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Do the drivers of innovation in KIBS differ with their knowledge base?

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Abstract

Knowledge intensive business services (KIBS) are known to play a significant role in innovation systems. Past research has however mostly treated KIBS as a homogenous group. In this study, we apply a mix of qualitative and quantitative methods to examine a dataset comprising 362 KIBS firms active in the UK in three ?sectors?: architecture and engineering consulting; specialist design; and software and IT consulting. Partly through the application of content analysis techniques of information drawn from firms? websites, we identify the primary ?knowledge type? central to each firm, be that analytical, synthetic or symbolic knowledge. We also examine how the ?drivers? of innovation vary between firms with different knowledge types. The paper therefore contributes to the literature by developing a methodology for empirically identifying ?knowledge types? by utilising website information and by showing that the factors associated with innovation differ with the primary knowledge type of the firm. This contributes to understanding variety among KIBS. We also find that investments in design are particularly important for some innovation in KIBS, and discuss the need for further research on design as a ?driver? of innovation. [183 words]

Distinguishing knowledge types and the differential drivers of innovation among KIBS

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Abstract

Knowledge intensive business services (KIBS) are known to play a significant role in innovation systems. Past research has however mostly treated KIBS as a homogenous group. In this study, we apply a mix of qualitative and quantitative methods to examine a dataset comprising 362 KIBS firms active in the UK in three ‘sectors’: architecture and engineering consulting; specialist design; and software and IT consulting. Partly through the application of content analysis techniques of information drawn from firms’ websites, we identify the primary ‘knowledge type’ central to each firm, be that analytical, synthetic or symbolic knowledge. We also examine how the ‘drivers’ of innovation vary between firms with different knowledge types. The paper therefore contributes to the literature by developing a methodology for empirically identifying ‘knowledge types’ by utilising website information and by showing that the factors associated with innovation differ with the primary knowledge type of the firm. This contributes to understanding variety among KIBS. We also find that investments in design are particularly important for some innovation in KIBS, and discuss the need for further research on design as a ‘driver’ of innovation. [183 words]

Keywords: Knowledge bases; innovation; knowledge intensive business services (KIBS); design

1. Introduction

Over the last 20 years or so, the economic significance of business and professional service, and especially ‘knowledge intensive business services’ (hereafter KIBS), has been increasingly appreciated, first by economic geographers (e.g., Gillespie and Green, 1987; Daniels and Moulaert, 1991; Wood, 2002; Wood, 2009; Doloreux et al., 2010), then by innovation and management scholars (Bessant and Rush, 1995, Miles et al., 1995, Howells, 2006; Tether and Tajar, 2008), and latterly by policymakers (e.g., European Commission, 2009; United Nations, 2011; BIS, 2012; OECD, 2012; Schricke et al., 2012).¹ These studies have advanced understanding of how innovation occurs in KIBS and, perhaps more importantly, how KIBS contribute to systems of innovation by, for example, helping their clients to innovate. However, most studies either consider KIBS as a whole, or divide them by ‘industry’, as defined by standard industrial classifications, or into broad categorisations such as P-KIBS (i.e., professional KIBS) and T-KIBS (technical KIBS). Few studies have considered the specificities of the various business and professional services that KIBS provide from a conceptual perspective (Von Nordenflycht, 2010, Malhotra and Morris, 2009, Tether et al., 2012, Consoli and Elche-Hortelano, 2010).

In this paper, we develop the idea that KIBS vary substantially in their “knowledge bases”, or the ‘type’ of knowledge at the core of their activities (Strambach, 2008; Consoli and Elche-Hortelano, 2010; Tether et al., 2012; Consoli and Elche, 2013). We also develop an empirical methodology for identifying these knowledge types based on extracting information from companies websites, and apply this to a dataset of 362 UK based KIBS active in three ‘sectors’: architecture and engineering consulting; specialist design; and software and IT consulting. We then relate these different “knowledge types” to different behaviours in terms of activities the firms invest in, and to the ways in which the firms innovate, finding significant differences.

