The Effect of Market Entry on Innovation: Evidence from UK University Incubators*

Christian Helmers
University of Oxford

This Version: February 2010

ABSTRACT

This paper investigates the effect of market entry of new firms on incumbent firms' innovative activity measured as patent applications. The basic assumption is that the effect of entry varies by geographical distance between entrants and incumbents due to the presence of localized unobserved spillovers. In order to avoid endogeneity problems commonly associated with the timing of entry and entrants' location choice, I analyze entry induced by the establishment of university business incubators, which are usefully exogenous in time and space. The results show that entry has a statistically and economically significantly positive strategic effect on incumbent patenting which is attenuated by the geographical distance between entrant and incumbent.

KEYWORDS: Patents, market entry, incubators, spillover

JEL Classification: L22, L26, O34

*I thank Steve Bond, Marcel Fafchamps, Georg von Graevenitz, Bronwyn Hall, Mark Rogers, Howard Smith, and Tony Venables for helpful discussions and comments. I also thank all universities, knowledge transfer offices, and incubators that have helped me collecting the information necessary for this research. I am particularly grateful to Peter Hanns Zobel for generously sharing his experience in managing a high-tech incubator. The paper was presented at the University of Oxford, the Oxford Intellectual Property Seminar, the Zvi Griliches Research Summer School, Barcelona, the European Investment Bank, LMU Munich, PUC-Rio, DIW Berlin, UC Berkeley, EBS, Universidad Carlos III, and the Royal Economic Society Conference 2010. Email: christian.helmers@economics.ox.ac.uk

1 Introduction

“We never anticipated at Fairchild that a lot of other participants were going to enter the business later on. So we tended to patent relatively few things [...]”

Gordon Moore (2004)

Since Schumpeter (1943) argued that monopolistic markets are more conducive to innovation than competitive markets, there has been an active debate on the link between market structure and innovation. Arrow (1962) shows that entrants may have larger incentives to innovate than an incumbent monopolist due to the *replacement effect*, i.e., a monopolist loses its current stream of profits by innovating. Gilbert and Newbery (1982) consider a model in which a monopolist and a potential competitor invest in R&D to obtain an innovation. Once the innovation occurs, the winning firm receives a patent of infinite lifetime on the innovation. In their model, the firm that invests more in R&D makes the innovation and receives the patent with certainty. Contrary to Arrow's (1962) findings, in such a set-up, the monopolist may have greater incentives to invest in R&D for non-drastic process innovations. This is explained by the fact that the monopolist has an incentive to invest more in R&D than the competitor in order to ensure the absence of competition. This is due to the *efficiency effect*, i.e., the monopolist wants to preempt entry (Tirole, 1988). The problem with this approach is that the firm that decides to invest more in R&D than its competitor receives the innovation with certainty at a predetermined point in time. The outcome of R&D, however, is far from deterministic; firms decide whether to invest in research based on expectations with regard to payoff and time by when the innovation will be obtained. Reinganum (1983) introduces a stochastic model in which the probability of success follows an exponential process. The arrival rate of innovations is a constant function of a firm's investment in R&D and its expected profits are also constant over time. In Reinganum's model, the monopolist has less incentives to innovate than the competitor for drastic innovations.

The theoretical literature discussed so far does not yield clear predictions with regard to the link between market structure and innovation and only considers a monotonic relationship between the two. More recently, Aghion and Howitt and diverse co-authors (1998, 2001, 2005, 2009) addressed the question of which market structure is conducive to innovation allowing for a non-monotonic relation between innovation and competition. Aghion, Harris, Howitt, and Vickers (2001), for example, explore the question of how market structure impacts innovation and growth within the Aghion and Howitt (1992) Schumpeterian growth model. In basic Schumpeterian models, such as Aghion and Howitt (1992), only outsiders innovate and constantly replace the current incumbent. This is due to the fact that each time a firm innovates, it turns into a monopolist as these models implicitly assume undifferentiated Bertrand competition and therefore the incumbent has no incentive to undertake R&D due to Arrow's replacement effect discussed above. If it is, however, assumed that there is more than one single incumbent before an innovation occurs, in other words, there is imperfect competition, Aghion et al. (2001) find that under 'neck-and-neck' competition, firms have more incentives to innovate than in markets characterized by a leader and a follower. This is due to the *escape competition effect*, i.e., innovating increases the incremental profit a firm can earn relative to not innovating as this avoids competition with a 'neck-and-neck' rival. Overall, these authors find that a marginal increase in product market competition always increases growth and therefore welfare. Aghion, Bloom, Blundell, Griffith, and Howitt (2005) extend the discussion of Aghion et al. (2001) and find empirically that the relation between product market competition and innovation is governed by an inverted U-shape. This non-linear shape arises as initially, for a low degree of competition, incentives to innovate are high as the incremental profit from innovating is high with firms trying to escape competition through innovation. This is particularly true for sectors in which firms compete at very similar costs, i.e., firms are 'neck-and-neck'. As competition rises, the reward for innovating falls for firms further away from the technological frontier and overall innovative activity falls.

While this recent empirical work yields clear predictions with regard to the link between market structure and innovation, it does not analyze the effect of entry on incumbent innovative activity. Indeed, the empirical literature assessing entry and incumbents' innovative activity is very limited. A notable exception is Aghion, Blundell, Griffith, Howitt, and Prantl (2009). They assess both the effect of foreign and domestic firm entry on incumbent firm total factor productivity and innovative performance, measured by incumbents' patent counts. The motivation for their analysis is the observation that entry of foreign firms in the UK has had a heterogeneous effect on incumbent TFP where positive effects are associated with technologically advanced UK industries and negative ones with laggard industries. They demonstrate theoretically, using a Schumpeterian multi-sector growth model, how the threat of entry has a differential impact on incumbent firms depending on how far these are from the technology frontier. The model rests on the assumption that entrants are always at the technology frontier, which may hold true in the case of large foreign firms entering. The authors label the two opposed effects as *escape entry* and *discouragement effects*. Domestic firms close to the frontier speed up innovation while laggards see their expected profit from innovating falling which leads them to reduce innovative efforts. In the empirical part of the paper, Aghion et al. are faced with principally two problems: (1) Entry threat is unobserved and using actual entry even worsens the endogeneity problem inherent in the analysis of the effect of entry on incumbent performance; (2) Distance to frontier is also endogenous. To overcome problem (1), they use instruments obtained from policy changes affecting the ease of (foreign) entry. To deal with (2), they link their UK data with US data to determine a firm's distance to frontier.

While not explicitly stated, by conducting the analysis at the 4- (for TFP) and 3-digit (for patents) SIC sector level, Aghion et al. assume that any effect from entry works through the channel of product market competition. But imagine that the foreign entrant has chosen a location in South East England, for example Oxfordshire. Aghion et al. assume that the channel through which (foreign) entry affects TFP and innovation of domestic firms is confined to domestic firms' competitive distance, measured by their SIC code, as well as distance to the technology frontier. This assumption implies that for two domestic firms, which are equally close to the frontier but one located in Scotland and the other in London, the effect of (foreign) entry in Oxfordshire is the same conditional on other observable firm characteristics. Yet, if there are unobservables, such as knowledge spillovers, which are locally confined, omitting location may cause the main variable of interest, the entry variable, to be correlated with the error term. Hence, if unobservable locally confined spillovers play a role, the effect of entry should also vary according to the incumbents' location, i.e., geographical distance to the entrant. In other words, if one assumes that an entrant also chooses its location optimally, not only the moment of entry but also its location is endogenous.

Recently, location has been recognized as an important strategic choice variable for firms in the empirical IO literature on market entry. This literature is mostly concerned with the strategic interaction between firms, which means firms use their geographic location as a tool to differentiate themselves in order to create local market power. Seim (2006), for example, proposes a model in which video stores can geographically differentiate themselves. The choice of when and where to enter a market is made based on the firm's expected post-entry profit across locations. Hence, firms are allowed to differ in their profitability according to their different locations and an idiosyncratic firm-specific element. Therefore, firms decide on their location based on location-specific demand characteristics, their expected competitors' choices, and on an idiosyncratic shock affecting profits. Other examples for incorporating location as a choice variable in firms' entry decisions include Mazzeo (2003), who looks at entry and location decisions of motels at isolated exits on interstate highways in the US and Toivanen and Waterson (2005), who look at the entry and location choices of McDonald's and Burger

King in the UK. More recently Orhun (2006) looks at spatial positioning choices of supermarkets in the US taking account of geographical distance between competitors and also allowing for location-specific unobservables as well as asymmetric types of retailers. Zhu and Singh (2006) propose a similar analysis of the US retail market also allowing for asymmetry among firms. Jia (2008) analyzes the effect of market entry of Wal-Mart and Kmart stores in US counties. Chain stores' location enters their profit function as Jia allows for positive externalities (the 'chain effect') from geographical proximity between stores of the same chain by weighting the strategic effect by geographical distance between the markets in which stores are located. Overall, focusing on the services sector, this literature has recognized the importance of strategic location choice for firms' expected post-entry profits. Yet, none of these papers is concerned with the effect of entry on incumbent firms' innovation activity.

In this paper, I propose a different approach to the question of how entry affects innovation by incumbent firms accounting for firms' location choice. I exploit the recent wave of new business incubators at universities in the UK.[1] These incubators have two convenient properties mitigating the problem of endogeneity of the timing as well as location of entry. These incubators are located at a university and the decision to establish an incubator is driven mostly by administrative and political factors. An incubator's location is automatically determined by the university's location. Universities have been in place in most cases for much longer than any firm in the sample, hence their location can be regarded as exogenous and by extension also the location of the incubator and the firms located in the incubator. The decision to set up an incubator depends on a range of factors most of which are outside of a firm's influence. Public funds have to be secured, in most cases also financial support from EU funds has to be applied for, and the university and other public institutions have to provide their support. The dependence on the disbursement of public funds and administrational and political factors produces some exogenous variation in the opening of the incubators

[1] *Business Incubation is a unique and highly flexible combination of business development processes, infrastructure and people, designed to support entrepreneurs and grow new and small businesses, products and innovations through the early stages of development and/or change* (UKBI, 2007). In other words, business incubators provide start-up companies with a range of support measures, including physical space within the incubator building, training and coaching, business contacts, access to finance etc. University incubators have the additional advantage that they can draw upon the resources available at the university, including academic support, access to research facilities, as well as easy access to the student pool to recruit employees. Note that incubators are distinct from science parks. According to the definition by UK Science Park Association (UKSPA), science parks represent *a cluster of knowledge-based businesses, where support and advice are supplied to assist in the growth of the companies.* The most important distinguishing feature is that science parks are not restricted to start-up companies and as a result may also host relatively large and well-established companies. For a broad literature review on business incubators see Hackett and Dilts (2004).

and thus of market entry of new firms located at these incubators when they open for the first time.

Hence, in order to assess the effect of market entry, I investigate the effect of the establishment of university incubators and by extension of entry of the firms located at the incubator (so called tenants) on innovation measured as patenting activity of incumbent firms that are not located within the incubator. It is important to stress that I look at tenants that enter the incubator and thus the market at the same point in time as when the incubator was initially established. Identification of the entry effect is obtained from location and timing, i.e., from variation in incumbent firms' patenting behavior before and after entry of new firms induced by the establishment of an incubator where the effect works through the channel of a firm's geographical distance from entrants. The underlying assumption is that distance plays a role due to unobservable spillovers originating from new firms affecting geographically close firms more than distant ones.

