The importance (or not) of patents to UK firms*

Bronwyn Hall[a], Christian Helmers[b], Mark Rogers[c], Vania Sena[d]

February 2012

Abstract

A surprisingly small number of innovative firms use the patent system. In the UK, the share of firms patenting among those reporting that they have innovated is about 6.2%, according to data assembled for this paper. Survey data from the same firms supports the idea that they do not consider patents or other forms of registered IP as important as informal IP for protecting inventions. We show that there are a number of explanations for these findings: most firms are SMEs, many innovations are new to the firm, but not to the market, and many sectors are not patent active. We assess the implications of patenting on a company's innovative performance measured in terms of turnover due to innovation and employment growth. We find strong evidence pointing to a positive association between patenting and both measures of firm performance, which raises the question of why more firms do not patent. The analysis relies on a new integrated dataset for the UK that combines a range of data sources into a panel at the enterprise level.

Keywords: IP, patents, secrecy
JEL code: L21, L25, O34

[a] UC Berkeley, University of Maastricht (corresponding author bhhall@econ.berkeley.edu)
[b] Universidad Carlos III de Madrid
[c] Harris Manchester College, Oxford University
[d] University of Essex

* We gratefully acknowledge financial support from the UK Intellectual Property Office. The views expressed here are those of the authors. They are not necessarily those of the UK Intellectual Property Office.

1. Introduction

One of the most puzzling findings in the empirical analysis of firms' patenting behaviour is the low proportion of patenting firms in the population of registered companies. Our investigation of this phenomenon in the UK finds that only 1.7 per cent of all registered firms in the UK patent and that even among those that are engaged in some broadly defined form of R&D, only around 4 per cent have applied for a UK or European patent during our period of analysis (1998-2006).[1] In our data, even in high-tech manufacturing sectors, which arguably produce the most patentable inventions, the share of patenting firms in the UK does not surpass 10 per cent. Restricting the high-tech sector to R&D-doing firms that also innovate, the share of patenting firms increases only to 16 per cent (Hall et al. 2011). Findings for the US are similar: Balasubramanian and Sivadasan (2009) find that only 5.5 per cent of US manufacturing firms own a patent. Moreover, shares of patenting firms differ dramatically across sectors – even within the manufacturing industry; for example in the UK, manufacturing of chemicals and chemical products has a share of nearly 10 per cent of patenting firms whereas manufacturing of tobacco products effectively has close to no patenting firms (Helmers et al., 2011). This suggests that (a) firms with patentable inventions do not patent, i.e., some firms avoid the patent system altogether, (b) patentable inventions may not be patented, i.e., firms do not automatically patent all of their patentable inventions, and (c) some innovations involve inventions that are not patentable.

The objective of this paper is threefold: first we document companies' patenting decisions taking into account their underlying innovative behaviour. Our evidence shows that patent propensities vary greatly across type of innovation, firm size and industry. The most important explanation of the low overall propensity to patent is that most firms are small and small firms are unlikely to patent. In addition, firms are less likely to patent if they have process innovations or innovations new to the firm, but not the market (as one might expect). Second, we analyze the determinants of a firm's relative importance ranking of patenting vs secrecy taking into account their innovative activity as well as the knowledge appropriation scheme prevalent in their sectors. Surprisingly, we find that innovation of any kind is *negatively* associated with a preference for patents over secrecy. Third, we provide some empirical evidence on the relationship of a firm's choice to patent to its subsequent

[1] European means a patent that was filed with the European Patent Office (EPO).

performance and find that because patents are positively associated with performance in terms of innovative sales and employment growth, there is some suggestion that they may be underused by firms.[2]

The analysis is based on a new firm-level dataset that combines information from a range of different sources. This dataset contains not only detailed information on firms' self-reported innovation activities from the UK Community Innovation Survey (CIS), but also on firms' actual patent holdings. The combination of the different data sources allows us to overcome a number of problems that have plagued existing work on the determinants of a firm's patenting propensity. If only patent data at the firm-level are available without information on a firm's innovative activities, strong assumptions regarding firms' underlying innovative activities are required in order to make inference on a firm's patenting propensity.[3] However, even when data on innovation input such as R&D are available, it is empirically difficult to determine whether patenting propensities differ due to differences in unobserved productivity, i.e., the way R&D is translated into patentable innovations, or due to genuine differences in patenting propensities (Brouwer and Kleinknecht, 1999). The availability of information on innovation output (and limited information on its "quality" or "novelty"), together with data on a firm's actual patent applications, allows us to overcome this problem and to assess the determinants of a firm's decision to patent conditional on innovating. Apart from the historical investigations of Moser (2011), there are few existing analyses of patenting that are able to control for the presence of an innovation; most of those available use spending on R&D as a proxy for innovative activity.

In a chapter of the Handbook of the Economics of Innovation, Mairesse and Mohnen (2010) review the extensive existing research based on the CIS data and conclude with a number of recommendations for future research, among which "merge innovation data with other data" and "create longitudinal datasets" stand out. This paper provides progress along these lines as we combine three CIS waves with patent data, a business survey as well as census data for the UK. Despite these advances, our data is still of observational nature, that is, the

[2] Although our empirical framework is not suited for making counterfactual statements, i.e., we are unable to say whether patenting and innovative performance would still be positively correlated if more firms patented.
[3] The required assumption is that firms face the same decision conditional on a range of observable characteristics, that is, they have a similar innovation that they can patent or exploit in a different way such as maintaining it secret.

variables of interest are subject to companies' endogenous choices. A company's decision to protect a specific invention through a patent or an alternative protection mechanism is far from random. This limits our ability to identify causal mechanisms that determine a firm's decision of how to appropriate returns to innovating. We are, therefore, constrained to pointing to robust empirical patterns in the data. This is a major shortcoming that applies to the literature on the decision to patent and its implications more generally due to the absence of experiments.[4] In addition, we discovered that the longitudinal nature of the data was a bit of mirage due to the sampling methodology used by the CIS, which resamples for each survey. The highly unbalanced nature of our CIS panel as well as little variation over time in terms of a firm's innovative activities and patenting decisions means that exploiting variation over time is of little help in achieving identification of the parameters of interest.

The results of our analysis underscore the trade-off that firms face in their patenting decision. Registered IP in the form of patents provides advantages and drawbacks and whether the advantages outweigh the drawbacks depends on a range of exogenous factors (e.g. some types of inventions are less patentable) and potentially endogenous factors (e.g. a firms' perception of the importance of IP within sectors) which help explain the enormous variation in patenting propensities across firms and industries. Yet, our findings suggest that patenting is correlated with superior performance, as indicated by a firm's sales of innovative products and growth in employment. This leaves us with a puzzle: why do so few firms patent despite the advantage in performance that it appears to confer to companies? It is true that patenting is generally more costly than informal protection methods but the differences in growth rates (12-15 per cent higher for patenting firms) that we observe seem too large to be accounted for by patent cost. It is much more likely that the explanation lies in the quality of the firm and of its innovation(s), which are of course difficult to measure using the type of data we have.

[4] In the context of patents it might not even be obvious how a randomized intervention should be designed to yield meaningful insights. This means that the `experimental paradigm' as advocated by Angrist and Pischke (2009) is of little direct applicability in this context although there is scope to exploit exogenous variation induced by policy interventions or idiosyncratic shocks to identify the effect of the variable of interest. In the innovation literature, examples exploiting such natural or quasi-experiments are rare. Exceptions include Scherer and Weisburst (1995) who use a decision in 1978 by the Italian Supreme Court ruling an existing law unconstitutional that excluded pharmaceuticals from patent protection in Italy to identify the effect of patent protection on innovation measured as R&D and U.S. patents. In a similar study, Sakakibara and Branstetter (2001) use a change in the Japanese patent law to identify the effect of the strength of patent rights protection on firms' R&D expenditure and patenting activity.

This paper is organized as follows. Section 2 briefly summarises the relevant literature that is based on the analysis of CIS data. Section 3 describes the structure and content of the dataset used for the analysis. Section 4 provides descriptive evidence on our principal research questions. Section 5 outlines our empirical approach and Section 6 discusses the corresponding results. Section 7 summarizes the main findings.

2. Literature

In this section, we briefly review a number of studies using CIS data or information on innovations that is not derived from patents. This is useful to frame our analysis within the existing research and to compare our results presented in Section 5 with the existing findings. Hall et al. (2011) offer a broader review of the existing literature on firms' choices between formal and informal IP.

Brouwer and Kleinknecht (1999) is one of the first papers based on the CIS 1 data (for Holland) that studies the determinants of a firm's decision to patent. The Dutch CIS 1 data also contains information on firm's patent holdings, which allows Brouwer and Kleinknecht to investigate the determinants of a firm's actual patent holdings. They find firm size, R&D intensity, sales of innovative products, and R&D collaboration agreements to be positively correlated with a firm's patenting propensity. Also firms in high-tech sectors appear to have higher patenting propensities. Their findings also hold when the authors consider patent applications that were filed two years before the CIS reporting period, a fact that might be explained by high persistence in a firm's patenting activity. Arundel (2001) uses CIS 1 data for 7 European countries to show that the propensity to use secrecy relative to patents falls with firm size (measured as R&D expenses and employment) for product innovations, while the association is much weaker for process innovations. Arundel also finds cooperation in R&D to decrease a firm's propensity to rely on secrecy relative to patents.

Pajak (2010) uses firms' responses on the importance of different protection methods to evaluate the determinants of a firm's choice between patenting and secrecy. Pajak uses the French CIS 4 data and limits his sample to small firms that report a product and/or process innovation.[5] His main variables of interest in determining a firm's choice are firm size and the size of the inventive step. In the French CIS, the answers regarding protection mechanisms are only binary variables; this means Pajak estimates a bivariate probit to model the correlated choice between patents and secrecy. As expected, Pajak finds that the use of patents is increasing in a firm's size (measured as employment). Moreover, for his sample of small firms in intermediate goods sectors, Pajak finds that firms reporting innovations new to the firm are more likely to use patents, whereas the same firms seem to prefer secrecy for inventions new to the market, which he considers in line with the theoretical predictions of Anton and Yao (2004). This empirical finding should be interpreted with caution, however, as the sample size is small (72 firms) and the share of innovating small firms is less than 10 per cent. The results presented in the present paper point the opposite conclusion.