The paper is structured as follows. In Section 2, we ground the study in the literature on ‘types of knowledge’. Section 3 then outlines the methods and measures used to identify ‘knowledge types’, while Section 4 relates these knowledge types to empirical differences in firm characteristics and behaviours. Section 5 discusses the findings, while Section 6 concludes the paper. This includes an outline of issues for further research.

¹ For example, a recent UK Government report states that: 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. [These firms also] provide a significant input to other sectors ... and therefore offer a channel for transmitting efficiency gains and spillovers to a wider group of industries (BIS, 2012, p. 33).

2. Conceptual background

Innovation studies has long appreciated that there are different ‘types’ or ‘forms’ of knowledge, and that these are associated with different modes of, or approaches to, innovation. This observation is for example fundamental to Pavitt’s taxonomy (Pavitt, 1984) and to the literature that followed (e.g., Jansen et al., 2007; Castellacci, 2008). Until recently, however, the literature on KIBS has, with a few exceptions (e.g., Strambach, 2008; Consoli and Elche-Hortelano, 2010; Tether et al., 2012; Consoli and Elche, 2013), either treated these firms/sectors as a homogeneous grouping, divided them according to ‘standard industrial classifications’, or applied somewhat awkward distinctions, such as between P-KIBS: “professional service firms” (e.g., legal and accountancy services), and T-KIBS: “technical service firms” (e.g. such as R&D services and computer services) (Miles et al., 1995). This categorisation is awkward because it is not always clear where to classify KIBS. For example, in the UK, architecture is a ‘profession’ in that an architect needs to qualify and be registered to practice, but are (all) architects technical service providers? Technical services are normally provided by structural and building engineers who work alongside architects. Design consultancy, meanwhile, is not a ‘profession’ as neither qualifications nor registration is required to practice as a design consultant, but while some of these are highly technical (having an engineering base), others certainly are not. Perhaps both architects and designers could be accommodated in a new classification of C-, or ‘creative’ KIBS, but this misses the point. These taxonomic difficulties imply the need for a stronger conceptual grounding of the characteristics of, and variety among, KIBS and ‘professional service firms’ (Malhotra and Morris, 2009; von Nordenflycht, 2010).

We conjecture that an interesting dimension of variety among KIBS is the (primary) knowledge base, or type, central to their activities. While these businesses are unified in their quantitative characteristics of being knowledge- (rather than capital)-intensive, they may be qualitatively differentiated on the basis of utilising different ‘types’ of knowledge. Furthermore, we conjecture that this variation will be associated with difference in both their propensity to innovate (as conventionally measured), and with differences in their approach to innovation. Various 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 ‘analytical’, ‘synthetic’ and ‘symbolic’ knowledge (Strambach, 2008; Strambach and Dieterich, 2011; Tether et al., 2012). With its roots in the literature of regional innovation systems, this typology has been used to classify the type(s) of knowledge that predominate in different industrial sectors. It provides an

alternative to other categorisations, such as that between tacit and codified knowledge (Polany, 1967); or that between ‘know-what’, ‘know-why’, ‘know-how’ and ‘know-who’ discussed by Lundvall and Johnson (1994). We favour this conceptualisation because we perceive it to be particularly appropriate to KIBS, or at least the KIBS sectors studied here, and because it highlights a significant form or type of knowledge that we perceive has received inadequate attention in innovation studies: i.e., 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 not only because it extends beyond the widely used but perhaps increasingly stale discussion of tacit and codified knowledge, but also because it specifically identifies ‘symbolic knowledge’ and thereby alludes to the social construction of (some types of) ‘expressive knowledge’ which is less rational or functional (Cappetta et al., 2006; Jahnke, 2013; Verganti and Öberg, 2013).

‘Analytical knowledge’ is Asheim and colleagues’ first knowledge ‘type’. This is strongly associated with specialised skills (and associated qualifications) related to rational abstraction, objective reasoning and empirical testing. Due to its cognitive and formally based procedural foundations, analytical knowledge is developed using (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 Gibbons and colleagues’ (Gibbons et al., 1994) Mode 1 of knowledge production, which is driven by the application of ‘scientific methods’. Firms with an analytical knowledge base tend, therefore, to be more reliant on scientific knowledge and techniques, and typically use internal (and external) R&D activities as key inputs to the development of their innovative products or processes (Asheim et al., 2005, Gertler and Levitte, 2005).

