Innovation, IP choice, and productivity:

Evidence from UK firms

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1. INTRODUCTION

The design of the intellectual property rights system is one of the main concerns of the innovation and technology policy. A balanced intellectual property rights system allows innovators to benefit from their investments in knowledge creation by protecting the returns from their innovation activities but at the same time it does not unduly hinder the diffusion of the newly created knowledge across the economic system (Levin et al., 1987; Gallini, 2002; Kultti et al., 2006).

Mechanisms to appropriate the returns to knowledge assets include formal methods (patents, trademarks, copyrights, and design rights) and informal methods (secrecy, lead time, confidentiality agreements, and complexity). Fo reasons of both economic saliency and data availability, much of the research on appropriability has focused on firms' patenting propensities (e.g., Kultti et al., 2006) while other mechanisms both formal and informal have received less explicit attention. With the advent of survey evidence on firms' use of these mechanisms, this is now beginning to change.

This paper describes the second part of an empirical investigation from Module 3 of the UKIPO funded project "The use of alternatives to patent and limits to incentives". The main purpose of this part of Module 3 was to model the impact that the choice of the IP methods has on firms' performance measured as total factor productivity (productivity henceforth) by using a "structural" model that explicitly models the relationship among the variables of interest. We report on an analysis of the determinants of a firm's choice between formal, registered intellectual property (IP) and unregistered informal knowledge protection mechanisms (such as secrecy and lead time) and it provides some empirical evidence on the impact of a firm's choice on its productivity.

Modelling the relationship between productivity and IP choice presents a series of challenges. First, it is necessary to define theoretically the channels through which the choice of the IP method can affect firms' productivity. The second issue pertains to the causality direction of the relationship between choice of IP method and firm-level productivity; indeed it well may be that more productive firms may opt for formal IP methods (in particular, patents) as this may for example signal its profitability and long-term viability to investors. Our main modelling assumption is that the choice of the IP method affects a firm's productivity through the type of innovation the IP method is protecting. In other words, firms that are in the process of developing new products or new processes simultaneously decide whether to use formal or formal IP methods to protect the intellectual capital attached to the innovation. Once the new products or/and processes are introduced we can observe changes on firms' productivity that do not stem directly from the choice of the IP method but rather from the "quality" of the innovation, which is related to the form of IP protection used.

Of course, one could argue that there may a reverse causality relationship between innovation output and productivity as more productive firms may also be those that also have a higher propensity to innovate. To partially address this issue, we assume that the production of innovation and the choice of the IP methods precede temporally the production of output. If so, we can then model the relationship between IP method, innovation and productivity in a semi-sequential fashion: in other words, we model the relationship between innovation and the choice of the IP method simultaneously assuming that the variables are correlated with each other conditional on observable firm characteristics; then we model the productivity gains a firm may experience conditional on the previous-period innovation output and the choice of the IP method. This does not solve the problem of simultaneity induced by permanent unobservable differences in innovative capacity and productivity across firms, but it does mitigate any bias arising from transitory productivity effects. Given the fact that the panel structure of our data is very sparse, we cannot do much better than this.

For our estimation, we use a variation of the model suggested by Crepon, Duguet, and Mairesse (CDM 1998), one that is close to the model in Griffith et al. 2006. In the CDM model, R&D is an input to the innovation production process and the knowledge produced by innovation becomes an input to the production function. In the first stage of the model, the decision to invest in R&D and the amount of R&D investment are estimated simultaneously while the innovation production functions and the productivity equations are estimated sequentially in the second and third stages respectively. Because of our interest in the choice of IP protection method, our specification differs from that of the usual CDM model. In the second stage, we assume that a firm simultaneously innovates and chooses the methods by which it will protect its IP (either formal or informal IP methods, both methods, or possibly nothing at all). In the third stage, we estimate the impact of the innovation output (conditional on the IP method choice) on firms' productivity by estimating a production function augmented by a measure of the lagged innovation output derived from the second stage and conditional on the IP choice.

For our empirical analysis, we identify two sets of firms: firms that use exclusively informal IP methods (secrecy, confidentiality, complexity and lead time) to protect their innovation and firms that use a mix of informal and formal (namely patents) protection methods. Therefore, we model the production of innovation and the choice of the IP method in a simultaneous fashion by using a system of trivariate probits where the first two equations model the firm-level choice of the IP method while the third equation models the production of innovation.

As in the first part of the report for Module 3, our analysis is based on a new firm-level dataset that combines information from a range of different sources. We merge the three waves of the UK Community Innovation survey (CIS 3, 4 and 5) to the Annual Respondents Database (ARD2) and the database of patents compiled by the UK Intellectual property Office (UKIPO). To account for the endogeneity of the innovation measures, we merge each wave of the CIS with the next period ARD (i.e. CIS 4 firms are matched to the 2005 ARD and so on). The resulting 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 as well as measures of inputs and outputs that allow to compute productivity at firm-level.

The results show that ....

This report is organised in the following way. Section 2 briefly summarises the relevant empirical literature. Section 3 illustrates the empirical framework we use for our analysis. The structure and the content of the datasets are presented in Section 4 and in an appendix, while the results are shown in Section 5. Finally some conclusions are presented in Section 6.

2. LITERATURE

In this section we will review very briefly the empirical literature concerning the role of intellectual property (IP) and alternative appropriation mechanisms in providing incentives for invention and innovation, as well as in shaping a firm's ability to commercially exploit its knowledge.

