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The Influence of Knowledge Types and Location on the Innovative Behaviours of KIBS

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Abstract

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Knowledge intensive business services (KIBS) are known to play a highly significant role in the innovation systems of advanced economies. These firms draw on an especially high concentration of highly skilled workers ? notably graduates ? in their workforce, and not only are they, as a group, highly innovative, but they are also important sources of knowledge and innovation for their client firms, thus spurring wider innovation. The growing recognition of this industry has motivated several studies on professional firms that have proposed to understand the way innovation occurs in knowledge-based industries. Indeed, past research has shown that KIBS are a more widely used source of information for innovation amongst client firms than universities and the public science base.
Yet most past research has tended to treat KIBS as a homogenous grouping. Therefore, this study aims to make a substantial contribution to understanding the competitiveness of different subsectors of knowledge based firms by examining whether, and to what extent, knowledge bases (analytical, synthetic and symbolic) and location (i.e., urban, rural, and different types of location with the urban hierarchy) affects the innovation related behaviours in terms of (for example) knowledge sourcing, team working, engaging with clients and performance amongst these firms. In particular, we examine 900 UK based KIBS firms active in a variety of sub-sectors, including architecture and technical services, specialist design services, the production of software and IT services, business and management consultancies, accountancy and legal services. We do this by drawing on a survey conducted for NESTA in 2009 to which additional data on knowledge types and location has been added. More specifically, the survey focused on the examination of four issues: 1) background information on the firms including size, age, etc.; 2) innovation output and performance measures; 3) information on innovation related behaviours including internal organisation and management, the use of

teams and collaboration; and 4) other information, such as investments in R&D and non-technical knowledge generation. We thus appended location- and knowledge- based information to this dataset from various sources to examine whether and to what extent, different knowledge bases and location impacts on innovation behaviours and performance.

Through a detailed understanding of the specificities of professional firms, this study aims to contribute to our as yet limited understanding of the production of new forms of knowledge. Also, the extent to which the behaviours of knowledge intensive business service firms are sensitive to differences in knowledge types and location is expected to provide a contribution to the literature on the relevance of geographical and cultural factors, and communities of practice, to the role of high level skills in innovation and innovation systems, especially within advanced economies. For example, are firms that focus on symbolic knowledge more sensitive to place than those based on analytical knowledge? Such insights will help advance understanding of R&D management theory and practice.

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What drives Innovation amongst KIBS, and does this differ by Knowledge Base?

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Abstract

Knowledge intensive business services (KIBS) are known to play a highly significant role in the innovation systems of advanced economies. 'Knowledge intensive' by definition, these firms are important sources of knowledge and innovation for their client firms, thus spurring wider innovation. However, most past research has tended to treat KIBS as a homogenous grouping. In this study, we investigate a dataset of 247 KIBS firms active in three sectors: architecture and engineering consulting; specialist design; and software and IT consulting and we examine to what extent different knowledge bases – analytical/ synthetic and symbolic/ synthetic – and location in the urban hierarchy relates to the introduction of innovations amongst these firms. We do this in the context of the United Kingdom by drawing on a survey conducted for NESTA in 2009, to which additional data on knowledge types and location has been added. From a theoretical point of view, this paper enriches the research framework concerning the drivers of innovation performance amongst KIBS/ PSFs. Additionally, our empirical evidence displays interesting innovative specificities on firms with different knowledge bases and concludes that further research should explore the way innovation happens in symbolic knowledge-based firms, but also, the role of design on driving innovation.

Keywords: Knowledge bases, innovation and knowledge intensive business services (KIBS)

1. Introduction

Over the last 25 years, substantial research has emphasised the economic significance of business and professional service firms, first amongst economic geographers and later amongst both innovation and management scholars (Marshall and Wood, 1992, Bryson et al., 1993, Asheim and Gertler, 2005). Most recently, and in the context of the desire to 'rebalance' the UK economy, the UK Government[1] has recognised the strategic significance of 'Knowledge-Intensive Traded Services', which it defines as including professional and business services, the information economy and traded aspects of higher and further education[2]. Knowledge services (excluding financial services) now account for over a fifth of UK Gross Value Added and employment, are amongst the fastest growing sectors of the UK economy (op cit). They are also an important source of overseas earnings, as British firms earn substantially more abroad than the aggregate value of imports to the UK of business services (BIS, 2012op. cit.). Ultimately, BIS argues:

Professional and business services are a source of UK comparative advantage and the sector has in the past made a very significant contribution to UK growth. Going forward, this sector is likely to benefit as other industries restructure and outsource activities and rising incomes increase demand for more sophisticated goods. Innovation surveys suggest that this sector has a high proportion of innovation active firms. They provide a significant input to other sectors with very little output going to end users and therefore offer a channel for transmitting efficiency gains and spillovers to a wider group of industries (BIS, 2012, p. 33).

Aside from their knowledge-intensity, 'Professional Service Firms' (PSFs) are distinguished by Von Nordenflycht (2010) as having two specific features: low capital intensity and a professionalized workforce. The term "professional" here relates not only to their knowledge-base but also their ideology, and the incorporation of norms and ethical codes disseminated by professional associations and education, plus professional self-regulation of appropriate practices which accord with expertize, values and ethic.