A ‘synthetic knowledge base’, by contrast, is essentially pragmatic and primarily focused on local problem solving; that is, providing a specific solution to a problem. It has characteristics similar to the Mode 2 production of knowledge identified by Gibbons et al (1994) and therefore, rather than being based on ‘pure’, abstract and (legitimate) ‘scientific methods’, synthetic knowledge is less formalised, but more practical and solution oriented: it is essentially based on ‘know-how’, without necessarily being grounded in theoretically grounded ‘know why’ knowledge (Lundvall and Johnson, 1994). Tacit knowledge is especially prominent in synthetic knowledge. Being focused on the efficacy of local solutions

to current problems (Asheim et al., 2005, Gertler and Levitte, 2005) innovation arises from the application of practical experience and organisational interactions between different actors, such as a consultant and the client. Typically incremental, innovations reliant on synthetic knowledge are usually incorporated as improvements to, or customisations of, existing products and processes.

While the ‘analytical’ and ‘synthetic’ knowledge types identified by Asheim and colleagues’ have close similarities to those previously identified in the literature (e.g., Pavitt, 1984; Gibbons et al., 1994), their most novel contribution lies in their identification of ‘symbolic knowledge’, as a third knowledge ‘base’, or type. Symbolic knowledge is transmitted through signs, symbols, images, narratives and sounds, and it is especially relevant to creative and cultural, or ‘expressive’, industries, such as the media, fashion and advertising (Asheim et al., 2005). This is because symbolic knowledge concerns expression and emotion, and is more intuitive and (arguably) subjective. Its value is more obviously socially constructed than is the case with analytical or 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 interpret, create or manipulate symbols and languages, but also to persuade of others of their value (Verganti, 2008, Martin and Moodysson, 2013).

Although a firm could conceivably be associated with a single ‘type’ of knowledge, most are likely to combine different knowledge bases to varying degrees, roughly in a continuum from (pure) analytical knowledge to (pure) symbolic knowledge (Strambach, 2008). In particular, virtually all firms are likely to apply pragmatic, synthetic knowledge to some degree (Kogut and Zander, 1996).

Conceptual distinctions can be interesting, but to be useful two things are required. First, a reasonably robust method needs to be developed that can apply the distinctions to empirical data. In other words, and in this context, how can we tell if Firm X has an analytical, synthetic or symbolic knowledge base, or some combination of these? Second, the applied distinction needs to be useful in explaining, or helping to explain, something of significance. In other words, why does it matter that Firm X has a different knowledge base from firm Y? This paper contributes to the literature by first developing a methodology by which the (primary) knowledge bases of KIBS (and possibly other) firms can be identified, and then demonstrating that this matters, because it relates to differences in behaviours with regard to investments, and the factors associated with innovation tend to differ amongst KIBS

with different knowledge bases. We do this for a sample of 362 UK based KIBS active in three ‘sectors’: architecture and engineering consultancy, specialist design, and computer services

3. Methods and Measures

3.1. Data-Source and Sample

Our empirical starting point is a dataset, compiled by OMB Research (a survey company) on behalf of a NESTA study team led by Stephen Roper (Roper et al., 2009).² The dataset we examine was created for a NESTA sponsored study that measured ‘sectoral innovation capability’ in nine sectors of the UK economy, where the ‘sectors’ were defined by Standard Industrial Classification (SIC) codes. For this paper we confine our attention to three KIBS sectors: ‘architecture (and engineering consultancy)’; ‘specialist design’, and ‘software and IT consultancy’. We do so for two reasons. First, we are primarily interested in how KIBS innovate, and second we consider that the typology of knowledge types identified by Asheim and colleagues’ to be particularly applicable to these sectors. It is less obviously applicable to other KIBS such as legal and accountancy services; developing an understanding of the ‘knowledge bases’ of these KIBS is a matter for further research.

