Oxford Economic Papers, 2020, 1–24
doi: 10.1093/oep/gpaa034

Technology entry in the presence of patent thickets

By Bronwyn H. Hall[a,b,c], Georg von Graevenitz[d,e], and Christian Helmers[f]

[a]UC Berkeley, 530 Evans Hall, Berkeley, CA 94720, USA, bhhall@berkeley.edu
[b]NBER, 1050 Massachusetts Ave, Cambridge, MA 02138, USA
[c]Max Planck Institute for Innovation and Competition, Marstallplatz 1, Munich 80539, Germany
[d]Queen Mary University, Mile End Rd, Bethnal Green, London E1 4NS, UK, g.v.graevenitz@qmul.ac.uk
[e]Centre for Competition Policy, University of East Anglia, Norwich NR4 7TJ, UK
[f]Santa Clara University, 500 El Camino Real, Santa Clara, CA 95053, USA, chelmers@scu.edu

Abstract

We analyse how patent thickets affect entry into patenting. A model of entry into patenting that allows for variation in technological opportunity, technological complexity and the extent of patent thickets is developed and analysed. Using UK data we then show that patent thickets are associated with a reduction of first time patenting in a technology controlling for the level of technological complexity and opportunity. Technologies characterized by more technological complexity and opportunity attract more entry into patenting. Our evidence indicates that patent thickets raise entry costs, which leads to less entry into technologies regardless of a firm's size.

JEL classifications: K11, L20, O31, O34

1. Introduction

The past two decades have seen an enormous increase in patent filings worldwide (Fink *et al.*, 2016). There are signs that the high level of patenting may be reducing innovation in certain technologies (FTC, 2003; Jaffe and Lerner, 2004; Bessen and Meurer, 2008; FTC, 2011; Schankerman and Schuett, 2016). Companies drawing on these technologies face elevated legal costs of commercializing innovative products when patents that contain overlapping claims form so-called 'patent thickets' (Shapiro, 2001). Patent thickets arise where products draw on technology protected by hundreds or even thousands of patents and these patents have fuzzy boundaries. The precision with which patent claims are formulated varies across technologies. Paradoxically claim language is quite loose in some high technology fields in which the volume of applications has been high.[1] In addition, resource constraints at patent offices have contributed to a flow of poorly delineated patents (Lei and Wright, 2017). Patents in thickets belong to many competing firms. This complicates licensing negotiations, raises the incidence of litigation, and creates incentives to add more, often weak patents to the patent system (Allison *et al.*, 2015). The increased transaction costs associated with patent thickets reduce profits from commercialization of innovation, and ultimately may reduce incentives to innovate.

Empirical research on patent thickets has been largely concerned with showing that they exist and measuring their density (Ziedonis, 2004; von Graevenitz *et al.*, 2011). There is less evidence on the effects patent thickets have on firms' objectives. Cockburn and MacGarvie (2011) demonstrate that patenting levels affect product market entry in the software industry. This result echoes earlier findings by Lerner (1995) who showed that first-time patenting in a given technology is affected by the presence of other companies' patents in a small sample of US biotech companies. Both papers use patent counts in narrow technological fields to measure thickets. In this article we use a network measure of patent overlap by technology area as a proxy for thickets. The measure is correlated with increased patenting (von Graevenitz *et al.*, 2013), increased acquisition of patents by Non-Practicing Entities (NPEs) (Fischer and Henkel, 2012) and a lower likelihood of patent opposition proceedings (Harhoff *et al.*, 2016).

Bessen and Meurer (2013) argue that patent thickets will lead to increased litigation due to hold-up. They use the term to describe a situation where an alleged infringer faces the threat of an injunction or high licensing costs after she has sunk investment.[2] Patent thickets have remained a concern of antitrust agencies and regulators in the USA for over a decade (FTC, 2003; U.S. Department of Justice and Federal Trade Commission, 2007; FTC, 2011). Reforms that address some of the factors contributing to the growth of patent thickets have recently been introduced in the USA (America Invents Act of 2011) and by the European Patent Office (EPO).

Another perspective is provided by authors who argue that patent thickets are a feature of rapidly developing technologies in which technological opportunities abound (Teece, 2018). Here thickets are a reflection of fast technological progress that is paired with increased technological complexity (Lewis and Mott, 2013). Increased transaction costs associated with patent thickets and the benefits of technological complexity and opportunity often coincide. There may be a trade-off between technological opportunity and growth on the one hand and increased transaction costs due to the emergence of patent thickets on

1 Allison *et al.* (2015) document that for the population of patents for which litigation was initiated in 2008 and 2009 in the USA, none or very few failed due to indefiniteness in Mechanical Engineering, Biotechnology or Chemistry, whereas this was true for nearly a third of cases in Electronics and a quarter in Software. Bessen and Meurer (2008) argue that language used to specify patent boundaries in Chemistry and Biology is more scientific than that used for software patents. Allison and Ouellette (2015) study all cases since 1982 in the USA decided on basis of claim indefiniteness. They find that patents from the Computer/Electronics industry failed on the basis of enablement more frequently than other industries. Enablement is the requirement that a patent must 'teach one skilled in the art to make and use' an invention (Burk and Lemley, 2008).

2 'High licensing costs' refers to costs that are higher than those that would have been negotiated *ex ante* in the presence of possible 'invent around' before the alleged infringer sank her investment. This possibility can arise because of either prohibitive search costs or fuzzy patent boundaries or both (Mulligan and Lee, 2012).

the other—if the transaction costs of patenting in complex technologies are not avoidable. The challenge in assessing technologies with high levels of patenting is to develop a framework that captures the main factors that incentivize patenting and the costs and benefits thereof.

This article focuses on entry into patenting across a wide range of industries. This is a focal outcome that has been analysed in specific industries (Lerner, 1995; Cockburn and MacGarvie, 2011). We make two contributions to this literature: first, we introduce a model to show how patent thickets, technological opportunity and complexity interact to determine levels of entry and second, we test predictions derived from the model using firm-level data on entry into patenting by firms in the UK.

We model how entry decisions are affected by technological opportunity and legal uncertainty over patent boundaries building on previous work by von Graevenitz *et al.* (2013). The model focuses on the interaction between firms through two channels: (i) legal costs associated with patent enforcement, and (ii) incumbency advantages in R&D fixed costs. In contrast to von Graevenitz *et al.* (2013), we distinguish between technological complexity *per se*, which is a feature of some technologies, and patent thicket density, which arises from poor drafting of patents in a complex technology. Poor drafting increases transaction costs for firms. Specifically, transaction costs may rise due to actual hold-up, or through higher costs of licensing and greater complexity of clearing products when patent breadth is uncertain. We refer to all three as hold-up potential. Our model shows that patent thickets reduce entry into patenting.[3] The model also shows that higher complexity and opportunity are associated with increased entry into patenting, because competition for each innovation is reduced and the probability that entrants can establish themselves in a technology is increased. Where incumbency implies lower costs of R&D, incumbents patent more than entrants.

