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Evidence from the UK

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Abstract

We use an extended version of the well-established Crepon, Duguet and Mairesse model (1998) to model the relationship between appropriability mechanisms, innovation and firm-level productivity. We enrich this model in several ways. First, we consider different types of innovation spending and study the differences in estimates when innovation spending (rather than R&D spending) is used to predict innovation in the CDM model. Second, we assume that a firm simultaneously innovates and chooses among different appropriability methods (formal or informal) to protect the innovation. Finally, in the third stage, we estimate the impact of the innovation output conditional on the choice of appropriability mechanisms on firms' productivity. We find that firms that innovate and rate formal methods for the protection of Intellectual Property (IP) highly are more productive than other firms, but that the same does not hold in the case of informal methods for the protection of a firm's IP, except possibly for large firms as opposed to SMEs. We also find that this result is strongest for firms in the services, trade, and utility sectors, and negative in the manufacturing sector.

JEL Codes: O34, O30, L25
Keywords: productivity, innovation, intellectual property, appropriability, patents, CDM

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1. INTRODUCTION

Innovation is the engine of long-run growth. However innovation does not flourish in isolation but it is the result of the interactions among firms, policy-makers and the institutions that shape the environment where firms innovate. Among the institutions that matter for innovation, the legal system for the protection of the intellectual property has a prominent role and unsurprisingly, its design has been one of the main concerns of the innovation and technology policy across the world. A welfare-enhancing legal system for the protection of the intellectual property has to balance different requirements (Nordhaus, 1969). On the one hand, it has to allow inventors to benefit from their investment by letting them appropriate some of the returns from their inventions. On the other hand, it has to do so in such a way that the social costs associated to the creation of a (possibly short-term) legal monopoly are minimised while not hindering the diffusion of the newly created knowledge across the economic system (Levin *et al.*, 1987; Gallini, 2002; Kultti *et al.*, 2006).

Most of the policy and academic debate around the benefits and the social costs associated to the existence of a legal system for the protection of a firm's intellectual property (IP) has revolved around patents (Boldrin and Levine, 2013; Moser, 2013). In reality, patents are just one of the instruments that the legal system offers to firms to protect their intellectual property. Other mechanisms for appropriating the returns to knowledge assets include formal methods (trademarks, copyrights, and design rights) and informal methods (secrecy, lead time, confidentiality agreements, and complexity). In fact, survey evidence finds that firms do not consider patents the most effective appropriation mechanism. In two seminal papers in this area, Levin *et al.* (1987) and Cohen *et al.* (2000) find that informal methods (lead time and secrecy) are considered by U.S. manufacturing firms to be more effective than patents for the protection of their IP. In addition, Cohen *et al.* (2000) find that patents are mostly used for strategic reasons. More recent data from the UK Community Innovation Survey show that the share of firms patenting among innovators is around 4% (Hall *et al.*, 2013).

The implication is that any analysis on the relationship among appropriability mechanisms, innovation and firm-level performance needs to take into account two main issues: a) formal and informal appropriability mechanisms are not mutually exclusive and firms can use both at the same time; and b) the choice of the appropriability mechanisms (be it formal or informal) is correlated with the type and quality of innovation. Thus understanding how IP protection can foster innovation and boost firm performance needs to control for the type of innovations (e.g., product versus process) as well as their quality where possible.

This paper builds upon the existing literature on the choice of the appropriability mechanisms and its impact on firm-level innovation and productivity. At the same time, it innovates in two ways: First, we explicitly model the emphasis firms place on formal and informal appropriability mechanisms and we test the extent to which this emphasis is correlated with the type of innovation, conditional on other firm characteristics. Second, we explore the relationship between firm performance and innovation conditional on the firm's preferred appropriability mechanisms.

Modelling the relationship between firm productivity, innovation and appropriability mechanisms presents a set of challenges, especially given the nature of the cross sectional data available to us. First, there is the issue of timing. We assume here that the 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 associated inventions. Following the innovation and choice of protection mechanism, we observe changes in firm performance due to the innovation that are mediated by the chosen protection mechanism.

Second, there may be a reverse causality relationship between innovation output and 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 (e.g., Czarnitzki *et al.* 2014). We are able to address this issue by using data on innovation and IP methods that is collected prior to the year in which performance (productivity) is measures, under the assumption that the production of innovation and the choice of the IP methods precede output temporally. This does not solve the problem of simultaneity induced by permanent unobservable differences in innovative capacity and output across firms, but it does mitigate any bias arising from transitory effects. Given the fact that the panel structure of our data is very sparse, we cannot do much better than this.

Our analysis is based on a new firm-level dataset for the UK that combines information from a range of different sources. We merge three waves of the UK Community Innovation survey (CIS 3, 4 and 5) to the Annual Respondents Database (ARD2) and the Business Strategy Database (BSD), which have information on firms' inputs and outputs. To reduce endogeneity bias in the production function, we use productivity data from the year after the innovation and R&D data. That is, we merge each wave of the CIS with the subsequent period ARD information (i.e. data from CIS 4 pertaining to 2002-2004 are matched to the 2005 ARD, etc.). The resulting dataset contains not only detailed information on firms' self-reported innovation activities from the UK Community Innovation Survey (CIS), but also measures of firm inputs and outputs that allow estimation of the production function.

Only 40 per cent of our sample of firms is in manufacturing, with the remainder in services, utilities, trade, and construction. Innovation in these sectors may be quite different from innovation in manufacturing, relying less on R&D and more on the introduction of new IT-based processes. Our data source provides information on a broader definition of innovation spending of which only about 20 per cent is R&D spending and we also explore the use of this new variable in our model.

Empirically, we use an extended version of the well-established Crepon, Duguet and Mairesse model (1998) (CDM, henceforth) which relates R&D, innovation, and productivity. Our version of the model is based on the model in Griffith *et al.* (2006). We enrich this model in several ways. 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. Our specification differs from the usual CDM model in several respects. First, we focus not only on R&D spending but also consider a broader definition of innovation spending and compare those results to those using R&D only. Second, we assume that a firm simultaneously innovates and chooses among the different appropriability methods. Finally, we estimate the impact on firm performance of the innovation output conditional on the choice of IP method(s).

Our key result is that firms who innovate and rate formal IP highly are more productive than other firms, but that innovating firms which rate only informal IP highly do not see a productivity gain, except possibly for larger firms. We also find that this result is strongest for firms in the services, trade, and utility sectors, and negative in the manufacturing sector, which is puzzling.

The paper 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 Sections 5 and 6. Finally some conclusions are presented in Section 7.

2. APPROPRIABILITY MECHANISMS AND FIRM-LEVEL PERFORMANCE: A BRIEF SURVEY

In other work we have provided an extended survey of the economic literature on appropriability (Hall *et al.*, 2014) and we briefly summarize what is known about appropriability and performance here. The first and most important fact to note is that in spite of the literature's emphasis on patents or more generally on formal mechanisms of IP protection, firms generally prefer informal mechanisms, although they use both. Large scale evidence for this point was first reported in Levin *et al.* (1987) and Cohen *et al.* (2000). Both papers report results of surveys of the extent to which firms in different industries chose legal and non-legal methods to secure returns from innovation and their findings were broadly consistent. In general, patents are not the most important mechanism to protect a firm's IP while secrecy and lead time are. However, there are exceptions, especially for product innovations in some industries such as pharmaceuticals, medical instruments, specialty chemicals, and machinery parts.

These two seminal papers have been followed by a raft of similar studies which have confirmed that the preference for informal appropriability mechanisms is not limited to US firms only. 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 intellectual property than patents.[3] Laursen and Salter (2005) found that the first mover advantage is the preferred appropriability mechanism for UK firms while Amara *et al.* (2008) confirmed these findings for Canadian firms from the KIBS sectors but they also found that patents and secrecy tend to be complementary, in line with what has been suggested by other authors (see for instance Howells *et al.*, 2003).

Why do firms use a variety of appropriability mechanisms? The strength of the legal mechanisms for the protection of a firm's intellectual property, the nature of the technology and the type of knowledge embodied in the technology all influence the nature of the appropriability regime in an industry (Teece, 1986; Hall *et al.*, 2013). So innovating firms may differ in their choice of the appropriability mechanisms and these differences may be due to the characteristics of the knowledge embodied in the invention (for instance, if some of the knowledge attached to an invention is tacit, secrecy may be sufficient to protect an invention), the type of innovation (process innovation can be protected by secrecy more easily than product innovation), industry- and firm-level characteristics (size, innovation strategies, etc.). Thanks to the volume of papers which have tried to understand why firms may find some appropriability mechanisms more effective than others, we now have a fairly good understanding of how each of the above factors influences the firms' choice. For instance, we know that the size of the firm matters. Arundel (2001) finds that large firms are more likely to patent than small firms, likely because of the patent application costs some of which can be spread across many patents.[4] Hurmelinna-Laukkanen and Puumalainen (2007) find that there exists a positive relationship between pursuing short-term value and the use of lead time in a sample of 299 Finnish firms, suggesting a relationship between business strategy and IP choice. Hanel (2005) also finds that Canadian firms whose strategy focuses on the development of new markets are likely to use formal

[3] In this survey, over 50% of firms ranked lead-time as the most important mechanism to appropriate returns to their innovation and nearly 17% regarded secrecy as the most important way to protect an innovation. In contrast, only about 10% regarded patents as the most effective way to secure returns.

[4] Arundel (2001) also states that this result may be counterintuitive as theoretically small firms may find patents more valuable than large firms as they would help them to enter an industry. Although this is clearly true for a small subset of small firms (those relying on external financing such as venture capital), it may not be true for small firms in general.

appropriability mechanisms like trademarks (but not patents), but that export strategies are not associated with the use of IPR. Involvement in R&D cooperation has been found to increase the value of patenting because patents help to define the property rights among the members of the consortium (Cohen, *et al.* 2000).[5]

We also know that the type of industry the firms operates in may influence the choice between different appropriability mechanisms. Some studies have focused on services (rather than manufacturing) and they all suggest that most service firms do not use any IP at all and among those which do, trademarks and copyrights (i.e. formal appropriability mechanisms) are the most used appropriability mechanisms. Among the informal mechanisms, lock-in of customers, suppliers and/or workers is preferred to secrecy (Mairesse and Mohnen, 2003; Hipp and Herstatt, 2006).

Much empirical work confirms that product innovations are more likely to be patented than process innovations (e.g., Harabi, 1995; Hanel, 2005). The type of product (discrete or complex) also matters. Cohen *et al.* (2000) divide manufacturing industries into industries where products are protected by one or a few patents held by a single firm (discrete) and industries where products involve technologies covered by a large number of patents held by more than one firm (complex). They suggest that in discrete products industries patents are typically used more often than secrecy. In contrast, in complex products industries it is often much easier to invent around technologies and this reduces the incentive to patent and may lead complex-product firms to rely on alternative appropriability mechanisms (like lead time, for instance). The stage of development of an innovation has a bearing on the choice between formal and informal mechanisms -- firms may use secrecy when developing a new technology but then apply for a patent when the new product is about to be commercialised (Hussinger, 2006).

Very little is known about the influence that the preference for secrecy (or informal appropriability mechanisms, in general) may have on firm performance. A few studies have focused on financial or innovation performance and have tried to relate them to

[5] However, Leiponen and Byma (2009) find that small firms cooperating in innovation with competitors prefer lead time to patents to protect their IP.

the firms' preferences for the different appropriability mechanisms. Using a dataset of German manufacturing firms, Hussinger (2006) finds a strong positive correlation between patents and sales of new products, whereas there is no correlation for secrecy. Hanel (2008) focused on profits among Canadian manufacturing firms, modelling the relationship between profits and the choice of the preferred IP mechanism(s) in a two-stage model where the first stage estimates the propensity of innovative firms to use IP mechanisms and the second stage estimates the impact of this choice on the profits. The main conclusion is that firms that use formal appropriability mechanisms increase or maintain their profit. Similarly, Hall *et al.* (2013) find that firms' preference for patents is positively associated to innovative performance measured as turnover due to innovation although there is little relationship between patenting and other measures of performance such as employment growth. These findings seem to suggest that patents are used to protect product innovations which have a direct bearing on profits and sales while secrecy may be rather used either for process innovation or for early-stage inventions that will be commercialised later on.

The studies reviewed here focus mainly on manufacturing where formal IP in the form of patents is traditionally associated to innovation. Services can be different: innovation among service firms may not be technology-related and there might be no benefit from using formal IP protection.[6] So we could potentially observe innovative service firms which are more productive than their non-innovative counterparts but at the same time, showing a preference for secrecy. A recent study by Masayuki (2014) presents some circumstantial evidence suggesting that higher productivity among services may be correlated with the preference for informal appropriability mechanisms (proxied by their trade secret holdings) among innovative Japanese service firms.

In summary, this short survey confirms the importance of the informal as well as formal appropriability mechanisms and their bearing on firm-level productivity and profits. It also identifies some characteristics of the firms, of the technology and of the industries

[6] Clearly this is an evolving area. To the extent that software and business method patenting are available, some parts of the service sector may indeed benefit from formal IP. In addition, copyright and trademark protection may be very useful in some services.

which are associated to the choice of the appropriability regime and which we will employ for our empirical analysis.

3. EMPIRICAL FRAMEWORK

The empirical framework we employ here is based on the CDM model (Crepon *et al.*, 1998). Our model captures the original flavour of the CDM model in that it models the relationship between R&D, innovation, and productivity in a sequential manner. Our innovations to this model are to include the choice of formal and informal appropriability mechanisms along with innovation success and to ask how these influence the resulting productivity from innovations. We also experiment with the use of innovation spending rather than R&D spending as an input to innovation, in line with our use of service sector data as well as manufacturing sector data.

One of the well established limitations of the CDM model is that it does not identify causal relationships among the variables but instead describes their correlation, due to the cross-sectional nature of the data to which it is applied. We have tried to mitigate this in two ways. First, our empirical model is based on a set of exclusion restrictions which are grounded in economic theory. For instance, we have assumed that the decision to invest in innovation and the amount invested depend on the general IP environment in the sector, but that the firm's own rating of IP is jointly determined with its innovation success or failure. Second, we have used productivity data in the year following the last year in each innovation survey, so that the R&D or innovation expenditure and innovation performance precedes the performance measure, although we are aware that this is a weak identification strategy and does not fully solve the endogeneity problem.

Our empirical model is formalised in three stages. In Stage 1, we model the firm's decision to invest in innovation as well as the intensity of the innovation expenditure. In Stage 2, we model in a simultaneous fashion the production of innovation and the choice of the appropriability mechanism. In the third stage, we model the process of exploitation of innovation by estimating an augmented production function that includes the predicted innovation output, with its impact allowed to vary with the choices of appropriability mechanisms. We describe each stage in more detail below.

Stage 1: the first two equations model the firm's decision to invest in innovation and the intensity of its innovation expenditure using a sample selection model. In the empirical work, we will measure innovation expenditure either by R&D or total innovation spending.

$$is_i = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \text{ if } is_i^* = w_i \alpha + \varepsilon_i \begin{pmatrix} > 0 \\ \leq 0 \end{pmatrix} \quad i = 1,...., N \qquad (1)$$

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

Conditional on firms investing in innovation, we observe the amount of resources invested in innovation (*isi,* measured here as innovation expenditure intensity, the logarithm of the innovation expenditure per employee):

$$isi_i = \begin{pmatrix} z_i \beta + e_i & \text{if } is_i \neq 0 \\ 0 & \text{if } is_i = 0 \end{pmatrix} \qquad (2)$$

where z_i is a vector of variables affecting the innovation expenditure intensity, β is the vector of coefficients and e_i is an error term. Assuming that the two error terms are distributed as a 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.

Stage 2. The second block consists of a set of innovation production functions and the equations which describe the choices among appropriability mechanisms. We distinguish between two types of innovation outcomes (product and process innovations) and between formal (patents, design and copyrights) and informal (secrecy, confidentiality agreements, complexity and lead time) appropriability mechanisms. Although ideally we would like to include product and process innovations in the same model, we found that their fitted values after instrumenting were so highly correlated that it was difficult to obtain sensible results when both variables were included in an equation.[7] Therefore, we chose to analyse one type of innovation at a time (product or process) due to lack of identifying power.

We assume that the choice of the appropriability mechanism and the innovation production functions are correlated conditional on their predictor variables and therefore we estimate using a multivariate probit model. Formally, the model is specified as a system of three equations:

$$\begin{pmatrix} INN_i \\ IIP_i \\ FIP_i \end{pmatrix} = \Phi\begin{pmatrix} \gamma_1 isi* + X_i^1\delta_1 + d_s^1 + d_t^1 \\ \gamma_2 isi* + X_i^2\delta_1 + d_s^2 + d_t^2, \Sigma \\ \gamma_3 isi* + X_i^3\delta_1 + d_s^3 + d_t^3 \end{pmatrix} \quad (3)$$

where *Φ (., Σ)* is the multivariate normal distribution, *isi** is the predicted value of the innovation expenditure intensity (controlling to some extent for the fact that the investment in innovation is endogenous to the production of innovation), the *X*s are vectors of variables that affect firms' propensity to innovate and their choice between formal and informal appropriability mechanisms, and d_s and d_t are industry and wave dummies. Each type of innovation output (either new to the firm or to the market) is proxied by a dummy variable (*INN*) indicating whether the firm has introduced at least one product/process innovation in the last three years. The dependent variables of the two IP equations are also proxied by dummy variables (*FIP* for the formal IP methods and *IIP* for the informal ones): each takes the value of one if the firm rated at least one of the relevant methods as of medium or high importance to the enterprise.

We estimate (3) simultaneously as a trivariate probit system using the GHK algorithm (Cappellari and Jenkins, 2006), assuming that the three disturbances are correlated. As

[7] This is by no means an uncommon finding when using Innovation Survey data (Hall, Lotti, and Mairesse, 2012).

in Griffith *et al.* (2006), the predicted values from the first stage estimation computed for all firms taking into account the probability that their innovation expenditure is observed are used to proxy innovation effort in the innovation production function. This approach assumes that a firm that reports no innovation expenditure may have still have some informal expenditure related to innovation that is not reported.

Stage 3. The augmented production function is a standard Cobb-Douglas model where the logarithms of labour (*l*), capital (*k*), and purchased goods and services (*m*) are inputs along with the innovation outputs. We interact the innovation variables with the two dummy variables for formal and informal IP in order to assess the contribution of IP to the exploitation of innovation. To control for the potential endogeneity of the innovation output, we use the predicted values from the innovation production functions (*INN**) rather than the actual values.[8] We also include the usual set of industry and survey dummies to control for unobserved characteristics that affect the output level.

Formally, the augmented production function is as follows:

$$\begin{aligned} y_i &= a + b_k k_i + b_l l_i + b_m m_i \\ &+ \pi_1 \widehat{INN_i^*} + \pi_2 IIP_i + \pi_3 FIP_i + \pi_4 IIP_i \bullet \widehat{INN_i^*} + \pi_5 FIP_i \bullet \widehat{INN_i^*} \\ &+ d_s + d_r + v_i \end{aligned} \tag{4}$$

4. DATA AND VARIABLES

4.1 Data

The dataset we have used for our analysis has been constructed by merging several databases compiled by the UK Office for National Statistics (ONS) and made available through the SecureLab at the UK Data Service (UKDS). The databases are the following: the Business Structure Database, containing basic information about the firm

[8] Due to the lack of independent instruments, we do not use predicted values of the IP variables but instead rely on the dummies themselves. As in the case of product and process innovation, exploration using interactions of the two sets of predicted values for these various dummy variables yielded highly insignifant and implausible results.

demographics, the Annual Respondents Database (ARD), containing information about firm inputs and outputs, and the UK Community Innovation Survey (waves 3, 4, 5, 6 and 7) which has information about innovation, R&D, and the preferred appropriability mechanisms. Appendix A has more details about the datasets and the merging procedure.

Our resulting dataset is an unbalanced panel containing detailed information on firm characteristics and innovative activities over the 1998-2010 period. However, the main results of the paper refer to the period 1998-2006, because the IP questions in CIS 6 and 7 were not comparable. In the later period, firms were asked only about their use of formal IP methods (rather than their importance) and no questions on informal methods were included.

As this paper is concerned with innovation and IP behaviour, it uses only the sample of firms surveyed by the CIS; we drop all firms from the integrated dataset that have not been sampled in at least one of the CIS waves. Thus the BSD and ARD2 are used only to enrich the dataset available from the CIS. Each CIS refers to several years (CIS 3 to 1998-2000, CIS 4 to 2002-2004, CIS 5 to 2004-2006, CIS 6 to 2006-2008, and CIS 7 to 2008-2010) with 2001 being a missing year. We linked each wave of the CIS with the next period ARD2 (i.e. CIS 4 (2002-2004) firms are matched to the 2005 ARD2 and so on) in order to reduce simultaneity problems between our innovation, appropriability and productivity measures. Note that because a new sample of firms is drawn for each CIS (in principle), there is relatively little overlap among the surveys and the average number of observations per firm is about 1.3.[9] This fact means that panel data estimation controlling for fixed firm effects is infeasible.

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 68,112 observations in the combined CIS 3-7 surveys, of

[9] In fact, the CIS 5 survey was based on the same stratified sample as the CIS 4 survey, so there is slightly more overlap than implied by drawing a new sample each year.

which 48,107 match to the ARD. About half of these either were missing industry, were in the primary industries or in service sectors that were not covered by all the CIS, or were non-profits or government firms.[10] We also lose an additional ~10,000 observations due to missing values in some of the key variables, or due to sparse coverage in certain 3-digit industries. The resulting sample contains 10,850 observations on 7,255 firms and the sample for CIS3,4,5 contains 7,144 observations on 5,684 firms (or enterprises).

4.2 Variables

In the empirical implementation of the model outlined in Section 2, we have followed the existing empirical literature on the determinants of the investment in R&D (and in other types of innovation expenditure) and of the production of innovation in the CDM model.

Stage 1. We assume that the industry-level appropriability environment can influence the amount of innovation expenditure undertaken by firms (although the firm's own innovation success affects its choice of IP directly). This assumption is reasonable as we would expect firms to invest more in R&D (or any other type of innovation expenditure) if the industry environment is such that they can appropriate most of the returns from their investment (Arrow, 1962). As in Griffith *et al.* (2006), the variables that capture the industry environment with respect to appropriability 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 3-digit industry.

Additional controls include the firm's propensity to export (here proxied by a dummy variable taking the value of one if the firms has exports) and whether the firm is foreign-owned. The first variable captures the notion that exporting firms may be more willing to invest in R&D (or any other innovation spending) as the competition and the learning effect of exporting should enhance its innovative effort (Crespi and Zuniga, 2012). The second variable controls for the possibility that foreign firms may be more innovative

[10] The industries deleted were the two-digit sectors (SIC 2007) 1-9 and 80-99.

(and therefore more willing to spend more in R&D) than national firms potentially because of their superior management practices and human capital (Griffith, 1999; Girma and Gorg, 2007; Kumar and Aggarwal, 2012). Additional controls include size (measured by the log of the number of employees) and age (measured by the log of the age). The expectation is that larger firms may be more inclined to invest in innovation as it is easier for them to spread the fixed costs of the investment in innovation than for smaller firms (Cohen and Levin, 1989; Cohen and Klepper, 1996). Equally, the empirical literature suggests that older firms tend to invest more in R&D than younger ones because of the need for specialist skills that younger firms may lack (see for instance Zahra *et al.*, 2005), although it is possible that new entrants in technology sectors actually invest at a higher rate in the hope of future sales. Thus the age effect can go either way.

We also control whether the firm has a cooperative arrangement with another organisation for innovation by introducing a dummy variable taking the value of one for those firms which have a cooperative arrangement. Several authors suggest that collaboration stimulates further innovation investment by allowing firms to share costs and internalising knowledge spillovers (see Kamien *et al.*, 1992). We include a set of categorical variables indicating the intensity of use of different information sources in innovation-related activities (Crespi and Zuniga, 2012; Griffith *et al.*, 2006); these take the value one if information from internal sources/ customers/ suppliers/ competitors/ universities was of high or medium importance. As in Griffith *et al.* (2006), we introduce demand-pull factors (namely related to the need to meet regulations and industry standards) in our equations which are proxied by 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).[11]

We control for the industry-level perception of barriers to innovation due to either financial constraints or uncertain demand for new products. Several papers suggest that financial factors are an important impediment to R&D spending (Hall, 2002; Hall and

[11] 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.

Lerner, 2010).[12] Equally, industries characterised by uncertainty in the new products' markets are characterised by low levels of R&D spending.[13] The average perception of financial constraints for innovation and constraints due to market risk (uncertain demand) in the 3-digit industry are each measured as the average of the qualitative indicator 0,1,2,3. Finally, we have included 25 dummy variables for the 2-digit industry to which the firm belongs, and 2 dummy variables for the CIS waves. The excluded industry is automobile manufacturing and the excluded wave is CIS3.

Stage 2. The key independent variable in Stage 2 (and appearing in all the equations of Stage 2) is the predicted value of the log of the innovation expenditure intensity (derived from the first stage estimates). As mentioned in Section 2, this way the model takes into account the fact that the innovation expenditure is endogenous to the production of innovation and firm preferences over appropriability mechanisms.

The innovation and appropriability equations share some independent variables with the equations from Stage 1: size, age, the dummy for cooperation and the dummies for the sources of information, the survey year, and the two-digit industry. The rationale for including them among the regressors in the innovation equations is that they may influence innovation success given innovation input. As for the appropriability equations, Arundel (2001) finds that large firms are more likely to patent than small firms because of the costs associated to the enforcement of patents. Involvement in inter-firm cooperation has also been found to influence the choice of the IP method. Firms that engage in cooperative arrangements may be interested in using formal IP methods as patents would help them when bargaining with the other partners of the research consortium (Cohen *et al.*, 2000). Finally, the use of different types of information sources can be associated to the preference for specific IP methods. For instance, firms which source information from universities may be more likely to patent

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[12] Also, Canepa and Stoneman (2008) report that firms from high tech industries are more likely to report a project being abandoned or delayed thanks to financial constraints.

[13] See for instance Tiwari *et al*. (2007) for a study of how financial constraints interact with market uncertainties (among the others) and influence R&D spending.

while those which source information from competitors or suppliers may prefer to use secrecy or lead time to protect their IP.

Consistently with the empirical literature in this area, we also control for the perceived financial constraints at the firm level (a dummy variable equal to one if the firm reports constraints) and the perceived demand for innovation (a dummy variable equal to one if the firm considers the demand for innovation too uncertain) in both the innovation and the appropriability equations. Financially constrained firms are less likely to produce innovation while at the same time they may prefer informal IP methods (see Hall *et al.*, 2013 and Scellato, 2007). Also, firms facing uncertain demand for innovation may decide to patent because of the real option that patents generate (Bloom and Van Reenen, 2002). We also include two indicators of demand-pull factors for innovation: whether the firm rated meeting regulations or standards of medium or high importance for innovation (as opposed to no or low importance) and whether environmental concerns were of medium or high importance for innovation (as opposed to no or low importance).