The original telephone based survey was undertaken in the summer of 2009, and gathered information on: 1) background characteristics, e.g., firm size, age, etc.; 2) innovation related behaviours and investments, including investments in R&D, design and information technologies and branding and reputation; 3) innovation output and performance measures, which were based on those outlined in the OECD’s Oslo Manual (2005) and implemented in the various European Community Innovation Surveys. One feature of this dataset which makes it more difficult to use is that the questionnaire was customised for each ‘sector’, such that a standard set of questions was not asked to all firms.

Following piloting in early June 2009, the survey was undertaken using Computer Aided Telephone Interviewing (CATI) in the late summer of 2009. The target population was all firms in the specified sectors, divided into three size-bands categories by employment: [Small] 5 to 19; [Medium] 20 to 99; and [Large] 100 or more employees. Furthermore, only ‘established firms’ that had been in business for at least 3 years were included. A random

² NESTA is the UK’s National Endowment for Science Technology and the Arts. It is an innovation charity whose mission is to help people and organisations bring ideas to life. As part of its activities, NESTA both undertakes and commissions research.

sample of firms was drawn within each sector and size-band from data provided by a commercial database provider. Telephone interviews were then conducted with the managing director, a member of the senior management team or the individual with lead responsibility for new product or service development within each firm. If a firm declined to participate a new firm was drawn from the random sample until the quota for each sector had been reached. The main difficulty encountered was securing responses from large companies, especially those in the specialist design sector, mainly because there are few large firms in this sector. 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 Identifying 'Knowledge Types'

Because the dataset contains no explicit information on the 'type' of knowledge central to each firm, we had to gather additional information from secondary sources. In particular, and following the provision of the company names and addresses (including postcodes) for all but 40 of the initial set of 591 firms recorded as being active in our three sectors of interest,³ we searched for these firms in the Financial Analysis Made Easy (FAME) database of company accounts, which provides among other things links to company websites. Websites were found for all but 46 of the firms.

The search of FAME and companies' websites revealed interesting information. In particular, we found that many firms were not (primarily) engaged in the activities that we had expected them to be active in, in accordance with their SIC classification. Especially among 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. Some firms were primarily active as contractors. Indeed, of the 206 'architecture (and engineering consultancy)' firms for which names and addresses were provided, and websites found, less than half (88: 43%) were considered by us to be primarily engaged in professional service, or KIBS activities. This problem also existed, albeit to a lesser extent, for firms engaged in 'computer software and IT consulting' and 'specialist design', among which we found (for example) several retailers, and a few manufacturing firms. Overall, we considered that 143 of the 176 (81%) software and IT consulting firms and 131 of the 169 (77%) of the 'specialist design firms' for which names were provided and websites found to be KIBS. This said, it should be acknowledged that it was not always easy to determine from website

³ The 40 firms for which names and addresses were not provided were those that refused permission for these details to be shared with the academic study team.

information whether or not a firm should be regarded as a KIBS firm. It is also possible that some of the firms were, at the time of the original survey, KIBS providers but have since changed, becoming for example manufacturing businesses in accordance with Bullock's 'soft to hard' model (Bullock, 1983). However, we think it is unlikely that the vast majority of these 'incorrectly classified' firms underwent such transformations. Overall, we considered 362 of the original sample of 551 firms to be KIBS firms (see Table 1).

Insert Table 1 about here

After reducing the sample to 362 firms we went back to the websites to analyse the 'type of knowledge' central to each firm. Websites can be considered public sources of information that provide information pertaining to a company's activities, strategies and identity (Scott and Lane, 2000, Gioia and Thomas, 1996), all of which are related to the firm's knowledge base. Specifically, we subjected the websites to content analysis, which is 'a technique for making inferences by objectively and systematically identifying special characteristics of messages' (Isaksen and Onsager, 2010, p.14; King, 2004). Through the analysis of patterns in written documents, website content analysis has previously been used to determine the *raison d'être* of a company (Stemler, 2001).