The growing recognition of this industry, has motivated several studies on PSFs that have sought to understand the way innovation occurs in knowledge-based service industries (Bessant and Rush, 1995, Miles et al., 1995, Howells, 2006, Wood, 2009). However, while progress has been made, little consideration has yet been given to the specificities of the various professional and quasi-professional services that constitute KIBS or PSFs (Von Nordenflycht, 2010, Malhotra and Morris, 2009, Tether et al., 2012). In this paper, we investigate two different subsectors amongst KIBS/PSFs, and examine to what extent different knowledge bases – analytical/synthetic and symbolic/synthetic, and location in the urban hierarchy relates to the introduction of innovations amongst these firms. We do this in the context of the United Kingdom by drawing on a dataset of 247 KIBS firms active in three sectors: architecture; specialist design; and software and IT consulting.

The paper is structured as follows. In Section 2, we review the literature on different 'types of knowledge'. In Section 3 we outline our data and methods, we then undertake the empirical analysis, in which the determinants of innovation are examine for two sets of firms. After presenting the results, we discuss the paper and conclude the paper, highlighting issues for further research.

2. Theoretical and conceptual background

KIBS and Professional Services Firms are all 'knowledge-intensive' by definition, but there is growing appreciation that not only does knowledge intensity vary in a quantitative dimension, but the different types of knowledge are qualitatively different, with different mechanisms of development and diffusion among actors and industries. For example, while highly codified knowledge is relatively easily transferred over long geographical distances, close geographic and cognitive proximity between the actors is required for the diffusion of tacit knowledge. But even this much used distinction between tacit and codified knowledge may be overly reductive and rational.

In the last decades, many different taxonomies of knowledge have been suggested (Kakabadse et al., 2003), but in this paper, we draw on the distinction made by Asheim and colleagues (Asheim and Coenen, 2005, Asheim et al., 2005) between synthetic, analytical and symbolic knowledge.

2.1 Knowledge Bases – Synthetic, Analytical and Symbolic (SAS Model)

Asheim and colleagues (Asheim and Coenen, 2005, Asheim et al., 2005) identification of three 'types' of knowledge is helpful because it not only extends beyond the widely used but perhaps increasingly stale discussion about tacit and codified knowledge, but it also by identifies 'symbolic knowledge' and alludes thereby to the social construction of (some types of) knowledge which is less rational or functional.

For Asheim and colleagues, an 'analytical knowledge base' is strongly associated with specialised skills (and associated qualifications) related to people's ability for rational abstraction, objective analytical thinking and empirical testing. Due to its cognitive and formally based procedural base, analytical knowledge is developed under (widely) recognised and 'legitimate' models and predefined methods, that are framed by systematic and organised structures and codes of conduct (Asheim et al., 2005). This type of knowledge has close associations with the Mode 1 of knowledge production driven by the application of 'scientific methods' as identified by Gibbons and colleagues (Gibbons et al., 1994). Firms with an analytical knowledge base tend, therefore, to be more reliant on scientific knowledge and internal or external research and development activities as an input for their development of innovative products or processes (Asheim et al., 2005).

A 'synthetic knowledge base', by contrast, is essentially pragmatic and focused on providing a specific solution to a problem. It has similar characteristics to the Mode 2 production of knowledge identified by Gibbons et al (1994). Thus, rather than being based on 'pure', abstract and legitimated methods, synthetic knowledge is less formalised, practical and solution oriented: it is essentially based on 'know-how' (without necessarily being grounded in 'know why'). Tacit knowledge is therefore an especially prominent in synthetic knowledge, and innovation results from practical experience and organisational interactions between different actors (customers and supplier); it if focused on the efficacy of local solutions to current problems (Asheim et al., 2005).

As mentioned, Asheim and colleagues identification of 'analytical' and 'synthetic' knowledge has close similarities to the two 'modes' of knowledge production (in academic contexts) identified by Gibbons and colleagues (1994). It also has connections with earlier literature on how firms innovate – for example, in the Pavitt taxonomy (1984), 'science-based firms' can be considered to be exploiting 'analytical knowledge' whilst 'specialist suppliers' are predominantly utilising 'synthetic knowledge'.

Asheim and colleagues novel contribution, at least to innovation studies, lies in their identification of 'symbolic knowledge' as a third 'knowledge base', or type. Symbolic knowledge transmitted through signs, symbols, images, narratives and sounds, and it is essentially relevant to creative and cultural industries, such as the media, fashion and advertising (Asheim et al., 2005). Symbolic knowledge is essentially about expression and emotion, and is more intuitive and (often) subjective; and value is more obviously socially constructed than is the case with analytical (and synthetic) knowledge. While the concepts of tacit and codified knowledge can be applied to 'symbolic knowledge', they are arguably less meaningful as languages and symbols are at once both explicit and loaded with hard to convey meanings. Engaging in activities rich in, or heavily dependent upon, symbolic knowledge requires the ability to undertake symbol interpretation and manipulation, which strongly depends on the capacity to create or manipulate symbols and languages, but also to persuade of others of their value (Verganti, 2008, Dell'Era and Verganti, 2007, Verganti and Öberg, 2013).

Although each (knowledge intensive) firm could conceivably be associated with one specific 'type' of knowledge, the majority of companies combine different knowledge bases to different degrees, roughly in a continuum from analytical knowledge to symbolic knowledge (Strambach, 2008). In particular, virtually all firms will apply pragmatic, synthetic knowledge to some degree.