Heger and Zaby (2012) exploit data from the Mannheim Innovation Panel (which represents the German CIS) for 2005 which offers firms' self-reported innovation measures as well as data on their patent holdings. They limit their analysis to firms reporting product and/or process innovations which leaves them with a cross-section of 740 firms, and they present a theoretical model which predicts that firms prefer secrecy when they have a considerable advantage relative to competitors, but patent when the technological lead is small. The intuition is that the information disclosure required by a patent is only worthwhile when the protection effect of a patent is large enough. While the cost of disclosure increases with the technological lead, the protection effect remains constant. This means that for firms with a larger technological lead, costs associated with disclosure outweigh the benefits from patenting. This relationship, however, is not directly confirmed by the data. Instead, Heger and Zaby (2012) find that a firm's propensity to patent increases in its technological lead in industries in which reverse engineering is relatively easy. That is, if a firm is highly successful but threatened by low cost imitation, it is more likely to patent because it has more to lose.

[5] The main reason for limiting the sample to small firms is the need to establish a correspondence between a firm's reported size of the inventive step and the reported innovation. This correspondence may be diluted for large multiproduct firms, whereas it may appear to be more reasonable to assume that small firms only have a single innovation.

The literature on the link between a firm's decision to patent or maintain an invention secret and its subsequent performance is much thinner. An exception is Hussinger (2006), who investigates the question of the impact of a firm's choice between patenting and secrecy on its innovative performance (measured as sales due to new products) also using the Mannheim Innovation Panel to which she adds patent filings at the German Patent and Trademark Office. She limits the sample to R&D-performing firms that report a product innovation. Hussinger finds patenting but not secrecy to be associated in a statistically significant and positive way with a firm's sales due to new products.

All studies discussed above rely on cross-sectional data using only a single CIS. Some of the studies merge in patent data at the firm-level. However, none of them are able to account for unobserved heterogeneity across firms, due to the absence of longitudinal variation, which is an inevitable consequence of the CIS sampling strategy.

One final study that does not use CIS data but uses an alternative source of innovation data should be mentioned here: that by Moser (2011) using data from 19th century World Fairs. She finds that only 11 per cent of innovations shown in Britain at the Crystal Palace Exhibition in 1851 were patented and that the main determinant of patenting is the industry of the invention. In particular, industries with easy reverse engineering and ineffective secrecy were those where inventions were patented. She is able to use the publication of the periodic table in Chemicals as an instrument that changed the effectiveness of secrecy in that sector and led to an increase in patenting. Thus her work supports the idea that secrecy is preferred to patenting as a mode of protection unless the bar to imitation is low.

3. Dataset

The dataset used in our analysis consists of three components, which are all linked by a unique enterprise business register number:[6]

1. Business Structure Database (BSD)
2. UK Community Innovation Surveys (CIS) 3, 4, and 5

[6] We conduct the analysis at the "enterprise" level where an enterprise comprises all legal units under common control. The patent and trade-mark data is available only at the enterprise level which motivates us for consistency to conduct our analysis at the enterprise level. When necessary, we aggregate data at the local unit level up to the enterprise level.

3. UK and EPO patent data.

The individual components are described in detail in Appendix A1.

The linked dataset is a firm-level panel that contains detailed information on firm characteristics, innovative activities as well as patent filings over the 9-year period 1998-2006. Due to the stratified nature of the sampling of the CIS data and a changing sampling frame over time, the panel is highly unbalanced. Since we rely on information on firms' innovative activities contained in the CIS, we drop all firms from the integrated dataset that have not been sampled in at least one of the three CIS waves.

Since the CIS refers to several years (CIS 3 to 1998-2000, CIS 4 to 2002-2004 and CIS 5 to 2004-2006), we collapse the panel to three time periods which cover the entire period 1998-2006 (with the exception of 2001).[7] In principle, this produces a panel of firms, in practice however, few firms appear in all three CIS waves. In fact, the overwhelming number of firms is sampled only once. Table 1 shows the panel structure of the data. The shaded rectangles indicate the availability of data. Only 541 firms have been sampled in all three CIS waves. The largest overlap between CIS waves exists for CIS 4 and 5 with a total of 6,504 firms. Overall, only 25 per cent of the sample firms appear in at least two CIS waves. Therefore, despite the panel dimension of the data, there are relatively few units that we observe multiple times which severely limits our ability to rely on variation over time in our analysis.[8] This means that for the most part of the analysis, we treat the data as a pooled cross-section although we also exploit the panel structure for the subset of firms for which there are at least two observations in time available. [9]

[7] All continuous variables from the BSD are averaged over each of the three CIS reporting periods, whereas we use the maximum value for discrete variables from the BSD and the registered IP data. This implies, for example, that the patent dummy variable measures whether a firm has taken out at least one patent during a three-year CIS reference period.

[8] Obviously Table 1 says nothing about item non-response, i.e., the number of firms that reports sufficient data to be included in any analysis is substantially lower than the numbers indicated in Table 1. Also, although the CIS panel has relatively little overlap, for economic data from the BSD we have considerably more overlap, which allows computing for example employment growth over the whole period.

[9] Note that for our analysis, we restrict the data to sectors that have been sampled in all three CIS waves, i.e., we exclude "sale, maintenance & repair of motor vehicles" (SIC 50), retail trade (SIC 52), hotels & restaurants (SIC 55), motion picture and video activities (SIC 921) and radio and television activities (SIC 922).

Tables A1 and A2 in the Appendix show the distribution of firms across sectors over the three CIS samples. The population sector shares in Table A1 have been produced using sampling weights to account for the stratified nature of the CIS samples. Because the sample stratification is largely by firm size, sectors with large firms are overweighted in our sample (that is, Chemicals, Food and beverages, High technology, Metals and machinery, Transportation, and manufacturing in general) and those with more small firms underweighted (Business and Computer services, R&D services).

4. Descriptive analysis

This section provides descriptive evidence of the patenting activities of firms and looks at how patenting differs as a function of firms' underlying innovative activities as well as the importance that firms attribute to different knowledge appropriation mechanisms in form of registered and informal IP, such as secrecy. The descriptive analysis also informs us about the relation between a firm's patenting decision and its innovative performance.

Table 2 shows the share of patenting firms in the whole sample as well as weighted using sampling weights to account for the stratified sampling of the CIS. The table shows that only 1.7 per cent of the population of registered firms patent. The figure is twice as large for manufacturing, which would be expected. The table also distinguishes between innovating and non-innovating firms (where innovating means reporting a product and/or process innovation) as well firms that undertake some broad form of R&D (either internal or external, via the purchase of related new hardware or software, or by spending on training, design, or marketing related to innovation). If we look at the unweighted shares, we see that the largest share of patenting firms is found in the manufacturing sector for firms that conduct R&D and report an innovation (10 per cent). We note that although there are a small number of observations where a firm has applied for a patent even though it has not innovated during the past three years, the share of innovating firms that patent is over five times that for non-innovating firms (6.2% versus 266/21760 = 1.2%). In general, the patenting rate is much higher in manufacturing than in non-manufacturing. Almost as many firms do R&D but do not innovate during a three year period as both do R&D and innovate, whereas very few firms innovate but do not do some form of R&D. In order to focus our attention on firms that have the potential to patent, the subsequent analysis in this paper is performed on the 11,358 firm-year observations shown in Table 2 where firms reported that they had introduced a product or process that was new to the firm or the market during the past three years.[10]

As discussed in the Introduction, even when focusing our attention on innovative firms, there may still be important differences across the types of innovation. Table 3 distinguishes between the four types of innovations reported in the CIS: (i) product innovation new to the market, (ii) process innovation new to the market, (iii) product innovation new to the firm, and (iv) process innovation new to the firm. Looking at the population-weighted shares, the table reveals that the largest share of innovators reports product innovations new to the market and process innovations new to the firm. However, firms with product as well as process innovations that are new to the market are considerably more likely to patent (conditional on conducting R&D). In particular firms that report a product innovation that is new to the market are more than twice as likely to patent as firms that report a process innovation that is new to the market. These findings support both the view that product innovations that are generally novel are more likely to jump the statutory novelty requirement to obtain patent protection and that process innovations are easier to keep secret and therefore less likely to be patented.

The experience of the `Patent Portfolio Races' in the semiconductor industry during the 1990s (Hall and Ziedonis, 2001) which have escalated into `Patent Wars' (FT October 17 2011) in the communication technology (ICT) industry during the past decade suggests that the importance attributed to patents or other forms of knowledge appropriation mechanisms may be an important determinant of firms' patenting decision. Figure 1 shows the CIS answers with regard to the importance of formal and informal IP protection mechanisms varied across patenting and non-patenting firms. Firms were asked in the CIS to evaluate the importance of the different mechanisms on a Likert scale between 0 and 3, where 0 means a firm does not use this type of protection mechanism whereas 3 means that it represents a "very important" mechanism for the firm. As would be expected, the share of firms regarding any of the registered IP rights (registered designs, trademarks, patents) as important is substantially larger for patenting than for non-patenting firms.

[10] The actual estimation sample consists of 11,160 observations, as we lose a few observations (<2 per cent) because of missing data problems.

Patenting firms are also seen to rely much more heavily on informal protection mechanisms than non-patenting firms. For example, 65 per cent of patentees consider secrecy as of medium to high importance whereas only 25 per cent of non-patenting firms do so (see also Table A-3 in the Appendix). This illustrates that, in practice, firms are likely to consider a mix of different appropriability mechanisms. This in turn suggests that if firms actively manage their innovative activities, they also actively manage the protection and exploitation of innovations. It also indicates that a firm's principal decision problem is not the choice between patenting and secrecy, but the choice of whether to rely on any form of IP, registered or unregistered.