Our content analysis followed Neuendorf (2007) in that we utilized an a priori approach driven by the use of pre-defined codes with a view to classifying each company by their primary, or most prominent, knowledge type. In an a priori approach to coding, the categories are theoretically-based and defined before the analysis (Stemler, 2001). The codes were initially developed from the differentiation between knowledge types as derived by Asheim and colleagues and applied to architecture and engineering consultancy by Tether et al. (2012): see Appendix Table A1 for the codes used. Specifically, the codes included: (1) forms of innovation and solutions; (2) type of knowledge: codified or tacit; (3) the locus of new knowledge production; (4) identification of exemplar industries; and (5) means of sharing and diffusing knowledge. For each firm's website, we extracted and coded textual content related to corporate or company information, organisational activities, work processes and the firm's core products and/or services. To do this we focused primarily on the 'Home', 'About Us', 'Our Business', 'Services', 'What We Do', 'Solutions', 'Experience', 'Portfolio', 'People' and 'Philosophy' webpages, or sections thereof.

Using both human and computer-based methods we then searched for words and content considered to be related to the differentiated features of the three 'knowledge types'

central to this study. Specifically, because firms with an analytical knowledge base tend to rely on scientific knowledge and research, we searched for content that suggested the use of rational models and frameworks, and the codification of information into documented reports or patents (Asheim et al., 2005). To identify synthetic knowledge, we searched for information that suggested a focus on effective know-how and (ad hoc) problem solving, looking for an emphasis on an applied, practical and problem-solving orientation – such as the provision of ‘solutions’, and for companies that made a frequent mention of co-operation and related behaviours, such as face-to-face interactions. With regard to symbolic knowledge, we looked for content suggesting a creative and artistic orientation (e.g., that work is undertaken in a ‘studio’ rather than in an office or laboratory) and for an emphasis on the production of symbolic and cultural artefacts. Appendix Table A2 provides further details on the rationale behind the content analysis. Especially useful in the analysis of different clusters within an organisational context, this approach to content analysis provides an organised and methodical way of interpreting and coding the textual and other content information.

We undertook the content analysis in four steps:

Step 1 involved a manual analysis of each firm’s webpages, and subsequent classification of the firm’s as having an orientation to ‘analytical’, ‘synthetic’ or ‘symbolic’ knowledge (or some combination of these). In order to ensure consistency in the interpretations of the data, two researchers (both authors) participated in the analysis and independently coded webpages. Specifically, in an initial discussion we agreed on the coding framework and independently analysed and coded the websites of a sample of 30 randomly drawn firms. This exercise achieved a high level of agreement, with agreement on 24 of the cases and disagreement on 6 (i.e., 80% inter-rater reliability). The cases where disagreement occurred were then discussed, after which another set of 30 firms were randomly drawn from the dataset and these were again classified independently. This time inter-rater reliability was 87% (agreement on 26; disagreement on 4). All disagreement concerned the extent of ‘synthetic knowledge’, rather than disagreeing whether the firm had an analytical or symbolic knowledge base. Subsequently, one researcher - the first author - manually classified the rest of the dataset, discussing any ‘problem cases’ with the second researcher.

Step 2 involved an automated coding of the data. Aware that: 1. Most of the dataset had only been coded by a single researcher; and 2. That human coding is prone to error, we undertook a computer-based analysis of the data. This involved using the NCapture tool in the NVIVO 10 qualitative software package, to capture the full textual information from the websites of the 362 firms for which websites were found. NVIVO was used to identify the

800 most frequently occurring words (strictly words with same four letter stem – e.g., inno* - includes innovate, innovation, innovations, innovator, etc.). Both researchers then independently evaluated all these words, selecting those they felt most closely associated with each of the three ‘types of knowledge’. After some discussion, this exercise resulted in an agreed list of 15 words that we considered associated with ‘symbolic’ knowledge (i.e., insight, idea, inspiration, art, studio, emotion, cultural, illustrator, feel, music, brand, identity, love, designer and creativity) and 16 which we associated with ‘analytical’ knowledge (i.e., data, tools, optimisation, models, analytics, computing, analysis, measurement, simulation, laboratory, evaluation, research, science, accurate, report and tests). Frustratingly, the same exercise was unsuccessful in identifying words associated with ‘synthetic’ knowledge, as words – such as ‘experience’ and ‘solutions’ - that might be associated with synthetic knowledge did not appear, either in sufficient number or in sufficient frequency to identify a set of words that could be associated with ‘synthetic knowledge’. Possibly, this relates to the more tacit and less explicit nature of synthetic knowledge, such that it is more difficult to define this knowledge type through associated terms. We then ran a 'word search' query in NVIVO 10 to count the occurrences of these 31 ‘analytical’ and ‘symbolic’ words in each firm’s website. This provided a dataset of word occurrences by firm.