The seminal studies in this area are those by Levin *et al.* (1987) – so called Yale I survey - and Cohen *et al.* (2000) – the Carnegie Mellon survey. Neither of these works attempted to directly test the empirical implications from economic theory but both surveys were concerned with the extent to which firms in different industries chose legal and non-legal methods to secure returns from their intellectual property. The findings are broadly consistent across the two studies. On average, patents are not the most important mechanism of IP appropriation while secrecy and lead time are. However, this is not entirely true for product innovations and for industries that are specialized in the production of "discrete" products like pharmaceuticals and other chemicals where patents are still the favorite tool to secure the returns to intellectual property.

Cohen at al. (2000) in particular find that many firms use patenting for strategic reasons rather than for protecting their intellectual property. Indeed they find that respondents use patenting to block competitors, to improve goodwill reputation and to improve bargaining power in the market. A similar type of analysis conducted on European firms confirms these overall trends. Arundel (2001) focused on the relative effectiveness of patents and secrecy using the CIS I survey for six EU countries and found that firms systematically regard lead-time and secrecy as more important ways to protect their IP than patents. Over 50% of firms rank lead-time as the most important mechanism to appropriate returns to their innovation and nearly 17% regard secrecy as the most important way to protect an innovation. In contrast, only about 10% regard patents as the most effective way to secure returns and only about 3% consider registered designs as the most important way to exploit an innovation. The relative greater importance of secrecy applies to firms across different size categories, although smaller firms regard secrecy as even more important than larger companies.

Following these early studies, the empirical literature in this field has then focused on the main determinants of the choice between the formal and informal IP methods while trying to identify the impact that the preference for informal IP methods has on firms' performance and on the diffusion of knowledge across the economy (Hussinger, 2006; Hurmelinna-Laukkanen and Puumalainen, 2007).

Firms that have a preference for informal IP methods do seem to share a common set of characteristics. For instance, Arundel (2001) finds that large firms are more likely to patent than small firms. Also, small firms often lack the resources necessary to legally defend their patents and furthermore, their patent enforcement costs tend to be higher because they rarely benefit from cross-licensing arrangements or reputations for aggressive IP protection strategies.

Involvement in inter-firm cooperation has also been found to influence the choice of the IP method. Firms that engage in cooperative arrangements with other firms benefit from specialized knowledge of their partners and interactive learning that takes place in a joint R&D project. It can be argued that R&D cooperation with other firms increases the value of patenting, because patents help to define partners' rights to emerging intellectual property explicitly, and, moreover, firms can use their portfolio of patents in negotiations with partners over cross-licensing and the ownership of the innovation output

Product innovations are more likely to be patented than process innovations (Harabi, 1995). A process innovation is typically more effectively kept within a firm and protected with trade secrets, while a product must be released to the market at large and may therefore be subject to reverse engineering. For process innovations, the legal protection offered by patents may not be worth the disclosure of information required by a patent application.

Industry-specific characteristics have also been found to influence firms' choices of IP strategies. For example, Arundel and Kabla (1998) find that the effectiveness of patents in preventing imitation varies across industries. Further, Cohen et al. (2000) divide industries into those producing discrete or complex products and argue that firms patent for different reasons in these two types of industries. Discrete products, such as food or chemicals, tend to have few components, and innovations in these areas are simpler to protect by patents. In contrast, complex products, for example, electronics products or machinery, typically require many different components in their construction. Cohen et al. (2000) argue that an innovation in these areas often requires licensing or other arrangements to gain access to technologies from other firms, making commercialization of an innovation more challenging. Therefore, patenting is pursued in complex-product industries for strategically different reasons than in discrete-product industries. Moreover, it is often much easier to invent around technologies in the engineering-based complex-product industries than it is in discrete-product industries. These factors reduce the incentive to patent and may lead complex-product firms to rely on time to market or secrecy instead.

A large body of economic literature suggests that competition (meant as competition among innovators or competition among the users of the innovation) should affect the choice of the IP mechanism. In spite of its obvious importance, few studies test the impact of competition on the choice between secrecy and patenting. An exception is the paper by Farooqui (2009) who, by using a panel from three waves of the UK CIS covering the period 1998-2006[3], finds that firms in more competitive sectors (proxied by import intensity) tend to use more legal IP methods (i.e. patents and trade marks).

A small literature has started to focus on the impact that the choice of the IP methods has on the firms' performance. It is not very developed and while issues associated to the identification strategy are still unresolved, it is still interesting to report on some early results that can offer guidance for future empirical analysis. Hanel (2008) analyzes the use of IP protection for the Canadian manufacturing, paying attention to a possible effect on profits. As a first step, he focuses on the propensity of innovative firms to protect their IP. Small firms use IP protection tools less often, whereas world-first inventors use every kind of IP protection more frequently than other firms. In the second stage he focuses on the impact that the use of IP protection has on the firms' profits. He finds that firms, which protect their IP, increased or maintained their profit. In a subsequent paper, Hussinger (2006) uses 626 manufacturing firms from the Mannheim Innovation Panel (1998-2000, CIS III) to analyse the impact on the

[3] Farooqui (2009) uses CIS3 (1998-2000), CIS4 (2002-2004), and CIS5 (2004-2006).

percentage of sales of the use of patents and secrecy. She finds a strong positive correlation between patents and sales with new products, whereas there is no effect for secrecy. This finding is in line with the hypothesis that patents are still used to protect valuable inventions in the market phase as opposed to secrecy and may indicate that secrecy may be rather applied for early-stage inventions that will enter the market in a later period.

