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ACADEMIC PATENTING: OPPORTUNITY, SUPPORT OR ATTITUDE?

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Academic Patenting: Opportunity, Support or Attitude?*

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Abstract

I provide evidence that university-industry collaboration is important for turning commercial opportunities into patents. I find that the number of publications and the support provided by the university are not conclusive in explaining a researcher's propensity to patent. Controlling for a variety of individual and departmental characteristics I find that research sponsored by industry is most likely to produce patents and more likely to produce patents owned by industry.

Keywords: University patenting; University-industry collaboration; Academic science; Technology transfer; Dynamic panel data models, Frailty models.

JEL codes: O31, O34, C23, C41

1 Introduction

Universities have traditionally been an important source for knowledge creation and economic growth. They support industrial innovation through solving fundamental research problems (e.g. Aghion et al., 2008; Gibbons and Johnson, 1974; Nelson, 1986) and contribute directly through licensing of inventions resulting from their research (e.g. Henderson et al., 1998; Thursby and Kemp, 2002). Since the 1980s universities have become increasingly proactive in their commercialisation efforts and the number of academic staff involved in patenting increased dramatically (e.g. Jensen and Thursby, 2001; Siegel et al., 2007; Verspagen, 2006).

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Numerous studies have investigated the determinants of academic patenting activity and have found three factors that potentially affect a researcher's propensity to patent. Firstly, many papers stress the importance of patenting support provided through the commercialisation unit of the university and through financial incentives (e.g. Foltz et al., 2003; Lach and Schankerman, 2008; Thursby and Kemp, 2002; Thursby et al. 2009). A second body of literature has focused on the patenting opportunities of individual researchers by measuring their scientific activity (e.g. Azoulay et al., 2007; Stephan et al. 2007). Some recent papers, especially in the field of organisational behaviour, have further highlighted that the influence of peers or mentors on researcher's attitudes towards commercialisation (patenting attitude) is one of the main factors for successful patenting (Bercovitz and Feldman, 2008; Ozgen and Baron, 2007; Stuart and Ding, 2006).

This paper aims to contribute to the latter stream of patenting literature by empirically investigating the influence of partners from industry on patenting. Interviews with engineers conducted by Agrawal and Henderson (2002) suggest that interactions with industry can steer academics towards commercialisation. Further, they can help academics to recognise opportunities for commercialisation (Ozgen and Baron, 2007). This points to the possibility that industry partners influence a researcher's attitude towards patenting as well as their perceived opportunities and control over their inventions (Goethner et al., 2011).

The inclusion of funding in the analysis of a researcher's patenting propensity, could moreover challenge the existing evidence on the impact of publication numbers on patents, due to the strong correlation between the two. In previous papers I have already shown a strong link between funding and publications and moreover have found no significant effect of patenting on publications (Banal-Estanol et al., 2010; Meissner, 2010). While a large number of studies find a positive impact of publication numbers on a researcher's propensity to patent (Azoulay et al., 2007; Breschi et al., 2005; Calderini et al., 2007; Carayol, 2007; Stephan et al., 2007), in a study by Bercovitz and Feldman (2008), that already controls for some public research funding and a series of peer group factors, this effect is observed to be very small.

This paper uses data from a 12 year panel of 479 engineering academics in the UK, and finds that collaboration with industry is the best predictor of patent numbers. This suggests that industry partners exert a positive effect on a researcher's approach towards patenting. I further find that researchers producing a high quality publications have more possibilities to produce patentable research, however, not to the extent suggested by other papers.

The paper is organised as follows: Section 2 reviews existing literature and describes the three different dimensions affecting commercialisation of academic research: opportunity, support and attitude, at the individual and institutional level. In section 3 I summarise the data and introduce the empirical model and the methodology, considering the panel structure of the data, the large number of zeroes and endogeneity present. Section 4 presents the results and section 5, finally, discusses and concludes.

2 Patenting: Opportunity, Support and Attitude

Previous research has shown that university researchers differ significantly in their commercial activities (Louis et al., 1989). Researchers differ in their opportunities to patent as well as in their attitudes towards the commercialisation of research. Moreover, do they receive different levels of support for patenting. This section reviews the most important individual and institutional factors affecting an academic's patenting propensity.

2.1 Individual Factors of Patenting

A first important individual factor recognised by economic literature is scientific excellence. It has repeatedly been argued that patents could potentially result from any applied research project that also generates publications. Agrawal and Henderson (2002), for instance, cites an engineering faculty member at MIT, saying that "most patentable research is also publishable" (Agrawal and Henderson, 2002, p. 58). Indeed both activities can be complementary as the effort associated with and nature of research do not differ (Dasgupta and David, 1994). Murray and Stern (2007), for example, find that 50% of a sample of articles in Nature Biotechnology are accompanied by a patent. Hence, academics with the ability to successfully conduct scientific research also have the assets to produce commercial outputs. Accordingly, research by Zucker et al. (1998) suggests that researchers with an excellent publication record are also most likely to patent their research (see also Di Gregorio and Shane, 2003; Louis et al., 2001; Zucker and Darby, 1996). Recent empirical work confirms the positive impact of publication numbers on the propensity to patent (Bercovitz and Feldman, 2008; Carayol, 2007; Stephan et al., 2007; Thursby and Thursby, 2007). Studies by Breschi et al. (2005) and Azoulay et al. (2007) using duration models, for example, report a positive correlation between the number of publications and patenting events. It therefore appears that only the most productive researchers in terms of publications have the opportunities to engage in commercial activities. However, Agrawal and Henderson (2002), while controlling for fixed effects, finds no significant correlation between the number of publications and patents for a sample of engineers at MIT and Calderini et al. (2007) finds some evidence for a curve-linear relationship. While most patentable research is also publishable, not all publishable research is patentable. However, publications are a first good indicator for the research activity of an academic.

Additionally to publication numbers, the access to external research funding can be considered an important factor for producing patentable research. Research funding, especially in applied engineering science, is essential to acquire laboratory equipment required for research and allows the employment of research assistants. Accordingly, surveys by Zucker et al. (1998), and Link et al. (2007) indeed find that experience in managing grants adds to more effective patenting. Moreover, the access of funding may support patenting directly through provision of expertise by the funding agent or specific appropriation requirements.