These predictions are tested empirically using data from the UK. We quantify of the importance of technological opportunity, complexity, and patent thickets on entry into patenting. To do this, separate measures of technological opportunity, technological complexity, and hold-up potential due to thickets are constructed and validated. Separating technological complexity and hold-up potential in patent thickets empirically is an important improvement over the analysis in von Graevenitz *et al.* (2013), who conflated complexity and hold-up potential arising from existing patent portfolios. We introduce a new measure of technological complexity that relies on US patent data to mitigate endogeneity concerns and we sharpen the definition of the network measure of patent overlap as a proxy for hold-up potential.[4]

The analysis of entry in this article confirms that greater technological opportunity and complexity *increase* entry and that hold-up potential *reduces* entry substantially. We show that these findings are robust to various assumptions underlying our empirical approach. While we cannot quantify the overall net welfare effect, our results indicate that patent

3 The model generates the same comparative statics for patent application *levels* as von Graevenitz *et al.* (2013).

4 To further validate our approach, we verify the effect of distinguishing between technological complexity and hold-up in the data used by von Graevenitz *et al.* (2013)for their analysis. The results, which are reported in Online Appendix D, are consistent with our interpretation of the patents thickets measure as a measure of hold-up potential, and of the citation network density as a measure of complexity.

thickets raise entry costs for large and small firms alike. This is true regardless of any positive effects that arise from greater technological opportunity and complexity. To the extent that more original and radical, rather than incremental ideas come from new entrants rather than incumbents (Tushman and Anderson, 1986; Henderson, 1993), reduced entry is likely to have negative long-run consequences on innovation and product market competition. In combination with earlier results by von Graevenitz *et al.* (2013), who point to a positive correlation between patenting levels and the presence of thickets, our results suggest that any increases in transaction costs due to thickets can potentially have important dynamic effects on innovation.

The remainder of this article 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 results of a model of entry into patenting.[5] We show how firms' decisions to enter into patenting depend on: (i) complexity of a technology, (ii) technological opportunity, and (iii) the potential for hold-up in patent thickets. The model has two stages: entry and patenting. The patenting stage generalizes analysis in von Graevenitz *et al.* (2013).[6] Here we focus on novel predictions derived from free entry that are then tested in Section 4. We solve the model by backward induction. Main results on entry into patenting are that greater technological opportunity and complexity increase entry, while the threat of increased legal costs in patent thickets reduces entry.

In the model a technology consists of a set of opportunities, each of which consists of a number of patentable 'facets'. Opportunities within a technology share the same number of facets, while complexity of the technology is determined by the count of facets per opportunity. More opportunity within a technology attracts entrants as more avenues arise to earn a profit through application of the technology. Greater complexity of a technology also attracts entrants, because entrants are more likely to gain a share of profits flowing from opportunities. Where multiple firms hold patents on the same opportunity, licensing negotiations or litigation ensue as firms divide the profits flowing from the opportunity. We assume that holding a larger share of patents on an opportunity is beneficial for firms in terms of licensing or litigation, but less so when thickets arise from poorly delineated patents that provide increased options to litigate. This captures the costs imposed by thickets on patentees.

2.1 Notation and assumptions

The key variables of the model are the complexity of a technology k, measured by F_k ($F_k \in \mathbb{R}_0^+$), the degree of technological opportunity, measured by O_k ($O_k \in \mathbb{R}_0^+$), and hold-up potential h_k. The value of all $\tilde{F}_k$ patents granted 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 complex technologies this is the value of owning rights to use all patents

5 Details are relegated to Appendices A and B.

6 We generalize their model to allow analysis of entry. Their main findings on patenting levels still hold. For sake of brevity we relegate analysis on levels of patenting to the Online Appendix.

(facets) granted for 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 seek to patent.

In equilibrium only $\tilde{F}_k = (1-(1-\hat{f}_k/F_k)^{N_o+1})$ facets are patented,[7] where $\hat{f}_k$ is the equilibrium number of facets chosen by applicants and N_O is the number of firms that applied for patents on a specific opportunity.[8] As $\tilde{F}_k$ may be smaller than F_k the total value of patenting in a technology is $V_k(\tilde{F}_k) \leq V_k(F_k)$.

To simplify the modeling of simultaneous patenting of facets on multiple opportunities we assume that firms choose how many opportunities o_i and facets f_i to invest in. Which subset of facets per opportunity each firm invests in is random. The allocation of a facet among the firms seeking to patent it is also random. Then probability p_i that a facet is allocated to firm i is:[9]

$$p_i(\mathbf{f}i\!\!\!/, F_k, N_O(O_k, \mathbf{o}i\!\!\!/, N)) = \sum_{j=0}^{N_O} \frac{1}{j+1} \binom{N_O}{j} \prod_{l=0}^{N_O-j} \left(1 - \frac{f_l}{F_k}\right) \prod_{m=N_O-j}^{N_O} \frac{f_m}{F_k} \quad . \tag{1}$$

where $\mathbf{f}i\!\!\!/, \mathbf{o}i\!\!\!/$ are vectors containing the choices of the number of facets and the number of opportunities to invest in, made by all rival firms j. The expected number of patents a firm owns when it applies for f_i facets is $\gamma_i \equiv p_i f_i$.

Profits of firm i patenting technology k, π_{ik}, increase in the share of patents the firm owns per opportunity s_{ik}, where $s_{ik} \equiv p_i f_i / \tilde{F}_k$. Profits are concave in this share through $\Delta(s_{ik})$, capturing the decreasing marginal benefit of patent portfolio size in complex technologies.

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

$$(\text{VF}):\ V_k(0) = 0, \frac{\partial V_k}{\partial \tilde{F}_k} > 0; \tag{2}$$

$$(\text{PB}):\ \Delta(0) = 0, \frac{d\Delta(s_{ik})}{ds_{ik}} > 0 \text{ and } \frac{d^2\Delta(s_{ik})}{d^2 s_{ik}} < 0\,. \tag{3}$$

The model contains three types of patenting costs:

- R&D costs per opportunity, a function of total R&D activity per opportunity: $C_o(\sum_j^{N_o} o_j)$;
- maintaining each granted patent in force: C_a;
- coordinating R&D on *different* technological opportunities $C_c(o_i)$, where $\frac{\partial C_c}{\partial o_i} > 0$.

These assumptions imply that R&D costs are fixed costs.[10] 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, e.g. scientists and engineers that are in fixed supply in the short run (Goolsbee, 1998).

Where multiple firms own facets on an opportunity, their legal costs $L(\gamma_i, s_{ik}, h_k)$ depend on the absolute number of patented facets γ_i, on the share of patents per opportunity that a

7 See Online Appendix A.3 for more details.

8 The properties of N_O are summarized in Online Appendix A.2.

9 See Online Appendix A.1.

10 It also implies that there is no technological uncertainty. Introducing technological uncertainty into the model does not change the main comparative statics results.

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: 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 transaction costs.