To help identify the separate equations, we assume that the direction of innovation (i.e. the reasons for innovating) is related to the type of innovation but not to the preference for formal and/or informal appropriability methods. Therefore, in the product innovation equation we include dummy variables indicating whether innovation was directed toward increasing the range of products, expanding to new markets or increasing market share, or improving the quality of products. In the process innovation equation we include dummy variables indicating whether innovation was directed towards improving the flexibility of production, increasing capacity, or lowering unit costs. We assume also that whether a firm prefers either of the IP methods is related to whether the innovation which is new to the market. Therefore, in the appropriability equations only, we introduce a dummy variable if the firm's innovation is new to the firm but not the market. We exclude the foreign ownership, exports, and the 3-digit industry-level variables from the equations in Stage 2. Our assumption is that these drive the innovation or R&D decision but do not predict innovation output once we control for the level of spending.

Stage 3. In the production function, output is measured as sales while labour is measured by the number of employees, capital by the total stock of physical capital, constructed from the investment series using a 10% depreciation rate, and materials by purchased goods and services. We also include the predicted value of innovation output from the second stage, the formal and informal IP dummies, and their interactions with innovation outputs.

Tables A3 and A4 in the appendix give descriptive statistics for all firms in the estimation sample as well as for the firms with positive R&D spending and the larger set of firms with positive innovation spending. Table A3 shows the medians and interquartile ranges for the continuous variables and A4 the means for all the dummy variables. The median firm has 305 employees, value added of 9 million pounds sterling, and a capital stock of 5 million pounds sterling. On average, the firms are 28 years old and 25 per cent are foreign-owned, but 48 per cent export. 33 per cent of the firms have introduced products new to the firm or market in the past three years (22 per cent new to the market), and 26 per cent have introduced a process innovation during the same period (7 per cent new to the market). 35 per cent rate some form of formal IP of medium to high importance, whereas 45 per cent rate informal IP of medium to high importance.

In addition to R&D spending, which has been well studied in the past, this paper also looks at the broader definition of innovation spending, which includes internal and external R&D, purchase of new capital equipment for innovation, purchase of external knowledge, and marketing and, training expense associated with the introduction of new products and processes. The total of this spending is substantially larger than R&D alone, and many more firms have non-zero expenditures. The median innovation expenditure per employee is 158 thousand pounds sterling. The R&D-doing firms are higher on all the IP and innovation dimensions. They are also large, and have higher non-R&D innovation expenditure, with a median that is five times the R&D median. When we add the firms that have other types of innovation expenditure to the R&D-doing firms, the IP and innovation indicators generally fall, but are still higher than those for firms with no innovation expenditure at all.

Table A5 gives some information about the composition of innovation spending. By far the largest share of such spending is for the acquisition of machinery and computer hardware and software, especially in SMEs and service firms. Internal R&D spending is a relatively small share (less than 20 per cent) of innovation spending, although it is somewhat more important for manufacturing firms. This confirms the fact that innovation in firms is a much broader concept than innovation associated with R&D. We expect that process innovation and innovation in services in particular to be associated with the acquisition of new equipment and software, rather than with R&D *per se*.

5. RESULTS

We present two versions of our estimates of the CDM model, one that uses R&D spending as the innovation input and one using the broader definition of innovation spending that includes R&D, new capital equipment, and training and marketing associated with innovation. Table 1 shows stage 1 estimates for both the R&D and the innovation models. Tables 2 and 3 show the innovation-IP equation estimates using R&D as an input; the analogous tables using innovation spending are in Appendix B. Finally, Tables 4 and 5 show the production function estimates for the two models. In the next two subsections of the paper, we discuss the results that use R&D as in input first, followed by those using innovation spending.

R&D spending

The results from Table 1 show that the choice of a sample selection model with correlated disturbances is supported by the data. The estimates show 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 formal appropriability mechanisms as of medium or high importance invest more in R&D, with a coefficient that implies a doubling of R&D per employee, even in the presence of two-digit sector dummies. For informal IP methods, the coefficient is somewhat lower, but the confidence interval overlaps with that for formal IP methods.

Looking at the predictor variables, firms that invest in R&D are exporters, and if they export, their R&D investment rate is about 65 per cent higher. Foreign-owned firms are slightly less likely to invest in R&D, but when they do, they have a higher R&D investment rate, other things equal. The uses of different sources of information for innovation are generally positive for investing R&D and R&D intensity, as is collaboration with other organizations and firms. As we control for two-digit industry, the sector-specific characteristics generally do not enter, with the exception of the attitudes toward IP protection, which has a positive impact on R&D intensity.

Tables 2 (product) and 3 (process) focus on the choice of the IP methods and on the innovation production function. The hypothesis that the type of innovation and the choice of IP methods are positively correlated conditional on the observables is confirmed by the data, with all correlations significantly positive, and ranging from 0.04 to 0.55; most are above 0.1.

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 larger firms with high R&D intensity and are likely both to rate demand uncertainty large and to consider themselves financially constrained. 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 or competitors, firms tend to rate the use of formal and informal IP highly. However, when customers are the main source of information or the source is within group, they are less likely to consider formal IP mechanisms as important, which is perhaps not surprising, as these entities are less capable of imitation. More surprising is the fact that firms collaborating for innovation are less likely to rate formal IP highly.

Turning to the innovation equations (third columns of Tables 2 and 3), we observe that product innovators have a high predicted R&D intensity from the previous stage of estimation but that process innovation appears to be less driven by R&D. Larger firms are more likely to innovate, but innovation does not depend on firm age. Information internal to the firm's group is rated as important for innovation, and information from suppliers is important only for process innovation. It appears that meeting regulatory requirements or standards reduces the probability of innovation, and that reducing environmental impacts and improving health and safety increases the probability of process innovation. This may be because the results of innovative activities directed in this way are somewhat more predictable.

The estimates of the production function are shown in Table 4, for four types of innovation: product, process, and new-to-the-market product and process. The coefficients of the usual production function inputs (labour, capital, and materials) are as expected, and imply a scale coefficient slightly greater than unity. Few of the innovation or IP coefficients are individually significant, with the exception of formal IP in the case of process innovation. However, when the coefficients are combined to identify the interaction of innovation probability with IP preferences, some highly significant results appear: for product innovation, formal IP coupled with high predicted innovation raises productivity by about 12 per cent (15 per cent for new-to-the-market innovation), whereas informal IP coupled with innovations has essentially no impact. For process innovation, there are similar results, although the precision is lower, especially for new-to-the-market process innovation. The conclusion is 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.

Innovation spending

The estimates for the model using innovation spending as an input are presented in Tables 1 (stage 1); to save space, the stage 2 and 3 estimates are in online Appendix B, as they differ little from those for R&D in Tables 2, 3, and 4.

Table 1 allows us to compare the estimates of a generalized Tobit model for innovation spending to those for R&D investment alone. Note first that there does not seem to be any correlation between the unobserved propensity to spend on innovation and its level, conditional on all the firm characteristics in the model, in contrast to the R&D model. Otherwise, the estimated coefficients are similar with a few exceptions. The most important is the difference in the sector's formal IP importance, which has little predictive power for innovation spending intensity and strong predictive power for R&D. The other significant differences are in the information sources: information from within the group is a less important predictor of innovation spending, whereas information from suppliers flips sign and is a much more important predictor than it is for R&D intensity. Both results undoubtedly reflect the importance of capital equipment and software spending as a component of the larger innovation spending variable. Innovation that depends on the acquisition of new hardware and software is less likely to be influenced by the importance of formal IP in the sector, and more dependent on information from the suppliers of that equipment.

The finding in Appendix B that there are few large differences between instrumenting innovation outcomes via R&D spending or innovation spending suggests that the choice will probably make little difference to the predicted innovation probability and that is indeed the case, as is shown in Table B3. There are essentially no differences in the estimates between Table 5 (which uses the R&D model) and Table B3 (which uses the innovation spending model). The conclusion is that it makes no difference to the CDM model whether one uses R&D spending or innovation spending as the innovation input, even though the two variables are in fact quite different for most firms. The correlation of the two variables is about 0.35 and approximately half of the firms with innovation expenditures have no R&D spending. However, it is important to keep in mind that these variables are being instrumented, which means that what it really says is that the values of R&D and innovation spending predicted by size, age, industry, exporting, ownership, collaborating, the IP and regulation environment, and sources of information have the same impact on productivity. It is possible that our instruments are not sufficiently powerful to see a differential effect, although this is a bit surprising, especially in the case of process innovation, where we might have expected innovation spending to have greater impact than R&D.

6. SIZE AND SECTOR

The previous results showed that firms favouring formal IP to protect their innovations have a productivity higher by 10-20 percent for the same set of inputs, but that favouring only informal IP did not have a similar impact. In this section we examine how this result varies over firm size and broad sector. To this end, we divide the sample into two groupings: 1) SMEs, defined as firms with fewer than 250 employees, and other (large) firms; 2) Manufacturing and Services, including construction, trade, utilities, and business services. The full R&D model was re-estimated for both groupings and a summary of the results for the production function is shown in Tables 5 (size) and 6 (sector).[14] Both groupings produced estimates with a slightly better fit than the pooled estimates.

Looking at Table 8, we first note that the IP variables enter productivity jointly significantly only for the SMEs, but not for the larger firms. However, the earlier results on the importance of formal IP for productivity in the case of product innovation still holds for SMEs; equally, both informal and formal IP are important for the productivity of both SMEs and large firms in the case of product innovation. The most interesting result is that when we split the sample like this, we can see that informal IP protection is much more important for large firm productivity than for SMEs, which is a somewhat surprising result. It can be rationalised in the light of the theoretical model of Anton and Yao (2004) who suggest that firms may be inclined to protect very valuable inventions (which may have a potential large impact on their productivity) with secrecy rather than with patents to avoid the risks of potential disclosure. That is, although the use of formal IP protection is more prevalent among large firms than among small firms (Hall *et al.* 2013), these firms also seem to find informal IP protection somewhat more useful for increasing their productivity than smaller firms. This may reflect the fact that SMEs have a greater need to access inputs external to the firm and therefore need to protect their knowledge more formally.

Turning to the sector-specific estimates in Table 6, we find first that the importance of formal IP over informal IP for productivity is supported strongly for the service sector, but much more ambiguously for the manufacturing sector, where informal IP is as important as formal IP and both impacts are negative. It turns out that this result is due primarily to the fact that a high probability of innovation in that sector is associated with substantially lower measured productivity, regardless of the firm's preference for IP protection. Further exploration did not turn up an explanation for this result. It may be due to the fact that there are longer lags between innovative activity and

[14] We also estimated the full innovation spending model, but as we saw earlier, it makes little difference for the productivity equation which model we use, so we do not show these estimates.

productivity in this sector, or to problems in measuring the inputs to productivity in innovative firms.

7. CONCLUSIONS

In this paper we have explored the estimation of an augmented CDM model that includes firm and industry ratings of the importance of various forms of intellectual property protection. We modelled the choice of the appropriability mechanisms simultaneously with innovation success and then included the interaction of the choice with innovation in the productivity equation. We also explored the use of innovation spending rather than R&D as an innovation predictor, and took a brief look at the differences across firm size and sector.

There are a number of key results from this exploration. First, we found that firms who innovated and rated formal IP highly were more productive than other firms, but that the same did not hold for informal IP by itself, except possibly for large firms as opposed to SMEs. We also found that this result was strongest for firms in the services, trade, and utility sectors, and negative in the manufacturing sector, largely due to the negative impact of predicted innovation probability.

Second, we provide evidence that R&D spending is only a fraction of total innovation spending, especially when we look beyond the manufacturing sector. However, the predictive power of the two types of spending for productivity is very similar, at least when we instrument the variables.

Third, we noted that in spite of the previous result, there were significant differences in the equations that predict R&D and innovation spending. R&D intensity is higher in exporting firms, those in formal IP sectors, and firms obtaining innovation information from within their group and from universities, whereas innovation spending is higher when suppliers are an important information source. This contrast appears to be one between the traditional technology-intensive sectors (patenting, exporting, and closer to university science) and innovation in sectors that rely on the acquisition of hardware and software to upgrade and change their processes.

Our study suffers from a number of limitations. Most importantly, we found that predicted process and product innovation probabilities were so highly correlated that it is not really possible to tease out their separate impact in the same productivity equation, and we chose to analyse them separately to look for differences. We found relatively few differences, with the exception of a clear association of process innovation and information from suppliers. Second, the use of an IP importance rating as a proxy for IP use is somewhat untested, although we know they are related from our earlier work (Hall *et al.* 2013). A related problem is that the relationship between IP preferences and innovation is also rather imprecise, as the preference is based on the general outlook of the firm and the innovation(s) something that may have happened any time during the prior 3 years. That is, we do not have a precise measure of an innovation and the choice of IP for that innovation, only broad firm-level indicators.

Another limitation of this analysis, which we share with most studies using innovation data, is that it is conducted at the enterprise level, so that we cannot be sure that the answers to the questions on methods of IP protection are directly related to the innovation(s) identified by the firm as introduced during the preceding three years. Thus our data and our results are likely to contain considerable noise. In general this will weaken rather than strengthen the results, especially for the larger firms that have many activities.

Nor do we have an indicator of the quality of the innovation. This means that our finding of higher productivity when innovating firms favour formal IP protection may reflect the fact that firms with high quality innovations leading to higher productivity are also those more likely to use formal IP. The precise interpretation of our result matters, because if the formal IP-productivity relationship is due to higher quality, there is no implication that firms should shift to using formal IP, whereas if protecting any type of innovation with formal IP increases productivity, there would be such an implication. We leave the resolution of this conundrum to future work.

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Table 1: Sample selection estimates - Investment in R&D or Innovation and its intensity

Dependent variable	*Invests in R&D (1/0)*			*Log (R&D/employee)*			*Invests in innov (1/0)*			*Log (IS/employee)*		
	Coefficient	*Standard Errors*		*Marginal Effects*	*Standard Errors*		*Coefficient*	*Standard Errors*		*Marginal Effects*	*Standard Errors*	
Log (number of employees)	0.073	0.013	***	-0.230	0.033	***	0.024	0.011	*	-0.263	0.021	***
Log (firm age in 2011)	0.011	0.056		-0.202	0.108		-0.077	0.051		-0.052	0.072	
D (foreign ownership)	-0.097	0.046	*	0.320	0.087	***	-0.071	0.043		0.291	0.061	***
D (export status)	0.314	0.045	***	0.651	0.096	***	0.163	0.042	***	0.418	0.060	***
D (collaborates)	0.415	0.047	***	0.475	0.091	***	0.272	0.055	***	0.393	0.057	***
Importance of formal IP in the 3-digit sector	0.256	0.170		1.050	0.299	***	-0.284	0.165		0.351	0.212	
Importance of informal IP in the 3-digit sector	0.242	0.188		0.637	0.315	*	0.378	0.183	*	0.710	0.231	***
Perception of market risk in the 3-digit sector	0.348	0.182		0.017	0.292		0.156	0.175		-0.017	0.212	
Perception of financial constraints in the 3-digit sector	-0.290	0.171		-0.256	0.284		-0.218	0.166		0.224	0.198	
Importance of regulation & standards in the 3-digit sector	0.016	0.198		0.427	0.354		0.127	0.197		0.150	0.250	
Importance of environmental, health & safety regs. in the 3-digit sector	-0.037	0.186		-0.296	0.347		0.059	0.185		-0.002	0.243	
D (within group important info source)	1.026	0.059	***	0.859	0.195	***	0.790	0.045	***	0.292	0.077	***
D (suppliers important info source)	0.044	0.048		-0.279	0.086	**	0.493	0.042	***	0.326	0.060	***
D (customers important info source)	0.305	0.056	***	0.392	0.112	***	0.401	0.049	***	0.145	0.068	*
D (competitors important info source)	-0.072	0.046		0.055	0.081		-0.026	0.048		0.169	0.055	**
D (universities important info source)	0.307	0.061	***	0.410	0.097	***	0.050	0.074		0.238	0.071	***
Year Dummies	51.8 (0.000)***			3.2 (0.206)			39.5 (0.000)***			2.4 (0.295)		
Two-digit sector dummies	101.6 (0.000)***			181.8 (0.000)***			34.7 (0.093)*			163.2 (0.000)***		
Correlation of the disturbances in the two equations				0.349	0.101	**				0.064	0.043	
Standard error of log R&D per employee residual				1.637	0.046	***				1.576	0.019	***
Log likelihood				-7097.7						-11696.9		
Wald test for model (d.f.)				914.7 (43)***						1082.7 (43)***		
Observations (nonzero share)				7,144 (30%)						7144 (62%)		

Standard Errors robsut to heteroskedasticity, clustered by enterprise

The method of estimation is maximum likelihood on a generalized Tobit model.

Table 2. Multivariate Probit estimates of IP choice and product innovation

7,144 observations on 5,684 firms; Log likelihood = -8967.1

	Formal IP methods			*Informal IP methods*			*Product Innovator or imitator*		
	Coeff.	*Std. err*		*Coeff.*	*Std. err*		*Coeff.*	*Std. err*	
Log (predicted R&D per employee)	0.843	0.045	***	0.638	0.044	***	0.304	0.046	***
Log (n of employees)	0.321	0.016	***	0.229	0.015	***	0.116	0.015	***
Log (firm age in 2011)	0.132	0.054	*	0.114	0.053	*	-0.057	0.057	
D (collaborates)	-0.191	0.052	***	-0.026	0.054		0.428	0.053	***
Firm perception of market risk	0.324	0.043	***	0.366	0.044	***	0.172	0.044	***
Firm perception of fin. Constraints	0.123	0.043	**	0.293	0.044	***	0.018	0.044	
Firm - impt. of reg & standards	0.140	0.050	**	0.121	0.052	*	-0.118	0.053	*
Firm - impt. of env, H&S regs	0.052	0.051		0.160	0.054	**	-0.023	0.054	
D (innov to improve range)							0.704	0.051	***
D (innov for new markets)							0.234	0.054	***
D (innov for quality improvement)							0.266	0.058	***
D (within group impt info source)	-0.234	0.066	***	0.096	0.064		0.311	0.068	***
D (suppliers important info source)	0.289	0.047	***	0.415	0.047	***	0.123	0.051	*
D (customers impt info source)	-0.127	0.054	*	0.140	0.053	**	0.139	0.058	*
D (competitors impt info source)	0.173	0.045	***	0.130	0.045	**	-0.113	0.047	*
D (universities impt info source)	0.058	0.064		0.049	0.071		-0.080	0.066	
D (imitator)	-0.270	0.060	***	-0.266	0.064	***			
Year dummies (2)	65.4 (0.000)***			80.1 (0.000)***			1.5 (0.464)		
Two-digit sector dummies (25)	298.2 (0.000)***			105.4 (0.000)***			52.9 (0.000)***		
Wald test for model (d.f.)				5,322.1 (125)***					
Corr (formal IP, informal IP)	0.548	0.019	***						
Corr (formal IP, innovation)	0.197	0.026	***						
Corr (informal IP, innovation)	0.236	0.026	***						

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

Table 3. Multivariate Probit estimates of IP choice and process innovation

7,144 observations on 5,684 firms; Log likelihood = -8,959.6

	Formal IP methods			*Informal IP methods*			*Process Innovator or imitator*		
	Coeff.	*Std. err*		*Coeff.*	*Std. err*		*Coeff.*	*Std. err*	
Log (predicted R&D per employee)	0.843	0.045	***	0.636	0.044	***	0.100	0.046	*
Log (n of employees)	0.321	0.016	***	0.228	0.015	***	0.085	0.016	***
Log (firm age in 2011)	0.136	0.055	*	0.116	0.053	*	0.015	0.057	
D (collaborates)	-0.201	0.052	***	-0.038	0.054		0.573	0.052	***
Firm perception of market risk	0.322	0.043	***	0.365	0.044	***	0.119	0.044	**
Firm perception of fin. Constraints	0.121	0.043	**	0.292	0.044	***	0.016	0.043	
Firm - impt. of reg & standards	0.144	0.050	**	0.122	0.052	*	-0.183	0.053	***
Firm - impt. of env, H&S regs	0.046	0.051		0.157	0.054	**	0.161	0.054	**
D (innov to increase flexibility)							0.480	0.055	***
D (innov to increase capacity)							0.408	0.053	***
D (innov to reduce unit cost)							0.180	0.054	***
D (within group impt info source)	-0.240	0.066	***	0.089	0.064		0.471	0.072	***
D (suppliers important info source)	0.287	0.047	***	0.413	0.047	***	0.319	0.051	***
D (customers impt info source)	-0.136	0.055	*	0.129	0.053	*	0.032	0.059	
D (competitors impt info source)	0.169	0.045	***	0.129	0.045	**	-0.109	0.047	*
D (universities impt info source)	0.068	0.064		0.066	0.071		-0.113	0.064	
D (imitator)	-0.084	0.056		-0.054	0.064				
Year dummies (2)	65.4 (0.000)***			80.1 (0.000)***			21.1 (0.000)***		
Two-digit sector dummies (25)	298.2 (0.000)***			105.4 (0.000)***			45.2 (0.000)***		
Wald test for model (d.f.)				5,115.5 (125)***					
Corr (formal IP, informal IP)	0.547	0.019	***						
Corr (formal IP, innovation)	0.039	0.024							
Corr (informal IP, innovation)	0.125	0.024	***						

Note: The method of estimation is maximum likelihood on a trivariate probit model. Standard Errors are robust to heteroskedasticity, and clustered on enterprise.

Table 4. OLS Estimates of the production function

Dependent variable	Log (turnover)											
Type of innovation	Product innovation			Process innovation			New-to-market product innovation			New-to-market process innovation		
	Coeff.	Std. err		Coeff.	Std. err		Coeff.	Std. err		Coeff.	Std. err	
Log (n of employees)	0.664	0.011	***	0.664	0.011	***	0.663	0.011	***	0.664	0.011	***
Log (capital)	0.096	0.007	***	0.097	0.007	***	0.096	0.007	***	0.096	0.007	***
Log (materials)	0.276	0.010	***	0.277	0.010	***	0.276	0.010	***	0.277	0.010	***
Scale coefficient#	1.036	0.006	***	1.038	0.006	***	1.035	0.006	***	1.037	0.006	***
Predicted prob of innovation	0.000	0.050		-0.105	0.056		0.054	0.069		-0.256	0.180	
D (formal IP important)*Pred P of innov	-0.007	0.038		-0.012	0.034		0.022	0.032		0.013	0.027	
D (informal IP important)*Pred P of innov	0.028	0.034		0.035	0.032		0.025	0.029		0.030	0.025	
D (formal IP important)	0.121	0.066		0.191	0.076	*	0.077	0.075		0.416	0.186	*
D (informal IP important)	-0.006	0.070		0.019	0.080		-0.020	0.083		0.088	0.216	
Prob innov and formal IP	0.114	0.055	**	0.074	0.068		0.153	0.075	**	0.173	0.216	
Prob innov and informal IP	0.022	0.041		-0.051	0.051		0.059	0.054		-0.138	0.157	
Prob innov and both	0.136	0.031	***	0.128	0.029	***	0.158	0.038	***	0.291	0.105	***
F-test for 4 IP variables	3.6 (0.009)***			6.6 (0.009)***			2.6 (0.037)**			5.6 (0.009)***		
F-test for 2 survey dummies	36.0 (0.000)***			34.2 (0.000)***			35.6 (0.000)***			34.0 (0.000)***		
F-test for 25 industry dummies	22.1 (0.000)***			22.3 (0.000)***			21.8 (0.000)***			22.0 (0.000)***		
F-test for model (df=35)	1360.9 (0.000)***			1357.5 (0.000)***			1357.7 (0.000)***			1357.2 (0.000)***		
R-squared	0.902			0.902			0.902			0.902		
SSR	2,572.9			2,571.7			2,573.4			2,572.4		
Standard error	0.602			0.602			0.602			0.602		

Standard errors robust to heteroskedasticity, clustered on firm.

Shaded coefficients are derived from the estimated coefficients.

7,144 observations on 5,684 firms.

Test is for the scale coefficient equal to unity

Table 5: Estimates of the production function by firm size

Dependent variable								*Log (turnover)*								
Type of innovation				*Product*									*Process*			
	SMEs			*Large firms*			*T-test#*		*SMEs*			*Large firms*			*T-test#*	
Log (capital)	0.115	0.009	***	0.069	0.011	***	3.24	***	0.116	0.009	***	0.069	0.011	***	3.31	***
Log (n of employees)	0.705	0.018	***	0.686	0.016	***	-0.79		0.707	0.018	***	0.686	0.016	***	-0.87	
Log (materials)	0.236	0.012	***	0.361	0.016	***	6.25	***	0.237	0.012	***	0.362	0.016	***	6.25	***
Prob innovation	0.006	0.074		0.075	0.065		0.70		-0.157	0.081		0.030	0.072		1.73	*
Prob innov and formal IP	0.162	0.083	**	0.111	0.070		-0.47		-0.027	0.109		0.131	0.083		1.15	
Prob innov and informal IP	-0.067	0.057		0.115	0.055	**	2.30	**	-0.122	0.073	*	0.047	0.065		1.73	*
Prob innov and both	0.095	0.048	**	0.151	0.040	***	0.90		0.008	0.067		0.148	0.046	***	1.72	*
F-test for 4 IP variables	2.8 (0.027)**			0.8 (0.554)					3.2 (0.011)**			1.6 (0.184)				
SSR	1,220.8			1,224.5					1,220.0			1,225.3				
Standard error	0.613			0.566					0.613			0.566				
Observations (firms)	3,285 (3,022)			3,859 (2,831)					3,285 (3,022)			3,859 (2,831)				

Standard errors robust to heteroskedasticity, clustered on firm.

F test for difference of product models = 10.5

F test for difference of process models = 10.4

SMEs are firms with employment less than 250.

The t-test is for the equality of the coefficient between manufacturing and services.

Table 6: Estimates of the production function by sector

Dependent variable								*Log (turnover)*								
Type of innovation				*Product*									*Process*			
	Manufacturing			*Services & other*			*T-test#*		*Manufacturing*			*Services & other*			*T-test#*	
Log (capital)	0.027	0.010	***	0.134	0.009	***	7.95	***	0.028	0.010	***	0.134	0.010	***	7.50	***
Log (n of employees)	0.764	0.016	***	0.587	0.014	***	8.33	***	0.765	0.016	***	0.587	0.014	***	8.37	***
Log (materials)	0.334	0.017	***	0.266	0.012	***	-3.27	***	0.333	0.016	***	0.266	0.012	***	-3.35	***
Prob innovation	-0.164	0.058	**	0.117	0.077		2.91	***	-0.297	0.066	***	0.067	0.086		3.36	***
Prob innov and formal IP	-0.086	0.061		0.254	0.096	***	2.99	***	-0.176	0.073	**	0.299	0.121	**	3.36	***
Prob innov and informal IP	-0.093	0.047	**	0.076	0.069		2.02	***	-0.171	0.056	***	0.042	0.087		2.06	***
Prob innov and both	-0.015	0.035		0.213	0.061	***	3.24	***	-0.050	0.040		0.274	0.080	***	3.62	***
F-test for 4 IP variables	2.1 (0.083)*			1.9 (0.111)					3.9 (0.004)***			2.8 (0.025)**				
SSR	711.7			1748.2					708.7			1747.8				
Standard error	0.482			0.658					0.481			0.658				
Observations (firms)	3,091 (2,430)			4,053 (3,272)					3,091 (2,430)			4,053 (3,272)				

Standard errors robust to heteroskedasticity, clustered on firm.

F test for difference of product models = 9.2

F test for difference of process models = 9.4

Services & other includes construction, trade, and utilities in addition to services.

The t-test is for the equality of the coefficient between manufacturing and services.

Online Appendices to Appropriability Mechanisms, Innovation and Productivity: Evidence from the UK

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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 SecureLab, UK Data Service. 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.[3]

Annual Respondents Database (ARD2): the ARD2 is constructed from the microdata collected in the Annual Business Inquiry (ABI) conducted by the ONS. The stratified survey sample is drawn from the IDBR.[4] The ARD covers both the production (including manufacturing) and the non-production sector (services). However the time series dimension varies across the two sectors: 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

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[3] 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.

[4] 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.

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 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. 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 organisations 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).

One problem that arises in combining these datasets is the identification of the relevant sampling unit. The ARD2 is apparently sampled at the reporting unit level (which may not coincide with the firm in the case of multi-unit firms), where it is possible that a reporting unit may belong to a larger enterprise, although most of the enterprises consist of a single reporting unit. In principle, the UK CIS is sampled at the enterprise level. Thus for multi-establishment enterprises, there is some ambiguity about whether we have the full complement of data from the ARD2. Fortunately this problem will affect relatively few firms in our sample.

Table A1: Choosing the sample

	Observations	Firms
Total CIS observations	**68,112**	**46,638**
Not matched to ARD	20,005	
ARD-CIS match	**48,107**	
Drop missing industries, primary inds, inds 80-98	26,092	
Drop non-profits, government, missing legal status	519	
Unable to construct capital stock	5,040	
Potential CIS sample	**16,456**	**11,421**
Missing employment on CIS	1,049	
Large estimation sample	**15,407**	**10,844**
Missing capital, turnover, or materials	3,761	
Trim ratios for production function at 1%	796	
Estimation sample	**10,850**	**7,255**
CIS 6 and 7 sample	**3,706**	**3,068**
CIS 3,4,5 sample	**7,144**	**5,553**

Note: the ratios trimmed are those for sales/capital stock, sales/employment, sales/materials, capital stock/employment, and R&D and innovation spending intensity. Observations in the one per cent tails of the distribution were excluded.

Table A2: Sectoral breakdown 1998-2010

		Number of observations			*Share*	
SIC	*Description*	*Total*	*Large*	*SMEs*	*Large*	*SMEs*
23-25, ex 244,245	Mfg of chemical, rubber, plastic, oil	445	267	178	60.0%	40.0%
30, 32	Mfg of computers & electronic inst	156	80	76	51.3%	48.7%
31	Mfg of elec equipment	192	92	100	47.9%	52.1%
28	Mfg of fabricated metal goods	318	117	201	36.8%	63.2%
15,16	Mfg of food, beverage, and tobacco	713	500	213	70.1%	29.9%
33	Mfg of medical & scientific inst	171	92	79	53.8%	46.2%
17-19, 36	Mfg of misc low-tech goods	502	237	265	47.2%	52.8%
34	Mfg of motor vehicales	294	176	118	59.9%	40.1%
29	Mfg of non-elec machinery	413	239	174	57.9%	42.1%
35	Mfg of other transport equipment	188	98	90	52.1%	47.9%
244	Mfg of pharmaceuticals	57	47	10	82.5%	17.5%
26, 27	Mfg of primary metals	301	153	148	50.8%	49.2%
22	Mfg of printed goods	285	202	83	70.9%	29.1%
245	Mfg of soap & toiletries	61	46	15	75.4%	24.6%
20, 21	Mfg of wood & furniture	243	97	146	39.9%	60.1%
	Total manufacturing	**4339**	**2443**	**1896**	**56.3%**	**43.7%**
45	Construction	803	413	390	51.4%	48.6%
64	Post, telephone, and telegraph	148	85	63	57.4%	42.6%
37,40,41,90	Utility services	134	68	66	50.7%	49.3%
50-52	Wholesale & retail trade	2077	1372	705	66.1%	33.9%
	Total utilites & trade	**3162**	**1938**	**1224**	**61.3%**	**38.7%**
72	Computer services	206	125	81	60.7%	39.3%
65-70	Financial, insurance, real estate	286	181	105	63.3%	36.7%
55	Hotel & restaurant services	499	401	98	80.4%	19.6%
71	Leasing services	163	72	91	44.2%	55.8%
52, 74	Other business services	1394	932	462	66.9%	33.1%
73	R&D services	76	49	27	64.5%	35.5%
60-63	Transportation services	725	455	270	62.8%	37.2%
	Total services	**3349**	**2215**	**1134**	**66.1%**	**33.9%**
	Total	**10850**	**6596**	**4254**	**60.8%**	**39.2%**

Table A3: Estimation sample - CIS 3, 4, 5 matched to BSD (2000-2006)

	All observations		*R&D firms*		*Inn. spend firms*	
Variable	*Median*	*IQ range*	*Median*	*IQ range*	*Median*	*IQ range*
Observations	7,144		2,162		4,414	
Number of employees	305	627.5	353.5	763	315	607
Turnover*	25000	71327	35811	89629	27385	73283
Value added*	8951	21916	11729	25951	9748	22167
Capital*	5002	15407	7572	19522	5661	16315
Purchased goods & services*	12014	39102	18794	42940	13490	39168
Output-employee ratio*	85.87	93.85	94.82	87.81	89.52	93.68
Output-capital ratio	5.22	10.49	4.69	8.30	5.02	10.21
Output-materials ratio	1.80	2.25	1.75	1.87	1.76	2.19
Capital per employee*	17.17	31.97	20.72	34.95	18.48	32.92
R&D -turnover ratio	0.0000	0.0004	0.0025	0.0092	0.0000	0.0024
Innovation spend -turnover ratio	0.0019	0.0155	0.0142	0.0380	0.0104	0.0290
R&D per employee*	0.000	0.036	0.246	0.942	0.000	0.234
Innovation spend per employee*	0.158	1.421	1.333	3.728	0.915	2.663
Age in 2011 in years	28	18	29	17	28	18
Importance of formal IP in the 3-digit sector	0.35	0.33	0.44	0.28	0.38	0.35
Importance of informal IP in the 3-digit sector	0.40	0.36	0.59	0.31	0.48	0.36
Perception of market risk in the 3-digit sector	0.37	0.34	0.40	0.24	0.38	0.29
Perception of financial constraints in the 3-d sector	0.34	0.25	0.34	0.22	0.34	0.25
Importance of regulation & standards in the 3-digit sector	0.33	0.32	0.39	0.25	0.36	0.31
Importance of environmental, H&S regs. in the 3-digit sector	0.29	0.29	0.37	0.30	0.31	0.32

* Units are 1000s of GBP.

Table A4: Dummy variable means

	All observations	*R&D firms*	*Innov. spend firms*
Number of observations	7,144	2,162	4,414
		Share of firms	
formal IP of med or high importance	35.1%	62.3%	46.7%
informal IP of med or high importance	44.8%	77.3%	60.7%
foreign ownership	25.0%	29.4%	26.3%
exports	48.1%	70.6%	57.0%
market risk high	43.2%	55.6%	50.0%
financial constraints	39.5%	46.2%	44.5%
innovate to improve range	39.2%	64.8%	52.0%
innovate for new markets	40.8%	66.6%	54.1%
innovate for quality improvement	47.3%	73.7%	62.4%
innovate to increase flexibility	37.1%	57.6%	49.0%
innovate to increase capacity	34.2%	52.3%	45.3%
innovate to reduce unit cost	37.2%	59.9%	49.3%
innovate to meet regulations or standards	34.3%	50.7%	43.7%
innovate for environment or health&safety	31.0%	49.0%	40.3%
collaborates	19.2%	37.0%	26.4%
within group important info source	58.4%	91.4%	78.3%
suppliers important info source	52.7%	75.2%	70.1%
customers important info source	55.9%	83.4%	73.7%
competitors important info source	41.9%	62.0%	54.8%
universities important info source	10.3%	20.8%	14.1%
product imitator only	11.0%	19.6%	15.8%
product innovator	33.4%	63.0%	47.1%
new-to-market product innovator	22.4%	43.4%	31.3%
process imitator only	19.2%	32.1%	26.8%
process innovator	26.4%	46.8%	37.2%
new-to-market process innovator	7.2%	14.7%	10.4%

Table A5: Average composition of innovation expenditure

	All	*SME*	*Large*	*Manu-facturing*	*Services & other*
Acquisition of mach. & comp. hardware/software	45.1%	48.0%	43.0%	43.2%	47.0%
Internal R&D spending	18.6%	17.7%	19.2%	25.1%	12.0%
Marketing expense	13.5%	11.8%	14.9%	10.6%	16.5%
Training expense	9.5%	10.2%	8.9%	5.4%	13.4%
Design expense	6.4%	5.9%	6.8%	8.8%	4.2%
External R&D spending	3.7%	3.5%	3.9%	4.2%	3.2%
Acquisition of external knowledge	3.2%	2.9%	3.4%	2.6%	3.7%
Observations with nonzero spending	4,414	1,876	2,538	2,199	2,215
Share with nonzero spending	61.8%	57.1%	65.8%	71.1%	54.7%

The shares shown are for firms that have some form of innovation spending reported.

Appendix B: Additional estimates

In this appendix we present some additional estimates of our model that use innovation spending in place of R&D spending as an explanatory variable.

Tables B1 and B2 show relatively few differences from Tables 2 and 3 (using R&D spending). That is, using innovation spending instead of R&D as a predictor of the preference for formal and informal IP and innovation makes little difference to the coefficient estimates. The largest differences statistically are the increase in the within group information source coefficients and the decrease in the suppliers information source coefficient. This may reflect the changes in these coefficients in the innovation spending equations, and raises some concern about the interpretation of these coefficients. That is, stronger coefficients in the innovation spending model seem to be reflected in strengthened coefficients of the opposite sign in the IP-innovation probability model. Recall that the latter model includes the value of R&D or innovation spending that is predicted based partly on these coefficients.

Table B1. Multivariate Probit estimates of IP choice and product innovation

7,144 observations on 5,684 firms; Log likelihood = -9,005.1

	Formal IP methods			*Informal IP methods*			*Product Innovator or imitator*		
	Coeff.	*Std. err*		*Coeff.*	*Std. err*		*Coeff.*	*Std. err*	
Log (predicted IS per employee)	1.026	0.065	***	0.945	0.063	***	0.453	0.066	***
Log (n of employees)	0.399	0.020	***	0.329	0.019	***	0.165	0.020	***
Log (firm age in 2011)	0.028	0.053		0.042	0.053		-0.092	0.056	
D (collaborates)	-0.182	0.054	***	-0.093	0.056		0.395	0.055	***
Firm perception of market risk	0.331	0.043	***	0.373	0.044	***	0.175	0.044	***
Firm perception of fin. Constraints	0.092	0.042	*	0.270	0.044	***	0.007	0.044	
Firm - impt. of reg & standards	0.151	0.050	**	0.131	0.052	*	-0.114	0.053	*
Firm - impt. of env, H&S regs	0.030	0.051		0.142	0.054	**	-0.031	0.054	
D (innov to improve range)							0.704	0.051	***
D (innov for new markets)							0.234	0.054	***
D (innov for quality improvement)							0.266	0.058	***
D (within group impt info source)	0.204	0.055	***	0.372	0.054		0.441	0.058	***
D (suppliers important info source)	-0.288	0.048	***	-0.067	0.048		-0.108	0.051	*
D (customers impt info source)	0.054	0.052		0.250	0.051	***	0.191	0.056	***
D (competitors impt info source)	0.048	0.046		0.007	0.046		-0.173	0.049	***
D (universities impt info source)	0.167	0.062	**	0.086	0.070		-0.063	0.065	
D (imitator)	-0.282	0.059	***	-0.275	0.064	***			
Year dummies (2)	65.4 (0.000)***			80.1 (0.000)***			1.5 (0.464)		
Two-digit sector dummies (25)	298.2 (0.000)***			105.4 (0.000)***			52.9 (0.000)***		
Wald test for model (d.f.)				5,269.2 (125)***					
Corr (formal IP, informal IP)	0.553	0.019	***						
Corr (formal IP, innovation)	0.202	0.026	***						
Corr (informal IP, innovation)	0.237	0.026	***						

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

Table B2. Multivariate Probit estimates of IP choice and process innovation

7,144 observations on 5,684 firms; Log likelihood = -8,994.8

	Formal IP methods			Informal IP methods			Process Innovator or imitator		
	Coeff.	*Std. err*		*Coeff.*	*Std. err*		*Coeff.*	*Std. err*	
Log (predicted IS per employee)	1.025	0.065	***	0.936	0.064	***	0.139	0.066	*
Log (n of employees)	0.400	0.020	***	0.327	0.020	***	0.098	0.021	***
Log (firm age in 2011)	0.036	0.054		0.045	0.053		0.002	0.056	
D (collaborates)	-0.172	0.054	**	-0.110	0.057		0.567	0.054	***
Firm perception of market risk	0.336	0.043	***	0.371	0.044	***	0.120	0.044	**
Firm perception of fin. Constraints	0.090	0.042	*	0.267	0.044	***	0.012	0.043	
Firm - impt. of reg & standards	0.153	0.050	**	0.133	0.052	*	-0.183	0.054	***
Firm - impt. of env, H&S regs	0.042	0.051		0.133	0.054	*	0.159	0.056	**
D (innov to increase flexibility)							0.482	0.056	***
D (innov to increase capacity)							0.410	0.053	***
D (innov to reduce unit cost)							0.176	0.054	***
D (within group impt info source)	0.213	0.056	***	0.358	0.054	***	0.516	0.062	***
D (suppliers important info source)	-0.271	0.048	***	-0.070	0.048		0.247	0.052	***
D (customers impt info source)	0.041	0.052		0.237	0.051	***	0.049	0.057	
D (competitors impt info source)	0.041	0.046		0.008	0.046		-0.127	0.049	**
D (universities impt info source)	0.169	0.063	**	0.110	0.071		-0.104	0.063	
D (imitator)	-0.197	0.061	***	0.042	0.065				
Year dummies (2)	65.4 (0.000)***			80.1 (0.000)***			21.1 (0.000)***		
Two-digit sector dummies (25)	298.2 (0.000)***			105.4 (0.000)***			45.2 (0.000)***		
Wald test for model (d.f.)				5,042.8 (125)***					
Corr (formal IP, informal IP)	0.556	0.018	***						
Corr (formal IP, innovation)	0.105	0.032	***						
Corr (informal IP, innovation)	0.118	0.033	***						

Note: The method of estimation is maximum likelihood on a trivariate probit model. Standard Errors are robust to heteroskedasticity, and clustered on enterprise.

Table B3 shows the production function estimates from the innovation spending model, which are essentially identical to those for the R&D spending model. The conclusion is that instrumenting either R&D or innovation spending and innovation itself by firm characteristics produces fitted values that are essentially the same in their relationship to productivity. Experiments using the components of innovation spending separately produced similar results. It appears that in the absence of better and more specific instruments, it may be difficult to see the differential impact of the different types of spending.

Table B3. OLS Estimates of the production function - innovation spending model

Dependent variable	*Log (turnover)*											
Type of innovation	*Product innovation*			*Process innovation*			*New-to-market product innovation*			*New-to-market process innovation*		
	Coeff.	*Std. err*		*Coeff.*	*Std. err*		*Coeff.*	*Std. err*		*Coeff.*	*Std. err*	
Log (n of employees)	0.664	0.011	***	0.664	0.011	***	0.663	0.011	***	0.664	0.011	***
Log (capital)	0.096	0.007	***	0.097	0.007	***	0.096	0.007	***	0.096	0.007	***
Log (materials)	0.276	0.010	***	0.277	0.010	***	0.276	0.010	***	0.277	0.010	***
Scale coefficient#	1.036	0.006	***	1.038	0.006	***	1.035	0.006	***	1.037	0.006	***
Predicted prob of innovation	0.003	0.051		-0.107	0.056		0.048	0.069		-0.282	0.180	
D (formal IP important)*Pred P of innov	-0.009	0.037		-0.013	0.034		0.019	0.032		0.012	0.027	
D (informal IP important)*Pred P of innov	0.028	0.034		0.035	0.032		0.026	0.029		0.030	0.025	
D (formal IP important)	0.126	0.066		0.194	0.076	*	0.088	0.075		0.433	0.186	*
D (informal IP important)	-0.008	0.070		0.020	0.080		-0.022	0.084		0.093	0.216	
Prob innov and formal IP	0.120	0.056	**	0.074	0.068		0.155	0.076	**	0.163	0.216	
Prob innov and informal IP	0.023	0.041		-0.052	0.051		0.052	0.054		-0.159	0.156	
Prob innov and both	0.140	0.031	***	0.129	0.031	***	0.159	0.038	***	0.286	0.105	***
F-test for 4 IP variables	3.7 (0.006)***			6.7 (0.009)***			2.7 (0.027)**			5.9 (0.000)***		
F-test for 2 survey dummies	36.0 (0.000)***			34.2 (0.000)***			35.5 (0.000)***			33.7 (0.000)***		
F-test for 25 industry dummies	22.1 (0.000)***			22.3 (0.000)***			21.7 (0.000)***			22.1 (0.000)***		
F-test for model (df=35)	1361.4 (0.000)***			1357.6 (0.000)***			1357.7 (0.000)***			1357.2 (0.000)***		
R-squared	0.902			0.902			0.902			0.902		
SSR	2,572.7			2,571.6			2,573.4			2,572.2		
Standard error	0.602			0.601			0.602			0.602		

Standard errors robust to heteroskedasticity, clustered on firm.

Shaded coefficients are derived from the estimated coefficients.

7,144 observations on 5,684 firms.

Test is for the scale coefficient equal to unity