Hurmelinna-Laukkanen and Puumalainen (2007) examine the efficiency of different appropriability mechanisms among a sample of 299 Finnish companies, mainly in manufacturing. The mechanisms included various forms of formal IP methods (patents, copyright, trademarks, design etc) as well as contracts and labour legislation, tacitness of knowledge, lead-time, secrecy and human-resource management (HRM). Lead-time and practical/concealment were viewed as being the strongest mechanisms, followed by tacitness and contracts. Formal IP methods, labour legislation and HRM were viewed as the weakest means to appropriate returns to innovation. This may be due to the fact that the principal question here related to preventing imitation by competitors. This study is possibly unique in trying to relate the firms' strategic goals on appropriability to the utilization of different mechanisms. For example, there was a positive relationship between pursuing short-term value and the use of lead-times, but formal IP methods did not seem to be used for this. Surprisingly, there appeared to be no support for the hypothesis that the more a company concentrates on preventing imitation, the more it uses tacitness to protect knowledge – indeed there was some suggestion of firms favouring explicit formal IP methods for this process.

3. EMPIRICAL FRAMEWORK

In this section we describe the empirical model we use to describe the process through firms produce innovation, choose an IP method and then exploit innovation to increase their productivity. Our model is based on the well-known Crepon, Duguet, and Mairesse (CDM) model for innovation survey data and productivity. This model is formalised in a set of stages: in the first stage we model the firm's decision to invest in R&D and the resulting R&D intensity measured as R&D per employee. In the second stage, we model innovation outcomes simultaneously with the choice of protection for the firm's intellectual property, as a function of R&D input and other firm characteristics. Because we treat these equations as simultaneous, we are assuming that there may be unobservables that drive both innovation and the choice of IP method. Finally in the last stage we estimate an augmented production function that includes innovation outcomes and the choice of IP method to protect the innovations.

It is important to emphasize that the CDM model is primarily descriptive rather than causal, because of the lack of true instruments. Thus we are able to use the estimates to describe the correlations in the data, but we cannot reliably predict the consequences of a change in firm behavior (shifting from are away from using patents) on its outcomes. To mitigate this drawback, we have used actual value added data in the year following the last year in each innovation survey, so that the R&D and innovation performance precedes the productivity measure.

Formally, the first two equations models simultaneously the firm's decision to invest in R&D and its R&D intensity using a standard Tobit type II or sample selection model. The decision to invest in R&D is governed by the following equation:

$$rd_i = \begin{cases} 1 \text{ if } rd^* = w_i\alpha + \varepsilon_i > 0 \\ 0 \text{ if } rd^* = w_i\alpha + \varepsilon_i \le 0 \end{cases} \qquad i = 1, \ldots, N \tag{1}$$

Where rd^* is an unobservable latent variable whose value determines whether the firm invests in R&D and rd is an observed indicator variable that is equal to zero for firms that do not invest in R&D and equal to one for R&D-investing firms. w is a vector of variables explaining the R&D investment decision, α is a vector of parameters to be estimated and ε_i is an error term.

Conditional on firms investing in R&D, we observe the amount of resources invested in R&D (modelled as R&D intensity, the logarithm of R&D per employee):

$$r_i = \begin{cases} z_i\beta + e_i & \text{if } rd_i \ne 0 \\ 0 & \text{if } rd_i = 0 \end{cases} \tag{2}$$

where z_i is a vector of variables affecting the R&D intensity, β is the vector of coefficients and e_i is an error term. Assuming that the two error terms are distributed bivariate normal with zero mean, variances $\sigma_\varepsilon^2 = 1$ and σ_e^2, and a correlation coefficient ρ, the system of equations (1) and (2) can be estimated as a generalised Tobit model by Maximum Likelihood estimation.

The next equations in our model are the innovation production function and the choice of the IP method. We distinguish between two types of innovation outcomes (product and process innovations) and between formal and informal IP methods. In this version of the paper we analyze one type of innovation at a time (product or process) due to lack of computational power. Formal IP methods include patents, design and copyrights while informal IP ones include secrecy, confidentiality agreements, complexity and lead time. We assume that the choice of the IP method and the innovation production functions are correlated and therefore we estimate them in a simultaneous fashion. Each type of innovation is measured by a dummy variable (INN) indicating whether the firm has introduced at least one product/ process innovation:

$$INN_i = \gamma_1 r_i^* + x_i^1 \delta_1 + d_s + d_r + u_i^1 \quad (3)$$

where *INN* is the measure of innovation, r^* is the predicted value of R&D intensity (this way we can control to some extent for the fact that the investment in R&D is endogenous to the production of innovation), x^1 is a vector of variables that affect firms' propensity to innovate, d_s and d_r are industry and region dummies and u^1 is the residual. The importance of formal and/or informal methods of IP protection to the firm are modelled by the following equations:

$$\begin{aligned} IIP_i &= \gamma_2 r_i + x_i^2 \delta_2 + d_s + d_r + u_i^2 \\ FIP_i &= \gamma_3 r_i + x_i^3 \delta_3 + d_s + d_r + u_i^3 \end{aligned} \quad (4)$$

where *IIP* is a dummy variable taking the value of one for firms that consider secrecy, confidentiality, complexity, or lead time important means to protect their IP and 0 if they do not; similarly for *FIP*, where formal IP is defined as patents, trademarks, design rights, or copyright. r^* is the predicted value of R&D intensity as before, x^2 and x^3 are vectors of variables that affect firms' propensity to use formal and/or informal IP methods, d_s and d_r are industry and region dummies and the u's are the residuals. We estimate (3) and (4) simultaneously as a trivariate probit system, assuming that the three disturbances are correlated.