Based on this discussion of 'knowledge types', it is reasonable to expect that industries with different knowledge bases will behave differently with regard to innovation. We therefore examine the drivers of innovation performance amongst a sample of 247 UK based KIBS firms in three industry sectors: architecture and engineering consultancy, specialist design, and computer software and IT consulting.

3. Methods and Measures

3.1. Sample and procedure

In this paper we use the dataset compiled by OMB Research, a survey company, on behalf of a NESTA study team led by Stephen Roper (Roper et al., 2009).[3] This dataset was compiled for a study which measured 'sectoral innovation capability' in nine sectors of the UK economy (with all of these defined by Standard Industrial Classification (SIC) codes)[4]. Interestingly, the nine sectors included six knowledge-intensive/ professional-service activities, i.e., accountancy; legal services; architecture (and engineering consultancy); specialist design; business and management consultancy; and software and IT consultancy.

For this paper, we confine our attention to firms identified by the NESTA study as being engaged in architecture (and engineering consultancy); specialist design, and software and IT consultancy. We consider that this selection provides an interesting mix of activities with respect to 'knowledge types'.

The original telephone based survey was undertaken in the Summer of 2009, and gathered information on: 1) background information, e.g., firm size, age, etc.; 2) innovation output and performance measures[5]; 3) innovation related behaviours and investments, including the use of teams and collaboration; and investments in R&D and non-technical knowledge generation.

Following piloting in early June 2009, the survey was undertaken using Computer Aided Telephone Interviewing in the summer of 2009. The target population was all firms in the specified sectors, divided into three size-bands by employment: [Small] 5 to 19 employees; [Medium] 20 to 99 employees; and [Large] 100 or more employees. The main difficulty encountered was securing responses large companies, especially in the specialist design, accountancy and management consultancy sectors. The overall response rate was 15%, which is reasonable for surveys of this type. The analysis in this paper treats the data-set as a simple, un-weighted sample.

3.2 Measures

Because the dataset contains no explicit information on the 'type' of knowledge central to each firm, we began by seeking additional information from secondary sources. In particular, and following the provision of company names and addresses (including postcodes) for all but 40 of the initial set of 591 firms recorded as being active in 'architecture and engineering consultancy', 'specialist design' and 'computer software and IT consultancy', we searched for these firms in the FAME company database. We also searched for their company websites, with websites found for all but 51 of the firms.

This search of FAME, and even more so of the companies' websites revealed interesting information: in particular, we found that many firms were not (primarily) engaged in the activities we expected them to be active in. Especially amongst the firms classified as being engaged in 'architecture (and engineering consultancy)' we found that over half the sample were (or appeared to be) primarily manufacturing firms rather than (professional) services firms such as architecture practices or engineering consultancies, whilst other firms were primarily active as contractors. Indeed, of the 206 firms for which names and addresses were provided, only 90 (44%) were considered to be primarily engaged in professional service activities. This problem also existed, albeit to a lesser extent, for firms engaged in 'computer software and IT consulting' and 'specialist design' amongst which we found (for example) several retailers (and manufacturing firms). Indeed, with 'software and IT consulting firms' many stated that they provide solutions, implying a significant degree of customisation. Overall, we considered that 142 of the 176 (81%) software and IT consulting firms for which names were provided were PSFs, whilst we considered 86% (145/169) of the 'specialist design firms' for which names were available to be PSFs. This said, it was not always easy to determine whether or not a firm should be regarded as a PSF. Overall, 377 of the original sample of 591 firms were identified as PSFs.

3.2.1 Types of Knowledge

Our main purpose in searching FAME and especially company web-sites was to examine the 'type of knowledge' being used and/or developed by the firm. We identified the type of knowledge at the heart of each company viewing their webpages. Company websites are public sources of information that informs about a company's identity (Scott and Lane, 2000, Gioia and Thomas, 1996) and business strategy (e.g. goals, processes, activities, and specific practices), therefore provide relevant insights into the company's knowledge base.

Hence, from around 500 UK Company's websites, we extracted and coded textual content that describes mainly corporate information, organisational activities, work processes and the company's core products and services. Also known as 'template analysis' (King, 1988, Crabtree and Miller, 1999) – we thematically analysed word-based data using a set of codes that aimed to represent the main subjects in the textual content. Following Neuendorf (2002) we utilized an a priori design of the template driven by five pre-defined codes to support the classification of each company in one of the three knowledge bases, as differentiated by Tether and colleagues (2012) (2012) – see Table A1. Specifically, the codes included: (1) forms of innovation and solutions; (2) type of knowledge: codified or tacit; (3) locus of new knowledge production; (4) identification of exemplar industries; and (5) means of sharing and diffusing knowledge. This qualitative assessment of the knowledge base allowed us to group the companies that are similar in their knowledge base independently of their original SIC code classification.

Especially useful in the analysis of different clusters within the organisational context (King, 2004), this technique provides an organised and methodological way of interpreting and coding the textual and content information. Moreover, in order to ensure consistency in the interpretations of the data one researcher (the first author) analysed and coded the data, identifying and highlighting any problematic cases, which were then discussed with the second researcher. The second researcher also examined and coded a random sample of non-highlighted codes to develop inter-coder reliability. This way, we assured an alignment between the thematic analysis and the original framework (Tether et al., 2012) improving reliability. This process meant that companies were grouped together based on the nature of their knowledge that ultimately contributes to their innovative and competitive performance.