Influenced by localized spillovers, the determinants of an incumbent's observed decision (not) to patent upon observing entry are of strategic nature. In order to take account of this strategic interaction, I estimate a discrete choice model for firms' patenting decisions allowing for endogenous strategic effects. Importantly, I allow for two types of strategic effects: other incumbent firms' patenting decisions as well as entrants' patenting decisions. The coefficient associated with entrants', i.e., tenant firms' patenting decisions is the main object of interest of this paper.

While incubators serve in the first place as a device to circumvent the endogeneity problems associated with market entry, from a policy perspective, the investigation of the effect of entry induced by incubators on incumbent firms is also interesting in its own right. Incubators are considered among policy makers not only to provide better opportunities for tenant firms, i.e., firms located within the incubator, but also to generate externalities at the local, regional, and even the national level.[2] One of the most important contributions of incubators to the economy is to encourage entry of new firms, which is assumed to generate spillovers for the economy. These spillovers should thus contribute to enhancing innovation and competitiveness in the UK economy, inline with government objectives (DTI, 2003). Incubators, therefore, receive considerable interest by policy makers and public financial support. For example, in 2005, the UK Department for Business, Enterprise and Regulatory Reform (BERR) es-

[2]See website of UK Business Incubation (UKBI).

tablished the Business Incubation Development Fund, which provides £5 million over three years specifically for business incubators. There is also the Higher Education Innovation Fund (HEIF) - established in 2001 - which makes funds available to universities to strengthen knowledge transfer to the private sector, which includes funding of own university incubators. Between 2001 and 2008, under this scheme total funding of more than £500 million has been made available to universities, although there are no figures available about the specific share used to support university incubators.[3] Regional Development Agencies (RDAs) also have a crucial role in the financial support of the establishment of incubators.[4] Also the European Union European Regional Development Fund (ERDF) provides considerable financial support to the establishment of business incubators through university-specific schemes which have the objective to encourage interaction between private business and universities. Despite the recent wave of the establishment of new business incubators and the considerable resources channeled into their support, I am not aware of any work attempting to quantify the externality argument brought forward by proponents of public support to business incubation. Hence, this paper also proposes the first quantitative evidence on the issue.

The remaining sections of the paper will progress as follows. Section 2 discusses the main advantages of using university incubators as a vehicle for identification of the effect of market entry on incumbents' innovative behavior. Section 3 describes the empirical approach taken and provides further assumptions made to ensure identification of the model. The data set used for the analysis is described in Section 4. Section 5 outlines the estimation procedure. Section 6 provides some descriptive statistics of the data used in the analysis. Results are discussed in Section 7. Section 8 reports results from several robustness tests. Section 9 concludes.

2 Identification

The empirical investigation of market entry on incumbent firm behavior is plagued by an endogeneity problem. Entrants optimally choose their timing, market, as well as physical location of entry. Hence, observed entry is correlated with both observed and unobserved market and firm characteristics. To the degree that these characteristics are observed, they can be included in the conditioning set of the regression function. Yet, a large range of characteristics is unobserved. Therefore, the response by incumbents may differ as a function of those unobservable market and firm characteristics. Aghion

[3] http://www.hefce.ac.uk/econsoc/buscom/heif/heif.asp

[4] Initially, RDAs received funds from the Department of Trade and Industry (DTI) amounting to £54.1 million from the Regional Innovation Fund (RIF) during 2001. The RIF was subsumed into the overall funds targeted at RDAs in 2002.

et al. (2009), for example, address this issue by using policy changes, which in their view, affected incumbents' innovative behavior exclusively through entry conditional on observable market and firm characteristics as instruments for observed entry. Once one also accounts explicitly for an entrant's location choice, such policy changes would have to affect innovative behavior only through a firm's entry decision as well as location choice. In the case of the rather sweeping policy changes used by Aghion et al., this seems unlikely to be the case.[5]

University business incubators, in contrast, achieve precisely that. They provide both exogenous timing of entry and choice of location:

Assumption 1 - Timing. *The decision and timing of the establishment of an incubator is the result of mostly administrational and political factors and therefore outside of tenants' influence. This produces exogenous variation in the timing of firms' entry decisions.*[6]

Assumption 2 - Location. *An incubator's location is chosen according to the availability of space on a university campus and not according to other criteria that a firm would usually optimally balance. Hence, tenant firms' geographical location choice conditional on entering the market through an incubator is exogenous with respect to incumbent firms.*

To illustrate the underlying motivation for the establishment of a typical university incubator, I use the example of the *Technium Digital* incubator located at the University of Swansea, Wales. The incubator is part of a larger 'Technium' network constructed by the former Welsh Development Agency (WDA) starting in 2001 in partnership with the University of Swansea to support the establishment of high-tech businesses. By 2007, the project had required investment of more than £42 million, which has come from the WDA, the university, local authorities and most importantly EU structural funds. This network constitutes the core of efforts of the Welsh Assembly Government to promote the development of knowledge-based companies in Wales. Hence, the establishment of the incubator was government-led (see Abbey et al. (2008) for a more detailed discussion). In terms of location, the *Technium Digital* incubator is located directly on the same site as the University of Swansea (See Table 1).

[5] Aghion et al. use for example the EU Single Market Programme, monopoly and merger rulings by the UK competition authority, and large scale privatization as instruments.

[6] The most likely scenario is the following: Assuming that an entrepreneur has decided to enter the market through a university business incubator at a given point in time, this may not automatically lead to market entry due to dependence on the actual opening of an incubator which may be delayed due to administrational and political reasons.

Geographical distance between incumbents and new entrants should play a role if one assumes that there are localized spillovers that require physical proximity. I therefore make the following additional assumption:

Assumption 3 - Spillovers. *The effect of entry on incumbents' innovative activity varies as a function of geographical distance because of the presence of unobserved spatial spillovers.*

Such spillovers may take various forms. One example may be information about research activities carried out by firms within the incubator. Firms that are located geographically nearby may be better informed about these activities than firms far away. Boschma (2005) notes that a 'shared knowledge base' between firms is a prerequisite for knowledge transmission. I therefore assume that such localized unobserved spatial spillovers occur between firms within the same SIC 3-digit industries. There is ample evidence for such localized spillovers in the literature. For example, Jaffe, Trajtenberg and Henderson (1993) constructed a patent citation data set where they matched the addresses of inventors to the addresses of those inventors that subsequently cited the patent as prior art. They show that cited and citing researchers are geographically closer than other researchers, which the authors interpret as evidence of localization of spillovers. Defining US states as their spatial units of analysis, Audretsch and Feldman (1996) find that even after controlling for geographical clustering of production, knowledge-intensive industries cluster more than less knowledge-intensive industries. These authors interpret this as evidence for localized spillovers and their importance. Therefore, there is reason to believe that localized spillovers between firms, above all high-tech firms, exist and are important in shaping firms' responses to market entry.

3 Empirical approach

The main objective of the analysis is to investigate whether entry of new firms through the establishment of an incubator influenced an incumbent firm's patenting propensity where the effect is a function of geographical distance between entrant and incumbent due to localized unobservable spillovers. In order to test this hypothesis, I propose a simple patenting decision model in which I regard a firm's decision to patent as a static discrete choice problem in which I allow for strategic interactions and incomplete information, i.e., firms' interaction is modeled as a static Bayesian game.

There are $i = 1, ..., N$ firms in the economy potentially simultaneously filing for a patent. The location of incumbents is taken as given. Firms simultaneously decide whether to patent and I denote a firm's observed choice by $p_{imt} \in \{0,1\}$, where m denotes markets, which are defined by 3-digit SIC industries (this implies that by construction there are only potential 'local' entrants).[7] $p_{imt} = 1$ means that firm i in market m decided to patent at time t, while $p_{imt} = 0$ means the opposite. The vector of possible actions of all firms is denoted by $P = \{0,1\}^n$, where $p = (p_1, ..., p_n)$ denotes a generic element of P. This implies that all firms have the same set of actions.

A firm's expected payoff π^e from patenting is given by (where I omit time and market subscripts to make the notation more readable)

$$\pi_i^e(p_i, p_j, x_i, \epsilon_i; \theta) = \pi_i(p_i, p_j, x_i; \theta) - \epsilon_i(p_i) \tag{1}$$

where $j \neq i$, i.e., j denotes other firms than i. $x_i \in X_i$ denotes known state variables, i.e., firm and market-specific characteristics for firm i. Each firm is subject to a stochastic shock $\epsilon_i(p_i)$ depending on its action p_i. Apart from the shock, firm i's payoff depends also on its own as well as other firms' actions, p_i and p_j respectively. The dependence on p_j allows for strategic effects arising from other firms' patenting decisions.[8] In order to analyze the effect of entry on π_i^e, I will distinguish in the analysis further below between strategic effects due to other incumbents and entrants. For now, to save on notation, I subsume both types of strategic effects under p_j.

In my application, I use a linear parametrization of $\pi_i(p_i, p_j, x_i; \theta)$

$$\pi_i(p_i, p_j, x_i; \theta) = \begin{cases} x_i'\beta + \chi \sum_{j \neq i} p_j & \text{if } p_i = 1 \\ 0 & \text{if } p_i = 0 \end{cases} \tag{2}$$

The parameters β, χ have to estimated. I make an important normalization in Equation (2) that mean utility from not patenting is zero (see below **Assumption 5 - Normalization**).

I assume that a firm's decision to patent is a function of its own characteristics as well as the random shock received. The corresponding strategy function is therefore $p_i = h(x_i, \epsilon_i)$. It is important to note that only a firm's own shock ϵ enters its decision rule as I assume that other firms' shocks are unknown to the firm. Due to the uncertainty about j's actions arising from the fact that firm i does not observe j's

[7]About 66 percent of patenting firms in the sample file only a single patent application in a given year and 82 percent file for either one or two patents in a given year. Hence, reducing the multinomial to a binomial discrete choice problem is representative of the choice problem faced by the overwhelming share of the sample firms.

[8]Note that I assume that players are limited to pure strategies, i.e., each player has a unique best response with probability one. This assumption holds if $\epsilon_i(\cdot)$ is atomless.

idiosyncratic shock ϵ, firm i forms beliefs about j's patenting behavior. Firm i's beliefs can be expressed as patenting probabilities. Hence, the probability that firm j chooses action $p_j = 1$ conditional on its state variables and idiosyncratic shock is

$$\sigma_j(p_j = 1|x_j) = \int \mathbf{1}\{h(x_j, \epsilon_j) = 1\} f(\epsilon_j) d\epsilon_j \tag{3}$$

where $f(\epsilon_j)$ is the density of ϵ_j and $\mathbf{1}\{h(x_j, \epsilon_j)\} = 1\}$ is an indicator function that firm j chooses action $p_j = 1$ conditional on its common knowledge state variables and the private random shock.

Using Equations (2) and (3), I can rewrite (1) as

$$\pi_i^e(p_i, p_j, x_i, \epsilon_i; \theta) = x_i'\beta + \chi \sum_{j \neq i} \sigma_j(p_j|x_j) - \epsilon_i(p_i) \tag{4}$$

Equation (4) gives firm i's expected payoff from choosing action p_i for a vector of parameters θ and beliefs about other firms' actions $\sigma_j(\cdot)$ with $j \neq i$. Hence, firm i chooses its action optimally such that

$$\pi_i^e > 0 \tag{5}$$

If I assume that the random error ϵ_i is standard normally distributed (see below **Assumption 4 - Error Distribution**), firm i's best response probability function is

$$Pr(\epsilon_i < x_i'\beta + \chi \sum_{j \neq i} \sigma_j(p_j|x_j)|x_i) = \Phi(x_i'\beta + \chi \sum_{j \neq i} \sigma_j(p_j|x_j)) \tag{6}$$

where Φ is the CDF of the standard normal distribution. Thus, in a Bayesian Nash Equilibrium (BNE), a firm's equilibrium choice probabilities solve the following fixed point problem

$$\sigma_i(p_i|x_i) = \Phi(x_i'\beta + \chi \sum_{j \neq i} \sigma_j(p_j|x_j)) \tag{7}$$

In equilibrium, the vector of probability functions maximizes the expected payoff for firm i for every state of x_i taking other firms' σ_j (where $j \neq i$) as given. Hence, in a BNE, beliefs held by i about j's actions are j's best responses to its own beliefs.

Given the objective of my analysis, I rewrite the additive linear specification in Equation (2) as (re-introducing time and market subscripts)

$$\pi_{imt}(p_{imt}, p_{jmt}, x_{imt}; \theta) = x'_{imt}\beta + \chi_{IN} \sum_{j \neq i} p_{jmt} + \chi_{EN} \sum_{k \neq i} p_{kmt} \tag{8}$$

where $\beta, \gamma, \chi_{IN}, \chi_{EN}$ are parameters to be estimated. The new term p_{ktm} denotes patenting decisions by tenant firms $k = 1, ..., K$. The strategic effect of market entry is captured by the term $\chi_{EN} \sum_{k \neq i} p_{kmt}$, i.e., incumbent firms' beliefs about entrants' patenting decisions. Given the one-to-one mapping of a firm's choice-specific pay-off function and its choice probabilities, the model specification of Equation (8) can be used to introduce separate strategic effects due to entrants and other incumbents into (7) to obtain equilibrium choice probabilities σ_i.

In order to assess the effect of localized spillovers captured by geographical distance between entrants and incumbents, I weight the strategic entry variable by distance between entrant and incumbent (which is equal to its distance from the incubator at which the entrant is located). In addition, to capture the effect of varying distance on incumbents patenting propensity, I compute strategic entry variables for three distance bands. I allocate all firms located within a distance band of slightly less than 5 km, which corresponds to the 2.5th percentile of the entire distance distribution, to the first distance band. The second distance band is defined for incumbents located within 5 km and 109 km from the entrant, which corresponds to the 2.5th and 30th percentile of the size distribution. The third distance band contains all incumbents located beyond 109 km. In this sense, my model is similar to Orhun (2006), who also interacts the strategic parameter with a continuous measure of distance between competitors and uses distance bands similar to Seim (2006).[9]

I have data of the form $\{x_{imt}, p_{imt}, p_{kmt}, d_{ik} : m = 1, 2, ..., M; i = 1, 2, ...N, t = 1, ..., T, k = 1, ..., K\}$, i.e., I have information on firm characteristics, market characteristics, location and time of the establishment of an incubator and I know whether incumbents and tenants applied for a patent. With this data, the model can be estimated by a two-step Pseudo Maximum Likelihood estimator as suggested by Bajari et al. (2006) which will be discussed in detail in Section 5.

Before proceeding with a description of the data used in the analysis, I have to

[9] When using distance bands, one assumes that the strategic effect is the same for all firms within the same band of distance whereas strategic effects can differ for firms in different distance bands. The difficulty lies in choosing cut-off distances to define bands, which necessarily involves a somewhat arbitrary decision. Section 8 reports a robustness check of my results with regard to the choice of cut-off values of distance bands.

return to the discussion of identification. Identification ensures that equilibrium choice probabilities correspond uniquely to a firm's equilibrium payoff and I am able to recover the structural parameters θ from the observed choice probabilities $\sigma_i(\cdot)$. Hence, different primitives of the model should generate different choice probabilities if the model is identified. Bajari et al. (2006) show how the above model is identified under the following assumptions.

The first assumption imposes a parametric assumption on the error term:

Assumption 4 - Error Distribution. *The error term ϵ is distributed standard normally, identically and independently across actions p and players i.*[10]

The second assumption is the normalization made above:

Assumption 5 - Normalization. *The payoff for $p_i = 0$ is normalized to zero: $\pi_i(p_i = 0, p_j, x_i; \theta) = 0$.*

This normalization is helpful as in this type of model I am only able to identify the the difference between $\pi_i(p_i = 1, p_j, x_i; \theta) - \pi_i(p_i = 0, p_j, x_i; \theta)$ but not each term separately. In order to avoid the problem, I normalize $\pi_i(p_i = 0, p_j, x_i; \theta) = 0$ as stated in **Assumption 5 - Normalization**.

A serious problem in games like the one described above is the possibility of multiple equilibria, i.e., there is no unique relation between players' observed strategies and those predicted by the model.[11] This problem arises when firms' best response function are not linear in other firms' decisions. Several approaches have been proposed in the literature to deal with the problem of multiple equilibria. These solutions rely either on additional structural assumptions or on a two-stage Maximum Likelihood approach for estimation (Tamer, 2003; Aguirregabiria, 2004; Bajari et al., 2006). One structural approach of avoiding the problem of multiple equilibria pioneered by Bresnahan and Reiss (1990, 1991) for entry models of complete information is to assume that every additional entrant lowers incumbent payoff, which generates a recursive structure of strategic interactions that has a unique equilibrium. This assumption is of little use in this context as it is far from clear whether additional patents lower the payoff from incumbents' patents; in fact, the effect may a priori be positive or negative. In order to avoid the problem of multiple equilibria, I make the following assumption:

[10]More generally, in order to ensure identification, one only has to assume that the distribution of players' private information is from a known family (Rust, 1994).

[11]Existence of at least one equilibrium is guaranteed by Brower's Fixed Point Theorem since firms' beliefs are continuous, monotonic and lie within the set $(0, 1)$ (**Assumption 4 - Error Distribution**). Also note that the problem of multiple equilibria is distinct from the problem of non-identification. A model may have multiple equilibria while it is still identified (Tamer, 2003).

Assumption 6 - Unique Equilibrium. *For a given value for the primitives of the model, either the model has a unique equilibrium, or if the underlying model generates multiple equilibria, firms select one equilibrium from the set of possible equilibria.*

Finally, both $\sigma_i(p_i|x)$ and $\sigma_j(p_j|x)$ depend on the common knowledge state variables x. However, identification can be achieved through exclusion restrictions, i.e., firm-specific payoff shifters. If I assume that a firm's decision to patent is unaffected by other firms' state variables, identification can be achieved.

Assumption 7 - Exclusion Restriction. *If Assumptions 4-6 hold, identification is achieved if firm j influences firm i's equilibrium payoff only through $\sigma_j(\cdot)$.*

The choice of my exclusion restriction is discussed in Section 5.

4 Data

The data used for the analysis consists of three components. The first component is the Financial Analysis Made Easy (FAME) data that covers the entire population of registered UK firms.[12] The FAME database is a commercial database provided by Bureau van Dijk.[13] To construct the data set, the December 2006 edition of FAME has been used. The financial data was updated using the December 2008 edition of FAME. FAME covers around 2.04 million active firms. For all of these firms, basic information, such as name, registered address, firm type, and industry code are available. Availability of financial information varies substantially across firms. The smallest firms are legally required to submit only very basic balance sheet information such as shareholders' funds and total assets, which imposes severe constraints on the analysis of start-up and small firms. The FAME database also lists around 0.9 million so called 'inactive' firms. These inactive firms are those that have exited the market and belong to one of the following categories: dissolved, liquidated, entered receivership or declared non-trading. Also, FAME gives exact dates for market entry in the form of a firm's incorporation date which I use in order to ensure that tenant firms entered the market at the time when incubators were set up. Geographical distances between firms have been obtained by matching firms' postcodes available in FAME with Code-Point data provided by Ed*i*na Digimap.[14] The Code-Point data provides a precise geographical location for each postcode unit in the United Kingdom determined by its National

[12]FAME downloads data from Companies House records. In the remainder of this work I use firms to mean registered firms. Hence firm refers to the legal entity that organizes production, in contrast to census-type data that uses the plant or production unit.

[13]http://www.bvdep.com/en/FAME.html

[14]http://digimap.edina.ac.uk/main/index.jsp

Grid co-ordinates given by Easting and Northing values and therefore allows a fairly accurate determination of distances between two objects in the United Kingdom.[15]

The second component is the intellectual property (IP) data, consisting of patents and trademarks. The patent data used here comes from the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT) version September 2008. Only patents applied for at the UK Intellectual Property Office (UKIPO) with the objective of obtaining patent protection in the UK, so called UK patents, have been extracted from PATSTAT. This analysis uses the application date of UK patents. However, only patents that have been published are in the public domain. Hence, it is not possible to observe those patents that were withdrawn before their publication. But given the usual 18 months period between application and publication date, all patents that made it to the publication stage should be included in the data set. Trademark data, both UK trademark publications and Community (OHIM) marks registered, comes from Marquesa Ltd. The patent and trademark data were matched to FAME.[16]

The third component consists of specific information on university incubators including location, year of establishment, and tenant firms. For this component of the data set, I collected information on the existence of incubators at 139 British universities.[17] I found 80 out of these 139 universities (58 percent) to offer business incubator facilities to start-up companies. Some of the universities are associated with more than one incubator so that I identified a total of 125 incubators. Tables 11-14 show the complete list of universities and their corresponding incubators. I contacted all of the 139 universities in order to verify that the information is correct. Universities / incubators that did not respond were contacted again. The final response rate was slightly above 80 percent. Since the firm-level data is available only for the period 2000-2005, I kept only incubators in the sample that were established between 2001 and 2004.[18] This left me with a sample of 49 incubators (these incubators are marked in bold in Tables 11-14). Out of these 49 incubators, I excluded the *Edinburgh Pre-Incubator Scheme* (EPIS) because tenant firms are not physically located at the incubator, which violates

[15]Given the grid points for firms i and j, Euclidean distances are calculated as $Distance = \sqrt{\mid northing_i - northing_j \mid^2 + \mid easting_i - easting_j \mid^2}$.

[16]For more information on the matching process see Helmers and Rogers (2009) and Rogers, Helmers and Greenhalgh (2007).

[17]Initially, I looked at a sample of 162 British institutes of higher education (HEIs), but I discarded 23 institutes which are specialized in subjects which normally do not give any incentive to start-up a high-tech company at an incubator. Examples for such specialized institutions are the Royal Academy of Music or the Royal Scottish Academy of Music and Drama.

[18]Here again the assumption that the moment of the establishment of an incubator is exogenous with respect to incumbent firm performance is essential to avoid any selection bias from restricting the sample to this specific period of time.

the location assumption (**Assumption 2 - Location**). Similarly, I also dropped the *European Centre for Marine Biotechnology* as the incubator is located in a different region than the institute it belongs to, the *UHI Millennium Institute*, since this also violates the location assumption for identification and appears to be a very unusual type of incubator. Then also the *Think Business* incubator at the University of Bradford, the *Stepping Stones* incubator at Keele University, the *SureStart* incubator at the University of Stirling, and the *Business Mine* incubator at the University of Huddersfield were dropped as they cater to student start-ups which are highly unlikely to operate in innovative sectors conducting any sort of R&D which would lead to patentable innovations. Finally, also the *Hive* incubator at Nottingham Trent University was dropped from the sample as it accommodates only ventures previous to their incorporation, thus before they enter the market. This leaves a set of 42 incubators. It is noteworthy that the establishment of incubators appears to be a very recent phenomenon since around 75% of all incubators were established since 2000.[19] The emergence of such a large number of new university business incubators across the entire UK corroborates my main identifying assumptions **Assumption 1 - Timing** and **Assumption 2 - Location**.

I then identified tenant firms located at the incubators established between 2001 and 2004. For this purpose, I used information from three sources. Firstly, most incubators offer an overview of their tenants, i.e., indicate the names of companies located at the incubator on their websites. The so obtained names were then used to retrieve the companies in FAME. However, it turned out that the information provided was sometimes not complete or entirely accurate and a relatively large number of firms could not be found in FAME.[20] Moreover, since I am interested in tenants that were located at the incubator in the moment when it opened, websites often do not contain names of those tenants as they may have left the incubator by 2009. When I was able to find tenants based on their firm name in FAME, I also verified that firms were incorporated during the same year as the incubator while allowing for an additional margin of ± 3 months. In a second step, to complement the information of step one, I searched in FAME for firms located at the same postcode as an incubator, i.e., the only search criterion is the incubator's postcode. For some incubators, this search method lead to a considerable number of false matches, i.e., firms that share the same postcode with an incubator but that are actually not located at the incubator. Hence, to refine the search algorithm,

[19] One possible explanation for this is the dramatic increase in the availability of funding in the UK and EU for universities to promote knowledge transfer and business links during this time period.

[20] In order to avoid possible mismatches from using a search-algorithm, I searched manually for all possible tenants given the information provided on incubator websites.

I used additional information obtained from firms that I had identified in step one to be indeed located at an incubator. Using a search algorithm based on an incubator's postcode as well as specific indicators in a firm's address allowed to retrieve more firms which could not be identified using only the information provided on incubators' websites. Again, I kept only firms that were incorporated during the same year as the incubator allowing for an additional margin of ±3 months. Thirdly, I contacted all universities and/or the corresponding incubators and asked them to verify the list of tenants that I had obtained from steps one and two. In cases where I was unable to retrieve any tenants in step one and two, I had to rely entirely on information obtained from universities/incubators. Unfortunately, a number of universities/incubators were unable to provide me with the necessary information principally due to confidentiality issues which led me to drop these incubators from the sample unless I had identified tenants in the first two steps.[21]

After also dropping tenant firms that had incomplete records, for example missing primary SIC codes, or which report an incorporation date previous to the establishment of the incubators in which they are hosted, I am left with a sample of 30 incubators for which I was able to identify tenant firms. Table 1 shows the incubators founded between 2001 and 2004 for which I was able to identify tenant firms and indicates the university these incubators belong to. The table indicates that the mean and median distance between a university and its incubator is 1.32 km and 0.42 km respectively, which effectively means that both are located at the same location. Figure 1 shows their location on a map. The map provides further support for the location assumption (**Assumption 2 - Location**) as it highlights the co-location of universities and incubators.

The firms that have been identified to have been located at an incubator at the moment of its establishment serve to disentangle the strategic effects $\chi_{IN} \sum_{j \neq i} p_{jmt}$ and $\chi_{EN} \sum_{k \neq i} p_{kmt}$. Hence, the information on tenant firms gives a measure of p_{ktm} and therefore allows me to specifically estimate the effect of entry of these new firms on incumbent innovative performance within each market m in which entry has occurred through any of the incubators listed in Table 1. Table 2 indicates the number of entrants for each incubator.

The set of incumbent firms is drawn from FAME and consists of any incumbent

[21] I also asked universities/incubators for specific entry and exit dates of tenants into and out of incubators which would have allowed to refine the analysis further, but faced the same data protection barrier.

firms that (1) belong to a 3-digit SIC industry in which entry occurred through the establishment of an incubator (see Table 2), (2) report data both before *and* after the establishment of an incubator, i.e., entry of new firms, and (3) had at least one patent during the period 2000-2005.[22] Condition (1) shows that I also maintain the assumption of the existing literature discussed above that the effect of entry works through product market competition.

Overall, there are 2,591 incumbents satisfying conditions (1), (2) and (3) and 128 entrants that could be identified through the three-step procedure outlined above.

5 Estimation

To estimate Equation (7), I implement a two-step Pseudo Maximum Likelihood procedure as suggested by Bajari et al. (2006). The difficulty in estimating (7) arises from the endogeneity of the strategic effects and ignoring this endogeneity would result in biased in inconsistent estimates.

Since the equilibrium is assumed to be a function of only the observed state variables, in a first stage, consistent estimates of a firm's beliefs can be obtained from a reduced form nonparametric regression of a firm's state variables on its observed patenting decision. The estimated beliefs can then be used in a second stage to account for strategic effects in order to recover the structural parameters. Bajari et al. (2006) show that this two-stage procedure generates consistent estimates of the structural parameters.

In the first step, I use both incumbent and tenant firms to estimate consistently individual firms' beliefs $\hat{\sigma}_i(\cdot)$ about their patenting behavior in market m nonparametrically through a nonparametric conditional mode estimator (Collomb et al., 1987; Li and Racine, 2007) instead of sieve series expansion as in Bajari et al. (2006).[23] I have data on actual patenting behavior and firm-level as well as market characteristics (p_{imt}, x_{imt}), I therefore estimate the conditional mode of $(p|x)$, which is denoted as $\sigma = \max_p g(p|x)$ where $g(p|x)$ is the conditional density of p given x. The conditional mode $\hat{\sigma}$ can be estimated using a generalized product kernel estimator for $g(p|x) = \frac{g(x,p)}{g(x)}$ where the conditional density $g(\cdot)$ is estimated using the nonparametric conditional density estimator proposed by Hall et al. (2004), i.e.,

[22] As a robustness check Section 8 reports results when extending the period to 1996-2005, i.e., also including firms in the incumbent firm set that patented before the beginning of the sample period.

[23] I use the *np* package by Hayfield and Racine (2008).

$$\hat{g}(p|x) = \frac{n^{-1}\sum_{i=1}^{n} K_\gamma(x, X_i) k_{h_0}(p, P_i)}{n^{-1}\sum_{i=1}^{n} K_\gamma(x, X_i)} \tag{9}$$

where K is defined as $K_\gamma(x, X_i) = \prod_{s=1}^{q} \frac{1}{h_s} w\big(\frac{x_s^c - X_{is}^c}{h_s}\big) \prod_{s=1}^{r} \lambda_s^{\mathbf{1}(X_{is}^d \neq x_s^d)}$. X_i^d denotes a $r \times 1$ vector of discrete regressors, X_i^c denotes a $q \times 1$ vector of continuous regressors. X_{is} denotes the sth component of X_i. w is a symmetric, nonnegative univariate kernel function and h_s is the smoothing parameter for x_s^c with $0 < h_s < \infty$. $\mathbf{1}(X_{is}^d \neq x_s^d)$ is an indicator function assuming the value of one if $X_{is}^d \neq x_s^d$ and zero otherwise. λ is the smoothing parameter for the discrete regressors with $0 \leq \lambda_s \leq 1$. $k_{h_0}(p, P_i) = h_0^{-1} k((p - P_i)/h_0)$ with h_0 being the bandwidth for p. The corresponding bandwidths are chosen according to the Silverman (1986) rule of thumb $1.06\hat{\sigma}n^{-1/5}$ to ease the computational burden.

I include in the first-stage regression as state variables a firm's total assets, its age, its number of directors as a proxy for employment and managerial as well as technical expertise available to the firm,[24] its number of trademarks, and the 3-digit SIC-level measure for market structure. The set of conditioning variables is limited due to data availability constraints. Tenant firms that have just entered the market are (at least initially) micro-sized companies and therefore legally not obliged to report a large range of financial data. The minimum set of information that is available for most start-up companies constitutes my set of conditioning variables.

In the second stage, I drop tenant firms from the sample, as the objective of the second approach is to assess the effect of beliefs formed about entrants' patenting behavior on incumbent actual patenting behavior. For the second stage, as discussed, I have to assume that the error term is normally i.i.d. distributed to ensure identification. Further, given **Assumption 5 - Normalization**, I can invert the equilibrium choice probability to obtain an estimate of the firm's payoff function. The structural parameters can then be recovered in a second step by estimating a simple probit estimator assuming that **Assumptions 4**, **6**, and **7** hold. The corresponding log likelihood function is:

[24] Availability of employment data in FAME is extremely limited - above all for smaller firms. For the six-year period 2000-2005, slightly less than five percent of all firms in FAME report employment data.

$$\ln L = \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{n=1}^{N} p_{imt} \ln \Phi(\pi_{imt}(p_{imt}, p_{jmt}, x_{imt}; \theta)) +$$
$$+ \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{n=1}^{N}(1 - p_{imt}) \ln[1 - \Phi(\pi_{imt}(p_{imt}, p_{jmt}, x_{imt}; \theta))] \quad (10)$$

where $\pi_{imt}(\cdot)$ is defined as in Equation (8) and obtained from using the estimates of step one. For the second stage, I drop a firm's number of directors from the estimation sample. Hence, I assume that the number of firm j's directors affects firm i's patenting propensity exclusively through its direct impact on σ_j as laid out in **Assumption 7 - Exclusion Restriction**. At the market level, I drop the 4-firm concentration ratio and use instead the total entry rate of new firms, which was computed using the entire population of firms, i.e., it is based on patentees as well as non-patentees. Since predicted values are used in stage two, instead of relying on analytical methods for inference, I rely on bootstrapping.[25] I include time and industry fixed effects in the second stage to account for possible trends in the data and time-invariant industry-specific factors. Note that the the structural parameters are identified only up to a scale, i.e., $\frac{\theta}{sd}$, where sd denotes the standard deviation. I therefore make the following normalization $sd = 1$.

While the two-step estimator is not a full information estimator such as for example the nested fixed-point estimator (Aguirregabiria and Mira, 2002; Seim, 2006), the two-step estimator represents a convenient choice for the purpose of this analysis as it is computationally simple which is important considering the relatively large number of observations in the empirical analysis. Also, the large number of observations makes the well-known problem of finite sample bias associated with the estimator less relevant.

6 Descriptive Analysis

In this section, I present a descriptive analysis of the data. Table 3 provides an overview of the main characteristics of incumbent firms. As discussed above, I use only a limited set of conditioning variables, a firm's total assets,[26] age, the number of a firm's directors as a proxy for employment and managerial as well as technical expertise available to the firm, number of trademarks, the entry rate at the 3-digit industry level and a

[25] Bajari et al. (2006) show that the asymptotic variance of the second-stage estimates is independent of the choice of nonparametric estimator in stage one and structural parameters estimated in stage two are asymptotically normal.

[26] Total assets were deflated using a GDP deflator from the UK HM Treasury (Version December 2008).

measure of market structure at the SIC 3-digit level. The market-level variables were computed based on *all* firms available in FAME in order to reflect appropriately firms' environment.

Figure 2 shows the percentage of patenting firms among incumbents over the sample period 2000-2005. The share of patenting firms in a given year varies between approximately 34 percent in 2000 and 25 percent in 2005. Overall, the percentage of patenting firms per year gradually declines during the period analyzed. This drop in patentees can to some extent be explained by generally lower patenting activity in the UK during later years of the sample (Rogers et al., 2007). This finding suggests the importance of controlling for a common trend in the data when implementing the empirical model presented in Section 3.

Table 3 indicates that on average a firm's number of patents is 0.673. For trademarks, the mean is slightly higher and also the standard deviation is with 4.566 considerably larger than for patents which have a standard deviation of 2.963. The average size of firms is £485 million which differs considerably from the median of £101,000. This is due to a highly skewed size distribution of firms which is also evident from the interquartile range of £121,000 and £6.649 million.[27] Incumbent firms are relatively young, as average firm age is around 14 years. This shows that I can comfortably treat universities' location as predetermined in my data set. The median number of directors is six, which is not too different from the mean of slightly more than eight.