The production function is a standard Cobb-Douglas model where the logarithms of labour (l) and capital (k) are inputs along with the (predicted value of the) innovation outputs. The basic idea is that firms' acquired knowledge has been codified into specific product or process innovations captured in the innovation output variables and that these variables might have a positive impact on the firms' performance. To allow for the fact that the innovation output can be endogenous, we use the predicted values from the innovation production functions rather than the actual values. More importantly, to test whether the impact of innovations from firms which use formal methods to protect their IP on their own productivity differs systematically from the impact of innovations of firms which use informal IP methods, we interact the innovation output indicator first with the dummy variable for the use of formal IP methods and then with the dummy variable for the use of informal IP methods. We also include the usual set of industry and regional dummies to control for unobserved characteristics that affect the output level. Therefore, the augmented production function can now be written formally as:

$$\begin{aligned} y_i &= a + b_k k_i + b_l l_i + \pi_1 \widehat{INN}_i + \pi_2 IIP_i + \pi_3 FIP_i \\ &\quad + \pi_4 IIP_i \bullet \widehat{INN}_i + \pi_5 FIP_i \bullet \widehat{INN}_i + d_s + d_r + v_i \end{aligned} \tag{5}$$

As in Griffith et al. (2006), the first stage equations are estimated on all the reported R&D figures and the predicted values for all firms are then used to proxy innovation effort in the knowledge production function. We estimate the relationship between R&D investment and innovation outputs using data on firms that report at least one of the two. This approach assumes that a firm that reports zero R&D does not actually have zero knowledge output.

4. VARIABLES AND DATA

Appendix A describes the construction of our dataset from the merge of four different datasets at the Office of National Statistics Virtual Microdata Laboratory (ONS VML): 1) the Business Structure Database; 2) the Annual Respondents Database; 3) the UK Community Innovation Surveys 3,4,5; 4) Patent data from the UK IPO.

We conduct the analysis at the `reporting unit' level which may belong to an enterprise. In turn an enterprise may be made of several reporting units although the overwhelming share of enterprises is a single reporting unit. The patent data is available only at the enterprise level and therefore it does not identify whether or not a patent is applied for by a specific reporting unit but rather the pool of patents pertaining to the whole enterprise. In principle, the linked dataset is a firm-level panel containing detailed information on firm characteristics, innovative activities as well as patent and trade-mark filings over the 9-year period 1998-2006. Due to the stratified nature of the sampling of the CIS and ARD data and a changing sampling frame over time, a panel dataset would be highly unbalanced. In linking the different datasets, we focus on the sample of firms covered by the CIS. Hence, we drop all firms from the integrated dataset that have not been sampled in at least one of the three CIS waves. This means that in this report, we use the BSD, ARD2, and patent data only to enrich the dataset available from the CIS.

Since the CIS refers to several years (CIS 3 to 1998-2000, CIS 4 to 2002-2004 and CIS 5 to 2004-2006) with 2001 being a missing year, creating a panel may be problematic and therefore we decided to link each wave of the CIS with the next period ARD2 (i.e. CIS 4 firms are matched to the 2005 ARD2 and so on) and to estimate our models on a pooled dataset constructed from each matched ARD2-CIS cross-section, with standard errors clustered on the enterprise level. This way, we can use the fact that the ARD2 is collected annually to control for the potential endogeneity of the innovation measures.

In the empirical implementation of the structural model outlined in Section 2, we follow Griffith et al. (2006) in selecting the relevant variables that affect our outcome variables. To explain whether or not firms invest in R&D and the level at which they invest (measured as the log of the R&D expenditure per employee) we use the following variables:

- A dummy variable indicating whether the international market is the firm's most important market, to capture its exposure to international competition.
- A binary indicator taking the value of 1 if the firm has a cooperative arrangement with another organization for innovation.

- A set of categorical variables reflecting different sources of information for innovation. These take the value of 1 if information from internal sources (customers/suppliers/competitors/universities) was of high and medium importance.

- A dummy variable that takes the value of 1 for firms that belong to the high-tech sectors (according to the OECD definition[4]).

- A dummy variable that takes the value of 1 if the firm is foreign-owned.

- Size dummies and the firm's age in years to control for the firm's basic characteristics. The categories for the size dummies are: 2—49, 50-99, 100-249, 250-999, >1000 employees.

- An indicator of demand-pull factors for innovation: the share of firms in the 3-digit industry for which meeting regulations or standards were of high, medium, or low importance for innovation (as opposed to no importance).[5]

Additionally, we have included dummy variables for the 2-digit industry, CIS wave and the region where the firm is located. We do not include the demand-pull factor in the decision to invest in R&D nor do we include size dummies in the R&D intensity equation, because R&D is already normalized and others have found that size does not enter this equation.

The key variables of interest in these equations are variables that capture the industry environment with respect to the appropriability of the returns to innovation. We use industry rather than firm level information because in the second stage we model the firm's choice of IP simultaneously with its innovation success. This approach recognizes that the general appropriability environment influences the amount of R&D undertaken,

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[4] The OECD definition of high tech is the following: pharmaceuticals SIC 2423; aircraft & spacecraft SIC 353; medical, precision & optimal instruments SIC 33; radio, television & communication equipment SIC 32; office, accounting & computing machinery SIC 30. Because we also include 2-digit dummies, the high tech dummy simply distinguishes pharmaceuticals from chemicals and aircraft from other transportation equipment. For this reason, it is generally insignificant in our regressions.

[5] Note that because we also include 2-digit industry dummies in the regressions, the demand pull effects are measured relative to the average for the relevant industry.

but the firm's own innovation behavior affects its choice of IP directly. As in Griffith et al. (2006), the IP variables are defined as binary variables equal to one if the firm rates any one of the formal (informal) IP methods as of high or medium importance. They are then averaged over industry.