To simplify our task, we confine the analysis in this paper to the subset of firms that were 'independent, single-site organisations', thereby excluding 'head-quarters of multi-site organisations' and 'subsidiary or associate companies'. In future research we will examine whether these other classes can be included in the analysis.

Table 3 shows the distribution of firms by sector and 'knowledge type(s)'. Whilst there is clear variation by sector – e.g., specialist design firms are concentrated in the 'symbolic' category, and software and IT consulting firms in the 'synthetic' and 'synthetic-analytical' categories, there is also considerable variation, most notably amongst the 'architecture (and engineering consulting)' sector firms. This shows that the knowledge-base does not have a one-to-one mapping to SIC codes.

Because the sample of firms with an 'analytical knowledge base' is too small for multi-variate statistical analysis, we divide the sample in two – between firms that have a 'symbolic-knowledge base' (including symbolic-synthetic), and those with an analytical (including 'analytical-synthetic' and 'all three types') knowledge base. This provides samples of 137 and 110 firms respectively.

3.2.2 Innovation Performance

We began by examining the determinants of (or at least factors associated with) innovation performance. Innovation performance is here measured by firms claiming that in the last three years they had introduced at least one new or significantly improved product of service. This is the basic measure of innovation laid out in the OECD's Oslo Manual (2005) and widely implemented in the (European) Community Innovation Surveys. Exactly half of the 136 firms considered to have a Symbolic or Symbolic-Synthetic (hereafter 'Symbolic' for brevity) knowledge based claimed to have introduced a product or service innovation, whilst 54% (59) of the 109 firms considered to have a Synthetic, Analytical, of Analytical-Synthetic (hereafter 'Synthetic-Analytical' for brevity) knowledge based had done this.

3.2.3 Modelling Innovation Performance

To investigate the determinants of innovation amongst these firms, we estimated two sets of logistic regressions (see Tables 4 and 5), one set for each sample, and adding variables in a hierarchical fashion. The first model (Model 1) contained a dummy variable for young firms established within the last ten years (26% of Symbolic; 22% of Synthetic-Analytical), a measure of firm size (the natural log of employment), and dummy variables identifying sectors (other than a reference sector). This found that none of these factors were significantly related to the introduction of innovations amongst the 'Symbolic' set of firms, whereas, with the exception of the new firms' identifier, all of these variables were significant amongst the 'Synthetic-Analytical' sample.

Next, we added an identifier for whether or not the firms had engaged in R&D: 16% of the Symbolic firms had done so, compared to twice this proportion (31%) amongst the Synthetic-Analytical Sample. Performing R&D had a powerful influence on the likelihood of innovating amongst the latter sample, but no significant influence amongst the Symbolic firms.

Next, we added engaging in design. Unlike R&D, design is not officially defined, and the firms were asked: "aside from any R&D you've just mentioned, has your firm invested in the design of new or improved products or services / products / services over the last year?": 29% of the Symbolic firms, and 44% of the 'Synthetic-

Analytical' firm stated that they had. Interestingly, both these proportions are considerably higher than the corresponding proportion of firms engaged in R&D. Engaging in Design is found to have a significant association with the introduction of innovations amongst both samples (Model 2b), although the magnitude of the effect is roughly twice as large amongst the 'Synthetic-Analytical' firms as amongst the 'Symbolic' firms.

The firms were also asked whether or not they had invested in improving their reputation and branding over the last year, including spending on advertising, PR and market research. Interestingly, a larger share of the Symbolic firms (58%) than the Synthetic-Analytical firms (44%) claimed to have done so. However, in neither case was investing in these activities found to be significantly associated with increasing the likelihood of introducing product or service innovations (Model 2c). The absence of significant effects here is perhaps reassuring, as it indicates the associations found between R&D and design and innovation are not simply due to these being 'better firms'.

Next, we introduce a set of categorical variables that capture the share of graduates in the workforce. Interestingly, this has no significant relationship with innovation amongst either sample. Put another way, amongst both the Symbolic and the Synthetic-Analytical firms those with a small proportion (i.e., not more than 10%) of graduates in their total workforce were as likely to introduce innovations as those with a high share (i.e., where graduates constitute at least half the workforce). This is perhaps surprising, given the emphasis placed on 'knowledge-intensity'.

Finally, using their postcodes, we added in where the firms were located. A substantial literature has developed on geographical patterns of innovation (Isaksen and Onsager, 2010). In this body of work, the innovation is considered to be the result of communication and collaboration between several and diverse types of actors, including the innovator, its clients, competitors, universities and governmental entities, and often these interactions occur in localised networks (Malmberg and Maskell, 2006). Indeed, there is general agreement that geographic proximity between different actors will tend to enhance knowledge exchange (Gertler and Levitte, 2005), stimulating innovation. Organisations are further stimulated by external challenges, partners, competitors and information exchange that together contribute to create and exploit innovative solutions among companies (Nelson and Winter, 1982, von Hippel, 1988).