However, not all researchers receiving external grants pursue commercialisation of their research equally and there exists evidence for a very skewed patenting process (Agrawal and Henderson, 2002; Azoulay et al., 2007; Thursby and Thursby, 2007). While scientific experience and funding enable academics to produce and better recognise potentially patentable research, the academic may simply not ascribe high value to commercial activities. Traditionalists amongst academic researchers might indeed feel that commercialisation threatens academia and that the two should be distinct (Owen-Smith and Powell, 2001b).

Building on this conflicting evidence, this paper investigates whether industry funding, rather than publications or external grants as such, are responsible for pushing researchers towards commercialisation. Collaboration with industry and other applied sponsors helps overcome the barrier between scientific and commercial activities. Several studies have shown that industry provides funds and ideas for research (Lee, 2000; Mansfield, 1995; Siegel et al., 2003), and may steer researchers towards commercialisation (Agrawal and Henderson, 2002; Gulbrandsen and Smeby, 2005). Exchanges with the business community and joint research projects may hence help to overcome an intrinsic fear of changes in academia and help academics to pursue patenting.

The individual factors described in this section refer to the three different aspects that enable patenting: opportunity, support and attitude. Figure 1 gives an overview over the different dimensions. While scientific publications and access to funding indicate a researcher's opportunity to produce patentable outcome, funding moreover provides the support necessary. Contacts with industry then may impact on a researcher's attitude towards commercialisation.

2.2 Institutional Factors of Patenting

Though undoubtedly patenting is prompted primarily by an academic's desire to solve research questions (Levin and Stephan, 1991) it is also affected by the opportunities of the scientific field, the nature of rewards associated with patenting and the support given to the academic (David and Dasgupta, 1994).

The characteristics of the scientific field and industrial relevance of research are important factors in the opportunities for patenting research findings. Firstly, not all areas of research produce patentable outcomes, and other forms of commercial output and intellectual property, such as software and architectural works, may be generated. Secondly, the benefits associated to patenting differ between fields (Owen-Smith and Powell, 2001a).

It has further been shown that the support provided through the university is essential for successful patenting. Since the 1980s most universities in the US and across Europe have established commercialisation units (e.g. Technology Transfer Offices (TTOs)) to better identify commercial opportunities, provide expertise for efficient patenting and to source potential licensees of university inventions. Characteristics of these commercialisation units have indeed been found to positively influence the number of invention disclosures (e.g. Siegel et al., 2003; Thursby and Kemp, 2002). Moreover, the share of licensing revenue positively effects the number of inventions disclosed to the university (e.g. Lach and Schankerman, 2008; Thursby et al., 2009). Thus, activities of the TTO may increase the willingness of academic staff to patent and license, encouraging strategic choices in the dissemination of research (Geuna and Nesta, 2006; Thursby and Thursby, 2002).

Although these findings suggest university policies and culture to have a strong impact on commercialisation activities, Louis et al. (1989) in a survey of US life-science researchers and Bercovitz and Feldman (2008) analysing the disclosure activity of researchers at two medical schools, find socialisation and peer effects to be better predictors. Bercovitz and Feldman, (2008) finds the patenting activity of researchers of similar rank in the same department to positively affect an academic's attitude towards patenting. Several other papers also report evidence that the proportion of inventors at the university level and in the department has a positive effect on patenting (Breschi et al., 2005; Louis et al., 1989).

The institutional factors again reflect the three different aspects that enable commercialisation of research (Figure 1): opportunities provided by the scientific field, support provided by the TTO and attitude shaped by the activities of peers.

To summarize, literature has identified several factors influencing academic patenting: (1) indicating the opportunity for commercial research, (2) the support for successful patenting, and (3) factors shaping a researcher's attitude towards commercialisation.

3 Data and Methods

3.1 Data and Descriptive Statistics

Longitudinal data on academic, commercial and collaborative histories of 479 tenured academics from 10 UK universities for the period 1996 to 2007 is used to analyse a researcher's propensity to patent (for a list of universities see Table 1). The data for this analysis comes from a larger dataset collected at City University in 2008 that comprises information on more than 4000 engineering academics from 40 universities over a 22 year period (see Banal-Estanol et al., 2010). Initially, researchers were identified using staff registers in academic calendars, which provided the basis for collecting individual information from the Internet, and researchers' publication and patent histories from existing databases. 10 universities additionally provided information on external funding received from industry, government and public bodies for the period 1996 to 2007. Only academics that remained in the sample for the first 10 years (1996 to 2005) were considered to allow for a sufficiently long observation period. Table 1 gives an overview over the average size of the engineering schools at the 10 universities and shows the distribution of the sample across universities. The sample includes approximately 50% of the engineering staff at the 10 schools. For three of the small universities this share is much lower, indicating that more academics stay for just a short period of time before perhaps moving on to more established engineering departments.

In this section I give a detailed overview over the collected data. Descriptive statistics for some key variables are presented in Table 2. Table 3 lists the variables used in the regression.

Patents. For each academic in the dataset, patents stating her as an inventor were collected from esp@cenet, developed by the European Patent Office (EPO). The web interface allows searches for patents filed with the EPO but also those filed with the UK Intellectual Property Office (UKIPO) and other national patent offices. I consider here all patents that state the researcher as an inventor and hence not only patents filed by the university but also those assigned to third parties, including industry. Data construction required a manual search in the inventors database to identify those entries where the identity of the academic was certain. This was done by comparing addresses, titles and technology classes for all patents potentially attributable to each researcher.[1] As each invention can lead to multiple patents, I additionally verified each entry with the Derwent World Patents Index (DWPI) that contains information grouped around a base patent, thus enabling me to uniquely identify the original invention and avoid multiple counts.

I collected all patents ever granted to each researcher and recorded the year of priority which represents the date closest to invention. The oldest collected patent dates from 1964, indicating that patenting is not a new phenomenon in universities in the UK. In total 196 inventors were granted 727 original patents. 149 patents were only issued at national patent offices (mostly UKIPO), 578 were registered at the EPO or WIPO (World Intellectual Property Office). 156 of the 196 academic inventors filed patents during the observation period 1996 to 2007. A third of the patenting researchers filed only one patent during their entire career to date. 40.6% of patents are assigned to a company and only 37.0% to universities. This confirms the importance of considering non-university patents when analysing academic patenting in Europe (Geuna and Nesta, 2006).