In the second stage we distinguish two different kinds of innovation outcome (product and process innovation) and two appropriability regimes (formal and informal). Each innovation indicator is measured by a dummy variable indicating whether the firms has introduced at one product or one process innovation (either new to the market or to the firm). In addition to the wave, size, age, sector, region, high-tech, foreign ownership, and sources of information dummies used in the first set of equations, we add the following independent variables:

- The predicted value of the log R&D intensity (derived from the first stage estimates).
- A dummy variable that measures whether the firm faces financial constraints for innovation, taking the value of 1 if the firm is constrained and 0 otherwise, in the IP equations only.
- A dummy variable taking the value of 1 if the firm considers the demand for the innovation too uncertain, in the formal IP equation only.
- A dummy variable if the firm's innovation is new to the firm but not the market (imitation), in the IP equations only.
- Two indicators of demand-pull factors for innovation: the share of firms in the firm's 3-digit industry for which meeting regulations or standards were of high, medium, or low importance for innovation (as opposed to no importance) and the share of firms in the firm's 3-digit industry for which environmental concerns were of high, medium, or low importance for innovation (as opposed to no importance). These are included in the innovation equations only.
- An indicator of firm concentration in the product market (Herfindal index), at the 3-digit industry level.

We exclude the cooperation variable, the international markets variable, and the two industry-level IP variables from the innovation and IP equations. The assumption is that these drive the R&D decision but do not predict innovation output once we control for R&D.

Finally, in the production function, output is measured as (deflated) value added while labour is measured by the number of employees and capital by the (deflated) total stock of physical capital, from the ONS estimates. We also include the predicted value of innovation output from the second stage, the formal and informal IP dummies, and their interactions with innovation output.

Table A1 in the appendix gives a quick overview of the main characteristics of the basic dataset. The interesting feature of these data is that there is not too much variation across the different CIS waves and this suggests that most of the variation is cross-sectional. There are a total of 38,764 observations in the combined CIS 3,4,5 surveys; unfortunately only about 8,561 (~22%) of them match to the ARD, and therefore we only have a subset for the full analysis including the production function. We also lose an additional 1400 observations due to missing values in some of the variables, or due to sparse coverage in certain 3-digit industries.

Table 1 gives descriptive statistics for the estimation sample. The median firm has 340 employees, value added of 9.6 million pounds sterling, and a capital stock of 13 million pounds sterling. On average, the firms are 18 years old and 44 per cent are foreign-owned. 35 per cent of the firms have introduced products new to the firm or market in the past three years (17 per cent new to the market), and 27 per cent have introduced a process innovation during the same period. Only 4 per cent of the matched firms are in the high technology sector, which is a bit surprising and suggests that the sample we are analyzing may not be completely representative after a successful match between the CIS and the ARD.

5. INITIAL RESULTS

Our estimates of the CDM model are presented in Tables 2 through 4. Table 2 shows the results for the first stage (investment in R&D and R&D intensity) while Tables 3a (product) and 3b (process) shows the results for the two different innovation production functions and the choice of IP methods. Finally, Table 4 presents the estimates of the augmented production function.

The results from Table 2 show that the choice of a sample selection model with correlated disturbances is supported by the data: the correlation coefficient between the two equation disturbances is high (0.8) and quite significant. This implies that firms which invest in R&D even though they are not predicted to also have higher R&D than predicted. Firms in industries that rate some form of IP as of medium or high importance do invest more in R&D, with a coefficient that implies a threefold increase in R&D per employee, even in the presence of two-digit sector dummies. Being in a high-tech sector has no impact on R&D intensity, suggesting that the IP coefficients and the two-digit sector dummies are better proxies for the characteristics of this sector.

Looking at the predictor variables, firms that invest in R&D are younger than average and tend to operate in international markets, and if they do, their R&D investment rate is twice as high. Foreign-owned firms have a slightly lower R&D investment rate, other things equal. The use of different sources of information for innovation are all positive for R&D intensity. Collaborating with other organizations and firms has a positive impact on the R&D intensity while the regulation-related demand-pull factor has a substantial negative impact (again, within 2-digit industry).

Tables 3a and 3b focus on the choice of the IP methods and on the innovation production function. First of all, do the data support our modelling choices? In other words, is the hypothesis that the type of innovation and the choice of IP methods are positively correlated conditional on the observables confirmed by the data? Our estimates tell us that this is the case for both product and process innovation, with most correlations being positive. However, the correlation is weakest between the use of formal IP and process innovation, which is plausible.

In general, the results for product and process innovators are quite similar but there are some important differences. Firms rating some form of IP highly are domestic firms with high R&D intensity and are likely to consider themselves financially constrained. Looking at the product innovation equations, firms that are imitators (that is, they produce innovations that are new to the firm but not to the market) rate formal IP of less importance. Where the source of information for innovation is suppliers, customers, competitors, or internal, firms tend to rate the use of formal and informal IP highly. However, when the source is higher education institutions, they seem not to consider either IP mechanism as important, which is an interesting result in light of the increased use of IP by universities. Apparently the firms themselves are less afraid of information leaking and being used against them in this case. Firms also prefer formal IP methods when there are substantial uncertainties associated to the profitability of a product innovation, but not in the case of process innovation.

Turning to the innovation equations (third columns of Tables 3a and 3b), we observe that innovators have a high predicted R&D intensity from the previous stage of estimation but that foreign/domestic ownership does not affect the likelihood of innovating. The concentration of their markets is unimportant, but recall that this is only the relative concentration of the 3-digit market within a 2-digit industry. Demand-pull factors are significant factors in explaining the propensity to innovate but the signs are different: if a large share of firms in the sector is innovating to meet regulatory concerns, this has a positive impact on the propensity to innovate, but the share of firms in the sector innovating for environmental concerns is strongly negative for the firm's process innovation and weakly negative for product innovation. Information from suppliers, customers, and internal to the firm is rated as important for innovation, whereas information from competitors is nearly insignificant, and sourcing information from higher education institutions is apparently negative for innovative activity. This result may be due to timing of the product cycle and development lags.