Specifically in relation to knowledge intensive business services location in the urban hierarchy may have a complex relationship with innovation. According to Christaller's (1933) 'central place theory', services can be considered to be of different 'orders', from low, through intermediate, to high-order services. The services offered by KIBS and PSFs are generally 'high order' (i.e., relatively infrequently used, and very often bespoke or highly tailored to clients' needs), and therefore tend to locate in larger urban places, and especially metropolitan areas, as this increases accessibility to a wider pool of potential clients. However, KIBS/PSFs are not all equally 'high-order'. For example, general practice law firms, or accountants that mainly audit the accounts of small businesses, are not as 'high-order' as specialist corporate law firms, or accountants that specialize in international taxation. This highlights the importance of different sub-markets among KIBS/PSFs. This said, the relationship between this and the introduction of innovations is not clear – as firms located in large metropolitan areas may more specialised than firms located in smaller places and rural areas. It may therefore be relatively easier for firms located away from the largest cities to innovate.

Also interesting is the relationship with 'knowledge bases', location in the urban hierarchy and innovation. We have argued previously that analytical knowledge is the most geographically "footloose", whilst synthetic knowledge depends especially on client-provider interactions. With the latter, innovation may be higher if the client base is particularly demanding. But the knowledge type most likely to be influenced by location in the urban hierarchy is symbolic knowledge, as large metropolitan cities especially provide a ‘buzz’ and excitement around ideas and symbols, and how these are developed and re-interpreted. This ‘buzz’ also attracts especially dynamic people (and employees), all of which could stimulate innovation especially amongst firms with a symbolic knowledge base located in the largest cities.

We coded the location of the firms within the UK’s urban hierarchy, first identifying firms based in the London Metropolitan area, as defined by the European Spatial Planning Observation Network (ESPON, 2007)[6]. Next, we classified firms being located in metropolitan areas other than London. ESPON identifies 17 metropolitan areas with populations exceeding half a million people.[7] Firms are then further identified as being located in Large Cities (with populations between ¼ and ½ million); Smaller Cities (populations of 50,000 to 250,000). The remaining firms were located in smaller towns and rural areas.

Two thirds of the firms with a Symbolic knowledge base were located in Metropolitan Areas, and half of these in London. However, 14 (10%) were also located in towns and rural areas. Amongst those with a Synthetic-Analytical knowledge base, a slightly lower proportion of firms were located in Metropolitan Areas, and London in particular, whilst almost twice as many were located in towns and rural areas, which broadly reflects the pattern we anticipated of a greater dispersion of Synthetic-Analytical firms than Symbolic firms.

Amongst both sets of firms, however, our modelling finds no statistically significant associations between location in the urban hierarchy and the propensity to innovate. Because metropolitan areas especially can be very large, we separately identified firms located within 2.5 miles, between 2.5miles and 10 miles, and beyond 10 miles of the centre of their respective metropolitan areas, but again this had no significant impact on the propensity to innovate.

3.2.4 Summary of Findings

Our modelling has found that ‘knowledge intensity’ and firm location does not seem to have any direct impact on the propensity to innovate amongst either firms with a Symbolic knowledge base or those with a Synthetic Analytical knowledge base. The first of these findings was not anticipated and is rather surprising. It suggests that firms that invest more heavily in highly educated people (i.e., graduates) are not more likely to introduce innovations than those that rely more heavily on non-graduates.

Our findings with regard to location are perhaps less surprising, as there may be missing information on the extent of specialisation amongst these firms. It may be that there is an inter-play between location and specialisation, such that whilst the propensity to innovate is higher amongst firms located in larger metropolitan areas, the propensity to innovate is also higher amongst firms that are more generalists, and these tend to locate outside of the largest cites. As such, these two factors may off-set one another, such that the propensity to innovate does not vary by location. These are however matters for further research.

Whilst ‘knowledge intensity’ and location did not have any significant impact on the propensity to innovate, we did find some striking differences between the ‘drivers’ of innovation amongst the two sets of firms.

Amongst those with a ‘Synthetic-Analytical’ knowledge base, a binary logistic regression model including just firm size, a dummy variable for newer firms, two sector dummies and whether or not the firm has engaged in R&D and/or design, was found to correctly predict 47 of the 59 firms that claimed to be innovators, and 43 of the 50 that did not (i.e., non-innovators), meaning that overall 83% of the cases were correctly classified, a substantial improvement on the ‘base case’ model with no variables which ‘successfully’ predicted 54% of the cases. The most important predictors were whether or not the firms engaged in R&D and/or design, and a model with only the two dummy variables for engaging these correctly predicted 78% of the cases (i.e., 46 of 59 innovators, and 39 of 50 non-innovators). Overall, this modelling of innovation amongst the 'Analytical-Synthetic firms' is surprisingly successful, and also notable is that these drivers of innovation are essentially those that we would expect to find if we were to analyse innovation amongst manufacturing firms.

By contrast, the modelling of the propensity to innovate amongst the firms with a Symbolic knowledge base was much less successful. A model with the same independent variables as defined above with respect to the Synthetic-Analytical firms correctly identified just 30 of the 67 firms that claimed to have introduced a new of significantly improved product or service (i.e., 45%); interestingly the model was rather more effective at identifying non-innovators, amongst the 68 of which 55 were correctly identified (i.e., 81%). Overall, this provides a 63% overall success rate at successfully identifying innovators and non-innovators. And in fact the only statistically significant predictor of innovation amongst these firms was whether or not they engaged in design. A model with only a dummy variable for this as explanatory variables correctly predicted 29 of the 67 innovators and 57 of the 68 non-innovators, providing the same overall success rate of 63%.

Note that running two separate models, one for firms with a Symbolic knowledge base and another for firms with a Synthetic-Analytical knowledge base increased the number of correctly identified innovators by one (from 76 to 77), and increased the number of correctly identified non-innovators by 9 (from 90 to 98) relative to running a single model.