Step 3 was a validation exercise. Since we are inferring that frequent appearance of typical words indicates an orientation to a ‘type of knowledge’, we assume that ‘symbolic words’ will occur particularly frequently in firms with a symbolic knowledge base, while ‘analytical words’ will occur particularly frequently in firms with an analytical knowledge base. A challenge is that the word content of websites varies enormously, both in the number of words used and in the frequency of words. We also found that initially both ‘symbolic’ and ‘analytical’ words tend to co-occur on firms’ websites, but with differing frequencies. To overcome this, we excluded from the analysis words that occurred with low frequency on any website. Initially, we instituted the rule that words occurring three or fewer times on a company’s website were omitted. This led to the exclusion of 84 firms (23% of the firms) on whose websites none of the 31 words occurred at least four times; but with this cut off still left both “analytical” and “symbolic” words co-occurring on individual firm’s websites. We raised the threshold, first excluding words occurring fewer than four times (which left 95 firms with no words), and then to requiring words to occur at least six times, which left 112 firms (31% of the sample) with no words to include in the analysis. This ‘six or more’ rule was effective in separating the occurrence of ‘analytical’ and ‘symbolic’ words on most firms’ websites. Interestingly most of the 112 firms excluded by this rule had been manually

coded as having a ‘synthetic knowledge base’. This indicates that while we had been unsuccessful in identifying words that could be strongly associated with a ‘synthetic knowledge base’, at least these firms (as manually classified) rarely use ‘analytical’ or ‘symbolic’ words with a high frequency.

To test the separation, we then subjected the remaining 250 firms to cluster analysis, using the UCINET 6 software package (Borgatti et al., 2002). This identifies clusters based on the co-occurrence of words on firms’ webpages. Specifically, we used a social network analysis technique called the dual-projection approach (Everett and Borgatti, 2013) which permits a faithful reconstruction of the dataset without any loss of information. UCINET can cluster the words into two, three and four ‘factions’ at the discretion of the researcher. This found that (1) when asked to cluster the information into two factions, the programme ‘correctly’ separated the symbolic words from the analytical words, and (2) regardless the number of factions selected (two, three or four), the symbolic words very largely remained in one faction, while the ‘analytical’ words tended to splinter into multiple factions. Table 2 reports the findings of this exercise. We decided to keep the aggregation into two factions, considering this achieved a very high fit (0.972) which reflects the almost perfect partition of the words into two factions of ‘analytical’ and ‘symbolic’ words. With the division of the words into two groups we were also able to automate the identification of firms associated with each group, thereby generating a software based classification of the firms by knowledge type.

Insert Table 2 about here

Step 4 involved comparing our initial manual classification of the firms’ primary knowledge base with the computer-based classification outlined above. Considering only the cases where firms were manually classified as either ‘analytical’ or ‘symbolic’, we found an 85% level of agreement with the software-based classification. We then reviewed all the ‘disagreements’ between the computer’s classification and our initial manual classifications, and this led to some changes. Overall, we consider that manual coding is more reliable but that the computer-based coding provides a valuable ‘second opinion’. Table 3 provides our final classification of the firms by their primary ‘knowledge type’, and Table 4 cross-tabulates this classification with the (SIC) sectors in which the firms were active (according to the initial survey). This shows that while there is clear variation by sector – e.g., specialist design firms are concentrated in the ‘symbolic’ category, and software and IT consulting

firms are predominantly ‘synthetic’ and ‘analytical’ , there is also considerable variation, most notably among the ‘architecture and engineering consulting’ firms. In other words, there is not a one-to-one mapping between knowledge types and SIC codes.