Figure 2 provides evidence of the association of a firm's innovative activity and its share in sales due to product innovation, which can be considered as a measure of a firm's innovative performance. For ease of illustration, in Figure 2, we have discretised firms' sales distribution into four size bands (0%; more than 0% and less than 10%; between 10% and less than 25%; and 25% and above). When looking at innovations that are "new to the firm", we do not see any strong discernable pattern in the distribution of firms across turnover bands. Firms appear to be distributed similarly across turnover size bands independently of how highly they rank patents or secrecy. This suggests that there is little correlation between a firm's innovative performance in terms of turnover due to innovative products that are merely "new to the firm" and the importance the firm attaches to the different protection mechanisms.

However, the data look different for innovations that are "new to the market". Firms that attach high importance to patents and/or secrecy also have a higher share of innovative sales. For example, only 20 per cent of firms that have no turnover due to a product innovation that is "new to the market" indicate heavy use of patents, whereas almost 40 per cent of firms in the ≥25% turnover category report heavy reliance on patents. The difference is similar with regard to the use of secrecy (40 per cent in the 0% turnover category and 64 per cent in the ≥25% turnover category). Overall, this suggests that firms that regard patents and/or secrecy as important, and that have a product innovation that is "new to the market" (i.e., high "quality" invention), outperform (in terms of innovative sales share) firms that have an innovation that is "new to the market" but that do not use patents and/or secrecy. It also highlights the fact that although both secrecy and patents are used to protect inventions, firms with innovative products seem to prefer secrecy to patents.

5. Empirical Analysis

Our principal objective is to assess the determinants of a firm's observed decision to patent.[11] Our data allow us to condition a firm´s choice on the firm having an innovation, which means we limit the sample to firms that report a product and/or process innovation during the CIS reference period in order to ensure that in principle all firms face the decision of how to protect their innovation. To account for the type and to some degree also for the `quality' of an invention, we also include information on whether an innovation is new to the market or new to the firm.

Our main equation of interest is therefore the following:

$$p_{ic} = \alpha + \beta_1 prodnM_{ic} + \beta_2 prodnF_{ic} + \beta_3 procnM_{ic} + \beta_4 procnF_{ic} +$$
$$+\gamma X_{ic} + \beta rip_{jc} + \theta iip_{jc} + \delta_c + \mu_j + \varepsilon_{ic} \quad (1)$$

p_{ic} denotes firm *i*'s actual patenting decision (firm *i* is in sector *j* and CIS wave *c*). This means that we reduce a firm´s decision to a binary choice, either the firm decides to patent or not.[12] Variables $prodnM_{ic}$ and $procnM_{ic}$ denote product and process innovations that are new to the market, respectively. Whereas variables $prodnF_{ic}$ and $procnF_{ic}$ denote product and process innovations that are new to the firm, respectively. Differences in the estimates associated with product innovations new to the market may arise if product inventions are more likely to represent patentable subject matter than process innovations (Cohen et al. 2001), which was also suggested by Table 3 above. In addition, the variable that indicates whether a product innovation is "new to the market" may also capture the costs associated with disclosing the invention to the public. If firms consider inventions characterized by a

[11] Our data allow us to look directly at a firm's decision to patent instead of proxying a firm's patenting behaviour by firms' self-reported importance attributed to patents as a protection mechanism as commonly done in the literature based on CIS data (see Section 2).

[12] We are aware that by collapsing the number of a firm´s patent applications to a binary variable, we lose potential information contained in the variation in the number of patents a firm applies for. However, given our main research objective, we are primarily interested in whether a firm applies for a patent at all and less in its patenting intensity.

larger inventive step to be more valuable, then disclosing the information through a patent application may be less desirable to the firm and hence a firm may be more likely to opt for secrecy (Anton and Yao, 2004). Variable rip_{jc} represents firms' perception of the importance of protection mechanisms in the form of registered intellectual property (registered design, trademark, patent) at the SIC 3-digit sector level. iip_{jc} denotes the importance a firm attributes to informal protection mechanisms including secrecy, lead time, and complexity.

X_{ic} is a vector of firm-level characteristics including age, size, and a dummy variable that indicates whether the firm conducts some form of R&D, which we define as doing R&D internally, acquiring R&D externally, and/or the acquisition of advanced machinery, equipment and computer hardware or software to aid in the introduction of new products or processes, including organizational processes.

In a second step, we analyze directly the importance that firms attribute to patents relative to secrecy. Arundel (2001) suggests using the difference between the importance attributed to patents and secrecy. While levels may be difficult to compare at the firm-level, differences should be internally consistent. For example, consider a firm that attributes a value of 1 to patents and 2 to secrecy while another attributes 2 to patents and 3 to secrecy. These differences in levels within protection mechanisms may not necessarily be comparable across firms, while the difference for both firms should be, i.e., both value secrecy by 1 unit more than patents. We thus estimate the specification of Equation (1) with the dependent variable being the difference between firms' self-reported importance of patents and secrecy:

$$(pat-sec)_{ic} = \alpha + \beta_1 prodnM_{ic} + \beta_2 prodnF_{ic} + \beta_3 procnM_{ic} + \beta_4 procnF_{ic} +$$

$$+\gamma X_{ic} + \beta rip_{jc} + \theta iip_{jc} + \delta_c + \mu_j + \varepsilon_{ic} \qquad (2)$$

Third, we look at the relationship between a firm's observed decision to patent and its (innovative) performance. As performance measures, we use (a) the share of a firm's turnover that is due to innovations where we use separate variables for innovations that are "new to the firm" and "new to the market". This allows us to distinguish between the effect of patenting on a firm's sales based on imitation ("new to the firm") and innovation ("new to the market”). In addition, we also use (b) firm growth measured by employment as a performance measure.[13] We refer to measure (a) as innovative performance to distinguish it from performance measure (b). The model specification is thus:

$$perform_{ic} = \alpha + \beta p_{ic} + \beta rip_{jc} + \theta iip_{jc} + \gamma X_{ic} + \delta_c + \mu_j + \varepsilon_{ic} \qquad (3)$$

where *perform* is the share of sales from products new to the market, the share of sales from products new to the firm, or employment growth. In Equation (3), the main object of interest is the variable p_{ic} which indicates whether a firm has applied for a patent during the reference period. All other variables are as in Equation (1).

6. Results

In this section we discuss the results from estimating Equations 1-3. Descriptive statistics for our regression sample are provided in Appendix Tables A-2 and A-4.

6.1 The decision between formal and informal IP

Table 4 shows the first set of results for the specification of the model in Equation (1). The first half of the table shows results for all sectors and the second half for manufacturing sectors only. We include a full set of time and sector dummies in all specifications. The table shows the marginal effect on the probability of having at least one UK or EPO patent during a three-year period for each of the right hand side variables. We note first that adding additional variables to this regression has little effect on the estimates of the other variables, so we focus our discussion on the full results in columns 3 and 6.

As expected, patenting is most strongly associated with the introduction of products new to the market, then to products new to the firm (especially in manufacturing), and finally to processes new to the market, but only outside manufacturing. Firm-level process innovations are not associated at all with patenting. In the sample as a whole, having a product innovation new to the market increases the probability of patenting by 5 per cent,

[13] We also investigated labour productivity as performance measures. However, labour productivity is only available for firms that are included in the ARD2. This means that the sample is considerably smaller and we therefore prefer to rely on the CIS-based turnover performance measure and employment growth computed using the BSD.

which is a large impact considering the low average patenting probability (6.3 per cent). For manufacturing, the increase is even larger, 7.8 per cent.

In this regression we included measures of the importance of registered (patents, designs, trademarks) IP and informal (secrecy, lead time, complexity) IP in the SIC 3-digit sector of the firm. Because we have included broad sectoral dummies (see Table A1 for a definition of the broad sectors), these impacts are measured within broad sectors. The only significant result is in manufacturing, where a one unit increase (e.g., medium to high or low to medium) is expected to increase the probability of a firm's own patenting by 3.7 per cent, albeit with a large standard error.

The other variables included in the model specification indicate that larger firms (measured as employment) and firms that report some form of R&D or innovation-related expense during the reference period are more likely to patent, but that the age of the firm is irrelevant, controlling for its innovating status. Both the R&D and the size effect are stronger for manufacturing firms. The coefficient associated with firm size measured as employment can also be interpreted as a measure for the effect of direct and indirect financial costs associated with patenting. While the fees associated with patenting are the same for all firms in absolute terms, they will weigh more heavily on smaller firms. This means that the effect of financial costs can be partially captured by including a measure of firm size.

Table 5 shows results for individual sectors that had at least 20 patenting observations. In this regression we included all eight of the individual measures of importance for formal and informal IP, but the only one that entered consistently was the one for patents. The others were rarely significant. There are some interesting differences across sectors. First, R&D is not strongly associated with patenting, except in manufacturing and computer services.[14] Second, the association of patenting with the size of the firm is stronger in manufacturing and almost nil in computer and business services. As before, the age of the firm rarely matters. In (almost) all sectors, and firms in SIC-digit industries that rate patents as important are more likely to have at least one UK or EPO patent, not surprisingly. Finally, although generally product innovation new to the market is strongly associated with

[14] The columns with no R&D coefficient reflect the fact that in those sectors there were no non-R&D firms that patented, so the coefficient was not identified. But this result means that R&D and patenting are strongly associated in those sectors.

patenting, in the high technology sector, the association is insignificant. In this sector patenting seems to be driven more by the perception that patents are important (the highest coefficient of all, 0.094) than by the firm's own innovative success.

In Table 6 we explore the firms' views of IP protection by looking at the factors influencing the relative ranking of patents versus secrecy at the firm level. The dependent variable is an integer representing the difference between the firm's assessment of the importance of patents and the importance of secrecy. Because both these variables range from 0 to 3, the relative importance takes on the values -3, -2, -1, 0, 1, 2, 3 so we use an ordered logistic model to estimate Equation (2). The idea is that measuring relative ratings controls for the possible differences across firms in their tendency to assign high or low ratings. From the results, we see that larger and older firms, but *not* R&D-doing firms prefer patents to secrecy. Interestingly, it appears that innovative firms of all kinds prefer secrecy to patents and that this is not affected by importance of registered and informal IP in their 3-digit sector, although it is clear that the sectoral rating influences their own rating, with registered IP increasing the relative importance of patents and informal IP decreasing it.