4. Discussion

This analysis contributes to understanding of KIBS (Research) in several ways. First, our classification of firms by 'knowledge base' does relate to interesting differences in how firm innovate. It is worth emphasising here that reliance on SIC codes to distinguish between firms' activities may be hazardous. This is for two reasons. First, it seems that many firms are not correctly categorised to their main activity in databases that researchers often rely on. Amongst the firms examined here, this was most notable amongst firms supposedly engaged in 'architecture and engineering consulting' amongst which we found numerous manufacturing firms. Of course these firms may be providing technical consultancy services, but our review of their websites showed that this was not their main activity. This problem of mis-allocation was also found amongst the Software and IT consulting firms and the Specialist Design firms, amongst which we found a significant number of retailers, for example. The second reason why the use of SIC codes may be hazardous is that, particularly at higher levels of aggregation, these codes include a range of activities. 'Architecture and engineering consulting', for example, includes both highly conceptual architecture practices and highly analytical engineering consultancies (and many activities in between). Conflating these by using standard industrial classifications obscures some interesting differences. This said, work remains to develop a scale to clearly identify these various knowledge bases.

Another issue for further research is developing a protocol for the identification of KIBS/PSFs. Whilst there have been advances in the conceptual understanding of these firms, the practical identification of what is a KIBS/PSF is sometimes not straightforward, especially outside of 'classic-PSF' activities such as law and accountancy (Von Nordenflycht, 2010).

One question that is frequently asked is 'do services innovate differently' from manufacturing firms? Our analysis indicates that this may not be a question of services versus manufacturing, but rather a difference according to the firm's knowledge base. For the firms in our study with an analytical or synthetic knowledge base, the same knowledge bases as deployed in the manufacturing sectors most heavily studied by scholars of innovation, the drivers of innovation were essentially the familiar ones. But the firms with a symbolic knowledge base, the drivers were different. Unfortunately not enough is known about the drivers of innovation amongst manufacturers of primarily symbolic products. Ultimately it is interesting that our modelling of the propensity to innovate amongst the KIBS firms with a symbolic knowledge bases was reasonably effective at identifying the non-innovators (with 80% correctly identified), but poor at identifying the innovators (with less than half correctly identified). This suggests we need to either or both: improve our knowledge of the 'drivers of innovation' in these activities, and/or improve the measure(s) of innovation used. Although conforming to the internationally agreed approach, asking firms whether they have introduced new or significantly improved products and/or services in the last three years presupposes: 1. That firms are able to identify these with a reasonable degree of accuracy; and 2. That this is a (if not the most) appropriate way to measure innovation outputs. Both of these assumptions may be in doubt.

An interesting finding in our study concerns the role of design. Design is found to be an important 'driver' of innovation amongst both our sets of firms. Quite what is meant by design here is open to question, and should be explored further, but the finding is interesting because design has generally been neglected, certainly relative to R&D. Future research needs to understand, and unpack, designs contribution to innovation, both in KIBS/PFSs, and beyond.

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Tables and Notes

Table 1: Initial Sample, and Sample of PSFs

	Initial Sample	Name not provided	PSFs	Manuf-acturing	Other Activities
Combined Sample	591	40	377	135	39
Architecture	217	11	90	106	10
Software and IT	189	13	142	13	21
Specialist Design	185	16	145	16	8

Table 2: Sample of PSFs by Type of Firm

	PSFs	Independent, single site organisation*	Head-quarters of a multi-site organisation	Subsidiary or associate firm
Combined Sample	377	247	77	53
Architecture	90	40	25	25
Software and IT	142	76	43	23
Specialist Design	145	131	9	5

* This includes 3 foreign owned companies. The remaining 244 are UK owned

Table 3: 'Knowledge Types' by Sector

	All	Symbolic Grouping		Synthetic and Analytical Grouping			
		Symbolic	Synth + Symb.	Synthetic	Synth + Analytic	Analytic	All Three
Whole Sample	247	107	30	60	44	2	4
Architecture	40	1	13	14	9	1	2
Software and IT	76	0	0	41	35	0	0
Spec. Design	131	106	17	5	0	1	2
Groupings		137		110			

N.B., Significant variations by sector – Architecture more likely to be symbolic and synthetic, and less likely to be only symbolic; Software more likely to be analytical and synthetic, or only synthetic; design much more likely to be symbolic, and much less likely to be only synthetic or synthetic and analytical

Table 4. Modelling Introduction of Product / Service Innovations amongst Analytical-Synthetic Firms