The estimates of the augmented production function are shown in Table 4. The coefficients of the usual production function inputs (labor and capital) are as expected, and imply a scale coefficient of about 0.9, which is plausible. In terms of productivity gains, product or process innovation has a positive impact on productivity (0.08 to 0.09). However, if the firm rates formal IP as important, the gains are increased to about 0.24. Rating informal IP as important does not have a significant impact on productivity, with or without formal IP. Thus we can conclude that innovating firms that rate formal IP as important for protecting their innovations achieve a substantial gain in the contribution of their innovations to productivity growth.

6. CONCLUSIONS

In this report we have presented empirical results for the UKIPO funded project "The use of alternatives to patent and limits to incentives". In this part of the project, we have estimated the impact that IP methods have on firms' productivity through innovation. Our main assumption is that the choice of an IP method is not affecting a firm's productivity *per se* but does so through the type of innovation the IP method is protecting. So, we have modelled the relationship between IP method, innovation and productivity in a semi-sequential fashion: in other words, we have first modelled the relationship between innovation and choice of the IP method in a simultaneous way assuming that these are correlated to each other; then we have estimated the productivity gains a firm may experience conditional on the introduction of the innovation and the choice of the IP method.

The main model we use is a variation of the model suggested by Crepon et al. (1998). In the Crepon et al. model, R&D is one of the inputs of the innovation production process and the knowledge produced by innovation becomes one of the inputs of the production function. In the first step, the decision to invest in R&D and the volume of investment are estimated simultaneously while the innovation production functions and the productivity equations are estimated sequentially in the third and the fourth stage. Our specification differs from the one of Crepon et al. in the third stage and fourth stage. In the third stage, we assume that firms simultaneously innovate and choose whether to protect its IP by using either a formal or an informal IP method. In the fourth stage, we estimate the impact of the innovation output (conditional on the IP method choice) on firms' productivity by estimating a production function augmented by the measure of the innovation output derived from the third stage and conditional on the IP choice.

The results show that the data support the hypothesis that innovating and the choice of the IP methods are chosen simultaneously and that the unobserved determinants of innovating and favoring both informal and formal IP protection are positively correlated. Another important result pertains to the relationship between innovation outputs and productivity gains. Our results show that product and/or process innovation always has a positive impact on productivity but that the impact is much greater for the firms that use formal IP methods, whereas the use of informal IP seems to have no additional impact on productivity.

Finally, one last point pertains to the relationship between product market competition and choice of IP protection methods. Economic theory suggests that patents are instruments used by firms to compete against each other. However, our results show that the degree of concentration in the product market has little impact on either the choice of the IP method or the probability to innovate, once we condition on the two-digit sector to which the firm belongs.

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Table 1. Descriptive Statistics for the estimation sample				
Variable	*Obs*	*Mean*	*Median*	*Standard Deviation*
Value Added (thousands of pounds)	8561	47424.1	9649.2	309369.2
Labour (number of employees)	8561	997.2	342.3	3348.8
Capital (thousands of pounds)	8561	96689.2	13037.3	553573.3
Concentration Index	8561	0.02	0.01	0.061
R&D (thousands of pounds)	6642	941.7	0.0	14804.9
D (R&D nonzero)	7338	0.43	0.00	0.49
D (product innovator or imitator)	8561	0.35	0.00	0.48
D (product imitator)	8561	0.19	0.00	0.40
D (process innovator)	8561	0.27	0.00	0.44
D (foreign ownership)	8561	0.44	0.00	0.50
Age of firm in years	8561	18.72	18.00	9.72
D (international market important)	8561	0.53	1.00	0.50
D (collaborates)	8561	0.21	0.00	0.41
D (formal IP important)	8561	0.34	0.29	0.17
D (informal IP important)	8561	0.45	0.43	0.19
Importance of reg. & standards in the 3-digit sector	8561	0.73	0.70	0.183
Importance of environmental reg. in the 3 digit sector	8561	0.71	0.70	0.207
D (internal to the firm info source)	8561	0.75	1.00	0.43
D (suppliers are important info source)	8561	0.78	1.00	0.42
D (customers are important info source)	8561	0.77	1.00	0.42
D (competitors are important info source)	8561	0.73	1.00	0.45
D (higher ed inst are important info source)	8561	0.40	0.00	0.49
D (high tech firm)	8561	0.04	0.00	0.21
D (market risk)	8561	0.52	1.00	0.50

Notes: The R&D and R&D dummy variables received different treatment in the three survey years. Zero R&D was recorded as missing in CIS 3 and CIS 5, and as zero in CIS 4. We treated zero and missing the same in estimation, but the means above are affected by this treatment.

Table 2. Sample selection estimates - Investment in R&D and R&D intensity

7269 (??? with R&D) observations

Dependent variable	*Invests in R&D (1/0)*			*R&D intensity*		
	Marginal Effects	*Standard Errors*		*Marginal Effects*	*Standard Errors*	
D (foreign ownership)	-0.063	0.022	***	-0.260	0.053	***
Age of firm	0.000	0.001		-0.026	0.003	***
D (international market important)	0.420	0.022	***	1.002	0.058	***
D (collaborates)				0.286	0.044	***
Formal IP importance (industry average)	0.681	0.175	***	1.904	0.380	***
Informal IP importance (industry average)	0.720	0.187	***	2.172	0.413	***
Importance of reg. & standards in the 3-digit sector				-1.714	0.321	***
D (competitors are important info source)	0.723	0.033	***	0.953	0.110	***
D (customers are important info source)	0.358	0.040	***	0.352	0.106	***
D (suppliers are important info source)	0.421	0.044	***	0.657	0.120	***
D (internal to the firm info source)	0.035	0.032		0.188	0.078	**
D (higher ed inst are important info source)	0.192	0.021	***	0.451	0.050	***
D (High-tech sector)	-0.160	0.212		-0.409	0.471	
Year Dummies		Yes			Yes	
Two-digit sector dummies		Yes			Yes	
Firm size dummies		Yes			Yes	
Correlation of the disturbances in the two equations				0.798	0.018	***
Standard error of log R&D per employee residual				2.196	0.045	***
Note: Standard Errors are clustered by enterprise						