As mentioned earlier, our data are only barely a panel, with about 1.3 observations per enterprise, so it is difficult to control for permanent differences across firms (if such an animal exists) or more realistically, left out factors that change slowly and might help explain the patenting behavior of the firms in our sample. Nevertheless, we performed a simple robustness check using a fixed effect model on the subset of the data that allowed such a model. The appendix (Table A-5) contains results when we use the panel dimension of the data and introduce firm-level fixed effects.[15] The table also reports results for a dynamic specification that allows a firm's patenting decisions in time period *t-1* to affect patent applications in time *t*. Note that given the (very) short panel and the binary dependent variable, these estimates are inconsistent and probably very downward biased. Indeed we find that the lag of patents enters negatively with a large coefficient suggesting regression to the mean, as one might have expected. The results for the other regressors are broadly consistent with the results shown so far if we look at the signs of the

[15] For this purpose, we limit the dataset to firms that have been sampled in at least two CIS waves. This reduces the sample to 1,527 firms, which corresponds to only 5 per cent of the overall CIS sample.

coefficients, but they are very imprecise. Reporting a product innovation that is new to the market is only statistically significant in Columns (5) and (6) when the lagged dependent variable is included. The lack of statistical significance is most likely explained by the fact that there is very little variation over time in terms of a firm's innovative activities, the importance of appropriation mechanisms, as well as firms' patenting decisions to identify the estimated parameters.

Our preliminary conclusions from this investigation into the reasons for the low patenting rate among UK firms are the following. First, only one third of firms have any innovations during a three-year period. Second, only about half of those have innovations new to the market. So at most, we might expect about 18 per cent of the firms to patent. In addition, size plays an important role, as we can see in Figures 3 and 4. Figure 3 uses the regression results in Table 4 to show the predicted patenting propensity as a function of size for four types of firms in the metals and machinery sector: non-innovating and non-R&D-doing, innovating and non-R&D-doing, new-to-the-firm innovating and R&D-doing, and new-to-the-market innovating and R&D-doing. As expected, there are huge differences in expected patenting propensities for these four types of firms. But it is important to observe that almost all (about 90-95 per cent) of our firms lie in the region below 500 employees, and that the median firm has 69 employees. At that size, all but the new to the market innovators have patenting propensities less than 10 per cent. So size explains a lot.

Figure 4 shows that another explanation is differences across sectors, as expected. It shows the patenting propensity-size distribution for a new-to-the-market innovator that does R&D in five different sectors, ranging from the least patent-intensive (financial intermediation firms) to the most (R&D services firms). At the median firm size, the propensities range from one per cent to almost 50 per cent.

A final explanation we have uncovered is in the attitudes of the firms surveyed by the CIS. On average, all types of innovators, including new-to-the-market innovators, rate secrecy as a more important IP protection mechanism than patents, which suggests that they are likely to place more reliance on that method of protection.

6.2 Innovative performance

This section analyses directly the relationship between a firm's choice to patent an innovation (or maintaining it as a secret) and its innovative performance, conditional on the firm having some kind of product innovation. We show results for the analysis of the relation between two measures of innovative performance (sales of products new to the firm and sales of products new to the market) and a firm's decision to patent. Following the literature (Mairesse and Mohnen 2010), we transform the sales share with a logit transform so that the dependent variable is quasi-normally distributed and the coefficients of the regression are close to elasticities or semi-elasticities. To see this, note that the estimated coefficient associated with the variable *X* in such a regression is the following:

$$\beta = \frac{\partial \log[s/(1-s)]}{\partial X}$$

where *s* is the sales share. With some manipulation we can derive the semi-elasticity of *s* with respect to *X*:

$$\frac{\partial \log s}{\partial X} = \beta(1-s)$$

which is approximately equal to *β* when *s* is small, and declines towards zero as *s* becomes large.

Columns (1) and (2) of Table 7 show the results when we consider only product innovations that are "new to the market", which we consider to be "true" innovations that could in principle be patentable. The most salient finding is the large positive coefficient associated with the patent dummy variable, which suggests a strong positive association between a firm´s decision to rely on a patent and its performance in terms of share in turnover due to an innovation, confirming the descriptive findings shown in Table 3. Having applied for a patent during the period increases the share of turnover from new products by about 50 per cent at the mean share of 8 percent.[16] Thus the use of patents suggests that the firm has a more marketable innovation and is operating in a market segment where formal IP protection is important. This finding is particularly interesting in combination with the fact that there appears to be no statistically significant association between trade-marking and

[16] Clearly, this does not imply any causal effect of patents on innovative sales, as we cannot rule out potential reverse causality or other unobservables correlated with patenting driving this effect.

innovative performance conditional on patenting and a range of other variables (not shown). In the presence of the firm's own patenting, the importance of registered IP within the firm's 3-digit SIC industry has no impact, although reliance on informal IP has a strong influence also, with a semi-elasticity of 0.3.

Columns (3) and (4) of Table 7 show the results when we consider innovative sales from product innovations that are "new to the firm". These are likely to be imitations of existing innovations and therefore far less patentable than innovations that are considered to be "new to the market". This is reflected in the results shown -- the patenting dummy is not statistically significant in either of the specifications shown, nor is the sector-level importance of registered IP. This means that the share of turnover generated with products that are derived from innovations that are only "new to the firm" is not associated in a statistically significant way with a firm's observed patenting behavior. This is particularly interesting given that the coefficients associated with the other regressors display the same signs and similar magnitudes as in the first two columns of Table 7. This suggests, therefore, that patents do not play any role for a firm's sales based on more imitative products, as one would expect.

6.3 Growth performance

Table 8 uses a different performance measure to look at the link between performance and a firm's choice between formal and informal IP from a different angle. We use a firm's average annual employment growth rate between 1998 and 2006 as the dependent variable. We note that this does not imply that the sample consists of only firms that have been sampled in all CIS waves. We rely on the BSD data to construct the employment growth measure which in principle is available for all firms if they existed throughout the 9-year period, or for shorter intervals if they enter or exit. Table 8 shows the results of regressions of the average annual growth rate of the firm on whether it has a patent, whether it does R&D, size and age, and the sectoral importance of registered and informal IP as well as time and sector dummies. All variables are measured at the beginning of the period (either 1998 or later if the firm enters the sample later). The results suggest a statistically significantly positive association between patenting and employment growth, especially in manufacturing. Firms with patents have growth rates that are on average 12 per cent (in level) above those without patents, controlling for sector, size, age, and R&D.

Consistently with intuition, we find that older firms grow much more slowly and that growth is negatively correlated with initial size. Doing R&D is also associated with growth. Controlling for a firm's own patenting, the sectoral importance of registered IP is negatively associated with growth, which suggests that own patenting is a better measure of the firm's innovative success, but that the two measures are correlated.

7. Conclusion

This paper provides an analysis of the determinants of a firm´s patenting decision and assesses the potential implications of the choice on its innovative performance measured in terms of turnover. The analysis relies on a new integrated dataset that combines a range of data sources into a panel at the enterprise level. Our findings suggest the following conclusions and policy implications with regard to (a) a firm's decision to patent or to rely on informal IP, and (b) the relation between this decision to patent and innovative performance.

Determinants of a firm´s choice of IP protection

Our descriptive analysis shows about one third of firms report any form of innovation. Strikingly, we find that only 2.9 per cent of firms in the sample of all firms patent and that even among firms that conduct R&D, only 4 per cent patent. In particular, the share of patenting firms is much lower than what one might expect given that nearly 24 per cent of firms report product innovations.

When we investigated the determinants of patenting versus not patenting for innovative firms (conditioning on having reported an innovation during a three-year period), we found that most of the predictor variables confirmed prior intuition: patentees are more likely to be product innovators rather than process innovators, they are larger, more likely to also use trademarks (results not reported), more likely to do R&D, more technological, and they are more likely to export (results not reported).

What then explains the fact that fewer than half the firms patent, even if we restrict ourselves to new to the market product innovators that do R&D? One possible reason is that the samples we are using contain a large number of smaller firms (<250 employees) who may find use of the formal IP system simply too costly. This hypothesis is weakly supported by the negative coefficient on the presence of financial constraints in the patent propensity regression (results not reported). Certainly size is a very important predictor in our patenting propensity regressions and coupled with the skew size distribution for firms, this can explain the low patenting rate. However, looking at the large sample (which includes sectors that generally do not have patentable inventions), we have seen in earlier work (Hall et al. 2011) that almost half of the large firms do not use formal or informal IP either. Because firms that use one IP mechanism are more likely to use another, another possibility is that firms have a "propensity" to use or not use IP, and that the problem is lack of familiarity with the system and suboptimal behavior on the part of some firms.

A final (and perhaps the most likely) explanation is that the use of any IP protection mechanism costs time and money and most firms find that the benefits do not exceed the costs, especially in the case of patents. However, our findings on performance call this explanation into question, at least for some firms.

The use of IP protections and (innovative) performance

The results on innovation performance suggest quite strongly that patented innovations are more successful in promoting both of our performance measures. However, because we do not know whether performance and patenting are both driven by the unobservable quality of the firm's innovation or by the quality of the firm itself, it is not possible to make a causal inference based on our analysis that patenting any innovation will lead to better sales performance.

Nevertheless, our findings do suggest that fewer firms rely on patents to protect and exploit their inventions than might be optimal given the evidence found for a positive link between innovative performance and the use of patents, and that the reasons for this might be the small size of most firms and the fact that firms seem to rank secrecy rather highly.

References

Angrist J. and S. Pischke (2009): `Mostly Harmless Econometrics,' Princeton University Press.

Anton J. and Y. Dennis (2004): Little Patents and Big Secrets: Managing Intellectual Property, *RAND Journal of Economics*, Vol. 35(1), pp. 1-22.

Arundel A. (2001): The relative effectiveness of patents and secrecy for appropriation, *Research Policy*, Vol. 30(4), pp. 611-624.

Balasubramanian N. and Sivadasan, Jagadeesh (2009): What Happens when Firms Patent? New Evidence from US Economic Census Data, *Review of Economics and Statistics*, forthcoming.

Brouwer E. and A. Kleinknecht (1999): Innovative output, and a firm's propensity to patent. An exploration of CIS micro data, *Research Policy*, Vol. 28, pp. 615-624.

Hall, B. H. and R. Ziedonis (2001): The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979-95,' RAND Journal of Economics, Vol. 32, No. 1, pp.101-128.

Hall B.H., C. Helmers, M. Rogers, and V. Sena (2011): *The choice between formal and informal intellectual property: a review*, mimeo.

Heger D. and A. Zaby (2012): Giving Away the Game? The Impact of the Disclosure Effect on the Patenting Decision, ZEW Discussion Paper No. 12-010.

Helmers C., P. Schautschick and M. Rogers (2011): Intellectual Property at the Firm-Level in the UK: The Oxford Firm-Level Intellectual Property Database, Oxford University, Department of Economics Discussion Paper No. 546.

Hussinger K. (2006): Is silence golden? Patents versus secrecy at the firm level, *Economics of Innovation and New Technology*, Vol. 15(8), pp. 735-752.

Mairesse J. and P. Mohnen (2010): Using Innovation Surveys for Econometric Analysis, Chapter for *Handbook of the Economics of Innovation*, B. H. Hall and N. Rosenberg (eds.), Elsevier.

Moser P. (2011): Innovation Without Patents - Evidence from the Word Fairs. Forthcoming in the *Journal of Law and Economics*, April 2012. Available at SSRN: http://ssrn.com/abstract=930241

OECD (1992): OECD Proposed Guidelines for Collecting and Interpreting Technological Innovation Data – Oslo Manual, OECD, Paris.

Pajak S. (2010): Do Firms Rely on Big Secrets? An Analysis of IP Protection Strategies with the CIS 4 Survey, Available at SSRN: http://ssrn.com/abstract=1538980.

Robson S. and G. Haigh (2008): First Findings from the UK Innovation Survey 2007, *Economic and Labour Market Review*, Vol. 2, No. 4, pp. 47-53.

Sakakibara M. and L. Branstetter (2001): `Do stronger patents induce more innovation? Evidence from the 1988 Japanese patent law reforms,' *RAND Journal of Economics*, Vol. 32, No. 1, pp. 77-100.

Scherer F.M. and S. Weisburst (1995): `Economic Effects of Strengthening Pharmaceutical Patent Protection in Italy,' International Review of Industrial Property and Copyright Law, Vol. 26 (6), pp. 1009-1024.

Appendices

A1: Data description

The dataset consists of four components, which are all linked by a unique enterprise business register number:

Business Structure Database (BSD): the dataset is derived from the Inter Departmental Business Register (IDBR) and provides longitudinal business demography information for the population of businesses in the UK. We use information on a company's industrial classification (SIC 92), employment, turnover, as well as incorporation and market exit dates from the BSD.[17]

UK Community Innovation Survey (CIS) 3, 4, and 5: the CIS is a stratified sample of firms with more than 10 employees drawn from the IDBR. The CIS contains detailed information on firms' self-reported innovative activities.[18] We use three surveys: CIS 3 which covers the period 1998-2000, CIS 4 which covers 2002-2004, and CIS 5 which covers 2004-2006. The sample frames differ for the three CIS waves both in terms of size and industry coverage. For CIS 3, the sample frame consists of 19,625 enterprises with responses from 8,172 enterprises (42 per cent response rate); CIS 3 covers both production (manufacturing, mining, electricity, gas and water, construction) and services sectors whereas the retail sector was excluded. CIS 4 has the largest sample size out of the three CIS waves with a sample frame of 28,355 enterprises and responses from 16,446 enterprises (58 per cent response rate); it also includes the following sectors: sale, maintenance & repair of motor vehicles (SIC 50); Retail Trade (SIC 52); and Hotels & restaurants (SIC 55). CIS 5 was answered by 14,872 firms which corresponds to a response rate of 53 per cent (Robson and Haigh, 2008). It covers the same industries as CIS 4 with the addition of SIC 921 (motion picture and video activities) and 922 (radio and television activities).

Patent data: we use a match of UK patents obtained from Optics and EPO patents (designating the UK and obtained from EPO's Patstat database, version April 2010) with the IDBR. The patents-IDBR match was carried out by the ONS/UKIPO using firms' names as patent documents lack unique firm identifiers.[19] Since the matched data is based on the IDBR, it has population coverage and covers all patents filed at

[17] The definition of market exit is problematic. It is not possible to identify whether a firm has ceased trading or if it has merely undergone a change in structure that leads to its original reference number becoming extinct.

[18] The survey structure follows the Oslo Manual (OECD, 1992). See Mairesse and Mohnen (2010) for a detailed discussion of the CIS data.

[19] For a detailed description of the methodological challenges see Helmers et al. (2011).

UKIPO, WIPO (possibly designating the UK through PCT route), and EPO (possibly designating the UK through the EPC route) by firms registered in the UK over the sample period.

The BSD and CIS data were cleaned and modified/adapted in order to combine them into a single integrated dataset. In particular, the structure of CIS 3 differs considerably from CIS 4 and 5, which required a number of changes to make the different datasets compatible and consistent.

A2: Supplementary tables

Table 1
Panel structure

Number of firms	Share (%)	CIS 3	CIS 4	CIS 5
541	1.78			
481	1.58			
6,504	21.36			
239	0.78			
6,809	22.36			
8,573	28.15			
7,307	23.99			
30,454				

Note: Grey-shaded rectangles indicate where data are available.

Table 2

Share of patenting firms (sample relative to the population)

	All sectors				Manufacturing only			
	All	*Has UK or EPO patent*	*Share with patents*	*Pop share with patents*	*All*	*Has UK or EPO patent*	*Share with patents*	*Pop share with patents*
Total	33118	967	2.9%	1.7%	12726	685	5.4%	3.4%
Does R&D	20087	831	4.1%		8662	610	7.0%	
Innovates	11358	701	6.2%		5475	513	9.4%	
No R&D or inno	12066	124	1.0%		3738	75	2.0%	
R&D but no innovation	9694	142	1.5%	0.7%	3513	97	2.8%	1.5%
Innovation but no R&D*	965	12	1.2%	1.0%	326	--	--	--
Does R&D and innovates	10393	689	6.6%	4.3%	5149	513	10.0%	7.2%

*The cells with patents for manufacturing are missing due to supression of data.

** Non-manufacturing consists of Construction, Trade, Utilities, Transportation, Financial, insurance, and real estate, and Business services including computing and R&D services.

Table 3

Types of innovation

	All innovators	*Innovators with product new to the market*	*Innovators with process new to the market*	*Innovators with product new to the firm, but not the market*	*Innovators with process new to the firm, but not the market*
			Number of firms		
All firms	11160	4370	1848	3314	4522
R&D doers	10218	4121	1750	3100	4210
R&D doers who patent	697	471	199	117	239
			Sample share innovating		
All firms		13.2%	5.6%	10.0%	13.7%
R&D doers		20.5%	8.7%	15.4%	21.0%
R&D doers who patent		67.6%	28.6%	16.8%	34.3%
			Population share innovating		
All firms		37.8%	15.7%	28.1%	38.2%
R&D doers		39.0%	16.5%	29.1%	38.8%
R&D doers who patent		65.3%	31.7%	13.7%	28.7%

Note that a negligible number of firms patent but don't do R&D.

Table 4
Logit estimation: dependent variable = firm has at least one EPO or UK patent

	11,160 observations (9,524 enterprises)			5475 observations (manufacturing only)		
	Marginal effects (s.e.)					
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Product innovation new to the market	0.046 (0.005)***	0.052 (0.006)***	0.051 (0.006)***	0.062 (0.008)***	0.078 (0.011)***	0.078 (0.011)***
Process innovation new to the market	0.014 (0.005)**	0.012 (0.006)**	0.012 (0.006)**	0.012 (0.009)	0.010 (0.010)	0.011 (0.010)
Product innovation new to the firm		0.014 (0.007)*	0.013 (0.007)*		0.031 (0.013)**	0.031 (0.013)**
Process innovation new to the firm		-0.005 (0.005)	-0.003 (0.005)		-0.005 (0.009)	-0.005 (0.009)
Registered IP important in the 3-digit sector			0.020(0.013)			0.037 (0.020)*
Informal IP important in the 3-digit sector			0.002 (0.013)			-0.023 (0.021)
D (does R&D)	0.062 (0.015)***	0.062 (0.015)***	0.062 (0.015)***	0.169 (0.044)***	0.170 (0.044)***	0.170 (0.044)***
Log age	-0.000 (0.004)	-0.000 (0.004)	-0.000 (0.004)	0.010 (0.008)	0.010 (0.008)	0.010 (0.008)
Log employment	0.024 (0.002)***	0.025 (0.002)***	0.024 (0.002)***	0.040 (0.003)***	0.040 (0.003)***	0.039 (0.003)***
Time dummies	yes	yes	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes	yes	yes
Share with dep var=1	0.063	0.063	0.063	0.095	0.095	0.095
Share correctly predicted	0.938	0.938	0.937	0.906	0.906	0.904
Share correctly predicted (dep var=1	0.073	0.072	0.069	0.088	0.086	0.074
Share correctly predicted (dep var=0	0.996	0.996	0.995	0.992	0.992	0.991

Heteroskedastic-consistent standard errors clustered on enterprise are shown in parentheses.
16 sector dummies and 2 time dummies for different periods included. The excluded categories are the CIS3 and metals & machinery.

Table 5

Logit estimation: dependent variable = firm has at least one EPO or UK patent

By sector

	Non-manufacturing				*Manufacturing*				
Variable	*Business servces*	*R&D services*	*Computer services*	*Trade*	*Chemicals*	*Food etc*	*Hightech*	*Metals & machinery*	*Other mfg*
Product innovation new to the market	0.029 (0.011)***	-0.033 (0.063)	0.407 (0.083)***	0.030 (0.018)*	0.042 (0.029)	-0.006 (0.018)	0.044 (0.034)	0.081 (0.021)***	0.064 (0.031)**
Process innovation new to the market	0.004 (0.008)	0.018 (0.070)	-0.020 (0.019)	0.028 (0.016)*	0.022 (0.029)	0.047 (0.030)	0.044 (0.031)	-0.019 (0.021)	-0.035 (0.031)
Product innovation new to the firm	-0.009 (0.015)	0.028 (0.086)	0.399 (0.083)***	0.018 (0.025)	-0.017 (0.038)	-0.029 (0.032)	0.014 (0.043)	0.040 (0.024)*	0.072 (0.036)**
Process innovation new to the firm	-0.000 (0.008)	-0.062 (0.071)	0.001 (0.017)	0.006 (0.015)	0.030 (0.025)	0.023 (0.027)	-0.044 (0.027)	-0.010 (0.017)	-0.002 (0.024)
Patents an important form of IP	0.022 (0.005)***	0.145 (0.032)***	0.047 (0.009)***	0.040 (0.011)***	0.048 (0.013)***	0.017 (0.012)	0.094 (0.015)***	0.077 (0.009)***	0.060 (0.013)***
D (does R&D)	0.019 (0.021)	-0.105 (0.165)	---	0.017 (0.024)	0.182 (0.102)*	--	--	0.114 (0.055)**	--
Log age	-0.004 (0.005)	-0.017 (0.043)	0.021 (0.015)	0.005 (0.013)	0.042 (0.025)*	0.012 (0.018)	-0.019 (0.025)	0.005 (0.015)	0.007 (0.021)
Log employment	0.006 (0.003)***	0.034 (0.019)	0.005 (0.005)	0.015 (0.005)***	0.036 (0.009)***	0.020 (0.006)***	0.051 (0.009)***	0.030 (0.005)***	0.032 (0.009)***
Observations	1779	248	621	762	872	471	865	1567	466
Share with dep var=1	0.024	0.253	0.033	0.035	0.128	0.030	0.158	0.106	0.063
Share correctly predicted	0.952	0.819	0.908	0.918	0.852	0.912	0.781	0.862	0.862
Share correctly predicted (dep var=1)	0.070	0.603	0.136	0.000	0.096	0.067	0.274	0.105	0.201
Share correctly predicted (dep var=0)	0.974	0.892	0.934	0.952	0.963	0.938	0.877	0.952	0.901

Heteroskedastic-consistent standard errors clustered on enterprise are shown in parentheses.

2 time dummies for different periods included. The excluded categories is the CIS3.

Importance ratings for design IP, trademarks, copyright, complexity, secrecy, confidentiality, and lead time were also included, but were almost never significant and then only at the 10 per cent level.

Table 6

Ordered logistic regression

Dependent variable is the importance of patents relative to secrecy

	Coefficient (s.e.)	
Variable	(1)	(2)
Product innovation new to the market	-0.14 (0.05)**	-0.13 (0.05)**
Process innovation new to the market	-0.22 (0.06)***	-0.20 (0.06)***
Product innovation new to the firm	-0.17 (0.05)***	-0.16 (0.05)***
Process innovation new to the firm	-0.20 (0.04)***	-0.08 (0.04)***
Registered IP important in the 3-digit sector		1.64 (0.14)***
Informal IP important in the 3-digit sector		-1.43 (0.12)***
D (does R&D)	-0.38 (0.06)***	-0.37 (0.06)***
Log age	0.06 (0.03)**	0.06 (0.03)**
Log employment	0.05 (0.01)***	0.04 (0.01)***
R-squared	0.012	0.013
Observations	10,880	10,880

Heteroskedastic-consistent standard errors clustered on enterprise are shown in parentheses.

16 sector dummies and 2 time dummies for different periods included. The excluded categories are the CIS3 and metals & machinery.

Table 7
Innovative performance

	All sectors			
Dependent variable	*Log (Share/(1-Share))*		*Log (Share/(1-Share))*	
Variable	*Sales share new to the mkt*		*Sales share new to the firm*	
D (has EPO or UK patent)	0.55 (0.09)***	0.52 (0.09)***	0.10 (0.08)	0.08 (0.08)
Registered IP important in the 3-digit sector		0.18 (0.13)		0.02 (0.13)
Informal IP important in the 3-digit sector		0.30 (0.11)***		0.24 (0.12)**
D (does R&D)	0.07 (0.08)	0.06 (0.08)	0.06 (0.09)	0.05 (0.09)
Log age	-0.30 (0.04)***	-0.30 (0.04)***	-0.39 (0.04)***	-0.39 (0.04)***
Log employment	-0.06 (0.01)***	-0.07 (0.01)***	-0.09 (0.01)***	-0.09 (0.01)***
R-squared	0.068	0.074	0.038	0.057
Standard error	17.4	19.5	15.5	18.0
Observations	9,028	9,028	9,225	9,225

Heteroskedastic-consistent standard errors clustered on enterprise are shown in parentheses.

16 sector dummies and 2 time dummies for different periods included. The excluded categories are the CIS3 and metals & machinery.

Table 8
Growth performance

	All sectors		Manufacturing only	
Dependent variable	*Annual employment growth for available years 1998-2006*			
Variable	*(1)*	*(2)*	*(3)*	*(4)*
D (has EPO or UK patent)	0.10 (0.06)	0.12 (0.06)**	0.15 (0.07)**	0.16 (0.07)**
Registered IP important in the 3-digit sector		-0.22 (0.07)***		-0.17 (0.08)**
Informal IP important in the 3-digit sector		0.02 (0.07)		0.09 (0.08)
D (does R&D)	0.06 (0.04)*	0.07 (0.04)*	0.11 (0.03)***	0.11 (0.03)***
Log age	-0.40 (0.03)***	-0.40 (0.03)***	-0.30 (0.05)***	-0.30 (0.05)***
Log employment	-0.05 (0.01)***	-0.05 (0.01)***	-0.08 (0.01)***	-0.08 (0.01)***
R-squared	0.062	0.062	0.038	0.038
Standard error	1.19	1.19	0.97	0.97
Observations	7,567	7,567	2,327	2,327

Heteroskedastic-consistent standard errors clustered on enterprise are shown in parentheses.

16 sector dummies and 2 time dummies for different periods included. The excluded categories are the CIS3 and metals & machinery.

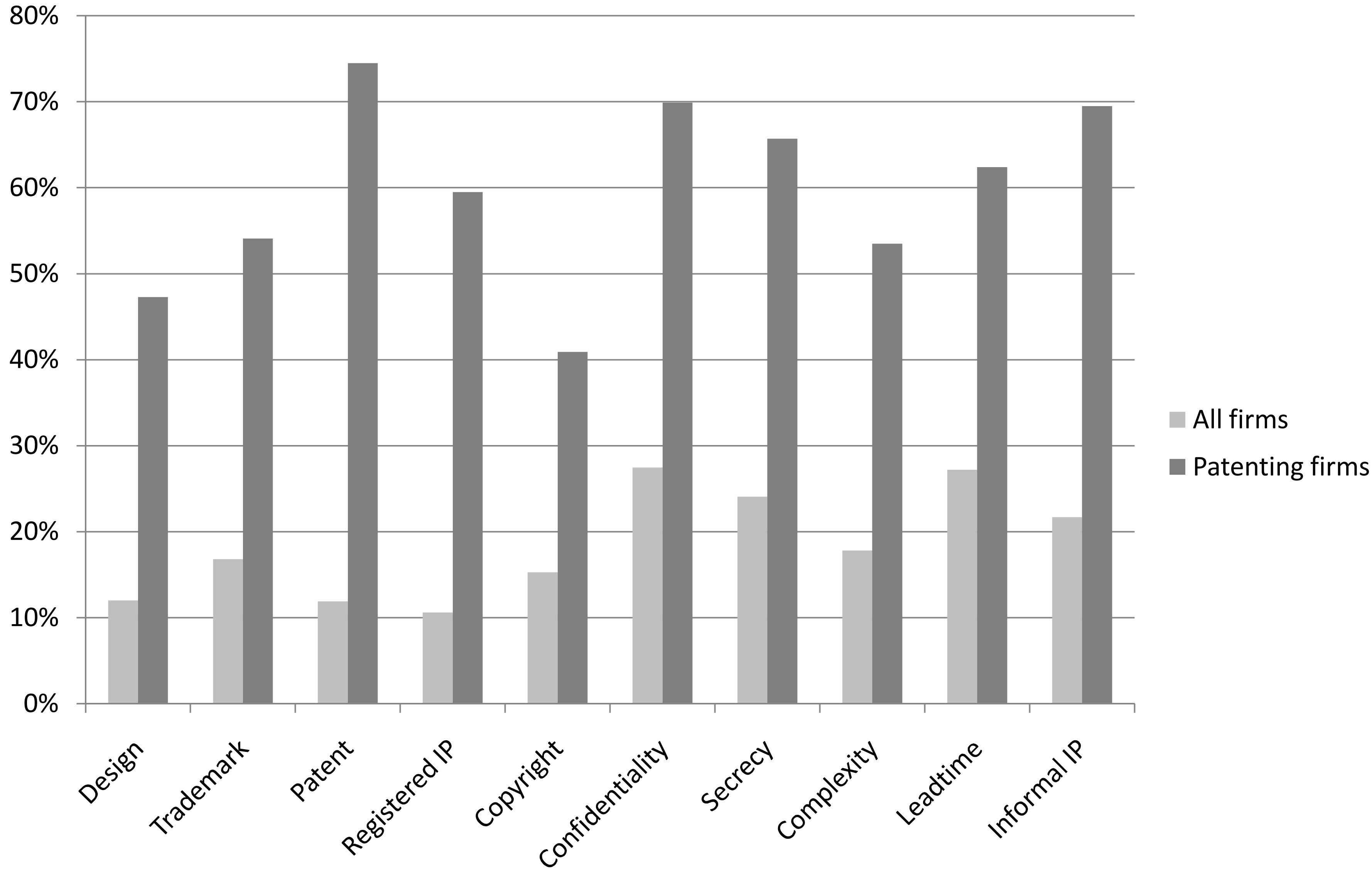

Figure 1: Population share of firms rating IP of medium or high importance

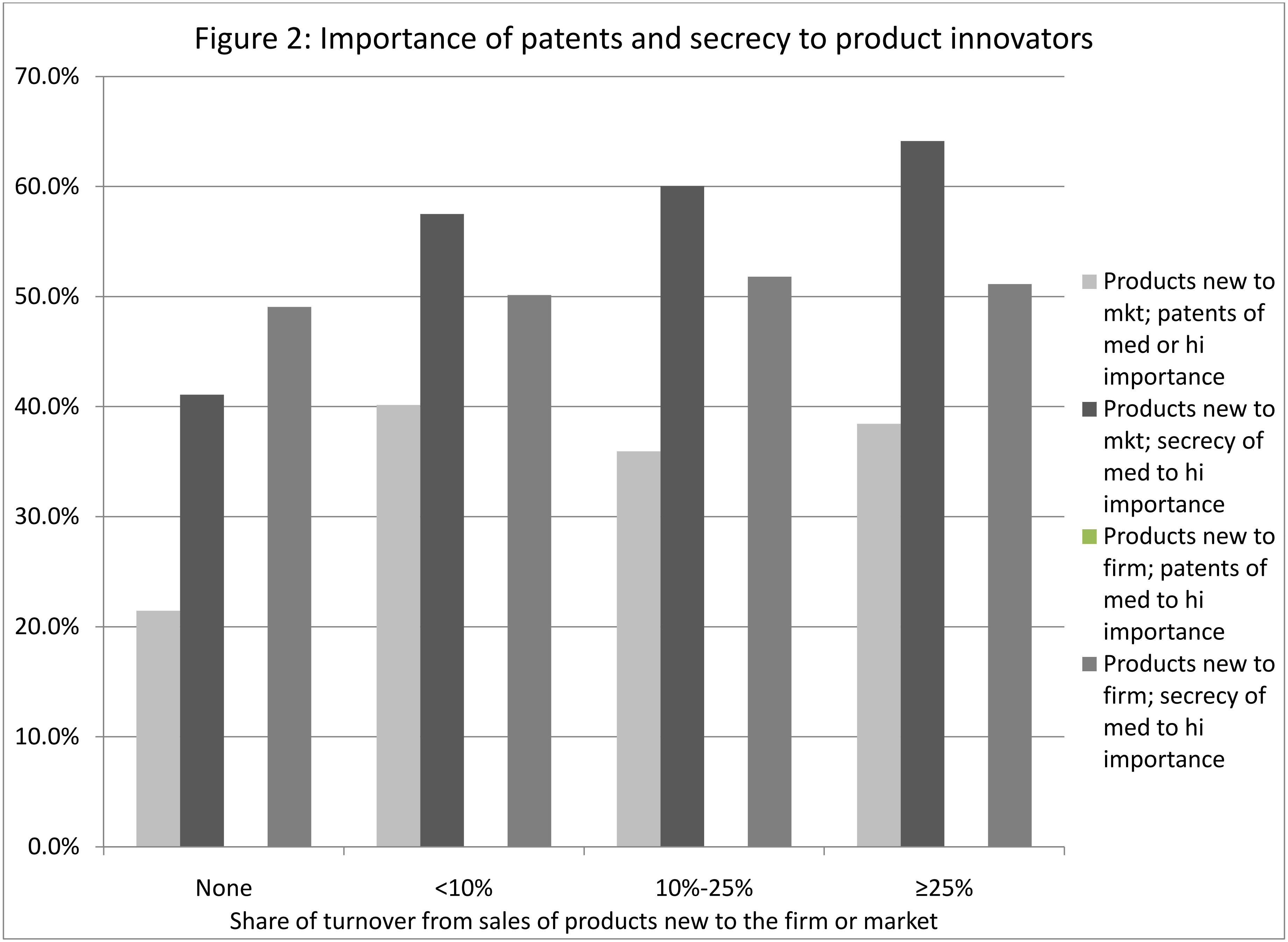
Figure 2: Importance of patents and secrecy to product innovators
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
None
<10%
10%-25%
≥25%
Share of turnover from sales of products new to the firm or market
Products new to mkt; patents of med or hi importance
Products new to mkt; secrecy of med to hi importance
Products new to firm; patents of med to hi importance
Products new to firm; secrecy of med to hi importance

Figure 3: Probability of patenting - metals and machinery sector

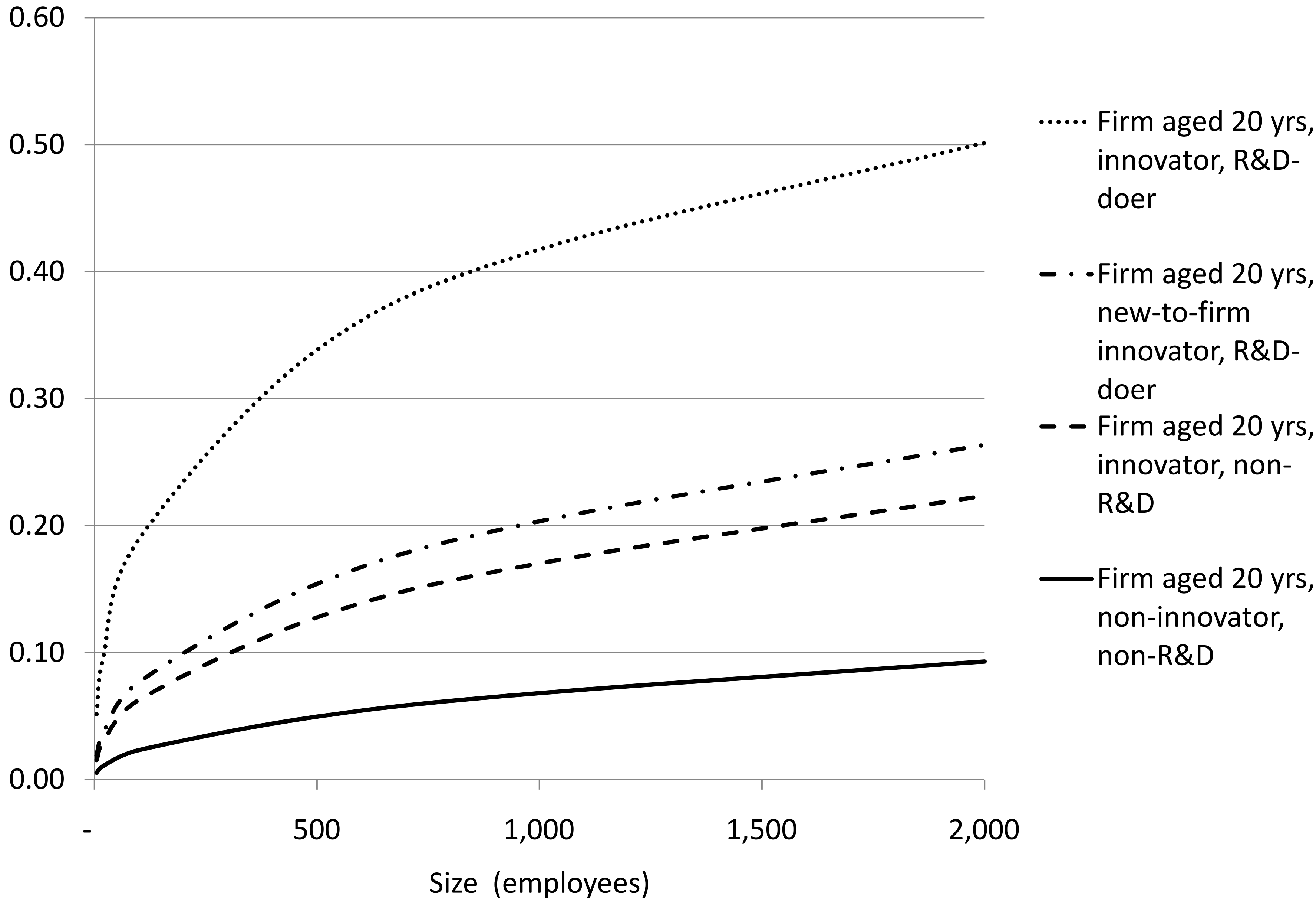

Figure 4: Probability of patenting - Innovating, R&D-doing firms aged 20 years

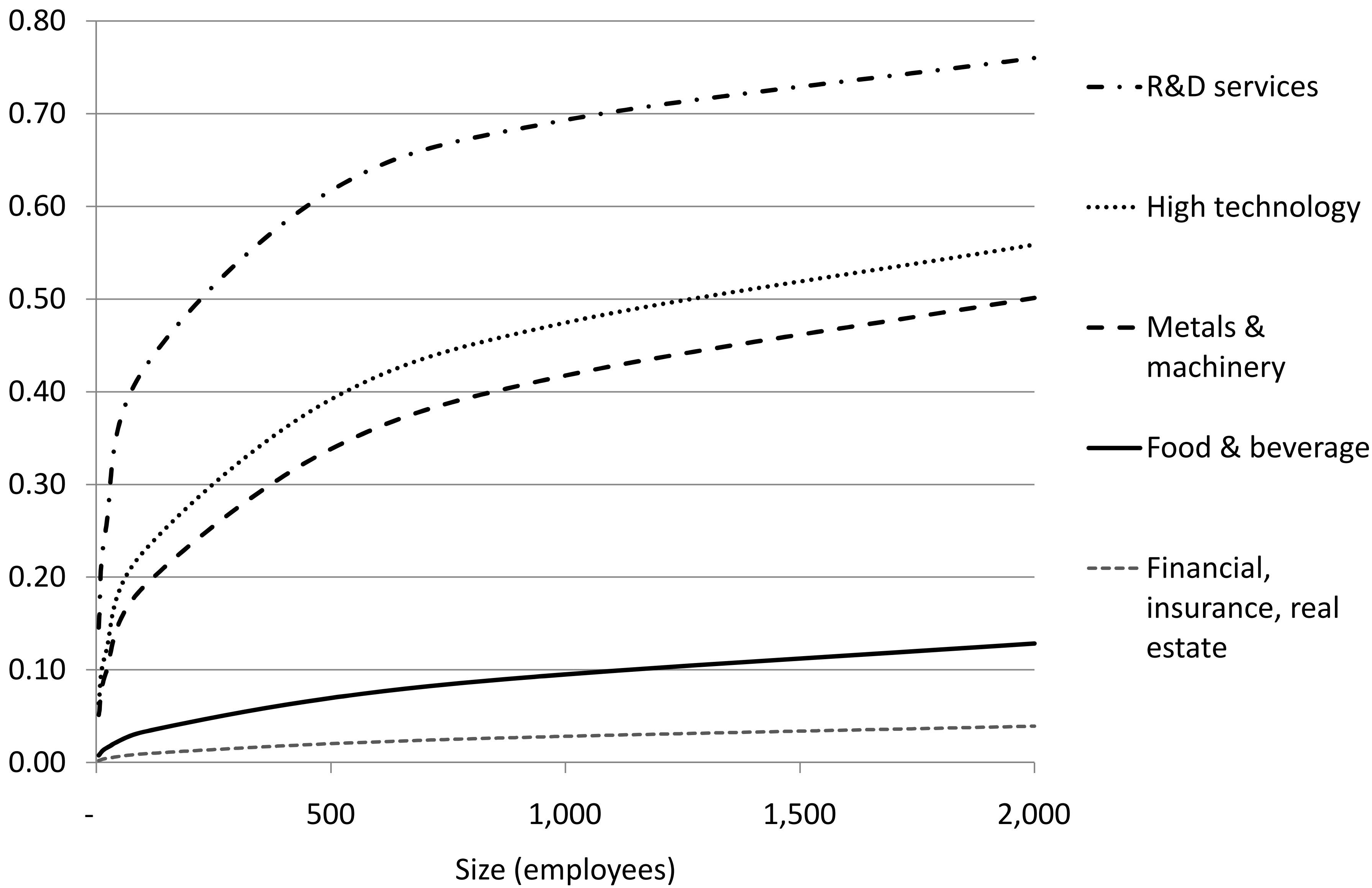

Table A1: Sector breakdown for population

	Population								
Sector	*All firms*	*Sector share*	*Pop sector share*	*Inno only*	*R&D only*	*R&D & inno*	*R&D*	*Sector share*	*Share doing R&D*
Business services	6265	18.9%	19.6%	197	2058	1675	3733	18.6%	59.6%
Chemicals	1825	5.5%	4.4%	46	490	854	1344	6.7%	73.6%
Computer services	1111	3.4%	4.6%	39	215	642	857	4.3%	77.1%
Construction	3539	10.7%	13.7%	67	1170	457	1627	8.1%	46.0%
FIRE	2776	8.4%	7.9%	89	788	773	1561	7.8%	56.2%
Food etc	1110	3.4%	2.2%	23	270	480	750	3.7%	67.6%
Hightech	1644	5.0%	3.3%	50	341	881	1222	6.1%	74.3%
Metals & machinery	4200	12.7%	10.7%	93	1250	1527	2777	13.8%	66.1%
Other mfg	1330	4.0%	2.5%	32	395	488	883	4.4%	66.4%
Printing	1145	3.5%	3.5%	40	346	430	776	3.9%	67.8%
R&D services*	406	1.2%	1.6%	..	66	..	311	1.5%	76.6%
Textiles & apparel	673	2.0%	2.0%	23	168	216	384	1.9%	57.1%
Trade	2756	8.3%	13.9%	128	752	675	1427	7.1%	51.8%
Transportation	2817	8.5%	6.6%	81	926	532	1458	7.3%	51.8%
Utilities	722	2.2%	1.4%	30	206	245	451	2.2%	62.5%
Wood & paper*	799	2.4%	2.1%	..	253	..	526	2.6%	65.8%
Manufacturing	**12726**	**38.4%**	**30.8%**	**326**	**3513**	**5149**	**8662**	**43.1%**	**68.1%**
Non-manufacturing	**20392**	**61.6%**	**69.2%**	**639**	**6181**	**5244**	**11425**	**56.9%**	**56.0%**
Total	**33118**		**100.0%**	**965**	**9694**	**10393**	**20087**		

* Cells suppressed for disclosure reasons.

Table A2: Sector breakdown for sample

	Sample				
Sector	*Inno*	*Sector share*	*Share innov-ating*	*Has UK or EPO patent*	*Share with patents*
Business services	1872	16.5%	29.9%	69	1.1%
Chemicals	900	7.9%	49.3%	163	8.9%
Computer services	681	6.0%	61.3%	26	2.3%
Construction	524	4.6%	14.8%	20	0.6%
FIRE	862	7.6%	31.1%	12	0.4%
Food etc	503	4.4%	45.3%	20	1.8%
Hightech	931	8.2%	56.6%	167	10.2%
Metals & machinery	1620	14.3%	38.6%	231	5.5%
Other mfg	520	4.6%	39.1%	44	3.3%
Printing	470	4.1%	41.0%	13	1.1%
R&D services	253	2.2%	62.3%	84	20.7%
Textiles & apparel	239	2.1%	35.5%	22	3.3%
Trade	803	7.1%	29.1%	48	1.7%
Transportation	613	5.4%	21.8%	10	0.4%
Utilities	275	2.4%	38.1%	13	1.8%
Wood & paper	292	2.6%	36.5%	25	3.1%
Manufacturing	**5475**	**48.2%**	**43.0%**	**685**	**5.4%**
Non-manufacturing	**5883**	**51.8%**	**28.8%**	**282**	**1.4%**
Total	**11358**			**967**	**2.9%**

Table A3

Importance of various IP protection methods

	All firms			*Patenting firms*		
Method of IP protection	*Number*	*Share*	*Pop share*	*Number*	*Share*	*Pop share*
Design	4487	13.5%	12.0%	493	51.0%	47.3%
Trademark	5879	17.8%	16.8%	539	55.7%	54.1%
Patent	4473	13.5%	11.9%	691	71.5%	74.5%
Registered IP	**4643**	**14.0%**	**10.6%**	**599**	**61.9%**	**59.5%**
Copyright	4976	15.0%	15.3%	414	42.8%	40.9%
Confidentiality	9328	28.2%	27.5%	660	68.3%	69.9%
Secrecy	8221	24.8%	24.1%	607	62.8%	65.7%
Complexity	6121	18.5%	17.8%	521	53.9%	53.5%
Leadtime	9065	27.4%	27.2%	598	61.8%	62.4%
Informal IP	**8733**	**26.4%**	**21.7%**	**677**	**70.0%**	**69.5%**

The cells show the numbers and shares of firms for whom the indicated form of IP is of medium or high importance.

Based on 33,118 firm-year observations, 967 with patents.

Table A4

Descriptive statistics for estimation sample of innovative firms

Variable	*Observations*	*Mean*	*S.D.*	*Median*
D (has a UK or EPO patent)	11160	0.062	0.242	0
Firm registered IP rating (0-3)	10880	0.856	1.037	0
Firm informal IP rating (0-3)	10880	1.310	1.009	1
Average registered IP rating in industry (0-3)*	11160	0.616	0.364	0.560
Average informal IP rating in industry (0-3)*	11160	0.917	0.410	0.892
Importance of design IP (0-3)	10880	0.775	1.095	0
Importance of trademarks (0-3)	10880	0.970	1.183	0
Importance of patents (0-3)	10880	0.823	1.162	0
Importance of copyright (0-3)	10880	0.874	1.129	0
Importance of confidentiality agreements (0-3)	10880	1.474	1.228	2
Importance of secrecy (0-3)	10880	1.349	1.166	1
Importance of complexity (0-3)	10880	1.102	1.080	1
Importance of lead time (0-3)	10880	1.477	1.179	2
Importance of patents relative to secrecy (-3 to 3)	10880	-0.526	1.208	0
D (firm does R&D)	11160	0.916	0.278	1
Log age	11160	2.704	0.690	2.833
Age in years	11160	17.080	9.508	16
Log employment	11160	-2.668	1.650	-3.016
Employment (1000s)	11160	0.390	1.668	0.048
Turnover share from prods new to market	9028	8.414	17.647	0
Turnover share from prods new to firm, not to mkt	9225	12.481	19.357	5
D (product innov. new to firm, not to mkt)	11160	0.297	0.457	0
D (process innov. new to firm, not to mkt)	11160	0.405	0.491	0
D (product innov. new to market)	11160	0.392	0.488	0
D (process innov. new to market)	11160	0.166	0.372	0

* These are computed across the sample at the UK SIC 3-digit level.

Table A5

OLS fixed effect panel estimation: dependent variable = firm has at least one EPO or UK patent

	OLS coefficients (s.e.)					
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Lagged dep var				-0.419 (0.125)***	-0.422 (0.125)***	-0.419 (0.124)***
Product innovation new to the market	0.003 (0.011)	0.021 (0.014)	0.022 (0.014)	0.082 (0.056)	0.171 (0.092)*	0.191 (0.090)**
Process innovation new to the market	0.009 (0.017)	0.009 (0.019)	0.009 (0.019)	0.087 (0.064)	0.046 (0.070)	0.033 (0.071)
Product innovation new to the firm		0.029 (0.013)**	0.030 (0.013)**		0.113 (0.080)	0.129 (0.080)
Process innovation new to the firm		-0.000 (0.012)	0.000 (0.012)		-0.048 (0.050)	-0.056 (0.051)
Registered IP important in the 3-digit sector			-0.052 (0.041)			-0.143 (0.180)
Informal IP important in the 3-digit sector			0.001 (0.046)			-0.080 (0.184)
D (does R&D)	0.029 (0.015)*	0.029 (0.016)*	0.029 (0.016)*	0.075 (0.052)	0.083 (0.053)	0.067 (0.061)
Log age	0.035 (0.040)	0.036 (0.040)	0.032 (0.041)	0.217 (0.282)	0.282 (0.280)	0.233 (0.291)
Log employment	0.019 (0.013)	0.020 (0.013)	0.019 (0.013)	-0.040 (0.101)	-0.054 (0.101)	-0.050 (0.098)
Observations (enterprises)		3163 (1527)			~2800 (1446)	
Standard error between	0.264	0.264	0.269	0.411	0.429	0.444
Standard error within	0.205	0.205	0.205	0.215	0.215	0.215

Heteroskedastic-consistent standard errors clustered on enterprise are shown in parentheses.

Time dummies included. The excluded category is the CIS3.