The majority of researchers (67.43%) does not patent during the observation period. Even among those academics who patent during the 12 year period, 69 (more than 44%) do not file more than one patent. Hence, the average number of patents in our sample is low with approximately 0.08 patents per academic per year (see Table 2) and a share of zero observations of 93.88%. This shows that patenting is not widely spread amongst university scientists even in applied engineering sciences.

To account for ownership and quality of patents I use different patent measures in my regressions. Inventions by academics can be filed with the university, the academic herself or an industry sponsor. Industry ownership is measured as the number of patents assigned to a firm. Further, I consider patent quality by considering the family size of a patent. Patents can be filed at several patent offices and sister patents or extensions to existing original patents can be taken out. As the patenting process is very costly

[1] 41 academics with common names had to be removed from the data as it was not possible to uniquely identify their patents.

it can be assumed that only the best inventions show a large number of sister patents. I consider those original patents as high-impact inventions that have a family of 6 or more patents. This represents the median of family size amongst EPO patents of UK engineering academics. Original patents with fewer associated patents are considered to be of lower impact.

Funding and Collaboration. Funding information for each academic was provided by the research offices of the 10 universities. They included names of principal investigators, funding periods, funding amounts and the natures of sponsoring agents. Researchers receive external funding from five different agents: (1) UK research councils, (2) industry, (3) government ministries (excluding research councils), (4) EU, and (5) not-for profit organisations. Academics receive half of their funding from the UK research councils, amounting to an average of 19,821 GBP per academic per year (see Table 2). An average of 8,626 GBP, 21% of funding, is received from industry sponsors. The other three funding agents contribute less than 10% each.

To account for the length of a grant and to avoid focusing all the funding on the start of a project, the grant value was divided by the length of the grant period and equally distributed across years except for the first and last year of a project, which were assigned half-year values as they do not represent full years. More than 60% of external funding extended over a period of one to three years, and a small number were long-term grants. Less than 1.5% of grants extended over six years or more. I generate 3-year moving averages of the different grant variables to account for the length of the research projects and to allow for a long term effect of external income on commercial research activity.

To account for patenting opportunities I create an indicator variable that takes the value one if a researcher receives less than 2000 GBP annually over a 3 year period. Such low amounts of funding are not targeted towards research but are perhaps providing travel or conference assistance. Approximately 50% of observations take the value 1.

To estimate the impact of industry funding on patenting propensity I calculate the share of funding from industry received over the previous 3 years. On average, 21% of funding comes from industry with some researchers receiving funding exclusively from private sponsors. The correlation coefficients in Table 4 show that industry funding correlates stronger with patenting than with publications though both coefficients are very small. Funding in general correlates stronger with publication numbers than with patenting. This might indicate that indeed considering funding in the analysis of patenting propensity may diminish the effect of publications.

Publications. Information on articles published during the observation period was extracted from the ISI Science Citation Index (SCI) for each academic in the sample. Entries were matched using authors' names, affiliations and article titles. The SCI includes journals based on a selection and reviewing process and is hence biased towards work of scientific importance. These journals represent the most important journals in their field and will serve as a measure for academic research output in this analysis. The average number of publications is approximately two articles, though we can observe large heterogeneity in publication numbers with the maximum number in one year being 27 articles for one academic (see Table 2). Additionally, to account for the quality of publications I consider their average impact. I employ the ISI Journal Impact Factor (JIF), a measure for the relative quality of a journal in which an article is published based on the number of citations it received over a 3 year period. Though not a direct measure for the quality of a paper, it reflects its importance attributed by peer-review and presents a good indicator for research impact. The average JIF for publications in my sample ranges from zero to 27.36, the mean value is 0.997 (see Table 2).

As patenting is expected to occur for very productive researchers that publish consistently over a long period, this productivity is measured using moving 3-year averages of publications. Alternatively, researchers that publish consistently in high impact journals might have many more opportunities to patent. I therefore measure the impact as the average JIF of a researcher's publications during the past 3 years. Table 4 shows that both measures are mildly correlated but that funding correlates stronger with publication numbers than with the average impact (though both coefficients are very small). I therefore expect funding to diminish the effect of publication numbers rather than that of publication quality.

I create an indicator variable of publishing activity that takes the value one if an academic publishes less than 1 article annually over a 3 year period, which represents just below 40% of the sample. This indicator should help to identify those researchers that have no opportunities for patenting.

Institutional Factors. Academics were grouped into engineering departments according to Research Assessment Exercise (RAE) categories. Five subject dummies were created, Electrical and Electronic engineering (107 academics), General engineering (118 academics), Mechanical engineering (117 academics), Chemical engineering (64 academics) and Civil engineering (73 academics). Table 5 shows the distribution of inventors and patent observations across the 5 fields of engineering. These first statistics show that patenting is most widely spread in Electrical and Electronic Engineering as well as Chemical Engineering. These two fields also show the largest average number of publications, indicating a strong link between both types of research output. Civil engineers generate the least number of patents and publications. They also show lower levels of funding and industry involvement. Funding levels, however, are lowest for researchers in Chemical engineering. There hence are significant differences in the research behaviour of researchers in different fields of engineering. Funding, publications and patent levels seem to be linked within each field, the only exception being Chemical engineering that shows a large number of publications and patents despite low levels of funding.

To control for differences across these engineering departments in terms of size, research activity, wealth and quality, I use data from the 2001 and 2008 RAE submissions which contains department information for all the years between 1996 and 2007. For each department I gather information on external research income reported to the RAE and calculate the share of income from industry contracts. I further use the number of PhD degrees awarded and RAE quality ratings as measures for department research quality. Additionally, based on information from the full sample of 4000 academics, I retrieve the number of active members of staff in the same department.

As proxies for peer effect I use an indicator taking the value one if there is a senior member of staff amongst the EPO inventors, based on information from the large dataset. Again, to account for the lag in effects, I use moving averages over 3 years as variables in my analysis.

Further, as mentioned above, studies have found TTO support to have a significant effect on patenting activity in the university. I use the number of TTO staff reported to the Higher Education Business and Community Interaction (HE-BCI) survey in 2006 as a proxy for support provided.

Promotion. I also include a control to account for an academic's recent promotion. Academic rank information was collected from university calendars and indicates whether the researcher has been promoted during the past 3 years. Promotion requirements of the university may effect the type of research done by the academic and a recent promotion may hence allow an alternative research behaviour.