Table 3a. Multivariate Probit estimates of IP choice and product innovation

7269 observations

	Formal IP methods			*Informal IP methods*			*Product Innovator or imitator*		
	Marginal Effects	*Standard Errors*		*Marginal Effects*	*Standard Errors*		*Marginal Effects*	*Standard Errors*	
Concentration Index	-0.108	0.224		-0.111	0.230		0.119	0.229	
Market Risk (1/0)	0.339	0.016	***						
R&D Intensity (predicted value)	3.897	0.130	***	4.058	0.138	***	3.605	0.129	***
Foreign owned (1/0)	-0.059	0.018	***	-0.050	0.018	**	-0.011	0.018	
Source of Information: Internal	0.109	0.025	***	0.198	0.024	***	0.270	0.026	***
Source of Information: Suppliers	0.127	0.029	***	0.374	0.027	***	0.235	0.031	***
Source of Information: Customers	0.239	0.033	***	0.428	0.031	***	0.401	0.036	***
Source of Information: Competitors	0.175	0.027	***	0.244	0.025	***	0.053	0.028	*
Source of Information: Higher Ed	-0.090	0.019	***	-0.373	0.019	***	-0.313	0.019	***
Financial Constraints (1/0)	0.200	0.023	***	0.309	0.023	***			
Product Imitator (1/0)	-0.140	0.026	***	0.020	0.027				
Importance of reg. & standards in the 3-digit sector							0.390	0.174	**
Importance of environmental concerns in the 3-digit sector							-0.250	0.145	*
Year dummies	Yes			Yes			Yes		
Two-digit sector dummies	Yes			Yes			Yes		
Firm size dummies	Yes			Yes			Yes		
Corr (formal IP, informal IP)	0.860	0.013	***						
Corr (formal IP, innovation)	0.336	0.013	***						
Corr (informal IP, innovation)	0.406	0.013	***						

Note: The method of estimation is maximum likelihood on a trivariate probit model. Standard Errors are clustered around the enterprise

Firm age and a dummy for high tech sectors at the 3 digit level were also included, but they were never significant.

Table 3b. Multivariate Probit estimates of IP choice and process innovation									
7269 observations									
	Formal IP methods			*Informal IP methods*			*Process Innovator*		
	Marginal	*Standard*		*Marginal*	*Standard*		*Marginal*	*Standard*	
Concentration Index	0.356	0.016	***	-0.133	0.235		-0.028	0.244	
Market Risk (1/0)	-0.333	0.173							
R&D Intensity (predicted value)	3.696	0.130	***	3.868	0.138	***	2.039	0.134	***
Foreign owned (1/0)	-0.057	0.018	***	-0.047	0.018	**	-0.001	0.019	
Source of Information: Internal	0.076	0.025	***	0.163	0.024	***	0.293	0.028	***
Source of Information: Suppliers	0.121	0.029	***	0.373	0.028	***	0.676	0.037	***
Source of Information: Customers	0.228	0.033	***	0.421	0.031	***	0.090	0.038	**
Source of Information: Competitors	0.163	0.027	***	0.232	0.026	***	-0.049	0.030	*
Source of Information: Higher Ed	-0.063	0.019	***	-0.348	0.019	***	-0.206	0.020	***
Financial Constraints (1/0)	0.207	0.024	***	0.321	0.024	***			
Product Imitator (1/0)	0.243	0.022	***	0.456	0.023	***			
Importance of reg. & standards in the 3-digit sector							0.517	0.182	**
Importance of environmental concerns in the 3-digit sector							-0.526	0.155	***
Year dummies	Yes			Yes			Yes		
Two-digit sector dummies	Yes			Yes			Yes		
Firm size dummies	Yes			Yes			Yes		
Corr (formal IP, informal IP)	0.842	0.013	***						
Corr (formal IP, innovation)	0.170	0.011	***						
Corr (informal IP, innovation)	0.273	0.011	***						
Note: The method of estimation is maximum likelihood on a trivariate probit model. Standard Errors are clustered around the enterprise									
Firm age and a dummy for high tech sectors at the 3 digit level were also included, but they were never significant.									

Table 4. OLS Estimates of the production function						
Dep. Var. = Log value added per employee (7269 observations)						
	Product Innovator or imitator			*Process Innovator*		
	Coeff.	*Standard Errors*		*Coeff.*	*Standard Errors*	
Labour (log employees)	0.655	0.020	***	0.654	0.020	***
Log capital	0.252	0.012	***	0.252	0.012	***
Innovation output (predicted value)	0.090	0.045	**	0.081	0.049	
Formal IP methods	0.097	0.031	***	0.123	0.029	***
Formal IP methods*Innovation output (predicted)	0.071	0.049		0.031	0.050	
Informal IP methods	0.058	0.030	**	0.054	0.029	**
Informal IP methods*Innovation output (predicted)	-0.064	0.056		-0.047	0.062	
Total formal IP*innovation effect	0.258	0.073	***	0.235	0.076	***
Total informal IP*innovation effect	0.084	0.078		0.088	0.084	
Both*innovation effect	0.252	0.118	***	0.242	0.124	**
Year Dummies	Yes			Yes		
Sector Dummies	Yes			Yes		
Size Dummies	Yes			Yes		
R-squared	??			??		
Standard error	??			??		
Note: Standard Errors are clustered by enterprise						

Appendix A: Construction of the dataset

For this study we have constructed an ad hoc dataset by using the following five components available at the ONS Virtual Microdata Laboratory. These are all linked by the unique reporting unit 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) as well as incorporation and market exit dates from the BSD to be able to define the age of the firm.[6]