Table 4 reports p-values for the Kolmogorov-Smirnov test where I test the null hypothesis that tenant firms' size measured as total assets is equal to the size of all other entrants within the same SIC 3-digit industry in the same year. The results show that in nearly all cases, the null hypothesis cannot be rejected, which suggests that tenant firms are not different from other entrants when looking at size.

Finally, Table 5 shows the transition matrix of firms' observed choice of whether to patent across time. The matrix reveals that there is little persistence in firms' patenting decision as only slightly more than 30 percent of patentees in one period also patent in the following period. This descriptive evidence supports my modeling decision to treat a firm's discrete choice problem as static.

[27] In order to verify whether this highly skewed size distribution has any effect on my results, Section 8 reports results when dropping the bottom and top deciles of the firm size distribution as measured by total assets.

7 Results

Table 6 shows the confusion matrix resulting from the first-stage nonparametric regression. It shows that the nonparametric model predicts 87.7 percent of the actual observed patenting choices correctly whereas the parametric probit as a comparison predicts only 72.6 percent correctly. Importantly, the probit model fares considerably worse than the nonparametric estimator with respect to correctly predicting the outcome $p_{itm} = 1$.

The predicted patenting choices from the first stage are used in the second stage to estimate Equation (10). Table 7 shows the corresponding results (all coefficients are expressed as marginal effects). The first column shows a specification with firm- and market-level characteristics, total assets, age, number of trademarks, as well as the industry-level entry rate as independent variables. In the first column, strategic effects are measured by $\chi_{IN} \sum_{j \neq i} p_{jmt}$ and $\chi_{EN} \sum_{k \neq i} p_{kmt}$, i.e., I do not use distance between entrant and incumbent. In the second column, I use distance to rewrite the strategic effect of entry as $\hat{\sigma}_{kmt}(\cdot)/d_{ik}$. The third column reports the results obtained when discretizing the geographical distance between entrants and incumbents into three distance bands as discussed in Section 3. In columns (2) and (3), I add incubator fixed effects. This means a zero-one indicator that is zero if an incumbent does not experience entry by a firm located at a specific incubator and one once entry occurred by a firm located at the incubator. Columns (4) and (5) use incubator fixed effects which are weighted by the geographical distance between the incumbent and the incubator, which introduces cross-sectional variation in the incubator specific effects. These incubator-specific effects capture factors associated with unobserved incubator characteristics which may influence the effect of entry on incumbents. Since these characteristics are assumed to be incubator-specific, they may indeed be expected to be time-invariant.

The marginal effect of a firm's total assets on patenting propensity of incumbents is statistically significant and positive. A firm's total assets can be interpreted as a measure of firm size. Hence, the coefficients imply a positive correlation of patenting propensity and firm size. The effect of a firm's number of trademarks is also positive. Trademarks can be regarded as a proxy for a firm's familiarity with IP and may capture some form of sunk cost associated with acquiring IP. Therefore, firms taking out trademarks may be able to distribute fixed costs associated with IP, such as acquiring knowledge on the IP system or employing an IP manager, across patents and trademarks or simply be more familiar with the IP application process and therefore are more likely to patent. However, this effect is not statistically significant. A firm's age is negatively associated with incumbents' patenting propensity, which may point to younger firms being more innovative than older ones. The entry rate at the 3-digit SIC level is negatively associated with patenting, which may be given the interpretation that more competitive markets are associated with lower patenting activity in line with Schumpeter's arguments (Schumpeter, 1943).

The marginal effects of the results shown in Table 7 indicate that the strategic effect of other incumbent firms' patenting activity is in magnitude effectively zero and the regression results across all specifications also indicate that the coefficients are statistically not different from zero. A possible interpretation for this finding is that incumbent firms find themselves already in an equilibrium and beliefs held about other incumbents do not affect a firm's own patenting activity. Regarding the effect of entry, in the first column, the effect of entry measured without accounting for distance between entrants and incumbents is positive and statistically different from zero. Dividing the strategic effect by distance between entrant and incumbent in Column (2) results in a considerable increase in the marginal effect associated with entry. Evaluating the marginal effect at the mean of the entry variable $\hat{\sigma}_{kmt}(\cdot)/d_{ik}$ for Column (2), yields the prediction that an increase in beliefs about entrants' patenting activity by one unit, increases incumbents' patenting propensity by 16 percentage points in a statistically significant way. This effect increases to 17 percentage points in Column (4) when incubator dummies are scaled by distance between incubators and incumbents.

In order to verify the effect of distance on incumbent patenting propensity, Columns (3) and (5) report results using distance bands. The results in Columns (3) and (5) suggest that the effect of entry on incumbents decays distinctly with increased distance given the reduced size of the coefficients of distance bands 2 and 3 relative to the coefficient associated with entry within distance band 1. Evaluating the marginal effect at the mean, the variables in Columns (3) and (5) indicate that an increase of one unit of the strategic entry variable within distance band 1 is associated with an increase of 0.9 and 1.5 percentage points respectively in incumbent patenting propensity. Whereas an increase of one unit of the strategic entry variable within distance band 2 results only in a 0.02 percentage point increase for both specifications displayed in Columns (3) and (5). The effect of entry in distance band 3, however, is negligible from an economic point of view although statistically significantly different from zero. Therefore, the drastically falling magnitude of the coefficients associated with entry in the different distance bands shows the importance of geographical proximity in inducing a reaction in innovative activity of incumbents.

Overall, these findings suggest that there is a positive association with the entry of new firms and incumbent patenting activity. The results suggest that patenting activity of entrants, weighted by distance between the incumbent and entrant, increases the propensity of an incumbent patenting. The results obtained when using distance bands imply that the effect of entry is stronger for incumbents that are closer to the entrant firm - a finding consistent with the notion of localized spillovers.

8 Robustness

In this section, I report results from a number of robustness tests. I vary the set of incumbents by (a) including any firm that has patented between 1996 and 1999 in any of the sectors that experienced entry through a tenant firm, and (b) also dropping firms in the tails of the size distribution. In addition, I use different cut-off values to define distance bands to assess the robustness of the findings reported in Section 7.

One of the criteria for choosing the set of incumbents is patenting activity between 2000 and 2005, i.e., only firms are included in the sample of incumbents that have applied for at least one UK patent between 2000 and 2005. In order to avoid sample selection based on the left-hand-side variable, I enlarge the incumbent set by also including firms that have patented before the beginning of the sample period, i.e., between 1996 and 1999. Table 9 reports the corresponding results. The sample size increased only slightly from 11,832 to 11,961 observations. The overall results are qualitatively very similar to the original results shown in Table 7. This dissipates concerns that one may have regarding the use of patenting activity within the sample period as a criterion for defining incumbent firms.

One of the most prominent concerns in empirical work at the firm level is the extremely skewed size distribution of firms. The summary statistics on firms' total assets shown in Table 3 suggest that this is also the case for the sample of firms used in this analysis. To test whether my results are driven by particularly large or small firms, I drop all incumbent firms from the sample which are in the tails of the distribution of total assets. More specifically, I drop firms that report average assets below the 10th or above the 90th percentile of the distribution. The results are reported in Table 10. The coefficients for the effect of entry $\hat{\sigma}_{kmt}(\cdot)/d_{ik}$ are still positive and statistically significant at the 1 percent level. When distance bands are used, the magnitude of the marginal effects associated with the different distance bands remain largely the same as in Table 7. Thus, these results suggest that there is still a positive effect of entry on incumbents' patenting propensity which decays with increased distance between entrants and incumbents.

Table 8 shows the results that are obtained when distance bands are defined using different percentiles of the distance distribution. Incumbent firms are now allocated within the first distance band if they are located within a radius of slightly less than 19 km from the entrant which corresponds to the 5th percentile of the distance distribution. The second distance band ranges up to 95 km, which corresponds to the 25th percentile. The third band contains all remaining incumbents firms. The results displayed in Table 8 show that the overall pattern of coefficients associated with entry across the different distance bands is very similar to the one shown in Table 7. Although the magnitude of the marginal effects for the first distance band is smaller. Given that the first band includes more remote firms than the distance band used for the main results of Table 7, these findings lend further support to the localization of spillovers and the entry effect being stronger the closer the incumbent is located to the entrant.

Finally, another issue relates to the overall quality of universities. If an incubator is associated with a top university, its tenants firms may be of higher quality than that of other universities. Hence, the effect of entry induced by top-university incubators could potentially be different from that induced by other universities. Column (2) of Table 1 contains the overall rank of universities resulting from the 2001 Research Assessment Exercise (RAE).[28] The ranks show that the sample contains incubators associated with universities from the entire quality spectrum. Imperial College is ranked second while the University of Derby is ranked 102nd. Most incubators are associated with universities that are ranked somewhere in the middle of the distribution. Apart from purging possible time-invariant quality effects through incubator fixed effects, the fact that the sample consists of incubators associated with universities of very diverse RAE ranks, makes it very unlikely that my results are driven by few entrants associated with top-university incubators.

9 Conclusion

The paper analyzes the effect of entry of new firms on incumbent firms' patenting activity. So far, there exists very little research on this topic, which may be explained by the type of endogeneity problem inherent in the analysis of market entry. To address

[28]The RAE collects information on all UK universities, including an assessment of the 'quality' of research. The method of assessing quality is predominantly based on publications of faculty and, specifically, the type and ranking of journals these publications were made in. Hence, the RAE is a rather research-oriented ranking which is more appropriate for my purpose than teaching-quality based rankings.

this problem, I propose to analyze the effect of entry induced by the establishment of university incubators, i.e., of new firms located at these incubators. This allows me to treat the timing and location choice of new firms as exogeneous in my analysis. I can therefore concentrate on modeling incumbent firms' patenting decisions taking the moment of entry as well as geographical location of the new firm as given. My empirical model allows for two types of strategic effects. First, incumbent firms patenting behavior may be influenced by patenting behavior of other incumbents. Second, entrant firms may influence incumbents' patenting activity. Moreover, I assume that this strategic effect of entry varies according to geographical distance between incumbents and entrants. There is a large body of literature supporting the argument in favor of distance affecting strategic effects between firms in the presence of localized spillovers. It is this strategic effect that constitutes the main object of interest of this paper.

My findings suggest that entry spurs incumbent patenting. Moreover, this *entry escalation effect* is attenuated by geographical distance between the entrant and the incumbent. The closer an incumbent firm is to an entrant, the stronger the *entry escalation effect* will be. The main explanation for the role played by physical distance is the presence and importance of localized spillovers in strategic interaction between firms.

Regardless of the progress made in this paper in terms of assessing the effect of entry on incumbent innovative activity, the analysis opens new questions. The findings suggest that patenting behavior is at least to some extent strategic. However, the analysis is unable to unveil the precise strategic motivations of incumbent firms which induce them to respond to entry with increased patenting. There are many candidate explanations: this behavior may serve as a signalling device to deter other potential entrants, as a way of anticipating knowledge leakage by making information accessible to the public through a patent publication, or as a response to increased competition in the spirit of the *escape entry effect* of Aghion et al. (2005). Boldrin and Levine (2008) argue that incumbents have a strong interest in preserving their competitive advantage through patents. However, their argument is different from the Schumpeterian argument, i.e., they are not arguing that incumbents have larger incentives to innovate, but rather that they have strong incentives to protect their status quo by patenting their inventions and blocking entrants. From this perspective, it is not even clear whether it is indeed beneficial that incumbents react to entry by increased patenting activity if this is interpreted as strategically blocking entrants from effectively competing in the market. More research is needed to analyze strategic patenting behavior in more detail.

References

[1] Abbey J., Davies G. and Mainwaring L. (2008): 'Vorsprung durch Technium: Towards a System of Innovation in South-west Wales', *Regional Studies*, 42:2, 281-293.

[2] Aguirregabiria V. (2004): 'Pseudo maximum likelihood estimation of structural models involving fixed-point problems', *Economics Letters*, Vol. 84, Issue 3, pp. 335-340.

[3] Aguirregabiria V. and Mira P. (2002): 'Swapping the Nested Fixed Point Algorithm: A Class of Estimators for Discrete Markov Decision Models', *Econometrica*, Vol. 70, No. 4, pp. 1519-1543.

[4] Aghion P. and Howitt P. (1992): 'A Model of Growth Through Creative Destruction', *Econometrica*, 60, 323-51.

[5] Aghion P. and Howitt P. (1998): 'Endogenous Growth Theory', MIT Press

[6] Aghion P., Harris C., Howitt P., and Vickers J. (2001): 'Comeptition, Imitation and Growth with Step-by-Step Innovation', *Review of Economic Studies*, Vol. 68, pp. 467-492

[7] Aghion P., Bloom N., Blundell R., Griffith R., and Howitt P. (2005): 'Competition and Innovation: An Inverted U Relationship', *Quarterly Journal of Economics*, pp. 701-728

[8] Aghion P., Blundell R., Griffith R., Howitt P., and Prantl S. (2009): 'The Effects of Entry on Incumbent Innovation and Productivity', *Review of Economics and Statistics*, Vol. 91(1), pp. 20-32.

[9] Arrow K. (1962): 'Economic Welfare and the Allocation of Resources for Inventions', in *The Rate and Direction of Inventive Activity*, R. Nelson ed., Princeton University Press

[10] Audretsch D. and Feldman M. (1996): 'R&D Spillovers and the Geography of Innovation and Production', *American Economic Review*, Vol. 86, Nr. 3, pp. 630-640.

[11] Bajari P., Hong H., Krainer J., and Nekipelov D. (2006): 'Estimating Static Models of Strategic Interaction', NBER Working Paper No. 12013.

[12] Boldrin M. and Levine D. (2008): 'Against Intellectual Monopoly', *Cambridge University Press.*

[13] Boschma R.(2005): ‘Proximity and Innovation: A Critical Assessment’, *Regional Studies*, Vol. 39, Nr. 1, pp. 61 74.

[14] Bresnahan T. and Reiss P. (1990): ‘Entry in Monopoly Markets’, *Review of Economic Studies*, Vol. 57, pp. 531-553.

[15] Bresnahan T. and Reiss P. (1991): ‘Empirical Models of Discrete Games’, *Journal of Econometrics*, Vol. 48, pp. 57-81.

[16] Collomb G., Härdle W., and Hassani S. (1987): ‘A note on prediction via conditional mode estimation’, *Journal of Statistical Planning and Inference*, Vol. 15, pp. 227236.

[17] Department of Trade and Industry (DTI) (2003): ‘Competing in the global economy: The innovation challenge’, Innovation Report.

[18] Gilbert R. and Newbery D. (1982): ‘Preemptive Patenting and the Persistence of Monopoly’, *American Economic Review*, vol. 72(2), pp. 514-526.

[19] Hackett S. and Dilts D. (2004): ‘A Systematic Review of Business Incubation Research’, *Journal of Technology Transfer*, Vol. 29(1), pp. 55-82.

[20] Hall P., Racine J. and Li Q. (2004): ‘Cross-Validation and the Estimation of Conditional Probability Densities’, *Journal of the American Statistical Association*, Vol. 99(468), pp. 1015-1026.

[21] Hayfield T. and Racine J. (2008): ‘Nonparametric Econometrics: The np Package’, *Journal of Statistical Software*, Vol. 27(5).

[22] Helmers C. and Rogers M. (2009): ‘Patents, entrepreneurship and performance’, Hitotsubashi University Global COE Hi-Stat Discussion Paper No. 95.

[23] Jaffe A., Trajtenberg M. and Henderson R. (1993): ‘Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations’,*The Quarterly Journal of Economics*, Vol. 108, No. 3, pp. 577-598.

[24] Jia P. (2008): ‘What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retail Industry’, *Econometrica*, Vol. 76, Issue 6, pp. 1263-1316.

[25] Li Q. and Racine J. (2007): ‘Nonparametric Econometrics: Theory and Practice’, Princeton University Press.

[26] Mazzeo M.J. (2002): 'Product Choice and Oligopoly Market Structure', *RAND Journal of Economics*, Vol. 33(2).

[27] Moore G. (and K. Davis) (2004): 'Learning the Silicon Valley Way,' in T. Bresnahan and A. Gambardella (eds.) *Building High Tech Clusters - Silicon Valley and Beyon*, Cambridge University Press.

[28] Orhun Y. (2005): 'Spatial differentiation in the supermarket industry', mimeo GSB University of Chicago.

[29] Reinganum J. (1983): Uncertain Innovation and the Persistence of Monopoly, *American Economic Review*, Vol. 73, pp. 741-748.

[30] Rogers M., Helmers C. and Greenhalgh C. (2007): 'An analysis of the characteristics of small and medium enterprises that use intellectual property', Oxford Intellectual Property Research Centre.

[31] Rust J. (1994): 'Structural Estimation of Markov Decision Processes', in Handbook of Econometrics, Vol. 4, ed. by Engle R. and McFadden D., North Holland, pp. 3082146.

[32] Tamer E. (2003): 'Incomplete Simultaneous Discrete Response Model with Multiple Equilibria', *Review of Economic Studies*, Vol. 70, No. 1, pp. 147-167.

[33] Schumpeter J. A. (1942): 'Capitalism, Socialism, and Democracy', New York: Harper and Brothers.

[34] Seim K. (2006): 'An Empirical Model of Firm Entry with Endogenous Product-Type Choices', *RAND Journal of Economics.*

[35] Silverman B.W. (1986): 'Density Estimation,' Chapman & Hall, London.

[36] Tirole J. (1988): 'The Theory of Industrial Organization', MIT Press - Chapter 10.

[37] Toivanen O. and Waterson M. (2005): 'Market Structure and Entry: Where's the Beef?', *RAND Journal of Economics*, Vol. 36(3), pp. 680-699.

[38] Zhu T. and Singh V. (2006): 'Spatial competition and endogenous location choices: An application to discount retailing', mimeo, Carnegie Mellon University.

Figure 1: Location of universities and incubators

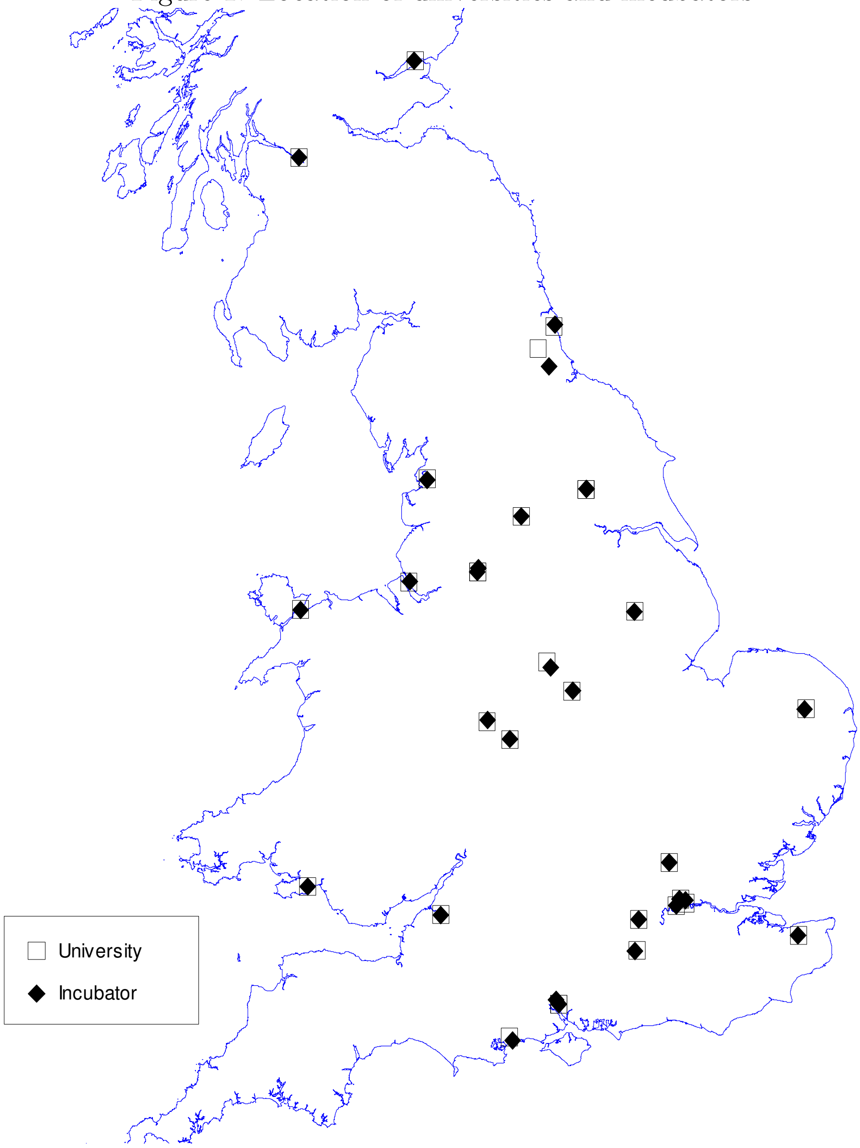

Figure 2: Share of patenting firms 2000-2005

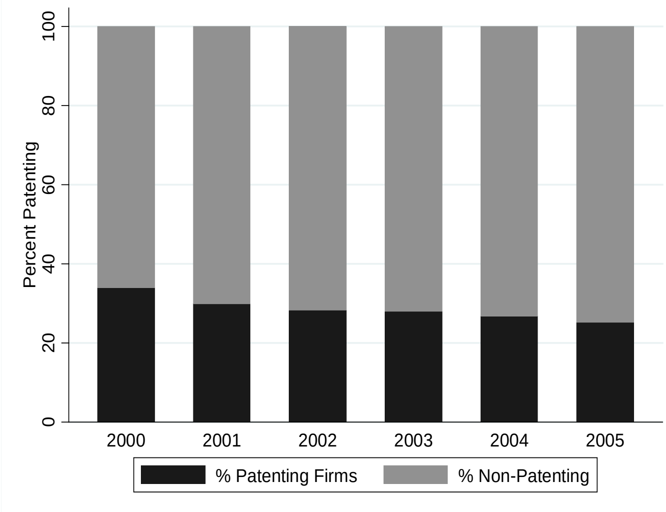

Table 1: Incubators

University	RAE 2001 Ranking	Incubator	Year of Establishment	Distance (km)
Aston University	31	Aston Science Park - Faraday Wharf	2001	0.34
University of Wales, Bangor	47	Bangor Bioincubators	2003	0.37
Bournemouth University	94	Bournemouth University Innovation Centre	2001	3.04
University of Bristol	15	Bristol SETsquared	2003	0.36
University of Kent	43	Canterbury Enterprise Hub	2004	0.38
University of Glasgow	26	Centre for Integrated Diagnostic Systems	2002	0
London Metropolitan University§	96/88	Digital Media Innovation Centre Accelerator	2004	1.73
University of Derby	102	ID Centre Derby	2002	4.21
Lancaster University	12	InfoLab21	2004	0.56
University of Hertfordshire	84	Innovation Centre	2003	0
University of Bradford	52	IPI Bioscience Business Incubator	2003	0
Royal Veterinary College	na	London BioScience Innovation Centre (LBIC)	2001	0.60
Loughborough University	37	Loughborough Innovation Centre	2002	0.62
Imperial College London	2	Low Carbon Technology Incubator	2004	0
University of Manchester	8	MBS Incubator	2002	0.26
University of Liverpool	38	MerseyBIO Incubator	2003	0.85
Durham University	11	NETPark	2004	13.89
University of Manchester	8	North Campus Incubator	2004	2.19
University of East Anglia	32	Norwich Bio-Incubator	2001	1.29
Royal Holloway, University of London	19	Royal Holloway Enterprise Centre	2002	0
University of Wolverhampton	90	SP/ARK	2004	1.29
University of Southampton	10	Southampton SETsquared	2003	0
University of Lincoln	99	Sparkhousestudios	2003	0
University of Dundee	30	Springfield Incubator	2002	0.43
University of Surrey	22	Surrey Technology Centre - SETsquared	2002	1.71
University of Wales, Swansea	60	Technium Digital	2003	0
University of Southampton	10	University of Southampton Science Park	2003	3.35
University of Sunderland	79	St Peter's Gate	2004	1.20
University of York	16	Bio Centre	2003	0.41
University of York	16	IT Centre	2003	0.41

Note:
§ Created on 1 August 2002 by the merger of London Guildhall University (Ranking: 96) and the University of North London (Ranking: 88)

Table 2: No. of tenants and incumbents by incubator

Incubator	Tenants' 3-digit SIC	No. tenants[§]
Aston Science Park - Faraday Wharf	295, 511, 519, 726, 741, 748, 804	10
Bangor Bioincubators	731	1
Bournemouth University Innovation Centre	724, 741	2
Bristol SETsquared	321, 331, 332, 334, 401, 722, 731, 743, 851	10
Canterbury Enterprise Hub	519, 524, 731, 741, 748	5
Centre for Integrated Diagnostic Systems	731	1
Digital Media Innovation Centre Accelerato	726, 748	2
ID Centre Derby	721, 726, 741, 743, 804	5
InfoLab21	722, 726	2
Innovation Centre	741, 748, 803, 923	4
IPI Bioscience Business Incubator	731	1
London BioScience Innovation Centre (LBIC)	244, 731, 741, 748	6
Loughborough Innovation Centre	724	1
Low Carbon Technology Incubator	241, 731, 748	4
MBS Incubator	341, 722	2
MerseyBIO Incubator	244, 731, 748	3
NETPark	651, 721, 731	3
North Campus Incubator	366, 514, 722, 731, 741, 748, 851, 921	10
Norwich Bio-Incubator	724, 731, 732, 748, 923	7
Royal Holloway Enterprise Centre	726, 731	2
SP/ARK	722, 726, 748, 804, 921, 923	8
Southampton SETsquared	642, 731	2
Sparkhousestudios	726, 921, 923, 930	4
Springfield Incubator	726, 748, 921	3
Surrey Technology Centre - SETsquared	322, 731, 748, 804, 930	6
Technium Digital	726, 731	2
University of Southampton Science Park	300, 642, 722, 741, 743, 748	6
St Peter's Gate	703, 744, 748, 804	6
Bio Centre	731, 741	4
IT Centre	722, 741, 748, 803, 911, 926	6
Total		128

Note:
[§] This number indicates the number of tenant firms from these incubators included in the sample.

Table 3: Summary Statistics - Incumbents

Variable	Mean	Median	25%	75%	St. Dev.
	(1)	(2)	(3)	(4)	(5)
No. UK Patents	0.673	0	0	1	2.963
No. Trademarks	0.678	0	0	0	4.566
Assets (£million)	485.857	0.101	0.121	6.649	11,701
Age (years)	14.685	9	5	18	16.394
No. Directors	8.251	6	4	10	7.015
Entry Rate (3-digit SIC)	0.131	0.123	0.081	0.173	0.068
CR4 (3-digit SIC)	0.326	0.254	0.185	0.472	0.185
Entrant Patent	0.295	0.083	0	0.535	0.396
Incumbent Patent	154.849	121.958	58.463	205.349	116.591

Table 4: Comparison: Total Assets of Tenants vs. all other Entrants (FAME) (Kolmogorov-Smirnov Test - H_0 distributions equal)

SIC	P-Value			
	2001	2002	2003	2004
241				0.476
244	0.722		0.958	
295	0.659			
300			0.198	
321			0.929	
322		0.980		
331			0.502	
332			0.639	
334			0.927	
341		0.776		
366				0.602
401			0.543	
511	0.361			
514				0.916
519	0.571			0.855
524				0.489
642			0.552	
651				0.206
703				0.266
721		0.804		0.399
722		0.440	0.692	0.677
724	0.829	0.340		
726	0.883	0.498	0.736	0.627
731	0.661	0.294	0.023	0.574
732	0.324	0.689		
741	0.426	0.689	0.036	0.078
743		0.191	0.506	
744				0.813
748	0.065	0.931	0.018	0.549
803			0.023	
804	0.341	0.652		0.569
851			0.298	0.218
911			0.290	
921		0.860	0.922	0.820
923	0.397		0.325	0.491
926			0.566	
930		0.735	0.678	

Table 5: Transition matrix: Patenting persistence of incumbents

	Patent = 0	Patent = 1
Patent = 0	73.74	26.26
Patent = 1	69.91	30.09

Table 6: 1st stage nonparametric conditional mode estimator - confusion matrix (for comparison also confusion matrix from Probit)

Nonparametric conditional mode			
		Predicted	
		0	1
Actual	0	10,347	70
	1	1,544	2,496
% correctly predicted	0.877		
Probit			
		Predicted	
		0	1
Actual	0	10,223	194
	1	3,765	275
% correctly predicted	0.726		

Table 7: Results for 2nd Stage Probit (Marginal effects - evaluated at mean for continuous variables)

Covariates	Patent dummy				
	(1)	(2)	(3)	(4)	(5)
Entrant Patent	**0.004*****				
	(0.002)				
Entrant Patent/Distance		**0.160******		**0.173******	
		(0.036)		(0.038)	
Entrant Patent Distance Band 1			**0.009*****		**0.015******
			(0.004)		(0.004)
Entrant Patent Distance Band 2			**0.002******		**0.002******
			(0.001)		(0.001)
Entrant Patent Distance Band 3			**0.001******		**0.001*****
			(0.000)		(0.000)
Incumbent Patent	0.0000	0.0000	0.0000	0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Assets	0.020**	0.019**	0.020**	0.020**	0.020**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
ln Age	-0.029**	-0.017*	-0.019**	-0.017*	-0.019**
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
No of Trademarks	0.007	0.007	0.007	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Entry Rate (SIC 3-digit)	-0.406**	-0.329*	-0.276*	-0.359**	-0.298*
	(0.111)	(0.134)	(0.126)	(0.134)	(0.136)
Incubator Dummies		Included	Included		
Incubator/Distance				Included	Included
Year Dummies	Included	Included	Included	Included	Included
Sector Dummies	Included	Included	Included	Included	Included
No. Obs.	11,832	11,832	11,832	11,832	11,832

Notes:
1. $^+$ indicates significance at 10%; * at 5%; ** at 1%.
2. Distance bands are defined based on the percentiles of the distribution of the distance between entrants and incumbents: **Distance Band** 1 for distance≤2.5th percentile; **Distance Band 2** for distance>2.5th percentile and distance≤30th percentile; **Distance Band 3** for distance>30th percentile.
3. There are 30 incubator dummies which assume the value of 1 if an incumbent firm experiences entry of a tenant firm from a specific incubator. Otherwise its value is 0.
4. Incubator/Distance are 30 variables which are the incubator dummies divided by the geographical distance between the incumbent and the incubator.

Table 8: Robustness Test - Distance Band Definition: Results for 2nd Stage Probit (Marginal effects - evaluated at mean for continuous variables)

Covariates	Patent dummy	
	(1)	(2)
Entrant Patent Distance Band 1	**0.006***	**0.009****
	(0.003)	(0.003)
Entrant Patent Distance Band 2	**0.003****	**0.003****
	(0.001)	(0.001)
Entrant Patent Distance Band 3	**0.001****	**0.001***
	(0.000)	(0.000)
Incumbent Patent	0.0000	0.0000
	(0.000)	(0.000)
ln Assets	0.020**	0.020**
	(0.002)	(0.002)
ln Age	-0.018**	-0.019**
	(0.006)	(0.007)
No of Trademarks	0.007	0.007
	(0.005)	(0.005)
Entry Rate (SIC 3-digit)	-0.276*	-0.298*
	(0.129)	(0.131)
Incubator Dummies	Included	
Incubator/Distance		Included
Year Dummies	Included	Included
Sector Dummies	Included	Included
No. Obs.	11,832	11,832

Notes:
1. $^+$ indicates significance at 10%; * at 5%; ** at 1%.
2. As a robustness check the distance bands are defined based on the percentiles of the distribution of the distance between entrants and incumbents: **Distance Band** 1 for distance≤5th percentile; **Distance Band 2** for distance>5th percentile and distance≤25th percentile; **Distance Band 3** for distance>25th percentile.
3. There are 30 incubator dummies which assume the value of 1 if an incumbent firm experiences entry of a tenant firm from a specific incubator. Otherwise its value is 0.
4. Incubator/Distance are 30 variables which are the incubator dummies divided by the geographical distance between the incumbent and the incubator.

Table 9: Robustness Test - Incumbent Sample *Patenting*: Results for 2nd Stage Probit (Marginal effects - evaluated at mean for continuous variables)

Covariates	Patent dummy				
	(1)	(2)	(3)	(4)	(5)
Entrant Patent	**0.003**$^{+}$				
	(0.002)				
Entrant Patent/Distance		**0.152****		**0.162****	
		(0.033)		(0.036)	
Entrant Patent Distance Band 1			**0.009***		**0.015****
			(0.004)		(0.004)
Entrant Patent Distance Band 2			**0.002****		**0.002****
			(0.001)		(0.001)
Entrant Patent Distance Band 3			**0.001****		**0.001***
			(0.000)		(0.000)
Incumbent Patent	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Assets	0.019**	0.019**	0.019**	0.020**	0.020**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln Age	-0.029**	-0.018**	-0.019**	-0.018**	-0.019**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
No of Trademarks	0.007	0.007	0.007	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Entry Rate (SIC 3-digit)	-0.381**	-0.299*	-0.258*	-0.333*	-0.285
	(0.108)	(0.141)	(0.129)	(0.136)	(0.135)
Incubator Dummies		Included	Included		
Incubator/Distance				Included	Included
Year Dummies	Included	Included	Included	Included	Included
Sector Dummies	Included	Included	Included	Included	Included
No. Obs.	11,961	11,961	11,961	11,961	11,961

Notes:
1. $^{+}$ indicates significance at 10%; * at 5%; ** at 1%.
2. As a robustness check the set of incumbent firms now includes any firm that had a UK patent between 1996-2005 instead of only 2000-2005 as in Table 7.
3. Distance bands are defined based on the percentiles of the distribution of the distance between entrants and incumbents: **Distance Band** 1 for distance≤2.5th percentile; **Distance Band 2** for distance>2.5th percentile and distance≤30th percentile; **Distance Band 3** for distance>30th percentile.
4. There are 30 incubator dummies which assume the value of 1 if an incumbent firm experiences entry of a tenant firm from a specific incubator. Otherwise its value is 0.
5. Incubator/Distance are 30 variables which are the incubator dummies divided by the geographical distance between the incumbent and the incubator.

Table 10: Robustness Test - Incumbent Sample *Asset Size*: Results for 2nd Stage Probit (Marginal effects - evaluated at mean for continuous variables)

Covariates	Patent dummy				
	(1)	(2)	(3)	(4)	(5)
Entrant Patent	**0.004***				
	(0.002)				
Entrant Patent/Distance		**0.163****		**0.174****	
		(0.036)		(0.116)	
Entrant Patent Distance Band 1			**0.009***		**0.016****
			(0.005)		(0.005)
Entrant Patent Distance Band 2			**0.002****		**0.002****
			(0.001)		(0.001)
Entrant Patent Distance Band 3			**0.001****		**0.001***
			(0.000)		(0.000)
Incumbent Patent	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Assets	0.023**	0.023**	0.023**	0.024**	0.023**
	(0.002)	(0.002)	(0.003)	(0.008)	(0.002)
ln Age	-0.025**	-0.013^{+}	-0.015^{+}	-0.013^{+}	-0.015*
	(0.007)	(0.008)	(0.008)	(0.023)	(0.007)
No of Trademarks	0.024**	0.023**	0.023**	0.024**	0.023**
	(0.004)	(0.004)	(0.003)	(0.011)	(0.004)
Entry Rate (SIC 3-digit)	-0.346**	-0.301*	-0.256	-0.329*	-0.275^{+}
	(0.125)	(0.143)	(0.159)	(0.425)	(0.146)
Incubator Dummies		Included	Included		
Incubator/Distance				Included	Included
Year Dummies	Included	Included	Included	Included	Included
Sector Dummies	Included	Included	Included	Included	Included
No. Obs.	9,624	9,624	9,624	9,624	9,624

Notes:
1. $^{+}$ indicates significance at 10%; * at 5%; ** at 1%.
2. As a robustness check the set of incumbent firms now excludes incumbent firms in the bottom and top 10th percentiles of the asset size distribution.
3. Distance bands are defined based on the percentiles of the distribution of the distance between entrants and incumbents: **Distance Band** 1 for distance$\leq$2.5th percentile; **Distance Band 2** for distance>2.5th percentile and distance$\leq$30th percentile; **Distance Band 3** for distance>30th percentile.
4. There are 30 incubator dummies which assume the value of 1 if an incumbent firm experiences entry of a tenant firm from a specific incubator. Otherwise its value is 0.
5. Incubator/Distance are 30 variables which are the incubator dummies divided by the geographical distance between the incumbent and the incubator.

Table 11: Overview University Incubators

University	Incubator	Start Year
Anglia Ruskin University		
Arts Institute at Bournemouth	Enterprise Pavillion	2005
Aston University	**Faraday Wharf**	**2001**
Aston University	iBIC	2005
Babraham Institute	Bioincubator	1998
Bath Spa University		
Birkbeck College		
Birmingham City University		
Bishop Grosseteste University	Sky Centre	2007
Bournemouth University	**Innovation Centre**	**2001**
Brunel University	Brunel Science Park	1986
Buckinghamshire New University	Buckingham House	2009
Canterbury Christ Church University		
Cardiff University	Cardiff Medicentre	1992
Cardiff University	Cardiff Business Technology Centre	1988
City University, London		
Coventry University	The TechnoCentre (Innovation Centre)	1998
Cranfield University	Business Incubation Centre	2005
Cranfield University	Cranfield University Technology Park	1991
De Montfort University	De Montfort Innovation Centre	1995
Durham University	**NETPark**	**2004**
Edge Hill University		
Glasgow Caledonian University	**Biotech Incubator**	**2003**
Goldsmiths College		
Harper Adams University College		
Heriot Watt University	Research Park	1971
Imperial College London	Imperial Incubator	2006
Imperial College London	**Low Carbon Technology Incubator**	**2004**
Institute of Cancer Research		
Keele University	**Stepping Stones**	**2002**
King's College London		
Kingston University		
Lancaster University	Daresbury Innovation Centre	2005
Lancaster University	**InfoLab21**	**2004**
Lancaster University	Centre for Ecology and Hydrology	2007
Leeds Metropolitan University	**Leeds Metropolitan Business Incubator**	**2001**
Leeds Trinity & All Saints		
Liverpool Hope University		
Liverpool John Moores University	**Digitalinc**	**2002**
Liverpool John Moores University	Liverpool Science Park	2006
London Business School		
London Metropolitan University	**Digital Media Innovation Centre**	**2004**
London School of Economics and Political Science		
London School of Hygiene and Tropical Medicine		
London South Bank University	London Knowledge Innovation Centre	2006
Loughborough University	**Loughborough Innovation Centre**	**2002**
Loughborough University	**Loughborough Science Park**	**2004**
Manchester Metropolitan University	Innospace	2007
Marjon (University College Plymouth St Mark & St John)		
Merthyr Tydfil College		
Middlesex University		
Napier University		
Newcastle University	CELS at Newcastle	2006
Newman University College		
North East Wales	Institute of Higher Education	
Northumbria University	**NETPark**	**2004**
Nottingham Trent University	**The Hive**	**2001**
Oxford Brookes University		
Queen Margaret University		
Queen Mary, University of London	BioEnterprises Innovation Centre	2009

Table 12: Overview University Incubators

University	Incubator	Start Year
Robert Gordon University		
Roehampton University		
Royal Agricultural College		
Royal College of Art		
Royal Holloway, University of London	**Royal Holloway Enterprise Centre**	**2002**
Royal Veterinary College	**London BioScience Innovation Centre**	**2001**
School of Pharmacy		
Scottish Agricultural College (SAC)		
Sheffield Hallam University	The Hatchery	2005
Southampton Solent University		
St George's Hospital Medical School		
Staffordshire University		
Swansea Institute of Higher Education		
Thames Valley University		
UHI Millennium Institute	**European Centre for Marine Biotechnology**	**2004**
University Campus Suffolk		
University College Birmingham		
University College Falmouth		
University College London		
University for the Creative Arts	Mode Future	2005 (closed 2007)
University of Aberdeen	University of Aberdeen	2009
University of Abertay	Embreonix	2000
University of Bath	**Carpenter House**	**2002**
University of Bedfordshire		
University of Birmingham	Birmingham Research Park	1986
University of Bolton		
University of Bradford	**IPI Bioscience Business Incubator**	**2003**
University of Bradford	**Think Business**	**2004**
University of Brighton		
University of Bristol	**SETsquared Business Acceleration Centre**	**2003**
University of Cambridge	St Johns Innovation Centre Limited	1987
University of Cambridge	Cambridge Science Park	1970
University of Central Lancashire	Northern Lights	2007
University of Central Lancashire	West Lakes Science & Technology Park	2009
University of Central Lancashire	Business Incubation Unit	2009
University of Chester		
University of Chichester		
University of Cumbria		
University of Derby	Bank's Mill Studios	1999
University of Derby	**ID Centre Derby**	**2002**
University of Derby	**Network House Derby**	**2001**
University of Dundee	Dundee University Incubator	2005
University of Dundee	**Springfield Incubator**	**2002**
University of Dundee	**The Greenhouse**	**2002**
University of East Anglia	**Norwich Bio-Incubator**	**2001**
University of East London	Royal Docks /Knowledge Dock	1999/2006
University of Edinburgh	Scottish Microelectronics Centre	2000
University of Edinburgh	Edinburgh Technology Transfer Centre	1987
University of Edinburgh ETTC	BioSpace	2005
University of Edinburgh	ETTC@Informatics	2008
University of Edinburgh	**Edinburgh Pre-Incubator Scheme (EPIS)**	**2004**
University of Essex	Business Incubation Centre	2007
University of Essex	Research Park	under construction
University of Exeter	The Innovation Centre	2000
University of Glamorgan	Gti	1999

Table 13: Overview University Incubators

University	Incubator	Start Year
University of Glasgow	**Centre for Integrated Diagnostic Systems**	**2002**
University of Glasgow	West of Scotland Science Park	1983
University of Glasgow	**The Technology Complex**	**2001**
University of Gloucestershire		
University of Greenwich	Medway Enterprise Hub	2006
University of Hertfordshire	**Innovation Centre**	**2003**
University of Huddersfield	**Business Mine**	**2004**
University of Hull	University of Hull-Knowledge Exchange	2007
University of Hull	Logistics Institute Incubation Offices	2007
University of Kent	**Canterbury Enterprise Hub**	**2004**
University of Kent	Medway Innovation Centre	2007
University of Leeds	Leeds Innovation Centre	2000
University of Leicester		
University of Lincoln	**Sparkhousestudios**	**2003**
University of Liverpool	**MerseyBIO Incubator**	**2003**
University of Liverpool	Liverpool Science Park	2006
University of Manchester	Bioscience Incubator	1999
University of Manchester	Technology Centre One Central Park	2005
University of Manchester	**MBS Incubator**	**2002**
University of Manchester	**North Campus Incubator**	**2004**
University of Manchester	Stockport Business Incubator CIC	2008
University of Manchester	Manchester Science Park	1984
University of Manchester	Daresbury Innovation Centre	2005
University of Northampton	**CLEO**	**2003 (closed 2007)**
University of Northampton	Portfolio Innovation Centre	2006
University of Northampton	Chesham House Business Centre	2009
University of Nottingham		
University of Northampton	University of Nottingham Innovation Park	2008
University of Oxford	Begbroke Centre for Innovation and Enterprise	2006
University of Oxford	Oxford Science Park	1991
University of Plymouth	Tamar Science Park Limited	1995
University of Plymouth	Formation Zone	2007
University of Portsmouth		
University of Reading	Reading Enterprise Centre	
University of Reading	Science & Technology Centre	1999
University of Salford	Technology House	
University of Salford	Innovation Forum	
University of Sheffield	Kroto Innovation Centre	2007
University of Sheffield	The Sheffield Bioincubator	2006
University of Southampton	**University of Southampton Science Park**	**2003**
University of Southampton	**SETsquared Business Acceleration Centre**	**2003**
University of St Andrews		
University of Stirling	Innovation Park	1986 (closed)
University of Stirling	**SureStart**	**2003**
University of Strathclyde	Strathclyde University Incubator	1990
University of Strathclyde	West of Scotland Science Park	1983
University of Sunderland	**St Peter's Gate**	**2004**
University of Surrey	**Surrey Technology Centre**	**2002**
University of Sussex	Sussex Innovation Centre (SInC)	1996
University of Teesside	**University of Teesside**	**2001**
University of the Arts, London		
University of the West of England, Bristol	UWE Ventures	2009
University of the West of Scotland		

Table 14: Overview University Incubators

University of Wales College, Newport		
University of Wales Institute		
University of Wales, Aberystwyth	**CRISALIS Germinator**	**2004**
University of Wales, Aberystwyth	Technium Aberystwyth	2005
University of Wales, Bangor	**Bangor Bioincubators**	**2003**
University of Wales, Lampeter		
University of Wales, Swansea	**Technium Digital**	**2003**
University of Wales, Swansea	Technium Sustainable Technologies	2005
University of Warwick	The Venture Centre	1984
University of Westminster	Innovation Labs	1999 (closed)
University of Winchester		
University of Wolverhampton	e-innovation Centre	2006
University of Wolverhampton	**First Base**	**2001**
University of Wolverhampton	**SP/ARK**	**2004**
University of Worcester		
University of York	The Innovation Centre	1995
University of York	**The Bio Centre**	**2003**
University of York	**The IT Centre**	**2003**
Writtle College	Micro-Incubator	2005
York St John University		