3.2 Model and Methodology

To explore the relationship between industry funding and patenting, while considering publication rate and other explanatory factors, I estimate two different models. Firstly, a zero-inflated negative binomial model, which takes into account the excessive number of zeroes and distinguishes between two different zero outcomes. Secondly, I estimate the patenting hazard rate of researchers, the probability that they will patent given that they survived for t years since the last patent. As patenting is a highly skewed process I consider dynamic feedback mechanisms and individual heterogeneity in all estimations. All factors are considered in the period $t-1$ to allow for a lag in the effects.

Negative Binomial Distribution with Zero Inflation. The first model I seek to estimate is described by the following equation:

$$Pat_{it} = \beta_0 + \beta_1 PatStock_{it-1} + \beta_2 \ln(PubAvg_{it-1}) + \beta_3 \ln(IndFund_{it-1}) + \beta_4 Prom_{it-1} + \beta_5 PeerPat_{it-1} + \gamma_1 r_{dt-1} + \gamma_2 Field_d + \gamma_3 s_d + \eta_i + \nu_{it} + \tau_t$$

Where Pat_{it} represents the number of patents filed by academic i in year t. $PatStock_{it-1}$ measures a researcher's accumulated patenting stock up to $t-1$, $PubAvg_{it-1}$ is the academic's scientific capital (mean number of articles published during the 3 years prior to t); and $IndFund_{it-1}$ represents the researcher's tangible industry income (share of industry funding during the 3 years prior to t). $Prom_{it-1}$ is the time variant variable indicating a researcher's promotion during the previous 3 years. $PeerPat_{it-1}$ are the variables indicating the patenting activity of researchers in the same department (number of patenting staff and existence of a senior inventor in the last 3 years) and r_{dt-1} are other time variant departmental variables including department size, department income and research activity of department d during the 3 years prior to t. $Field_d$ indicates the scientific field and s_d then represents other department and university specific time invariant characteristics including department quality and university fixed effects. η_i is the individual specific fixed effect, τ_t is the time specific effect and ν_{it} the disturbance term.

The data used in this analysis is characterised by an excessive number of zeroes (more than 90% of observations). Some of these zeroes are expected to be "certain zeroes" (those researchers assumed never to have opportunities for patenting), thus, the number of zeroes may be inflated and non-patenting cannot be explained in the same manner as patent events.

Several methods have been employed to deal with large numbers of zeroes in economic research and the most flexible approach is known as the double-hurdle or two-step model (Cragg, 1971). This model makes a distinction between e.g. un-patentable research and not patenting patentable research. Cragg (1971, p. 831) described this process as follows: "First a positive amount has to be desired. Second, favourable circumstances have to arise for the positive desire to be carried out". Accordingly, zero patenting may mean either non-participation in patentable research or non patenting due to factors such as patenting support, individual attitudes or research opportunity. There are hence two hurdles or steps in this model that a researcher must pass before patents are filed: produce potentially patentable research and actually patent.

In this study, the zero-inflated negative binomial (ZINB) model is chosen to estimate patenting. It represents a mixing specification which adds extra weight to the probability of observing a zero. It can incorporate the framework of a double-hurdle or two-step model by distinguishing between two different zero outcomes. It further allows for potential overdispersion of patenting frequency, which is indicated by $Var(Pat_{it}) >> E[Pat_{it}]$, and for unobservable heterogeneity (Carayol, 2007; Greene, 1994). Zero inflated count data models have commonly been used to model traffic accidents and health treatments, and have increasingly become popular in the analysis of innovation, including academic patenting (e.g. Carayol, 2007; Franzoni et al., 2009; Stephan et al., 2007).

Patent production is assumed to result from two different regimes underlying scientific research: (1) the engagement in potentially patentable research, and (2) the decision on how many patents to produce, illustrated in Figure 2.

The first process relates to an academic's research effort and orientation. An academic can decide to abstain from research and focus her efforts on teaching and administrative tasks. If she decides to conduct research she can devote different levels of effort to research activity, where active research can potentially lead to a patent. The probability that an academic's work does not lead to a patentable discovery (that a researcher belongs to the "certain zero" group) can then be represented by the zero-inflation parameter p. This can be interpreted as a splitting mechanism that divides researchers into non-patenters, with probability p, and potential patenters, with probability $1-p$. p is determined by covariates w_{it} including measures for research activity (indicators for external funding and publications in the 3 years prior to t). The first-hurdle equation then is:

$\Pr(patentable_{it} = 0|w_{it}) = p = F(\gamma\prime w_{it})$

where $patentable_{it}$ can be interpreted as a researcher's involvement in patentable research. If academic i is not conducting research, $patentable_{it}$ is zero, whereas, if academic i is conducting research, $patentable_{it}$ is one. The function $F(\gamma\prime w_{it})$ can then be modeled as a Logit distribution (Greene, 1994):

$F(\gamma\prime w_{it}) = \exp(\gamma\prime w_{it})/(1 + \exp(\gamma\prime w_{it}))$

The second regime relates to the actual number of patents issued from patentable research for researchers other than those in the "certain zero" group. This includes academics that produce patentable research, but chose not to patent. Reasons for this choice can be a lack of knowledge regarding the patenting process, an inability to recognise commercial opportunities, a lack of administrative support, or individual attitudes that favour open dissemination. These researchers could potentially be steered towards commercialisation, e.g. by an industry sponsor, and are hence not "certain zeroes". As mentioned above, the data is characterised by a large number of zeroes along with a long right tail (prolific inventors). I assume that patenting follows a highly overdispersed Poisson distribution, with small probability of success. To account for overdispersion and the unobserved heterogeneity among academics I assume a negative-binomial distribution, where the probability to patent is determined by covariates x_{it}, which includes all the individual and department level variables of interest to this model. The second hurdle equation is then given by:

$\Pr(Pat^*_{it} = j|x_{it}) = f(j|x_{it})$

where $f(j)$ is the negative binomial probability distribution for Pat^*_{it}.

The two hurdle equations are jointly estimated by means of maximum likelihood. The second hurdle equation is only maximized for observations with $\Pr(patentable_{it} = 0) \neq 1$. The probability to patent is then equal to the probability of the unobserved variable Pat^*_{it} conditional on $patentable_{it}$:

$\Pr(Pat_{it} = j|x_{it}, w_{it}) = patentable_{it} \times Pat^*_{it} = F(\gamma\prime w_{it}) - F(\gamma\prime w_{it})f(j|x_{it}) + f(j|x_{it})$

Thus,

$\Pr(Pat_{it} = 0|x_{it}, w_{it}) = \Pr(patentable_{it} = 0|w_{it}) + \Pr(patentable_{it} = 1|w_{it}, Pat^*_{it} = 0|x_{it}) = p + (1 - p)f(0|x_{it})$

$\Pr(Pat_{it} = j|x_{it}) = \Pr(Pat^*_{it} = j|x_{it}) = (1 - p)f(j|x_{it})$, $j = 1, 2, ...n$

This represents the basic equations of the first ZINB model that I will estimate.

Proportional Hazard Model with Shared Frailty. In a second approach to verify my results I estimate the patent hazard rate $h(t)$, which is the probability that a researcher will patent t years after their last patent or since they entered the sample in 1996. I hence allow multiple patenting events for each researchers. As I expect reoccurring patenting events to be highly correlated, I adopt a proportional hazard model that allows for unobserved heterogeneity (frailty model). Frailty models have previously been used in the analysis of patenting risk and patent citation hazards (e.g. Breschi et al., 2005; Marco, 2007) and given evidence for unobserved heterogeneity amongst researchers or patents.

The hazard function for observation j for researcher i is specified as:

$h(t_{ij}|x_{ij}, \alpha_i) = \alpha_i h_0(t_{ij}) \exp(x_{ij}\beta)$, $j = 1, 2, ...n_i$

where α_i is the latent random effect (the frailty), which follows a gamma distribution and is assumed to have mean 1 and variance θ. The estimate of θ is used to measure the degree of heterogeneity.

One problem poses itself in the hazard model. I only observe a 12 year period and am unable to estimate the effect of industry collaboration on patenting before 1996. However, I know that 25% of researchers patented before 1996 and have been at risk of patenting again since that last patent. I therefore specify t as the number of years since the last patent or since the year of PhD for those that have not filed any patents prior to 1996. Additionally I specify the year 1996 as the year when the researcher came under observation. This left-censored estimation shall help to verify the results.

Dynamic Feedback and Fixed Effect. It has been discussed above that patenting activity is highly skewed and the majority of patents are produced by a small number of researchers. This difference is unlikely to be explained by observable individual heterogeneity. Instead unobserved differences between individuals have to be an important feature of this analysis as they are most likely correlated with the regressors, potentially creating endogeneity. This endogeneity arises in two ways. Firstly, we are faced with the problem of reverse causality as researchers who patent more may be better able to attract funding from external sources (Jensen and Thursby, 2001; Meissner, 2010). Further, endogeneity may arise through omitted variables as publications, patenting, promotion and grant receipt are correlated to a researcher's skills and effort allocation (see Banal-Estanol et al., 2010).

In order to control for unobserved heterogeneity and control for potential reverse causality I follow Blundell et al. (1995) and estimate a model using the pre-sample values of the dependent variable. I assume that unobserved heterogeneity in my data is mainly caused by the different knowledge stocks with which individuals enter the sample, and that patenting experience should contribute positively to a researcher's propensity to patent. The pre-sample value is given by the number of patents filed by the academic before 1996 whether she was employed by a university or a company at the time.

Theory suggests that research activity and technological innovation are subject to dynamic feedback and it is therefore important to also consider continuous, sample-period dynamics when modeling patent counts (Blundell et al., 1995). To proxy for patenting experience accumulated within the sample period I calculate the depreciated stock of patents filed during the observation period. I use Blundell et al.'s (1995) assumption that previous patents provide knowledge of the patenting process but that the quality of this knowledge decreases over time. The sample period patenting stock is hence defined as:

$PatStock_{it} = Pat_{it-1} + (1 - \delta)PatStock_{it-1}$,

with a depreciation value of $\delta = 30\%$ (following Blundell et al. (1995))

In order to confirm the specifications of the models I carry out several tests. The first step is to test the endogeneity of publications and external funding using Hausman's specification tests. The null-hypotheses of exogeneity is not rejected, suggesting that there is no need for instrumental variable estimations. To test for the selection of the ZINB model I firstly use the dispersion parameter alpha which is significantly different from zero, suggesting that the data is overdispersed and that a negative binomial (NB) model is preferred over a Poisson model. The Vuong test is used to discriminate between NB and ZINB models and suggests that the ZINB model represents an improvement over a NB (Vuong, 1989). In the hazard model the frailty assumption is not rejected.

4 Results

Table 6 present the results of the ZINB model for the 3 different patent measures. Column 1 considers all patents regardless their assignee or quality. The patent count variable in column 2 uses measures for industry owned patents. Column 3 shows results for patents of high quality. All models include year dummies. Standard errors are robust and clustered at the individual level. The results show that the fixed effect proxy, pre-sample patent control, is significant and works in the expected direction. Also the stock of patents is highly significant. The predicted number of patents increases by a factor of approximately 1.8 if an academic were to increase the patent stock by one while holding all other variables in the model constant. These first results indicate the dynamic nature of the patenting process and hence the importance of considering dynamic effects in this estimation.

Table 7 presents the results of the frailty model. Odds ratios are reported. Again the fixed effect proxy and patent stock are positive and highly significant.

Below I first present the results reported in table 6 and then compare them to the results from the hazard model.

Inflation (First Regime) Model. I am predicting the "certain zeroes" with indicators for low levels of publications and funding during the last 3 years. For the base specification the results show that researchers that published no high quality articles in the past 3 year and received less than £2000 funding each year over the last 3 years are more likely to enter the "certain zero" group. The odds of being a "certain zero" are increased by exp(1.2) and exp(14.1) respectively. The effect of low publication activity and no access to industry funding are not statistically significant. While academics generally are at little risk of entering the "certain zero" group (The mean probability of being in the "certain zero" group is 0.151) this probability increases dramatically for academics with little external research income and low quality publications.

For industry owned patents, publication quality predicts the likelihood of being a certain zero, indicating that researchers with low quality publications might be more likely to patent with industry.

Also, publication and funding indicators are not determining whether a researcher is certain not to file a high-quality patent (specification 3). The inflation model is not a good fit for the last specification.

The inflation model does not identify any "certain zero" in the sample with a probability of 1 and hence all 4137 observations enter the negative binomial regressions.

Negative Binomial (Second Regime) Model. The negative binomial model predicts the number of patents for all observations conditional on the probabilities calculated by the logistic regression. The mean probability of a count of zero patents is 0.934. If all predictor variables in the model are evaluated at zero the expected number of patents for the baseline model would be negative. Results are reported for each regressor separately for all three specifications to compare the different dependent variables.

The regression results show that the share of funding received from industry during the last 3 years has a strong positive effect on the predicted number of patents. Receipt of other types of funding also has a positive effect on patent rate, but the effect is weaker. As the model models the log of expected patents and I have additionally taken logs of most of my explanatory variables to normalise the distributions, the coefficients can be interpreted as elasticities. For illustration let me consider the results reported in column one of Table 6, if the share of industry sponsored research increases by e.g. 10% the predicted number of patents would increase by 10%. The positive effect of industry sponsorship is much larger in column 2. An increase in the rate of industry funding increases industry owned patents at a rate of 2.51. Also the number of high-impact inventions increases stronger at a rate of 1.41, though the effect is significant only at 10%.

Additionally I consider the number of articles published in the last 3 years. I find no significant effect of publications on patenting in the negative binomial part of the regression. Thus, researchers who have produced some research in the previous 3 years, do not have an increased number of patents commensurate with an increase in the number of publications. This is consistent across all three specifications. I additionally include the average impact score of publications to the regression. The quality indicator has a positive albeit insignificant effect in the main regression in column one and a positive effect significant at the 5 and 10% level on the predicted number of patents in columns 2 and 3. Doubling the average impact score would increase the number of patents or industry owned patents by 72%. A similar increase in impact score increases the number of high-quality inventions by 60%. The significant positive effect for industry and high-quality patents is partly due to the misfit in the inflation equation.

Promotion has a positive albeit insignificant impact on a researcher's patenting propensity.

A measures for the patenting activity of researchers in the same department was included to measure the effect of peers. I include a dummy variable for senior (professor) inventors present in the department. The effect is very strong and positive. The expected number of patents for an academic whose senior colleagues are involved in patenting is 2.31 ($= exp(0.84)$) times that of her peers.

Most other departmental factors have no significant impact. Only the research orientation of the department measured as the average number of PhD degrees awarded during the last three years has a positive effect on the expected number of patents. One additional PhD degree awarded by the department increases the number of patents at a rate of 1.02 (= $exp(0.020)$). This effect is not significant for high-impact inventions (column 3). Those departments that ranked highest in the RAE 1996 and 2001 respectively seem to be less likely to patent than engineers at other departments. The effect is strongest in the third specification. The impact of external funding received by the department, the number of department staff and the number of TTO staff are insignificant. Department indicators were included in the model and show that researchers in civil engineering patent less than their colleagues at other engineering departments. The lowest number of high-impact inventions is found for Mechanical Engineering.

Frailty Model. Table 7 reports the results of the frailty models, which confirm the results of the ZINB estimation. Researchers with a high share of industry funding in the 3 years prior to t are more at risk of patenting. Also researchers receiving other types of funding increase the hazard rate of patenting. Publications are not found to have a significant impact on patenting.

Amongst the control variables only peer effect is strong and positive. The results also confirm the field effects with researchers in Chemical and Electrical and Electronic Engineering having a higher probability to patent than researchers in other fields of engineering.

The results are robust if I control for left-censoring of the data.

5 Discussion and Conclusion

The results presented in this paper represent the first evidence of the impact of funding sourcing practices on the propensity and the intensity of patenting at universities. I provide evidence that UK researchers receiving funding from industry are more likely to produce patents, controlling for a variety of individual and departmental characteristics. I take into account the number of "excess zeroes" using a ZINB model, and control for potential endogeneity in the patenting process and individual heterogeneity by including pre-sample values of the dependent variable as regressors to the analysis. I perform a robustness check using frailty models that estimates the probability of observing a patent in t.

I conclude that the research activity of an academic measured in quantitative terms and the support provided by the department are not conclusive in explaining a researcher's propensity to patent. Indeed, as already argued by e.g. Bercovitz and Feldman (2008), Owen-Smith and Powell (2001a) or Ozgen and Baron (2007) the support of pro-commercialisation partners is key in steering researchers towards patenting. I find the effect of an industry partner to be strongest and most consistent in explaining the number of patents.

This paper represents an attempt to find different individual and department level measures for patenting opportunity, support and attitude in order to estimate their combined effect on the propensity to patent. The model is regressed on three different counts of patenting, the overall count, industry owned patents and patents from high-impact inventions. Results for most of the regressors were robust across all three specifications and also for an alternative model estimating patenting hazard rates.

I find that researchers respond positively to funding, indicating the importance of financial inputs for the research process. Funding increases the probability of producing patentable research perhaps by providing necessary equipment. This result confirms evidence found by Zucker et al. (1998) in their survey. Publications can also increase the propensity to identify commercial opportunities and are an important indicator for determining whether a researcher has assets to patent, particularly for determining high-impact patents, but the effect is not robust and varies across different specifications. Also, there is no additional significant effect of publications on patent numbers.

In the main regression I considered factors that might influence a researcher's attitude towards patenting. I find a positive effect of the share of funding received from industry on the number of patents. This confirms results from survey studies (Gulbrandsen and Smeby, 2005; Goethner et al., 2011) and anecdotal evidence (Agrawal and Henderson, 2002), indicating a pull or learning effect from industry. Partners from industry perhaps have a strong interest in pushing academics towards commercialisation to recover their research investments or are more likely to sponsor research for commercial application. I secondly considered a peer effect by measuring the impact of having a senior inventor in the department and indeed find a positive effect. This confirms the evidence found by Bercovitz and Feldman (2008) that reported a strong effect of peer behaviour on a researcher's behaviour and attitude towards patenting.

TTO support and department level factors have no significant impact on the number of patents in the main regression. Support offered by the university does not seem to be decisive in a researchers decision to patent.

In terms of policy implications I conclude that (1) patentable research benefits substantially from external funding, hence monetary incentives stimulate research for industrial application, and that (2) university-industry collaboration is most effective for transforming knowledge into commercial opportunities. Finally, the opportunities to engage in patentable research may differ between scientific fields even within engineering sciences, policy makers should hence be careful in their expectations of patents.

This paper has added some important evidence to the discussion on university-industry collaboration, but further data and a longer panel is required to draw more robust conclusions. The nature and purpose of grants needs to be investigated to understand whether industry sponsors commercial research or whether it is more efficient in steering academics towards exploitation of research. Additionally, it is necessary to build better department and university level indicators that may effect a researcher's decision to patent. The next version of this papers aims at achieving this.