Annual Respondents Database (ARD2): the ARD2 is constructed from the microdata collected in the Annual Business Inquiry (ABI) conducted by the ONS (see Robjohns, 2006). The stratified survey sample is drawn from the IDBR.[7] The ARD covers both the production (including manufacturing) and the non-production sector (services). However the time series dimension varies across the twos: while for the production sector it is possible to have information available up to 1980 (and early 70s for some industries), the data for the services sector is available only after 1997. The information is assembled from the replies to the Census forms: as this is a mandatory requirement for UK-based business, the response rates to the ARD are rather high and this makes it highly representative of the underlying population. Each establishment has got a unique reference number that does not change over time and so allows us to build up a panel dataset. The ARD is a stratified random sample where sampling probabilities are higher for large establishments: indeed for establishments with more than 250 employees, the sampling probability is equal to one. The ARD contains all the basic information (namely the inputs and output variables) needed to estimate the production function. Output is measured by the deflated added value. Employment is measured by the total number of employees. As for capital, it is well known that the ARD does not contain

[6] 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.

[7] The stratification sample weights are as follows: businesses with (a) <10 employees 0.25, (b) 10-99 employees 0.5, (c) 100-249 employees all or ≥ 0.5 depending on industry, and (d) >250 employees all. Moreover, if a firm with <10 employees is sampled once, it is not sampled again for at least three years.

information on capital stock. However, stock of capital has been constructed at the ONS by using the perpetual inventory method.

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. This covers firms' innovation activities over a three-year window targeting firms with more than ten employees. The CIS is a survey carried out by national statistical agencies in all 25 EU member states under the coordination of Eurostat. The sampling frame for the UK CIS was developed from the Interdepartmental Business Register (IDBR) with the survey being conducted by post. Weights were used to make the sample representative of the British services sector. Firms are asked whether they have produced any innovation in the reference period (i.e. the three years before the survey starts) and if so, what type of innovation they have introduced. In turn innovation can be of three types: product innovation, process innovation and wider (or organisational) innovation. Unsurprisingly, firms can be simultaneously produce two type of innovations (or even three types) and this allows us to construct our dependent variable as the total number of innovations produced by a firm over the period 2005-07. This variable can then vary between 0 (as firms may not produce any innovation in the reference period and therefore are recorded as non-innovators) and 3 (if firms produced a product, a process and a wider innovation at the same time). The CIS provides information on what external sources of information a firm uses and whether it collaborates with other companies, suppliers, customers, competitors, laboratories and universities to develop innovation. In addition, the Survey contains information on R&D expenditure, the proportion of the workforce with a degree in engineering or a science subject and whether or not the plant is part of a group. 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% response rate); CIS 3 covers both production (manufacturing, mining, electricity, gas and water, construction) and services sectors whereas the retail sector has been 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% 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 correspond to a response rate of 53% (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. Since the matched data is based on the IDBR, it has population coverage and covers all patents filed at UKIPO, WIPO (designating the UK through PCT route), and EPO (designating the UK through the EPC route) by firms registered in the UK over the sample period. Matching rates (shown in Table 1) with the UKIPO data are better than the ones with the EPO data, with the only exception of the matching with the CIS4 where 59 per cent of the reporting units have been matched with the patents filings from EPO.

Table A1. Descriptive Statistics for the complete CIS sample

		CIS3			CIS4			CIS5	
Variable	*Obs*	*Mean*	*Std. D*	*Obs*	*Mean*	*Std. D*	*Obs*	*Mean*	*Std. D*
Value Added (pounds)	8070	7638	6947262	16101	12335	127817	14593	10655	6269920
Labour (number of employees)	8070	200.65	913.68	16101	292.06	1687.12	14593	322.21	221534.00
Capital (pounds)	1748	100559	6502580	3612	101059	6107451	3288	93062	4093250
Concentration Index	8070	0.02	0.06	16101	0.02	0.05	14593	0.02	0.05
R&D (pounds)	3350	705	1691987	16101*	174	4959	8497	245	3681
D (product innovator or imitator)	8040	0.21	0.41	16101	0.29	0.45	14593	0.26	0.44
D (process innovator)	8007	0.18	0.39	16101	0.20	0.40	14593	0.15	0.36
D (foreign ownership)	8070	0.27	0.45	16101	0.35	0.48	14593	0.20	0.40
Age of firm in years	8070	15.33	9.01	16101	17.17	9.77	14593	18.22	10.51
D (international market important)	8070	0.55	0.50	16101	0.32	0.47	14593	0.33	0.47
D (collaborates)	8070	0.10	0.31	16101	0.15	0.36	14593	0.13	0.34
D (formal IP important)	8070	0.24	0.43	16101	0.30	0.46	14593	0.34	0.47
D (informal IP important)	8070	0.32	0.47	16101	0.43	0.49	14593	0.45	0.50
Importance of reg. & standards in the 3-digit sector	8070	0.53	0.10	16101	0.62	0.08	14593	0.94	0.04
D (internal to the firm info source)	8070	0.52	0.50	16101	0.66	0.47	14593	0.69	0.46
D (suppliers are important info source)	8070	0.68	0.47	16101	0.69	0.46	14593	0.75	0.43
D (customers are important info source)	8070	0.65	0.48	16101	0.70	0.46	14593	0.75	0.43
D (competitors are important info source)	8070	0.58	0.49	16101	0.64	0.48	14593	0.70	0.46
D (higher ed inst are important info source)	8070	0.37	0.48	16101	0.28	0.45	14593	0.37	0.48
D (high tech firm)	8070	0.05	0.21	16101	0.03	0.16	14593	0.02	0.15

* The R&D variable in this column includes zero values.