Insert Tables 3 and 4 about here

4. Relating Knowledge Types to Differences in Firm Characteristics and Behaviours

Having arrived at this classification, the next question is whether or not it matters, in, for example, relating to differences in the characteristics of firms or the ways in which they behave. The descriptive statistics shown in Table 5 reveal some other interesting differences between these sets of firms, including:

Insert Table 5 about here

- That firms with a ‘symbolic knowledge base’ tend to be small; three quarters of them having fewer than 20 employees. By contrast, over a third of the ‘analytical firms’ are large, with over 100 employees. This difference is likely to reflect fundamental differences in the ability to scale these different types of business. ‘Symbolic knowledge’ is often highly personal and associated with an individual or small group, which makes it difficult to operate at scale without diluting the identity of the business. Analytical knowledge, by contrast is impersonal, which makes it much easier to scale up the business. Synthetic firms are in-between.
- In all three categories the share of graduates tends to be high, with graduates comprising over half the workforce in three-quarters of the ‘analytical firms’, 70% of the ‘symbolic firms’ and over half of the ‘synthetic firms’. Meanwhile, in only 13% of the miscoded ‘manufacturing firms’ do graduates comprise more than half the workforce. It is notable, however, that graduates comprise a minority share of the workforce in a minority of firms coded as KIBS, and that this share tends to be greater among the practically oriented ‘synthetic firms’.
- That the firms in each category differed greatly in their propensity to engage in different activities. For instance, 42% of the ‘analytical firms’ reported investing in Research and Development, a perhaps surprisingly low share, this was 50% higher than the share among ‘synthetic firms’ and three times the share among ‘symbolic firms’, of which

14% reported engaging in R&D. Meanwhile, all three firm types were more likely to invest in design than R&D,⁴ with the propensity to invest in branding and reputation higher still; this being most widespread among the symbolic firms. Investments in IT were also most widespread among the symbolic firms. We will analyse these differences further shortly, using regression techniques.

- The propensity to innovate was highest among the ‘analytical firms’, of which three quarters claimed to have introduced a new or significantly changed product or service in the last three years, and over two thirds of which claimed to have introduced a new or improved process and/or to have changed their organisational structure in the last three years. Meanwhile the propensity to innovate was lowest among the ‘symbolic firms’, about half of claimed to have introduced each of product/service innovations and process/organisational innovations. We will also examine these differences further in the section below.

4.1 Relating Knowledge Types to Investment Behaviours

Table 5 shows that firms with different ‘knowledge-types’ appear to differ in their propensity to invest in different activities and assets such as R&D, design, branding and IT. Here we test more formally whether our categorisation can add to understanding.

In relation to R&D and design, questions about investing in these activities were asked together, so we estimate a multinomial logistic regression with four possible outcomes: the firm invested in neither of these (188 cases), the firm invested R&D but not design (36 cases), the firm invested in design but not R&D (78 cases) and the firm invested in both R&D and design (60 cases). We use ‘neither’ as the reference case, and include size (ln employment), sector (dummy variables for two of the three sectors) and age (a dummy variable for firms founded in the last 10 years) in the first model. After this, we also include two dummy variables in a second model: one for firms identified as having an ‘analytical knowledge base’; the other for firms identified as having a ‘symbolic knowledge’ base. Firms with a ‘synthetic knowledge base’ serve as the reference category. Insignificant variables are deleted, leaving the final model. The findings are shown in Table 6.

Insert Table 6 about here

⁴ 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?”

This shows that, while these characteristics are not very powerful determinants of firms' behaviour, we do find that after controlling for size, age and sector, firms with a 'symbolic knowledge base' are significantly less likely to simultaneously engage in R&D and design. Meanwhile, firms with an analytical knowledge base are significantly more likely to engage in both R&D and design, while the coefficients on engaging in both only R&D and only design are both positive but not significant. Also notable is that larger firms are more likely to engage in R&D (and design), but not design on its own. Meanwhile architecture and engineering consultancy firms were significantly less likely to engage in these activities.