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Figure 1: Aspects of Patenting

	Opportunity	**Support**	**Attitude**
Individual factors	Research Active – Publications Grants	Grants	Industry Links
Institutional factors	Scientific Field – Department	TTO Support University Resources	Peer Behaviour

Figure 2: Two Regimes of Patenting Activity

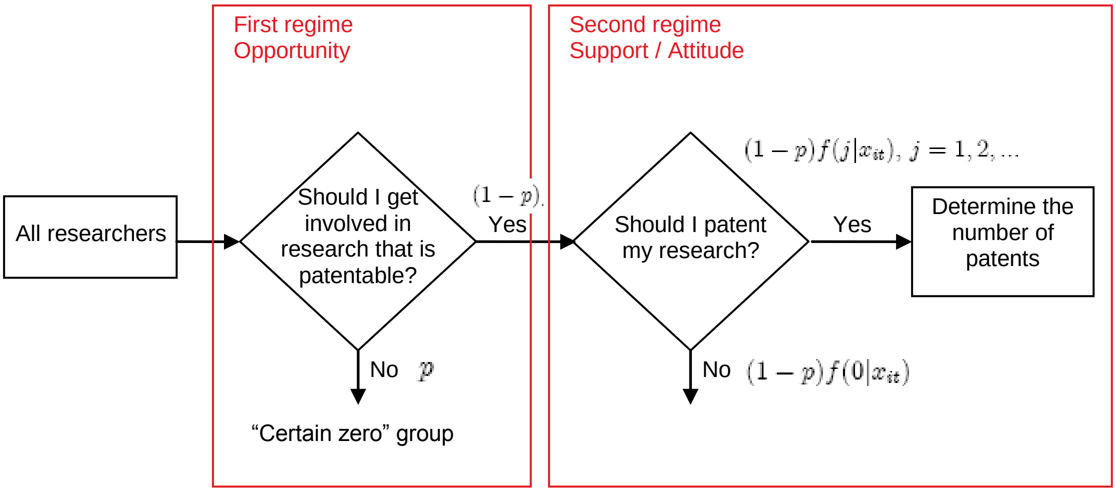

Table 1: List of Universities

University Name	Avg # of Enginnering staff between 1996 and 2007	# Academics in Sample (% of all staff)	% Inventors in Sample
University of Cambridge	158	88 (56%)	47%
University of Durham	33	13 (39%)	38%
University of Glasgow	100	52 (52%)	21%
University of Lancaster	23	9 (39%)	22%
University of Leicester	32	22 (69%)	32%
Loughborough University	191	101 (53%)	37%
University of Reading	39	10 (26%)	60%
University of Sheffield	155	67 (43%)	47%
University of Strathclyde	155	81 (52%)	58%
University of Swansea	70	36 (51%)	28%
Total	**956**	**479 (50%)**	**41%**

Table 2: Descriptive Statistics

	Mean	SD	Min	Max
Individual				
Number of Patents	0.079	(0.368)	0	9
Number of Publications	2.190	(3.067)	0	27
Average Journal Impact Factor	0.996	(1.092)	0	27.36
Funding from Research Councils	19822	(75367)	0	1086509
Funding from Industry	8626	(47942)	0	2005569
Funding from Government Ministries	3916	(17864)	0	300030
Funding from Charities etc.	3513	(31344)	0	826078
Funding from EU	3871	(19271)	0	427209
Institutional				
Number of Department Patents	2.730	(4.144)	0	23
Average Department Funding per PhD	210206	(150327)	0	2944966
Share of Department Industry Funding	0.207	(0.127)	0	1
Number of PhD degrees awared	23.252	(25.298)	0	108
Staff at University TTO	31.552	(14.258)	10	58

Standard Deviations in parantheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Definitions of Variables used in the Regressions

Regression Variables	**Description**
Patent $\#_t$	Number of patents filed by individual *i* in *t*
Pre-observation Patents	Number of patents filed by individual *i* before 1996
Patent $Stock_{t-1}$	Depreciated stock of patents filed by individual *i* since 1996 (= pat[t-1]+0.7*patstock[t-1])
Opportunity	
ln(publications in last 3 $years)_{t-1}$	Log of Average number of articles published by individual *i* in the 3 years prior to *t*
ln(avg JIF in last 3 $years)_{t-1}$	Log of Average impact of articles published by individual *i* in the 3 years prior to *t*
Low Publication $Activity_{t-1}$	Zero-one dummy if less than one article published in one year during last 3 years
Low Funding $Activity_{t-1}$	Zero-one dummy if less than 2000 £ were sourced in one year during last 3 years
Chemical $Engineering_t$	omitted category
General $Engineering_t$	Zero-one dummy if General Engineering
Mechanical $Engineering_t$	Zero-one dummy if Mechanical Engineering
Electrical and Electronic $Engineering_t$	Zero-one dummy if Electrical and Electronic Engineering
Civil $Engineering_t$	Zero-one dummy if Civil Engineering
$Promotion_{t-1}$	Zero-one dummy if promoted in the last 3 years
Support	
ln(funding in 3 last $years)_{t-1}$	Log of Average amount of funding received by individual i in last 3 years
ln(department funding in 3 last $years)_{t-1}$	Log of average amount of funding received by individual i's department in last 3 years
Department $staff_t$	Average number of staff in individual i's department
TTO $staff_t$	Number of staff working in dedicated commercialisation unit in 2006
Attitude	
ln(share of funding from $industry)_{t-1}$	Log of the average share of funding from industry received by individual i in last 3 years
Public $funding_{t-1}$	Zero-one dummy if researcher received other types of funding during last 3 years
Professor $inventor_{t-1}$	Zero-one dummy if a professor filed a patent in last 3 years
Industry orientation of $department_{t-1}$	Average share of industry funds received by individual *i's* department in last 3 years
Research orientation of $department_{t-1}$	Average number of PhD degrees awarded by individual *i's* department in the 3 years prior to *t*
RAE_t	Zero-one dummy if department received the highest quality ranking in the 1996 and 2001 RAE

Table 4: Correlation Matrix for Individual Measures

	Patent #	Publications in last 3 years	Avg JIF in last 3 years	Funding in 3 last years
Publications in last 3 years	0.1421			
Avg JIF in last 3 years	0.1261	0.4092		
Funding in 3 last years	0.1058	0.2693	0.1754	
Share of funding from industry	0.0618	0.0118	0.0139	0.0988

Table 5: Descriptive statistics by department (scientific field)

Scientific Field	**# Academics**	**% Inventors**	**% of Observations with zero patents (4121 obs)**	**Average Publication Number**	**Average Funding in GBP**	**Share of Funding from Industry**
Chemical Engineering	64	55%	90%	3.839	17178	24%
General Engineering	118	39%	93%	2.217	59274	27%
Mechanical Engineering	117	35%	95%	1.653	26824	28%
Electrical and Electronic Engineering	107	60%	90%	2.488	55918	24%
Civil Engineering	73	14%	99%	1.093	22407	16%
Total	**415**	**41%**	**93%**	**2.19**	**39428**	**25%**

Table 6: Zero Inflated Negative Binomial Estimation.

	VARIABLES	(1) All Patents	(2) Industry owned	(3) High-impact
Patent $\#_t$	Pre-observation Patents	0.071**	0.15**	0.071
		(0.032)	(0.064)	(0.053)
	Patent Stock_{t-1}	0.56***	0.69***	0.60***
		(0.079)	(0.092)	(0.11)
	Public funding_{t-1}	0.35**	1.21***	0.29
		(0.17)	(0.43)	(0.30)
	ln(share of funding from $\text{industry})_{t-1}$	1.02***	2.51***	1.41*
		(0.31)	(0.77)	(0.84)
	ln(publications in last 3 $\text{years})_{t-1}$	0.098	-0.36	0.13
		(0.13)	(0.28)	(0.29)
	ln(avg JIF in last 3 $\text{years})_{t-1}$	0.31	0.72**	0.60*
		(0.20)	(0.31)	(0.35)
	Promotion_{t-1}	0.13	0.39	0.052
		(0.17)	(0.26)	(0.24)
	Professor inventor_{t-1}	0.84***	0.87**	0.74**
		(0.22)	(0.37)	(0.36)
	ln(department funding in 3 last $\text{years})_{t-1}$	-0.055	-0.82**	0.27
		(0.17)	(0.41)	(0.31)
	Industry orientation of department_{t-1}	-0.25	0.40	-0.47
		(0.71)	(1.74)	(1.05)
	Research orientation of department_{t-1}	0.020*	0.050*	0.021
		(0.010)	(0.030)	(0.019)
	Department staff_t	-0.014	-0.060**	-0.0087
		(0.011)	(0.027)	(0.018)
	RAE_t	-0.55*	0.18	-1.29***
		(0.28)	(0.77)	(0.45)
	Chemical Engineering	omitted	omitted	Omitted
	General Engineering	-0.45	-0.43	-0.12
		(0.30)	(0.54)	(0.46)
	Mechanical Engineering	-0.42	0.079	-0.96**
		(0.26)	(0.58)	(0.46)
	Electrical and Electronic Engineering	-0.048	-0.62	0.42
		(0.24)	(0.71)	(0.42)
	Civil Engineering	-1.22***	-19.2***	-0.46
		(0.43)	(0.50)	(0.54)
	TTO staff	0.31	0.29	0.60
		(0.27)	(0.54)	(0.49)
	Year Dummies	YES	YES	YES
	Constant	-3.86*	-14.4***	-10.6***
		(2.11)	(4.01)	(3.67)
Inflation (logit)	Low Publication Activity_{t-1}	-0.72	1.95*	-32.4
		(0.70)	(1.04)	(45.1)
	No High Quality $\text{Publications}_{t-1}$	1.24**	-15.2***	19.6
		(0.61)	(2.82)	(45.8)
	Low Funding Activity_{t-1}	15.1***	0.025	3.71
		(2.39)	(1.01)	(44.3)
	No Industry $\text{Funding}_{t.1}$	0.42	2.20	19.3
		(0.69)	(1.40)	(40.6)
	Constant	-16.1***	-2.52**	-23.6
		(2.21)	(1.26)	(88.0)
	Ln-alpha	0.47*	0.91***	1.25
	Observations	4137	4137	4137
	Zero Observations	3853	4062	4031
	Log-Likelihood	-1041	-329	-459

Odds ratios reported. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Proportional Hazard Estimation (Shared-Frailty).

VARIABLES	(1) Start 1996	(2) Left-Truncated
Pre-observation Patents	0.11***	0.093***
	(0.036)	(0.034)
Patent Stock$_{t-1}$	0.22***	0.26***
	(0.050)	(0.056)
Public funding$_{t-1}$	0.46***	0.35**
	(0.16)	(0.16)
ln(share of funding from industry)$_{t-1}$	0.86***	0.97***
	(0.30)	(0.31)
ln(publications in last 3 years)$_{t-1}$	0.17	0.093
	(0.13)	(0.13)
ln(avg JIF in last 3 years)$_{t-1}$	0.42*	0.31
	(0.22)	(0.23)
Promotion$_{t-1}$	0.051	0.14
	(0.15)	(0.15)
Professor inventor$_{t-1}$	0.54**	0.49*
	(0.25)	(0.26)
ln(department funding in 3 last years)$_{t-1}$	-0.014	0.0100
	(0.17)	(0.17)
Industry orientation of department$_{t-1}$	-0.31	-0.20
	(0.76)	(0.80)
Research orientation of department$_{t-1}$	0.010	0.014*
	(0.0078)	(0.0080)
Department staff$_t$	0.00091	-0.0012
	(0.0089)	(0.0092)
RAE$_t$	-0.46	-0.41
	(0.28)	(0.29)
Chemical Engineering	omitted	omitted
General Engineering	-0.57**	-0.70**
	(0.28)	(0.30)
Mechanical Engineering	-0.57**	-0.65**
	(0.28)	(0.29)
Electrical and Electronic Engineering	0.051	-0.018
	(0.26)	(0.26)
Civil Engineering	-1.37***	-1.17***
	(0.45)	(0.45)
TTO staff	0.14	0.12
	(0.13)	(0.14)
Observations	4137	3405
Number of groups	479	394
theta	0.67***	0.52***
Log-Likelihood	-2220	-1967
Observations	4137	3405
No of Failures	284	256
No if Groups	479	394

Dependent variable is duration until patent. Odds ratios reported.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1