	Model 1 Exp(B)	Model 2 Exp(B)	Model 3 Exp(B)	Model 4 Exp(B)	Model 5 Exp(B)	Model 6 Exp(B)
Young Firm (D)	0.585	0.303	0.391	0.353	0.351	-- X --
LnEmp	1.651**	1.742**	1.842**	2.068**	2.054**	1.813**
S_Architecture (D)	0.309**	0.237*	0.194**	0.183**	0.174**	0.259**
S_Design (D)	0.183*	0.320	0.265	0.212	0.211	0.310
R&D (D)	-- X --	13.718***	14.458***	11.858***	12.692***	13.828***
Design (D)	-- X --	8.324***	7.067***	9.212***	9.250**	6.061***
Reputation (D)	-- X --	0.948	0.806	0.750	0.774	-- X --
Graduates 11-20 (D)	-- X --	-- X --	2.852	4.770	4.723	-- X --
Graduates 21-50 (D)	-- X --	-- X --	0.630	0.821	0.900	-- X --
Graduates >50% (D)	-- X --	-- X --	0.805	1.046	1.082	-- X --
Graduates DK (D)	-- X --	-- X --	0.752	1.177	1.281	-- X --
L_Other Metro (D)	-- X --	-- X --	-- X --	0.622	0.555	-- X --
L_Large City (D)	-- X --	-- X --	-- X --	2.413	2.690	-- X --
L_Smaller City (D)	-- X --	-- X --	-- X --	0.441	0.492	-- X --
L_Towns/Rural (D)	-- X --	-- X --	-- X --	2.040	2.323	-- X --
InnerMetrop Area (D)	-- X --	-- X --	-- X --	-- X --	1.484	-- X --
MidMetrop Area (D)	-- X --	-- X --	-- X --	-- X --	1.354	-- X --
N.	109	109	109	109	109	109
% Innovating	54%	54%	54%	54%	54%	54%
Model χ^2	18.8***	59.3***	61.35***	64.5***	64.7***	56.2***
-2 LL	131.6	91.0	89.01	85.8	85.6	94.2
Nagelkerke R^2	0.211	0.561	0.575	0.597	0.598	0.538

*** = Significant at 1%; ** = Significant at 5%; * = Significant at 10%

Reference Sector is Software and IT Services; Reference re Graduates is 0-10% of workforce;

Reference location is London; Reference metropolitan area location is beyond 10 miles from centre

Table 5. Modelling Introduction of Product / Service Innovations amongst Symbolic Firms

	Model 1 Exp(B)	Model 2 Exp(B)	Model 3 Exp(B)	Model 4 Exp(B)	Model 5 Exp(B)	Model 6 Exp(B)
Young Firm (D)	0.902	0.988	0.968	1.103	1.104	-- X --
LnEmp	1.256	1.165	1.127	1.136	1.142	-- X --
S_Architecture (D)	0.366	0.473	0.476	0.370	0.368	-- X --
R&D (D)	-- X --	0.709	0.750	0.786	0.786	-- X --
Design (D)	-- X --	3.675***	3.603***	3.715***	3.759***	3.853***
Reputation (D)	-- X --	1.480	1.496	1.500	1.496	-- X --
Graduates 11-20 (D)	-- X --	-- X --	0.473	0.352	0.349	-- X --
Graduates 21-50 (D)	-- X --	-- X --	1.136	0.981	0.979	-- X --
Graduates >50% (D)	-- X --	-- X --	0.725	0.609	0.612	-- X --
Graduates DK (D)	-- X --	-- X --	n.a.	n.a.	n.a.	-- X --
L_Other Metro (D)	-- X --	-- X --	-- X --	1.019	1.014	-- X --
L_Large City (D)	-- X --	-- X --	-- X --	1.042	1.033	-- X --
L_Smaller City (D)	-- X --	-- X --	-- X --	1.141	1.129	-- X --
L_Towns/Rural (D)	-- X --	-- X --	-- X --	3.307 (11%)	3.292 (13%)	-- X --
InnerMetrop Area (D)	-- X --	-- X --	-- X --	-- X --	0.964	-- X --
MidMetrop Area (D)	-- X --	-- X --	-- X --	-- X --	1.046	-- X --
N.	135	135	135	135	135	135
% Innovating	50%	50%	50%	50%	50%	50%
Model χ^2	3.6	14.8**	16.3*	19.3	19.3	11.8***
-2 LL	183.5	172.4	170.8	167.8	167.8	176.7
Nagelkerke R^2	0.035	0.138	0.152	0.178	0.178	0.111

*** = Significant at 1%; ** = Significant at 5%; * = Significant at 10%

Reference Sector is Design (as no Software and IT Services are included). Otherwise, same as above.

Table A1. Template analysis based on the five pre-defined codes to support the classification of each company in one of the three knowledge bases, as differentiated by Tether and colleagues (2012)

	Analytical	Synthetic	Symbolic
Innovations and solutions	Fundamental innovation by the creation of new knowledge. Solutions found by applying scientific models or equations	'Local' solutions developed by applying or combining existing knowledge. Occasionally these become general purpose 'killer applications'	Solutions based on hard to explain tacit insights. Major innovations often recognized ex post (as value is socially constructed)
Codified or tacit?	Predominantly codified and 'scientific', based on deductive processes and formal models	Predominantly tacit and applied, problem related. Largely practical, and often developed through inductive processes	Predominantly tacit and 'artistic'. Importance of building and challenging conventions: the 'power of persuasion' matters.
Locus of new knowledge production	R&D departments and collaborations, including with the 'science base'	Interactive learning, especially with clients, but also in the community of practice	'Studio' projects, and learning through interaction with the professional/ artistic community, and wider cultural
Exemplar industry	Biotechnology and other 'science-based' industries (Pavitt, 1984)	'Lower-tech.' engineering-based industries and other 'specialist suppliers' (Pavitt, 1984)	Film directors and other 'cultural industries' (Scott, 1999)
Means of sharing and diffusing knowledge	Patents, publications and the internet, but also scientific conferences	Attending to 'field problems' (von Hippel, 1988), mainly through face-to-face interactions	Hard to share or diffuse. Developed in practice over time and 'possessed' by key individuals.
Data analysis – Coding the sample based on their website's information	To identify an analytical base germane to website textual statements we looked for words such as "analytical", "scientific", "models", "equations", "codified", "R&D", "patents", "publications", "engineering" and "high-tech" suggesting the presence of a fundamentally analytical type of knowledge.	We coded the synthetic type of knowledge by identifying words such as "applied", "practical", "problem-based", "interactive learning" and "lower-tech" skills. Companies that make a frequent mention of problem solutions based on "face-to-face interactions", strong aptitude to "operationalization" and frequent use of existing knowledge would therefore manifest a higher orientation towards a synthetic knowledge base.	We coded the textual content of the website information as symbolic type of knowledge through the identification of words such as "creative", "artistic", "web design", "ideas", "beliefs", "symbols" and "cultural artefacts". Companies that are project based and develop their work in studios and creative based contexts would therefore suggest a higher orientation towards a symbolic type of knowledge.

Table A2. Qualitative data analysis: Websites textual content codification rational

Type of Knowledge	Type of knowledge (brief description) and codification rational for each one of the companies' website (e.g. corporate info, organisational activities, work processes and core products and services)
Analytical	**Brief description:** Analytical knowledge requires a greater level of qualification and specialised skills related to people's ability for abstraction, analytical thinking and empirical testing. Due to its cognitive and formally based process, analytical knowledge is developed under recognised models and predefined methods, that are framed by systematic and organised structures and relationships, such as R&D departments or university links (Asheim et al., 2005). **Codification rational:** Since analytical knowledge based companies tend to be more reliant on scientific knowledge and internal or external research studies (Asheim et al., 2005), we tried to identify in the website information, textual content that suggested the use of rational models, frameworks, and information, that are codified in documented reports or official patents (Asheim et al., 2005). More specifically, to identify an analytical base germane to website textual statements we looked for words such as "analytical", "scientific", "models", "equations", "codified", "R&D", "patents", "publications", "engineering" and "high-tech" suggesting the presence of a fundamentally analytical type of knowledge.
Synthetic	**Brief description:** Synthetic knowledge refers to an orientation towards less focused on research and development activities. Nevertheless, when these actions are undertaken, they are frequently product or process reliant, and are developed as a specific solution to a problem. Thus, rather than consisting of pure basic and abstract research, synthetic knowledge is more concrete, practical and solution oriented (Asheim et al., 2005). Due to the relevance of effective know-how and problem resolution by knowledge application, tacit knowledge is more dominant in a synthetic knowledge base organisation. Innovation results from practical experience and organisational interaction between different business actors (customers and suppliers), and it is focused on the efficiency of innovative solutions by knowledge application and/or new combinations of current knowledge (Asheim et al., 2005). **Codification rational:** Therefore, we coded the synthetic type of knowledge by identifying words such as "applied", "practical", "problem-based", "interactive learning" and "lower-tech" skills. Companies that make a frequent mention of problem solutions based on "face-to-face interactions", strong aptitude to "operationalization" and frequent use of existing knowledge would therefore manifest a higher orientation towards a synthetic knowledge base.
Symbolic	**Brief description:** Finally, a 'symbolic knowledge base' is transmitted through signs, symbols, images, narrative and sounds and it is essentially relevant to media, fashion and advertising industries, whose business models involve the constant creation of innovative and creative designs, ideas, products and services (Asheim et al., 2005). In this knowledge base, qualifications need to be related to the ability to undertake symbolic interpretation and manipulation which strongly depend on tacit knowledge and also on socialisation and interaction between professional communities. Innovation is achieved by the modification and recombination of current knowledge in innovative outcomes (Asheim et al., 2005). **Codification rational:** Thus, we coded the textual content of the website information as symbolic type of knowledge through the identification of words such as "creative", "artistic", "web design", "ideas", "beliefs", "symbols" and "cultural artefacts". Companies that are project based and develop their work in studios and creative based contexts would therefore suggest a higher orientation towards a symbolic type of knowledge.

[1] BIS (2012) Industrial Strategy: UK Sector Analysis, BIS Economics Paper No. 18, Department for Business, Innovation and Skills, HM Government, September (http://www.bis.gov.uk/assets/biscore /economics-and-statistics/docs/i/12-1140-industrial-strategy-uk-sector-analysis)

[2] Advanced manufacturing and 'enabling sectors' such as energy and construction are also recognised as key sectors of the UK economy.

[3] http://www.nesta.org.uk/library/documents/measuring-sectoral-innovation.pdf

[4] The other three covered were automotive, construction and energy. We do not consider these here, given our focus is on professional, knowledge-intensive services.

[5] These were designed to be similar to those outlined in the OECD's 'Oslo Manual' and implemented in the various waves of the 'Community Innovation Surveys'.

[6] EPSON (2007) Study on Urban Functions, Final Report. http://www.espon.eu/export/sites/default/Documents/Projects/ESPON2006Projects/StudiesScientificSupportProjects/UrbanFunctions/fr-1.4.3_April2007-final.pdf

7[7] These are Birmingham (the West Midlands); Manchester, Leeds-Bradford; Liverpool-Birkenhead; Tyneside; Sheffield; Portsmouth-Southampton; Nottingham-Derby; Glasgow; Cardiff; Bristol; Belfast; Edinburgh; Brighton-Worthing; Leicester; Middlesbrough; and Bournemouth-Poole