We undertook a similar exercise with regard to investing in branding (and reputation), and information technologies (Table 7). Because unlike R&D and design these were asked about in separate sections of the survey, we examine each independently, using binary logistic regressions, but following the same procedure of estimating the propensity to invest with firm size, sector and age as independent variables, before adding the knowledge type variables and deleting insignificant variables.

Insert Table 7 about here

With regard to investing in branding (and reputation), although the overall model is rather weak, this is strongly associated with firm size and with the 'specialist design' sector, prior to the introduction of the knowledge types variables. After their introduction, 'analytical firms' are not found to differ significantly, but there is evidence that symbolic firms are more likely to invest in branding (and reputation), although this is not highly significant unless the dummy variable for 'specialist design' sector firms is excluded. Ultimately, a model with the 'symbolic knowledge base' dummy included and the 'specialist design sector' firms excluded is very slightly stronger than a model with the knowledge types variable excluded and sector variable included.

With regard to the model for investing in information technologies (in the last three years), the overall model prior to the introduction of the 'knowledge types variables' is not significant: there is no effect of size, or of age, but architecture and engineering consultancy firms were more likely to have made these investments. After their introduction, the dummy identifying 'symbolic knowledge based firms' is found to be insignificant and deleted, while that for the 'analytical knowledge based firms' is found, perhaps surprisingly, to be strongly negative and significant. This shows that adding the 'knowledge types' variables adds explanatory power to the regression.

4.2 Relating Knowledge Types to Innovation: Are there different *'drivers' of innovation?*

Next, we investigate whether firms with different 'knowledge bases' (according to our classification) behave differently with regard to their 'drivers of innovation'. Innovation performance is here measured as the firms claiming that in the last three years they had introduced one or more new or significantly improved products/services and (secondly) as the firms claiming to have introduced a new or significantly changed process and/or a significant organisational innovation. We combine process and organisational innovations because these are often difficult to disentangle in service businesses (Hipp 2000; Preissl, 2000). With this modification of combining process and organisational innovations, these are the basic measures of innovation that are laid out in the OECD's Oslo Manual (2005) and which are widely implemented in the (European) Community Innovation Surveys.

To investigate the 'drivers' of (or 'factors associated with') innovation amongst these firms, we estimated separate logistic regressions for each set of firms, categorised to a knowledge type and for each dependent variable: i.e., 1. firms that had introduced a product/service innovation in the last three years (coded 1, else 0), and 2. firms that had introduced processes/organisational innovations in the last three years (coded 1, else 0).

We included the following independent variables in the models: (1) Firm size ($\ln(\text{employment})$); (2) A dummy variable for young firms established in the last ten years; (3) Dummy variables for the original sectors classification: S_ArchEng, S_Design and S_ITServ. Except when there are very few cases – i.e., specialist design among 'analytical firms' and software and IT among 'symbolic firms', two of these were initially included in each model, with the most frequently represented being used as the reference sector; (4) A set of categorical dummy variables for the share of graduates in the firm's workforce, categorised as follows: 0 to 5% of the workforce, 6 to 20%, 21 to 50%. The reference case was over 50%. (5) An estimate for the intensity of the firm's investment in R&D: i.e., $\ln(\text{R\&D}/\text{Employment})$. This was set to zero if the firm did not invest in R&D; (6) An estimate for the intensity of the firm's investment in design (which was specifically separate from any investment in R&D), i.e., $\ln(\text{Design}/\text{Employment})$. This was set to zero if the firm did not invest in design; (7) An estimate for the intensity of the firm's investment in branding and reputation i.e., $\ln(\text{Brand}/\text{Employment})$. This is was set to zero if the firm did not specifically invest in branding or its reputation; (8) An estimate for the intensity of the firm's investment in information technologies, i.e., $\ln(\text{IT}/\text{Employment})$. This was set to zero if the firm did not invest in IT in the last three years.

In each case, we began with a fully specified model, and then removed the insignificant variables until the model contained only significant variables, or where the further removal of variables would disrupt the modelling.

4.2.1 Relating Knowledge Types to Product/Service Innovation: Findings

With regard to the introduction of product or service innovations (Table 8), we find the following.⁵

Insert Table 8 about here

- