to develop new products. Having invested, firms can choose to protect their acquired knowledge by applying for patents on *facets* of each opportunity. Where the technology is discrete, e.g. chemistry, an opportunity consists of one facet. Opportunities in complex technologies comprise multiple facets. An increase in technological opportunity corresponds to an increase in the number of opportunities in a technology area. An increase in complexity corresponds to an increase in the number of facets per opportunity.

We assume that all facets and opportunities are symmetrical. Then firms can randomly select which facets and opportunities to patent. The role of the patent office in this model is to randomly assign facets to firms, when multiple firms apply for the same facet. Firms only decide how many technological opportunities to invest in and how many facets in each opportunity to patent.

The value of a firm's patent portfolio within a given technological opportunity depends on the number of facets of an opportunity that have been patented overall and the share of those patents held by the firm. In deciding how many patent applications to submit each firm takes into account costs of researching an opportunity, costs of upholding the patent and legal costs of exploiting the patent portfolio.

In this model opportunity increases incentives to patent in discrete technologies, but reduces these incentives in complex technologies. Opportunity relaxes firms' competition to patent all facets per opportunity in complex technologies. However, given the level of opportunity, greater complexity leads firms to patent more as they seek to ensure that they can exploit the opportunity fully and as they seek to protect their bargaining position among firms holding patents on an opportunity. This leads to countervailing effects of opportunity and complexity on patenting incentives in complex technologies. Graevenitz *et al.* (2013) provide evidence of this using data on European patenting.

The countervailing effects of complexity and opportunity on patenting incentives in complex technologies raise the question how complexity and opportunity affect entry. We show below that complexity and opportunity both increase incentives to enter complex technologies. It is perhaps surprising that, conditional on the number of firms, more opportunity should reduce patenting incentives, while increasing incentives to enter into patenting. As we show below one effect is the precondition for the other.

Greater complexity increases incentives to enter a technology area as firms are less likely to compete for the same patents within each opportunity when complexity rises. Complexity is frequently associated with increased potential for hold-up. Hold-up potential derives to some degree from the allocation of patents within an opportunity that results from firms' patenting efforts. Where more than two firms hold a substantial stake on an opportunity the complexity of bargaining increases. We account for the threat of hold-up separately and show that increases in that reduce patenting and entry. Therefore we measure complexity and hold-up separately in our empirical model.

2.1 Notation and Assumptions

The key variables of the model are the complexity of a technology k, measured by $(F_k \in \mathbb{R}_0^+)$, the degree of technological opportunity, measured by $(O_k \in \mathbb{R}_0^+)$, and hold-up potential h_k. The value of all F_k patents in an opportunity is V_k. In the simplest discrete setting this is the value of the one patent (facet) that covers each technological opportunity. In more complex technologies this is the value of controlling all patents (facets) on a technological opportunity. Firms (indexed by i) choose the number of opportunities o_i to invest in and the number of facets f_i per opportunity to patent.

In equilibrium only $\tilde{F}_k = (1-(1-(\hat{f}_k / F_k)^{N_0+1}))$ facets are patented, where $\hat{f}_k$ is the equilibrium number of facets chosen by applicants and N_0 is the number of firms that have chosen a specific opportunity.[2] Since $\tilde{F}_k$ may be smaller than F_k the total value of patenting in a technology is $V(\tilde{F}_k) \le V(F_k)$. Graevenitz *et al.* (2013) assume that the value function $V_k(\tilde{F}_k)$ is convex in covered facets. In Appendix C we show that this assumption can be relaxed. We generalize the model by introducing a concave function relating the share of patents the firm holds on an opportunity (s_{ik}) to the proportion of the value V_k the firm can extract through licensing and its own sales: $\Delta(s_{ik})$. This captures the benefits that a patent portfolio confers in the market for technology.

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[2] The properties of N_0 are summarized in Appendix C.

In sum the assumptions we make on the value function and portfolio benefits are:

$$(VF):\quad V(0)=0,\quad \frac{\partial V}{\partial \tilde{F}_k}>0 \tag{1}$$

$$(PB):\quad \Delta(0)=0,\quad \frac{d\Delta(s_{ik})}{ds_{ik}}>0 \text{ and } \frac{d^2\Delta(s_{ik})}{ds_{ik}^2}<0 \tag{2}$$

The model contains three types of patenting costs:

- Costs of R&D per opportunity, which depend on overall R&D activity in that technology area: $C_0\left(\sum_j^{N_O} o_j\right)$.
- Costs of maintaining each granted patent in force, C_a.
- Costs of coordinating R&D on *different* technological opportunities $C_c(o_i)$, where

$$\frac{\partial C_c}{\partial o_i}>0 \tag{3}$$

These assumptions imply that R&D costs are fixed costs.[3] We allow for the endogenous determination of the level of R&D fixed costs, which rise as more opportunities are researched simultaneously by rival firms. This reflects competition for inputs into R&D that are fixed in the short run. Coordinating different R&D projects also limits the scope of the firm's R&D operations.

Where multiple firms own facets on an opportunity, their legal costs $L(\gamma_{ik}, s_{ik}, h_k)$ depend on the absolute number of patented facets (γ_{ik}), on the share of patents per opportunity that a firm holds (s_{ik}), and on the extent to which they face hold-up (h_k). The first two channels capture the costs of defending a patent portfolio as the number of patents increases, while leaving scope for effects on bargaining costs that derive from the share of patents owned:[4] The hold-up parameter captures contexts in which several firms' core technologies become extremely closely intertwined. Then each firm has to simultaneously negotiate with many others to commercialize its products, which significantly raises costs.

[3] It also implies that there is no technological uncertainty. However, introducing technological uncertainty into the model does not change the main comparative statics results.

[4] Graevenitz et al. (2013) analyse alternative assumptions on legal costs.

$$(LC):\quad L(\gamma_{ik}, s_{ik}, h_k),\quad \text{where}\quad \frac{\partial L}{\partial \gamma_{ik}} > 0, \frac{\partial^2 L}{\partial \gamma_{ik}^2} \geq 0, \frac{\partial L}{\partial s_{ik}} \leq 0, \frac{\partial^2 L}{\partial s_{ik}^2} \geq 0, \quad (4)$$
$$\frac{\partial L}{\partial h_k} > 0, \frac{\partial^2 L}{\partial \gamma_{ik} \partial h_k} > 0, \frac{\partial^2 L}{\partial s_{ik} \partial h_k} > 0$$

All remaining cross partial derivatives of the legal costs function are zero.

In what follows, we use the following definitions:

$$\omega_k \equiv \frac{o_i}{O_k}, \quad \phi_k \equiv \frac{f_i}{F_k}, \quad \mu_k = \frac{\tilde{F}_k}{V(\tilde{F}_k)} \frac{\partial V(\tilde{F}_k)}{\partial \tilde{F}_k}, \quad \xi_k = \frac{s_k}{\Delta(s_k)} \frac{d\Delta(s_k)}{ds_k}, \quad \text{and} \quad \eta_k = \frac{f_i}{\tilde{F}_k} \frac{\partial \tilde{F}_k}{\partial f_i} .$$

2.2 Patenting and Entry

Firm *i*'s profits in technology *k*, $\pi_{ik}(o_i, f_i, F_k, O_k, N_k, h_k)$ is a function of the number of opportunities o_i in which the firm invests, the number of facets per opportunity f_i the firm seeks to patent, the total number of patentable facets per opportunity F_k, the number of technological opportunities a technology offers O_k, the number of firms entering the technology N_k, and the degree of hold-up in that technology h_k.

In this section we analyze the following two-stage game G^*:

Stage 1: Firms enter until $\pi_{ik}(o_i, f_i, F_k, O_k, N_k, h_k) = 0$;[5]

Stage 2: Firms simultaneously choose the number of opportunities, o_i, to invest in and the number of facets per opportunity, f_i, to patent in order to maximize profits π_{ik}.

We solve the game by backward induction and derive local comparative statics results for the symmetric extremal equilibria of the second stage game. For the subsequent analysis it is important to note that all equilibria of this second stage game are symmetric. In case that the second stage game has multiple equilibria we focus on the properties of the extremal equilibria when providing comparative statics results (Milgrom and Roberts, 1994; Amir and Lambson, 2000; Vives, 2005). Equilibrium values of the firms' choices are denoted by a superscript and we drop the firm specific subscripts in what follows, e.g., $\hat{\phi}_k$.

At stage two of the game each firm maximizes the following objective function:

$$\pi_{ik}(o_i, f_i) = o_i \left(V(\tilde{F}_k)\Delta(s_{ik}) - L(\gamma_{ik}, s_{ik}, h_k) - C_0 (\textstyle\sum_j^{N_O} o_j) - f_i p_k C_a \right) - C_c(o_i) \quad (5)$$

[5] We treat N_k as a continuous variable here, which is an abstraction that simplifies our analysis.

This expression shows that per opportunity k, the firm derives profits from its share $s_{ik} \equiv p_k f_i / \tilde{F}_k$ of patented facets, while facing legal costs L to appropriate those profits, as well as costs of R&D C_0, costs of maintaining its patent portfolio C_a, and coordination costs across opportunities C_c.

2.3 Simultaneous Entry with Multiple Facets

2.3.1 Comparative statics of patenting

We show that the second stage of this game is smooth supermodular:

Proposition 1

The second stage patenting game, defined in particular by assumptions (VF, eq. 2), (PB, eq.3) and (LC, eq. 5) is smooth supermodular if $\mu_k > \xi_{ik}$ *and if ownership of the technology is expected to be fragmented.*

This result generalizes Proposition 1 derived by Graevenitz *et al.* (2013).[6] Given this result we can show that:

Proposition 2

The potential for hold-up in complex technologies reduces patenting incentives.

In Appendix D we show that the expected legal costs of hold-up reduce the number of opportunities that firms invest in. In addition, firms with larger portfolios are more exposed to hold-up and benefit less from the share of patents they have patented per opportunity. Both effects combine to reduce the number of facets each firm applies for.

2.3.2 Comparative statics of entry

In Appendix C we show that there is a free entry equilibrium. In this equilibrium the following propositions hold:

Proposition 4

Under free entry greater complexity of a technology increases entry.

In the model, complexity has countervailing effects: first of all it increases profits, because it is less likely that duplicative R&D arises making each opportunity more valuable, this clearly increases incentives to enter. Next, given the level of patent applications ($\hat{f}_k$), complexity reduces the probability that each facet is patented, which reduces profits and entry incentives. Finally, complexity reduces competition for each facet, which increases the probability of patenting and increases innovation incentives.

[6] In our version of the model, it is no longer the case that the value function has to be increasing in the number of patented facets for supermodularity of the patenting game. We relegate further discussion of this result to Appendix C.

Overall we show that the positive effects outweigh the negative effects and incentives for entry rise with complexity of a technology.

To derive Proposition 4, consider how equilibrium profits are affected by the complexity of the technology F_k, the degree of technological opportunity O_k, and the potential for hold-up h_k:

$$\frac{\partial \pi(\hat{o},\hat{f})}{\partial F_k} = \hat{o}\frac{s_k}{F_k}\left((\varepsilon_{\tilde{F}_k,F_k} - \varepsilon_{p_k,F_k}\hat{\eta}_k)\left[V(\tilde{F}_k)\frac{\Delta(\hat{s}_k)}{\hat{s}_k}(\mu_k - \hat{\xi}_k) + \frac{\partial L}{\partial \hat{s}_k}\right]\right) > 0 \tag{6}$$

$$\frac{\partial \pi(\hat{o},\hat{f})}{\partial O_k} = \hat{o}\frac{\partial N_O}{\partial O_k}\frac{\hat{s}_k}{N_O}\left((\varepsilon_{\tilde{F}_k,N_O} - \varepsilon_{p_k,N_O}\hat{\eta}_k)\left[V(\tilde{F}_k)\frac{\Delta(\hat{s}_k)}{\hat{s}_k}(\mu_k - \hat{\xi}_k) + \frac{\partial L}{\partial \hat{s}_k}\right] - \frac{\partial C_O}{\partial N_O \hat{o}}\frac{N_O \hat{o}}{\hat{s}_k}\right) > 0 \tag{7}$$

$$\frac{\partial \pi(\hat{o},\hat{f})}{\partial h_k} = -\hat{o}\frac{\partial L}{\partial h_k} < 0 \tag{8}$$

Proposition 4 follows from the Implicit Function theorem once we know the sign of the derivative of profits w.r.t. F. Under free entry firms' profits decrease with entry:

$$\frac{\partial N}{\partial F_k} = -\frac{\partial \pi}{\partial F_k} \bigg/ \frac{\partial \pi}{\partial N_k} \tag{9}$$

Therefore, the Implicit Function theorem implies that the sign of the effect of complexity F on entry depends on the sign of the effect of complexity on profits.

Equation (6) shows that the effect of complexity on profits depends on the difference between the elasticities $\varepsilon_{\tilde{F}_k,F_k}$ and $\hat{\eta}_k$. The elasticity $\varepsilon_{p_k,F}$ is derived in Appendix C.1:

$$\varepsilon_{p_k,F_k} = N_O^2 \frac{\hat{\phi}_k - \frac{1}{2}\left(1 + \frac{1}{N_O}\right)}{1 - \hat{\phi}_k} \tag{10}$$

This elasticity is negative for $\hat{\phi}_k < 1/2$. The result implies that the first term in brackets in equation (6) is positive. The second term is positive when game G* is supermodular. Overall this implies that greater complexity induces entry. $\hat{\phi}_k < 1/2$ is one of two restrictions required for supermodularity of game *G**. This demonstrates that complexity increases entry in settings in which firms are playing a supermodular game and in which complexity also induces more patenting.[7]

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[7] When $\hat{\phi}_k \geq 1/2$ we no longer have the assumptions necessary to show supermodularity. This situation corresponds to the case where one firm has more than half the patents in a particular technology opportunity within a technology area. Thus our results may not hold when a specific opportunity is highly

Proposition 5

Under free entry greater technological opportunity increases entry.

For any given number of entrants an increase in technological opportunity reduces competition between firms for patents. This increases firms' expected profits and increases entry.

Continuing from the proof of Proposition 4 above, by the Implicit Function theorem the sign of the derivative of profits w.r.t. technological opportunity determines the effect of technological opportunity on entry:

$$\frac{\partial N}{\partial O_k} = -\frac{\partial \pi}{\partial O_k} \Big/ \frac{\partial \pi}{\partial N_k} \tag{11}$$

An increase in technological opportunity increases profits and entry. In Appendix C we show that the term in brackets in Equation (7) is negative under free entry. Profits increase as technological opportunity increases, because fewer firms enter per opportunity.

Proposition 6

Under free entry the potential for hold-up reduces entry.

An increase in the potential for hold-up raises firms' expected legal costs. This reduces expected profits and lowers potential for entry.

To derive this prediction, note that by the Implicit Function theorem the sign of the derivative of profits w.r.t. the level of hold-up in a technology area determines the effect of hold-up on entry:

$$\frac{\partial N}{\partial h_k} = -\frac{\partial \pi}{\partial h_k} \Big/ \frac{\partial \pi}{\partial N_k} \tag{12}$$

Hence, equation (8) shows that the effect of hold-up on entry derives from the increased legal costs that the possibility of hold-up imposes on affected firms.

2.4 Entry and Incumbency

The previous section sets out a model in which all firms entered and then invested in patents. At both stages firms' decisions were simultaneous. In Appendix D.5 we extend the model to a setting in which some firms, the incumbents, face lower costs ($C_O - \Psi$, where $\Psi > 0$) of entering opportunities. This captures the fact that incumbents have

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concentrated. In general this will not be the case, especially at our level of empirical analysis, but it would be interesting to explore this possibility in future work.

previous experience of doing R&D in a technology area. We demonstrate that our results are robust to this extension of the model.

2.5 Predictions of the Model

Our model predicts how the probability of entry into patenting depends on opportunity, complexity, hold-up potential and incumbents' experience. Here we summarize these predictions, which are tested empirically below:[8]

Prediction 1

Greater technological opportunity increases the probability of entry.

Greater technological opportunity reduces competition for facets per opportunity, which raises expected profits and thereby attracts entry.

Prediction 2

Greater complexity of a technology increases the probability of entry.

Greater complexity has countervailing effects: it reduces competition per facet as well as duplicative R&D, attracting entry. It also increases the likelihood that some of a technology remains unpatented, reducing its overall value and entry. Our model shows that overall complexity increases entry.

Prediction 3

Greater potential for hold-up reduces the probability of entry.

Hold-up potential increases expected costs of entry, reducing it.

Prediction 4

More experienced incumbents are more likely to enter technological opportunities new to them.

We show that incumbency advantage raises the number of opportunities that incumbents enter. This implies that they also enter new opportunities, which they have not previously been active in. This expansion of activity by incumbents crowds out entry by new entrants.

3 Data and Empirical Model

This section of the paper describes the data we use in the empirical test of our theoretical predictions. In particular, we discuss how we measure entry, how the set of potential entrants is identified, and which measures and covariates are used.

[8] Graevenitz *et al.* (2013) tested predictions from a more restrictive version of the model on the level of patent applications using data from the European Patent Office.

Our empirical model is a hazard rate model of firm entry into patenting in a technology area as a function of technological opportunity, technological complexity, hold-up potential that characterize a technology area. We test the predictions set out at the end of the previous section for these variables and for the effect of a firm's prior experience in patenting. Additional firm level covariates include the age and size of firms. The models we estimate are stratified at the industry level. That is, the unit of observation for each entry hazard is a firm-technology area, but the hazard shapes and levels are allowed to vary by the industry that the firm is in. This approach recognizes that patenting propensities vary across industries for reasons that may not be technological (e.g., strategic reasons, or reasons arising from the historical development of the sector).

We use a combination of firm level data for the entire population of UK firms registered with Companies House and data on patenting at the European Patent Office and at the Intellectual Property Office for the UK. The firm data comes from the data held at Companies House provided by Bureau van Dijk in their FAME database. European patent registers do not include reference numbers from company registers, nor does Bureau van Dijk provide the identification numbers used by patent offices in Europe. Linking the data from patent registers to firm register data requires matching of applicant names in patent documents and firm names in firm registers. In our work both a firm's current and previous name(s) were used for matching in order to account for changes in firm names. For more details on the matching of firm- and patent-level data see Appendix A.

Economic studies of entry are frequently hampered by the problem of identifying the correct set of potential entrants (Bresnahan and Reiss, 1991; Berry, 1992). In our case this problem is slightly mitigated by the fact that one set of potential entrants into patenting in a specific technology area consists of all those firms that currently patent in other technology areas. We complement this group of firms with a set of comparable firms from the population of UK firms that have not patented previously.

To construct the sample we deleted all firms from the data for which we have no size measure, because of missing data on assets. We select previously non-patenting firms from the population of all UK firms in two steps: 1) we delete all firms in industrial sectors with little patenting (amounting to less than 2 per cent of all patenting); and 2) we choose a sample of non-patenting firms that matches our sample of patenting firms by industry, size class, and age class. In principle, this approach will result in an endogenous (choice-based) sample. However our focus is on industry and technology area level effects rather than firm-level effects. Therefore we do not expect the sampling approach we adopt to introduce systematic biases into the estimates we report. We provide a number of robustness checks to ensure that our results are stable. These reveal that sample composition does not affect the key results we present below. All estimates are based on data weighted by the probability that a firm is in our sample.[9]

The sample that results from our selection criteria is a set of firms with non-missing assets in manufacturing, oil and gas extraction and quarrying, construction, utilities, trade, and selected business services including financial services that includes all (approximately 10,000) firms applying for a patent at the EPO or UKIPO during the 2001-2009 period and another 10,000 firms that did not apply for a patent.

The definition of technology areas that we use is 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 with priority dates between 2002 and 2009. A comparison of the frequency distribution of patenting across the technology areas from the two patent offices shows that firms are more likely to apply for patents in Chemicals at the EPO, while Electrical and Mechanical Engineering predominate in the national patent data (see the bottom panel in Table 1).

We treat entry into each technology area as a separate decision made by firms. More than half of firms we observe patent in more than one area and 10 per cent patent in more than four. From the 20,000 firms observed, each of which can potentially enter into each one of the 34 technology areas, we obtain about 700,000 observations at risk. We cluster the standard errors by firm, so our models are effectively firm random effects models for entry into 34 technology areas. Allowing firm choices to vary by technology area is sensible under the assumption that firms' patenting strategies are contingent upon technology and industry level factors and are not homogeneous across technology areas. We confirmed the validity of this assumption through interviews with leading UK patent attorneys.

There are some technology-industry combinations that do not occur, e.g. audio-visual technology and the paper industry, telecommunications technology and the pharmaceutical industry. In order to reduce the size of the sample, we drop all technology-industry combinations for which Lybbert and Zolas (2014) find no patenting in their data and for which there was no patenting by any UK firm from the relevant industry in the corresponding technology category. This removes about 30 per cent of observations from the data. We provide a robustness check for this procedure in Appendix B.

[Table 1 here]

[9] To check this, we estimated the model with and without weights based on our sampling methodology and find little difference in the results.

3.1 Variables

Dependent Variable - Entry

The dependent variable is a dichotomous variable taking the value one if a firm has entered a technology area k at time t and otherwise the value zero. Entry into a technology area is measured by the first time a firm applies for a patent that is classified in that technology area, dated by the priority year of the patent.

Technological opportunity

Our first prediction from the theoretical model is that there will be more entry in technology areas with greater technological opportunity. Additional reasons that a sector may have more or less patenting include sector "size" or "breadth" and the propensity of firms to patent in particular technologies for strategic reasons or because of varying patent effectiveness in protecting inventions. To control for both technological opportunity and these other factors, we include the logarithm of the aggregate EPO patent applications in the technology sector during the year. To capture opportunity more specifically we also include the past 5-year growth rate in the non-patent (scientific publication) references cited in patents in that technology class at the EPO.[10] We have found that the growth rate in non-patent references is a better predictor of entry than the level of non-patent references, which has been used previously. Presumably the growth rate is a better indicator because it capture new or expanded technological opportunity.

Technology complexity

The second prediction of the theoretical model is that technological complexity increases entry, other things equal. Our interpretation of complexity is that it implies many interconnections between inventions in a particular field, rather than a series of fairly isolated inventions that do not connect to each other. To construct such a measure, we use the concept of network density applied to citations among all the patents that have issued in the particular technology area during the 10 years prior to the date of potential entry. We use citations at the U.S. patent office, both because these are richer (averaging 7 or so cites per patent during this period versus 3 for the EPO) and also to minimize correlation with the thickets measure, which is based on EPO data.[11]

The network density measure is computed as follows: in any year t, there are N_{kt} patents that have been applied for in technology area k between 1975 and year t. Each of these patents can cite any of the patents that were applied for earlier, which implies that the

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[10] See Graevenitz *et al.* (2013) for a more extensive discussion of this variable in the literature.

[11] It is important to emphasize that although patent offices cooperate and share search reports citations listed on U.S. patents are largely proposed by the applicant, whilst the citations listed on EPO and IPO patents are inserted by the examiner. This explains why the two measures are not highly correlated.

maximum number of citations within the technology area is given by $N_{kt}(N_{kt}-1)/2$. We count the actual number of citations made and normalize them by this quantity, scaling the measure by one million for visibility, given its small size.

Patent Thickets

The third prediction of our model is that greater potential for hold-up reduces entry. We measure the potential for hold-up in patent thickets using the triples count proposed by von Graevenitz *et al.* (2011). This is a narrower interpretation of this measure than in several previous papers, where it has been used as a proxy for complexity of a technology. In those papers complexity and hold-up potential have the same effect. In contrast, our model provides opposite predictions for the effects of complexity of a technology and potential for hold-up.

The triples measure corresponds to a count of the number of fully connected triads on the set of firms' critical patent citations. At time t each unidirectional link between two firms A and B corresponds to one or more critical references to firm A's patents in the set of patents applied for by firm B in the years t, $t-1$ and $t-2$. We use the same measure of triples as Harhoff *et al.* (2015), which contains all triples in each technology area. The citation data used is extracted from PATSTAT (October 2011 edition).[12] 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.

The triples measure has been used in a number of papers since it was suggested by Graevenitz *et al.* (2011). They 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). Fischer and Henkel (2012) find that the measure predicts patent acquisitions by Non-Practicing Entities. Graevenitz *et al.* (2013) use the measure to study patenting incentives in patent thickets and Harhoff *et al.* (2015) show that opposition to patent applications falls in patent thickets, particularly for patents of those firms that are caught up in the thickets.

As a robustness check, we have also explored the use of duples, i.e. the count of mutual blocking relationships, to measure hold-up potential. Combining both measures in one regression leads to thorny problems of interpretation. Taken alone the measure has similar effects as the triples measure in this context.

[Table 2 here]

[12] Triples data was kindly provided by Harhoff et al. (2015).

Covariates

It is well known that firm size and industry are important predictors of whether a firm patents at all (Bound *et al.* 1984 for U.S. data). Hall *et al.* (2013) show this for UK patenting during the period studied here. Therefore, in all of our regressions we control for firm size, industrial sector, and year of observation. We include the logarithm of the firm's reported assets and a set of year dummies in all the regressions.[13] To control for industrial sector, we stratify by industry, which effectively means that each industry has its own hazard function, which is shifted up or down by the other regressors.

We also expect the likelihood that a firm will enter a particular technology area to depend on its prior patenting experience overall, as well as its age. Long-established firms are less likely to be exploring new technology areas in which to compete. Thus we include the logarithm of firm age and the logarithm of the stock of prior patents applied for in any technology by the firm, lagged one year to avoid any endogeneity concerns. The variables on firm size and patent stock also allow us to test *Prediction 4* about the effect of incumbency advantage on entry.

3.2 Descriptive Statistics

Our estimation sample contains about 20,000 firms and 700,000 firm-TF34 sector combinations. During the 2002-2009 period there are about 10,000 entries into patenting for the first time in a technology area by these firms. Table A-2 shows the distribution of the number of entries per firm: 2,531 enter one class, and the rest enter more than one. Table A-2 shows the population of UK firms obtained from FAME in our industries, together with the shares in each industry that have applied for a UK or European 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.

Empirical Model

We use hazard models to estimate the probability of entry into a technology area. The models express the probability that a firm enters into patenting in a certain area 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. 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,

[13] 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.

how to interpret the results, and present some robustness checks. 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. In the body of the paper we present results using the well-known Cox proportional hazards model stratified by industry. Results from the accelerated failure time models were similar but the estimated effects are somewhat larger (shown in Appendix B).

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 presents estimates of our model using 1900 instead of 1978 as the earliest at risk year and finds little difference in the estimates.[14] 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 the Cox proportional hazards 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 a different distribution of the time until entry into patenting conditional on the regressors. That is, each industry has its own "failure" time distribution, where failure is defined as entry into patenting in a technology area, but the level of this distribution is also modified by the firm's size, aggregate patenting in the technology, network density, and the triples density.

4 Results

Our estimates of the model for entry into patenting are shown in Table 3. All regressions control for size, age, and industry. Both size and age are strongly positively associated with entry into patenting in a new technological area. Our indicator of technological opportunity and technology class size, the log of current patent

[14] The main difference is in the firm age coefficient. Because the models are nonlinear, this coefficient is identified even in the presence of year dummies and vintage/cohort (which is implied by the survival model formulation). However it will be highly sensitive to the assumptions about vintage due to the age-year-cohort identity.

applications in the technology class, is also positively associated with entry into that class, as predicted by our model.

Column 3 of Table 3 contains the basic result from our data and estimation, which is fully consistent with the predictions of our model: greater complexity as measured by citation network density increases the probability of entry into a technology area, as does technological opportunity, measured both as prior patenting in the class and as growth in the relevant science literature. Controlling for both technological opportunity and complexity, firms are discouraged from entry into areas with a greater density of triple relationships among existing firms. We interpret this latter result as an indicator of the discouraging effect of holdup possibilities or the legal costs associated with negotiation of rights or defense in the case of litigation.

We were concerned that our network density (complexity) and triples density (hold-up potential) measures might be too closely related to convey separate information, but we found that the raw correlation between these two variables was -0.001. To check for the impact of potential correlation conditional on year, industry, and the other variables, in columns 1 and 2 of Table 3 we included these two measures of complexity/thickets separately and found that although the coefficients were very slightly lower in absolute value, the results still hold, although it is clear that the aggregate class size is correlated negatively with the triples density via the denominator of the density (compare the change in the log (patents in class) coefficient between columns 1 and 2).

As we show in Appendix B, the estimated coefficients in the table are estimates of the elasticity of the yearly hazard rate with respect to the variable, and do not depend on the industry specific proportional hazard. A one standard deviation increase in the log of network density is associated with a 32 percent increase in the hazard of entry (0.13*2.78), while a one standard deviation in the log of triples density is associated with a 20 percent decrease in the hazard of entry (0.14*1.44). Thus the differences across these technology areas in the willingness of firms to enter them is substantial, bearing in mind that the average probability of entry is only about 1.5 per cent in this sample.

[Table 3 here]

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 fourth column of Table 3, we add the logarithm of past patenting by the firm. 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 100% higher hazard of entry.

In the last column we interact the log of assets with the log of patents, the log of network density, the growth of non-patent literature, and the log of triples density to see whether these effects vary by firm size. The results show that the network density and technological opportunity effects decline slightly with firm size. The triples density effect does not show any size relationship, suggesting that hold-up concerns affect firms of all sizes proportionately. We show this graphically in Figure 1, which overlays the coefficients 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 network density, and that both fall to zero for the largest firms. Growth in non-patent literature is positively associated with technology entry for small firms, but negatively for large firms, suggesting the role played by the smaller firms in newer technologies based on science. Large firms seem not to be as active in these areas. Controlling for all these features of a technology, the impact of triples density is uniformly negative across firm size, which contradicts the view that the potential for hold-up discourages entry by smaller firms more than by larger firms.

4.1 Robustness

Table B-2 in the appendix explores some variations of the sample used for estimation in Table 3. Column 1 of Table B-2 is the same as column 4 of Table 3 for comparison. The first change (column 2) was to add back 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. These observations are about 20 per cent of the sample. The impact of network density on entry is weaker, but the impact of triples density and the technological opportunity variables is considerably stronger. That is, technology area-industry combinations with no patenting are also those where the technology area displays low technological opportunity.

Next we removed all the firms with assets greater than 12.5 million pounds, to check whether large firms were responsible for our findings.[15] This removed about 2 per cent of the 20,000 firms. Column 3 of Table B-2 shows that the results do not change a great deal, although they are somewhat stronger. In column 4, 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. The last column of Table B-2 shows the results of defining the minimum entry year as 1900. With the exception of firm age, the coefficients are nearly identical to those in column 1 of the table.

[15] 12.5 million pounds is a cutoff based on the definition of Small and Medium-sized Enterprises (SMEs) as firms with fewer than 250 employees. We do not have employment for all our firms, so we assume that assets are approximately 50 thousand pounds per employee in order to compute this measure. For small firms only, this yields an assets cutoff of 2.5 million pounds.

5 Conclusion

Patent thickets arise for a multitude of reasons; they are mainly driven by an increase in the number of patent filings and concomitant reductions in patent quality (that is, the extent to which the patent satisfies the requirements of patentability) as well as increased technological complexity and interdependence of technological components. The theoretical analysis of patent thickets (Shapiro, 2001) and the qualitative evidence provided by the FTC in a number of reports (FTC, 2003; 2011) suggest that thickets impose significant costs on some firms. The subsequent literature has focused on the measurement of thickets (e.g. Graevenitz *et al.* 2011; Ziedonis, 2004) and has linked thickets to changes in firms' IP strategies in a number of dimensions. There is still a lack of evidence on the effect of patent thickets as well as their welfare implications at the aggregate level.

The empirical analysis of the effects of patent thickets must contend with two challenges: first, patent thickets have to be measured and secondly, effects of thickets must be separated from effects of other factors that are correlated with the growth of thickets, in particular technological complexity.

This paper confronts both challenges. We show that our empirical measure for the density of thickets captures effects of patent thickets predicted by theory. This supports results by von Graevenitz *et al.* (2011, 2013) and Harhoff *et al.* (2015) showing that the coefficients on the triples measure capture predicted effects of patent thickets on patenting and opposition. The paper also separates the impact of patent thickets on entry from effects of technological opportunity and complexity and shows that the hold-up potential created by thickets reduces entry into patenting. Controlling for technological opportunity and complexity is important because both are correlated with entry into patenting and the presence of thickets. It is also worth emphasizing that our measure of thickets is purged of effects that are driven by patenting trends in particular technologies. That is, our results are not due to the level of invention and technological progress within a technology field.

Our results demonstrate that patent thickets significantly reduce entry into those technology areas in which growing complexity and growing opportunity increase the underlying demand for patent protection. These are the technology areas, which are associated most with productivity growth in the knowledge economy. However, the welfare consequences of our finding are unclear. Reduced entry into new technology areas could be welfare-enhancing: As is well known from the industrial organization literature, entry into a market may be excessive if entry creates negative externalities for active firms, for instance due to business stealing. This is likely to be true of patenting too. Furthermore, Arora *et al.* (2008) show that the patent premium does not cover the costs of patenting for the average patent (except for pharmaceuticals). These and related facts might lead one to conclude that lower entry into patenting is likely to increase welfare and that thickets raise welfare by reducing entry.

In contrast, reduced entry into patenting in new technology areas may also be welfare-reducing, for at least two reasons. First, there is the obvious argument that the benefits from more innovation may exceed any business stealing costs (as has been shown empirically in the past by others, e.g., Bloom *et al.* 2013), so that some desirable innovation may be deterred by high entry costs. Even if this were not true, there is no reason to believe that firms that do not enter into patenting due to thickets are those we wish to deter. Given the incumbency advantage, it is likely that the failure to enter into patenting in these areas reflects less innovation by those who bring the most original ideas, that is, by those who are inventing "outside the box."

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Appendix A: 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.[16] 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 be constructed consistently. The update undertaken by the 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.

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

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).

[Tables A-1, A-2, and A-3 here]

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:

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

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

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:

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

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:

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

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

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*:[17]

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

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 Table B-2, 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.

[Tables B-1 and B-2 here]

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