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

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

In what follows, we use the following definitions:

$$\omega_{ik} \equiv \frac{o_i}{O_k}, \quad \phi_{ik} \equiv \frac{f_i}{F_k}, \quad \mu_k \equiv \frac{\tilde{F}_k}{V_k(\tilde{F}_k)} \frac{\partial V_k(\tilde{F}_k)}{\partial \tilde{F}_k}, \quad \xi_{ik} \equiv \frac{s_{ik}}{\Delta(s_{ik})} \frac{\partial \Delta(s_{ik})}{\partial s_{ik}}, \quad \eta_{ik} \equiv \frac{f_i}{\tilde{F}_k} \frac{\partial \tilde{F}_k}{\partial f_i} \quad . \tag{5}$$

Here ω_{ik} is the share of opportunities each firm chooses to pursue, ϕ_{ik} is the share of facets each firm seeks to patent per opportunity, μ_k is the elasticity of the value function with respect to the level of complexity, ξ_{ik} is the elasticity of the benefits function Δ with respect to the share of patents each firm is granted and η_{ik} is the elasticity of the number of covered facets with respect to the number of patent applications of each firm.

2.2 Patenting and entry

Firm i's profits in technology k, $\pi_{ik}(o_i, f_i, F_k, O_k, N_k, h_k)$, are a function of the number of opportunities o_i which the firm invests in, 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 analyse the following two-stage game G^*:

Step 1: Firms enter until $\pi_{ik}(o_i, f_i, F_k, O_k, N_k, h_k) = 0$;[11]

Step 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).

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

11 N_k is the superset of all firms applying for patents within all opportunities of technology k. We treat N_k and the N_O as a continuous variables to simplify analysis of the model.

$$\pi_{ik}(o_i, f_i) = o_i \left(V_k(\tilde{F}_k)\Delta(s_{ik}) - L(\gamma_i, s_{ik}, h_k) - C_o(\sum_j^{N_o} o_j) - f_i p_i C_a \right) - C_c(o_i) \quad . \tag{6}$$

This expression shows that per opportunity k, the firm derives profits from its share s_{ik} 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.

This objective function generalizes that analysed by von Graevenitz *et al.* (2013). They assume that the value of patenting increases linearly in the share of patents the firm owns per opportunity ($\Delta(s_{ik}) = s_{ik}$) and do not allow for a direct effect of hold-up (h_k) on legal costs. Under free entry the model in von Graevenitz *et al.* (2013) does not have a solution, while the model developed here does. Generalizing the objective function also has direct implications for an empirical test of the theory: separate measures of complexity and hold-up are required. The measures we employ in our empirical analysis are discussed in Section 3.

2.3 Simultaneous entry with multiple facets

In Online Appendix B we show that the results derived by von Graevenitz *et al.* (2013) for patenting hold in our generalized model. This section summarizes new results on entry.

2.3.1 Comparative statics of entry In Online Appendix B.4 we show that there is a free entry equilibrium. In this equilibrium the following propositions hold:

Proposition 1 Under free entry greater complexity of a technology increases entry.

Complexity has countervailing effects: first, 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. It is shown that the positive effects outweigh the negative effects.

First, 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:[12]

$$\frac{\partial \hat{\pi}_k(\hat{o}_k, \hat{f}_k)}{\partial F_k} = \hat{o}_k \frac{\hat{s}_k}{F_k} \left(\left(\hat{\varepsilon}_{\tilde{F}_k, F_k} - \hat{\varepsilon}_{p_k, F_k} \hat{\eta}_k\right) \overbrace{\left[V_k\left(\hat{\tilde{F}}_k\right) \frac{\Delta(\hat{s}_k)}{\hat{s}_k} \left(\hat{\mu}_k - \hat{\xi}_k\right) + \frac{\partial L}{\partial \hat{s}_k} \right]}^{\Lambda} \right) > 0 \tag{7}$$

$$\frac{\partial \hat{\pi}_k(\hat{o}_k, \hat{f}_k)}{\partial O_k} = \hat{o}_k \frac{\partial \hat{N}_O}{\partial O_k} \frac{\hat{s}_k}{\hat{N}_O} \left(\left(\hat{\varepsilon}_{\tilde{F}_k, N_O} - \hat{\varepsilon}_{p_k, N_O} \hat{\eta}_k\right) \Lambda - \frac{\partial C_o}{\partial \hat{N}_O \hat{o}} \frac{\hat{N}_O \hat{o}}{\hat{s}_k} \right) > 0 \tag{8}$$

$$\frac{\partial \hat{\pi}_k(\hat{o}_k, \hat{f}_k)}{\partial h_k} = -\hat{o}_k \frac{\partial L}{\partial h_k} < 0 \tag{9}$$

12 Equilibrium values of the firms' choices are denoted by a hat $\hat{()}$ and we drop firm specific subscripts, e.g. $\hat{\phi}_k$. We define $\Lambda \equiv \left[V_k(\hat{\tilde{F}}_k) \frac{\Delta(\hat{s}_k)}{\hat{s}_k} (\hat{\mu}_k - \hat{\xi}_k) + \frac{\partial L}{\partial \hat{s}_k} \right]$ to simplify expressions.

Proposition 3 follows from the Implicit Function theorem once we know the sign of the derivative of profits with respect to F_k. Under free entry firms' profits decrease with entry:

$$\frac{\partial N_k}{\partial F_k} = -\frac{\frac{\partial \hat{\pi}_k}{\partial F_k}}{\frac{\partial \hat{\pi}_k}{\partial N_k}} \tag{10}$$

and the sign of the effect of complexity F_k on entry depends on the sign of the effect of complexity on profits.

Equation (7) shows that the effect of complexity on profits depends on the difference between the elasticities $\hat{\varepsilon}_{\tilde{F}_k,F_k}$ and $\hat{\varepsilon}_{p_k,F_k}\hat{\eta}_k$, which are derived in Appendices A.1 and A.3. Specifically, $\hat{\varepsilon}_{p_k,F_k}$ is shown to be:

$$\hat{\varepsilon}_{p_k,F_k} = \hat{N}_O^2 \frac{\hat{\phi}_k - \frac{1}{2}\left(1 + \frac{1}{\hat{N}_O}\right)}{1 - \hat{\phi}_k} \tag{11}$$

This elasticity is negative for $\hat{\phi}_k < \frac{1}{2}$, which is also a precondition for supermodularity of game G*. We find that both terms in brackets in eq. (7) are positive, when game G* is supermodular. This implies that greater complexity raises profits and this induces entry.[13]

Proposition 2 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 1 above, by the Implicit Function theorem the sign of the derivative of profits with respect to technological opportunity determines the effect of technological opportunity on entry:

$$\frac{\partial N_k}{\partial O_k} = -\frac{\frac{\partial \hat{\pi}_k}{\partial O_k}}{\frac{\partial \hat{\pi}_k}{\partial N_k}} \tag{12}$$

An increase in technological opportunity increases profits and entry. In Online Appendix B.4 we show that the term in brackets in eq. (8) is negative under free entry and that $\frac{\partial N_O}{\partial O_k} < 0$. Profits increase as technological opportunity increases, as entry per opportunity falls.

Proposition 3 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 with respect to the level of hold-up in a technology area determines the effect of hold-up on entry:

13 When $\hat{\phi}_k \geq \frac{1}{2}$ game G* is no longer supermodular. 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 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.

$$\frac{\partial N_k}{\partial h_k} = -\frac{\frac{\partial \hat{\pi}_k}{\partial h_k}}{\frac{\partial \hat{\pi}_k}{\partial N_k}} \tag{13}$$

Hence, eq. (9) 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

In our model firms' decisions on entry are simultaneous, which is motivated by a focus on first-order effects as in the literature on excess entry (Mankiw and Whinston, 1986; Suzumura and Kiyono, 1987). Our purpose is to make predictions across a wide range of patenting industries, which we can do without recourse to data on product market outcomes. While this means that we cannot analyse dynamic evolution of patent thickets or sequential entry, we can allow for asymmetries between firms.

In Online Appendix B.6 we extend the model to asymmetric equilibria, in which some firms (incumbents), face lower costs ($C_O - \Psi$, where $\Psi > 0$) of entering opportunities. This way we model observable heterogeneity in the experience of doing R&D in a technology area. The main results derived above are robust to this variant of the model. In addition, we show that more experienced incumbents enter more opportunities, crowding out new entrants.

2.5 Predictions of the model

Here we summarize the predictions of the model that we test empirically:[14]

Prediction 1 The probability of entry increases in technological opportunity.

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

Prediction 2 The probability of entry increases in complexity of a technology.

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 The probability of entry falls in the potential for hold-up.

Hold-up potential increases expected costs of entry, thereby 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 firms.

14 Note that von Graevenitz *et al.* (2013) test predictions from a more restrictive version of the model on the *level* of patent applications using data from the EPO. We replicate their analysis in Online Appendix D using additional variables suggested by the generalized model we present here.

3. Data and empirical model

Our empirical model is a hazard rate model of firm entry into patenting in a technology area as a function of the technological opportunity, technological complexity, and hold-up potential that characterize a technology area. Additional firm level covariates include the age, size, and prior patenting history, and the concentration of their four-digit industry. The models we estimate are stratified at both the firm and 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 either by firm or by the industry containing the firm. This approach recognizes that patenting propensities vary across firms and industries for reasons that may not be technological (e.g. strategic reasons, or reasons arising from the historical development of the sector).

We use firm-level data for the entire population of UK firms registered with Companies House and data on patenting at the EPO and at the UK Intellectual Property Office (UKIPO). The firm data come from the data held at Companies House provided by Bureau van Dijk in their Financial Analysis Made Easy (FAME) database. The patent data were linked to firm register data by matching applicant names in patent documents and firm names in firm registers (see Online Appendix C for details).

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 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 had 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: (i) we delete all firms in industrial sectors with little patenting (amounting to less than 2% of all patenting), and (ii) we choose a sample of non-patenting firms that matches our sample of patenting firms by industry, size class, and age class. This approach results in an endogenous (choice-based) sample at the firm level. The focus of our work is on industry and technology area level effects rather than firm-level effects. Therefore we do not expect this sampling approach to introduce systematic biases into the estimates we report. We provide a number of robustness checks, including aggregate instrumental variable regressions.

All estimates are based on data weighted by the probability that a firm is in our sample.[15] 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 11,000) firms applying for a patent at the EPO or UKIPO during the 2001–2009 period and another 11,000 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 (Schmoch, 2008). The list is shown in Table C.1 in the Online Appendix, along with the number of EPO and UKIPO

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

patents that were matched to UK firms with priority dates between 2002 and 2009. A comparison of the frequency distribution of patenting across 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 UK patent data (see the bottom panel in Table C.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% patent in more than four. From the 22,000 firms observed, each of which can potentially enter into each one of the 34 technology areas, we obtain about 550,000 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.[16]

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% of observations from the data. We provide a robustness check for this procedure in Table E.2 in the Online Appendix.

3.1 Variables

3.1.1 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.

3.1.2 Technological opportunity Our first prediction from the theoretical model is that there will be more entry in technology areas with greater technological opportunity.

Opportunity to generate inventions can arise from the recombination of conventional knowledge, or it can arise from a mixture of conventional and atypical knowledge (Uzzi *et al.*, 2013). We use two measures of opportunity, the first to capture opportunity arising from conventional knowledge and the second, to capture opportunity arising from the introduction of atypical knowledge:

1. Opportunity for recombination of conventional knowledge is measured through the logarithm of the aggregate EPO patent applications in the technology sector in a given year.
2. Opportunity from the introduction of atypical knowledge is measured through the past 5-year growth rate in the non-patent (scientific publication) references cited in patents in a technology class at the EPO.[17]

Given the difficulty of measuring technological opportunity we note 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 to measure technological opportunity. Presumably

16 We confirmed the validity of this assumption through interviews with leading UK patent attorneys.

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

the growth rate is a better predictor because it captures new or expanded technological opportunity coming from recent scientific work.

The first measure of opportunity is quite broad and may be correlated with other influences on entry. Our model of patenting predicts that aggregate patenting and entry are functions of technological opportunity, complexity and patent thickets. We control for the effect of complexity, patent thickets and science derived opportunity, so that the coefficient on aggregate patenting will reflect primarily variation in the remaining, conventional knowledge dimension of opportunity.

3.1.3 Technological complexity The second prediction of the theoretical model is that technological complexity increases entry, other things equal. Technology is complex when there are many ways to combine inventions in a particular field to obtain novel applications of these inventions. The opposite, a discrete technology is characterized by a series of fairly isolated inventions that do not connect to each other. To construct a measure of complexity, we use the concept of network density applied to all citations among patents that issued in the particular technology area during the decade prior to the date of potential entry. We use citations at the US patent office, because these are richer (averaging seven cites per patent during this period versus three for the EPO) and to minimize correlation with the thickets measure, which is based on EPO data.[18]

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 years t-10 and t. Each of these patents can cite any of the patents that were applied for earlier, which implies that the 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.

In any given cohort of new patents this measure captures how intensively innovations introduced by the new patents are linked to preceding innovations. The measure contains no information about whether these links indicate overlap in the innovations claimed by patent holders or not. This additional information is contained in the EPO classification of citations and is exploited in the patent thicket measure we discuss next.

3.1.4 Patent thickets The third prediction of the model is that greater potential for hold-up reduces entry. We measure the potential for hold-up in patent thickets using the total triples count per technology area, as previously used by Harhoff *et al.* (2016). The triples count is the number of fully connected triads on the set of firms' critical patent references. At time t a 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. These critical references, so-called X- and Y-references, are obtained from examiner search reports issued by the EPO and represent prior art that calls into question novelty and/or the inventive step of the patent application under examination. Triples are then formed by groups of three firms where each firm has at least one patent that is cited as critical prior research for at least one patent held by each of the other two firms. That is, in a triple, each firm holds patents that potentially block the other firms' patents creating

18 It is important to emphasize that citations listed on US patents are largely proposed by the applicant, whilst the citations listed on EPO and UKIPO patents are inserted by the examiner. This explains why the two measures are not highly correlated.

mutually blocking triads. This indicator captures instances in which European patent examiners have identified poorly drafted claims that indicate each firm in the triple is claiming technology already claimed by the other firms in the triple. In the instances in which the examiners identify overly expansive claims, these can be re-drafted. But examiners are unlikely to spot overlapping claims in all patent applications in a technology area due to constraints on their time and ability to search for prior art. Moreover, the re-drafting of claims flagged by examiners, which often involves adding specific language to narrow the scope of claims, is unlikely to eliminate all potential overlap between the relevant patents. Therefore a higher triples count in a technology area indicates the existence of overlapping technologies and the patents that cover them, and hence an increase in hold-up potential in this technology area.[19]

The citation data used to construct this measure is extracted from PATSTAT (October 2011 edition).[20] We normalize the count of triples by aggregate EP patenting in the same technology class and year, 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.[21]

By adding a measure of technological complexity to our model we can interpret the triples count more narrowly than von Graevenitz *et al.* (2013), who used it as a proxy for complexity and hold-up potential together.[22] In contrast, our model separates the effect of previously existing patent thickets on entry from that of technological complexity. The triples measure is more likely to be elevated in complex technologies, but complexity alone does not lead to an elevated hold-up potential. Hence we use separate measures of complexity and hold-up potential.

3.1.5 Covariates It is well known that firm size and industry are important predictors of whether a firm patents at all (see Bound *et al.*, 1984, for US 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.[23] 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.

19 Note that Fischer and Henkel (2012) find that NPEs are more likely to acquire patents in fields with higher triple count, providing additional support for the notion that the measure captures patent overlap and hold-up potential.

20 Triples data was kindly provided by Harhoff *et al.* (2016).

21 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.

22 In Online Appendix D, we show that this confounded the separate effects of complexity and hold-up. Including the measures of complexity and hold-up potential proposed here in their empirical model, we find that the effects on patenting incentives predicted by our theoretical model for complexity (positive) and hold-up potential (negative) apply in their data.

23 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 data set.

We also expect the likelihood that a firm will enter a particular technology area to depend on its prior patenting experience, 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.[24] The variables on firm size and patent stock also allow us to test Prediction 4 about the effect of incumbency advantage on entry.

Finally, to check that our technology entry results are not driven by concentration in the firm's industrial sector, we compute the Herfindahl-Hirschman index (HHI) for each four-digit sector using all the firms (about 3 million) on the Companies House FAME files and include that variable in our regressions. Because broad industrial sectors are being controlled for via stratification, the HHI variable only measures variations within those sectors.

3.2 Descriptive statistics

Our estimation sample contains about 22,000 firms and 550,000 firm-TF34 sector combinations. During the 2002–2009 period there are about 14,000 entries into patenting for the first time in a technology area by these firms. Table C.2 in the Online Appendix shows the distribution of the number of entries per firm: 3,110 enter one class, and the rest enter more than one. Table C.3 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% in Pharmaceuticals and R&D Services to less than 0.2% in Construction, Transportation, and Financial Services. Table C.4 shows the number of entrants and their share among all patentees by technology area. It shows that there is a substantial amount of entry but it also varies significantly across technologies. Finally, Table C.5 shows our different measures for technological opportunity, complexity, and patent thickets by TF34 technology class and Table C.6 shows descriptive statistics for the key technology class and firm level variables.

3.3 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.

We estimate two classes of failure or survival models:[25] (i) 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 (ii) accelerated failure time (AFT), where the survival rate is accelerated or decelerated by the characteristics of the firm. In the body of the article we present results using the well-known Cox proportional hazards model stratified by industry. The effect of the stratification is that we allow firms

24 We compute the past stock of patents using a declining balance formula with a 15% depreciation rate, in order to reduce the impact of very old patents.

25 In Online Appendix E, we discuss the choice of the survival models that we use for analysis, how to interpret the results, and present some robustness checks.

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. To check for omitted firm specific effects, we also estimate hazard models stratified by firms, where each firm has its own failure time distribution.

Online Appendix Table E.1 shows exploratory regressions made using various survival models. The AFT estimates are not well identified and typically have larger coefficients with larger standard errors than the other two, but of the same sign. Unlike the Weibull model, these models allow for a baseline hazard that may first increase and then decrease, which is difficult to identify in our relatively short time period.

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 data set 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 E.2 in the Online Appendix presents estimates of our model using 1900 instead of 1978 as the earliest at risk year and finds little difference in the estimates.[26] 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.

4. Results

4.1 Main results

Our estimates of the model for entry into patenting are shown in Table 1. 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 applications in the technology class, is also positively associated with entry into that class, as predicted by our model.

Column 2 of Table 1 contains the basic result from our data and estimation, which is fully consistent with the predictions of our theoretical model: greater complexity as measured by citation network density increases the probability of entry into a technology area (Prediction 2), as does technological opportunity (Prediction 1), 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 (Prediction 3). We interpret this latter result as an indicator of the discouraging effect of hold-up 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

26 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.

Table 1. Hazard of entry into patenting in a TF34 class

Variable	Cox Proportional Hazard Model				
	(1)	(2)	(3)	(4)	(5)
Log (network density)		0.112***	0.118***	0.116***	0.117***
		(0.022)	(0.021)	(0.021)	(0.021)
Log (triples density in class)	−0.147***	−0.150***	−0.111***	−0.112***	−0.117***
	(0.010)	(0.009)	(0.008)	(0.009)	(0.009)
Log (patents in class)	0.558***	0.598***	0.573***	0.573***	0.605***
	(0.027)	(0.026)	(0.024)	(0.024)	(0.025)
Five-year growth of	0.122***	0.096***	−0.126***	−0.125***	−0.094***
non-patent refs in class	(0.033)	(0.034)	(0.031)	(0.031)	(0.031)
Log assets	0.288***	0.287***	0.200***	0.200***	0.676***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.084)
Log firm age in years	1.203***	1.205***	1.178***	1.169***	1.203***
	(0.093)	(0.093)	(0.103)	(0.103)	(0.103)
Log (pats applied for by			1.074***	1.071***	1.071***
firm previously)			(0.038)	(0.039)	(0.038)
Herfindahl for firm's				0.442**	
Four-digit industry				(0.217)	
Log (network density)					0.000
× Log assets					(0.006)
Log (triples density)					0.008***
× Log assets					(0.003)
Log (patents in class)					−0.056***
× Log assets					(0.008)
Log (average NPL refs)					−0.067***
× Log assets					(0.010)
Log likelihood	−84.40	−84.38	−77.24	−76.34	−77.20
Degrees of freedom	13	14	15	16	19
Chi-squared	2,450.7	2,583.5	3,520.8	3,408.5	3,452.9
551,981 firm-TF34 observations with 14,709 entries (22,316 firms).					

Source: Authors' calculations.

Notes: The sample is matched on size class, sector, and age class. Estimates are weighted by sampling probability. Time period is 2002–2009 and minimum entry year is 1978. Sample is UK firms with non-missing assets, all patenting firms and a matched sample of non-patenting firms. A complete set of year dummies is included in the hazard function. Method of estimation is Cox proportional hazard. Coefficients for the hazard of entry into a patenting class are shown. Estimates are stratified by industry—that is, each two-digit industry has its own baseline hazard. Standard errors are clustered on firm. ***(**) denote significance at the 1% (5%) level. The degrees of freedom are those for the chi-squared test versus a model with hazard rate only.

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 column 1 of Table 1 we included the measure of thickets without that for network density and found that although the coefficient was very slightly lower in absolute value, the result still hold.[27]

27 In results not shown, we also included the network density variable separately, with similar effect.

As we show in Online Appendix E, 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 7% increase in the hazard of entry (0.112×0.59), while a one standard deviation in the log of triples density is associated with a 23% decrease in the hazard of entry (-0.150×1.56). 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% in this sample.

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 column of Table 1, we add the logarithm of past patenting by the firm. In line with Prediction 4, 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. Accounting for differences across firms in patenting propensity also changes the sign of the non-patent references coefficient, which we are using as one of the proxies for technological opportunity in the technology sector. Apparently firms with strong patenting histories are not more likely to enter sectors with recent growth in scientific input.[28] Controlling for past patenting also weakens the triples coefficient somewhat, which is consistent with the idea that patenting strength renders a firm less vulnerable to hold-up possibilities.

Industry concentration may also affect a firm's willingness to enter new technology areas. Recall that we already control for the level of entry by two-digit industry via stratified hazard rate model estimation. In the next column, we add the Herfindahl for the firm's four-digit industry and find that within two-digit industry, variations in four-digit concentration impact entry positively, but the effect is unrelated to any of the other variables, especially those describing the technological context. That is, entry into new technology areas is more likely in concentrated industries, but the impact of complexity, potential hold-up, and technological opportunity is the same regardless of the firm's industry concentration.

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 technological opportunity effect declines slightly with firm size. The triples density effect shows a small decrease with size, suggesting that hold-up concerns affect larger firms somewhat less than smaller firms. We show this graphically in Fig. 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 hold-up potential, 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.

28 The negative sign of the non-patent references coefficient appears to be driven by firms in the pharmaceutical industry. When we exclude firms in the pharmaceutical industry and the relevant technology categories organic fine chemistry, biotechnology, and pharmaceuticals, the coefficient on the non-patent references is close to zero and statistically not different from zero (results not reported here).

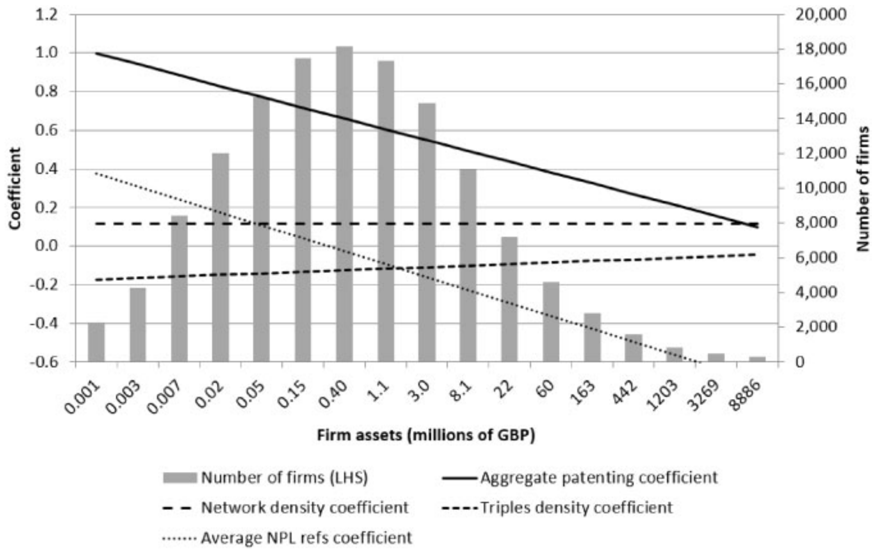

Fig. 1. Firm size and the effects of technological opportunity, complexity, and patent thickets

4.2 Firm effects

In the previous regressions we controlled for firm size, age, industry and past patenting behavior. But obviously firms can differ in other unobservable ways and it would be desirable to control for these left out variables. Because firms in our data can enter into any one of 34 technology areas, this turns out to be straightforward, as we have variability across technology as well as years to provide identification. The cost is that we can no longer identify the coefficients of the firm-level variables.

Table 2 displays the results of estimating proportional hazard models on our data stratified by firm rather than industry, with standard errors also clustered by firm. The results are similar but differ in places from those using industry stratification. Complexity of a sector has a much weaker impact but the impact of the thickets or hold-up variable is strengthened, implying that firms avoid those sectors with a high potential for hold-up.

With the exception of past non-patent literature growth, the interaction coefficients (which are identified even though the simple log assets coefficient is not) all suggest weakened impacts for larger firms. The impact of growth in the past non-patent literature used by patents in the class is negative within firm and even more negative for larger firms. Looking at the raw data in the appendices, it appears that organic fine chemistry, biotechnology, and pharmaceuticals have both the lowest first time entry rates and the highest growth in the use of non-patent literature. In these technologies, it appears that other forces beyond thickets discourage entry.

4.3 Robustness

One concern we may have with the relationship between entry and the triples variable is simultaneity. That is, technology areas with lots of entry may also be prone to a higher triples density, just because of the entries. To address this possibility, we use the aggregate form of our entry regression. For each year we regress the log of the number of first time entries in each technology-industry sector combination on the characteristics of the

Table 2. Hazard of entry into patenting in a TF34 class—firm effects

Variable	Cox Proportional Hazard Model			
	(1)	(2)	(3)	(4)
Log (network density)	0.000		0.036**	0.041**
	(0.017)		(0.017)	(0.017)
Log (triples density in class)		−0.206***	−0.207***	−0.212***
		(0.008)	(0.008)	(0.008)
Log (patents in class)	0.361***	0.735***	0.752***	0.782***
	(0.018)	(0.022)	(0.023)	(0.024)
Five-year growth of non-patent refs in class	−0.574***	−0.636***	−0.644***	−0.634***
	(0.026)	(0.026)	(0.026)	(0.026)
Log (network density) × Log assets				−0.022***
				(0.006)
Log (triples density) × Log assets				0.011***
				(0.002)
Log (patents in class) × Log assets				−0.071***
				(0.008)
Log (average NPL refs) × Log assets				−0.025***
				(0.009)
Log likelihood	43.45	43.87	43.87	43.92
Degrees of freedom	3	3	4	8
Chi-squared	964.9	1,468.3	1,478.5	1,565.2
551,981 firm-TF34 observations with 14,709 entries (22,316 firms).				

Source: Authors' calculations.

Notes: The sample is matched on size class, sector, and age class. Estimates are weighted by sampling probability. Time period is 2002–2009 and minimum entry year is 1978. Sample is UK firms with non-missing assets, all patenting firms and a matched sample of non-patenting firms. Method of estimation is Cox proportional hazard. Coefficients for the hazard of entry into a patenting class are shown. Estimates are stratified by firm—that is, each firm has its own baseline hazard. Standard errors are clustered on firm. ***(**) denote significance at the 1% (5%) level. The degrees of freedom are those for the chi-squared test versus a model with hazard rate only.

technology class together with industry and year dummies. As instruments for the triples density, we use the median examination lag in the technology for patents applied for five and six years prior to the current year, which is long enough so that most of them will have been granted, rejected, or withdrawn. The idea is that classes with long examination lags may also be those where it is more difficult to assess patentability, leading to the hold-up potential captured by the triples proxy variable. We find that the instrumental variables regression easily passes the specification tests for under-, weak and over-identification, justifying our choice of instruments.

Table 3 shows the results, both ordinary least squares and instrumental variables.[29] We include all the technology area variables, a count of the number of firms in the tech class-industry sector-year cell, and the average HHI for the industry of those firms. Note that we do not expect results to be identical when comparing the aggregate regressions to individual

29 We also estimated this model by LIML and GMM, with almost no change in the resulting coefficients (not shown).

Table 3. Aggregate regressions for entry into patenting classes 2001–2009

Variable	Log number of first time entries by a firm into class by sector			
	OLS		IV[a]	
	Coef. (1)	s.e.[b]	Coef. (2)	s.e.[b]
Log (US network density)	0.034	0.030	0.054	0.031 *
Log (triples density)	−0.099	0.011***	−0.214	0.033***
Log (patent apps in class)	0.318	0.033***	0.484	0.058***
Past five year growth in NPL refs	−0.303	0.032***	−0.297	0.035***
Log (number firms in class)	0.719	0.017***	0.664	0.020***
Average four-digit HHI in sector	−0.179	0.148	−0.198	0.146
R-squared	0.625		0.600	
Standard error	0.581		0.598	
Nine years_34 tech classes_25 sectors = 7,650 observations				

Notes:
[a]Instruments are lag 5 and 6 median exam duration for patents in the class. Tests for under-identification and weak identification pass easily. Hansen J-stat for over-identification has a p-value of 0.826. Log of triples density is treated as endogenous in the IV estimates.
[b]Standard errors are clustered on tech class-industrial sector (which allows free correlation over time).
***(*) denote significance at the 1% (10%) level.
Source: Authors' calculations.

firm-level hazard rate estimations, as the functional forms and aggregation level of the models differ. However, the results are similar in sign to those in column 4 of Table 1, with the exception of the HHI coefficient, which is insignificant. For our purposes, interest centers on the coefficient of triples density. The least squares estimate of the elasticity is negative and implies a 15% reduction in entry per year when the triples density increases by one standard deviation. Instrumenting this variable doubles its coefficient, which suggests that our hazard rate estimates may be an underestimate of the true impact of potential hold-up on entry.

Table E.2 in the Online Appendix explores some variations of the sample used for estimation in Table 1. Column 1 of Table E.2 is the same as column 3 of Table 1 for comparison. The first change (column 2) was to add back all the technology-industry combinations where Lybbert and Zolas (2014) 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% of the sample. The impact of network density on entry is considerably weaker, but the impacts of triples density and the technology class size are considerably stronger. The growth in non-patent references in the class is again negative, contrary to our prediction. This may be because the sector-class combinations added were weighted towards chemicals and pharmaceuticals, where non-patent references are much more important, and where we have already seen that entry is low.

Next we explored the differences across firm size, first removing all the firms with assets greater than 12.5 million pounds and then keeping only the firms with more than one billion pounds in assets.[30] The former restriction removed only 2% of the 20,000 firms, while

30 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

the latter left only 273 firms. Column 3 of Table E.2 shows that the results for the SMEs do not change a great deal, although they are somewhat stronger, and the growth in non-patent literature is no longer significant. The coefficients for the giant firms appear different, but they have very large standard errors. So our results do not appear to be dominated by a particular size class of firms.

In column 5, 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 E.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. Age is nearly collinear with firm entry dates so changes in that coefficient are to be expected when we redefine the entry year.

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 can impose significant costs on some firms. The subsequent literature has focused on the measurement of thickets (e.g. Ziedonis, 2004; von Graevenitz *et al.*, 2011) and has linked thickets to changes in firms' intellectual property 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 article confronts both challenges. We show that our empirical measure for the density of thickets captures effects of patent thickets predicted by theory. We separate the impact of patent thickets on entry from effects of technological opportunity and complexity and show that thickets reduce 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 not so clear. Reduced entry into new technology areas could be welfare-enhancing: Entry into a market may be excessive if entry creates negative externalities for active firms, for instance due to business stealing (Mankiw and Whinston, 1986; Suzumura and Kiyono, 1987). This is likely to be true of patenting too. Furthermore, Arora

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.

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'.

The view that firms generally identify and preempt the emergence of patent thickets through private contractual arrangements sounds optimistic in this light (Barnett, 2018). While firms have the ability to privately contract around blocking patents, transaction costs associated with contracts of this nature may be sufficiently important to deter some firms, specifically smaller ones, from doing so. Our evidence also casts doubt on the suggestion that in response to a thicket, firms will simply resort to unlicensed use of patented technology (Teece, 2018). This is much more likely to be a response adopted by large corporations with strong patent portfolios, as is apparent in the many patent cases brought by smartphone vendors after 2011 (Paik and Zhu, 2016). The key question for public policy in this context is whether or not to employ more resources to change incentives for patentees to submit clearly delineated patent claims and to strengthen the examination of patents such that patent notice is strengthened. Menell (2019) discusses a range of approaches that could be taken in this regard. Our analysis suggests that these measures might primarily benefit smaller patent applicants.

Supplementary material

Supplementary material is available on the OUP website. These are the data and replication files and the Online Appendix. Some of the data used in this article are available from Bureau van Dijk's FAME database.

Funding

This work was supported by the Intellectual Property Office of the United Kingdom.

Acknowledgements

We are grateful to the National Institute of Economic and Social Research (NIESR) for hospitality while this article was being written. The views expressed here are those of the authors. They are not necessarily those of the UK Intellectual Property Office (UKIPO) or NIESR. The revision of this article has benefitted from comments by participants in seminars at the UKIPO, the USPTO, the NBER Summer Institute, the University of California at Berkeley, Tilburg University, ETH Zurich, the University of Wuppertal and the TIGER Conference in Toulouse. We would like to thank the editor, Alan Beggs, and two anonymous referees for their helpful comments and suggestions which have greatly improved the article. We also thank Jonathan Haskel, Scott Stern, Dietmar Harhoff, Stefan Wagner and Megan MacGarvie for comments, and Iain Cockburn, Dietmar Harhoff, and Stefan Wagner for very generous support with additional data.

References

Allison, J.R., Lemley, M.A., and Schwartz, D.L. (2015) Our divided patent system? *University of Chicago Law Review*, **82, 1073–154.**

Allison, J.R. and Ouellette, L.L. (2015) How courts adjudicate patent definiteness and disclosure, *Duke Law Journal*, **65, 609–95.**

Amir, R. and Lambson, V.E. (2000) On the effects of entry in Cournot markets. *Review of Economic Studies*, **67**, 235–54.

Arora, A., Ceccagnoli, M., and Cohen, W.M. (2008) R&D and the patent premium. *International Journal of Industrial Organization*, **26**, 1153–79.

Barnett, J. (2018) Has the academy led patent law astray? *Berkeley Technology Law Journal*, **32**, 1313–80.

Berry, S.T. (1992) Estimation of a model of entry in the airline industry. *Econometrica*, **60**, 889–917.

Bessen, J. and Meurer, M.J. (2008) *Patent Failure*, Princeton University Press, Princeton, NJ.

Bessen, J. and Meurer, M.J. (2013) The direct costs from NPE disputes. *Cornell Law Review*, **99**, 387–424.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013) Identifying technology spillovers and product market rivalry. *Econometrica*, **81**, 1347–93.

Bound, J., Cummins, C., Griliches, Z., Hall, B.H., and Jaffe, A. (1984) Who does R&D and who patents? in Griliches, Z. (ed.) *R&D, Patents and Productivity*, University of Chicago Press, Chicago, IL, 21–34.

Bresnahan, T.F. and Reiss, P.C. (1991) Entry and competition in concentrated markets. *Journal of Political Economy*, **99**, 977–1009.

Burk, D.L. and Lemley, M.A. (2008) Fence posts or sign posts—Rethinking patient claim construction. *University of Pennsylvania Law Review*, **157, 1743–99.**

Cockburn, I. and MacGarvie, M. (2011) Entry and patenting in the software industry. *Management Science*, **57**, 915–33.

Fink, C., Khan, M., and Zhou, H. (2016) Exploring the worldwide patent surge. *Economics of Innovation and New Technology*, **25**, 114–42.

Fischer, T. and Henkel, J. (2012) Patent trolls on markets for technology–an empirical analysis of NPEs' patent acquisitions. *Research Policy*, **41**, 1519–33.

FTC (2003) To promote innovation—the proper balance of competition and patent law and policy, Report, Washington.

FTC (2011) The evolving IP marketplace: aligning patent notice and remedies with competition, Report, Washington.

Goolsbee, A. (1998) Does government R&D policy mainly benefit scientists and engineers? *The American Economic Review*, 88, 298–302.

von, GraevenitzG., Wagner, S.,[N/A]andHarhoff, D.(2011)How to Measure Patent Thickets—a Novel Approach, *Economics Letters*, **111**, 6–9.

von Graevenitz, G., Wagner, S., and Harhoff, D. (2013) Incidence and Growth of Patent Thickets: The Impact of Technological Opportunities and Complexity, The Journal of Industrial Economics,**61**, 521–63.

Hall, B.H., Helmers, C., Rogers, M., and Sena, V. (2013) The importance (or not) of patents to UK firms, *Oxford Economic Papers*, **65**, 603–29.

Harhoff, D., von Graevenitz, G., and Wagner, S. (2016) Conflict resolution, public goods and patent thickets, *Management Science*, **62**, 704–21.

Henderson, R. (1993) Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry. *The RAND Journal of Economics*, **24**, 248–70.

Jaffe, A.B. and Lerner, J. (2004) *Innovation and Its Discontents: How Our Broken Patent System is Endangering Innovation and Progress, and What to Do about It*, Princeton University Press, Princeton, NJ.

Lei, Z. and Wright, B.D. (2017) Why weak patents? Testing the examiner ignorance hypothesis, *Journal of Public Economics*, **148**, 43–56.

Lerner, J. (1995) Patenting in the shadow of competitors, *The Journal of Law and Economics*, **38**, 463–95.

Lewis, J.I.D. and Mott, R.M. (2013) The sky is not falling: Navigating the smartphone patent thicket, *WIPO Magazine*.

Lybbert, T.J. and Zolas, N.J. (2014) Getting patents and economic data to speak to each other: An "algorithmic links with probabilities" approach for joint analyses of patenting and economic activity. *Research Policy*, **43**, 530–42.

Mankiw, N.G. and Whinston, M.D. (1986) Free entry and social inefficiency. *The Rand Journal of Economics*, **17**, 48–58.

Menell, P.S. (2019) Economic analysis of intellectual property notice and disclosure, in Depoorter, B., Menell, P. and Schwartz, D. (eds) *Research Handbook on the Economics of Intellectual Property Law*, vol. **1**. Edward Elgar, Cheltenham, 424–71.

Milgrom, P. and Roberts, J. (1994) Comparing equilibria. *American Economic Review*, **84**, 441–59.

Mulligan, C. and Lee, T.B. (2012) Scaling the patent system. *NYU Annual Survey American Law*, **68, 289–318.**

Paik, Y. and Zhu, F. (2016) The impact of patent wars on firm strategy: Evidence from the global smartphone industry. *Organization Science*, **27**, 1397–416.

Schankerman, M. and Schuett, F. (2016) Screening for patent quality: Examination, fees and the courts. CEPR, Discussion Paper 11688, London.

Schmoch, U. (2008) Concept of a technology classification for country comparisons, *Final Report to the World Intellectual Property Organization (WIPO), Fraunhofer Institute for Systems and Innovation Research*, Karlsruhe.

Shapiro, C. (2001) Navigating the patent thicket: cross licenses, patent pools, and standard setting, in A. Jaffe, J. Lerner, and S. Stern (eds) *Innovation Policy and the Economy*, vol. **1**, MIT Press, Cambridge, MA, pp. 119–50.

Suzumura, K. and Kiyono, K. (1987) Entry barriers and economic welfare. *The Review of Economic Studies*, **54**, 157–67.

Teece, D. (2018) The "tragedy of the anticommons" fallacy: A law and economics analysis of patent thickets and FRAND licensing. *Berkeley Technology Law Journal*, **32**, 1489–526.

Tushman, M. and Anderson, P. (1986) Technological discontinuities and organizational environments. *Administrative Science Quarterly*, **31**, 439–65.

U.S. Department of Justice and Federal Trade Commission (2007) Antitrust enforcement and intellectual property rights: promoting innovation and competition, Report, Washington.

Uzzi, B., Mukherjee, S., Stringer, M., and Jones, B. (2013) Atypical combinations and scientific impact. *Science*, **342**, 468–72.

Vives, X. (2005) Complementarities and games: new developments. *Journal of Economic Literature*, **43**, 437–79.

Ziedonis, R.H. (2004) Don't fence me in: Fragmented markets for technology and the patent acquisition strategies of firms. *Management Science*, **50**, 804–20.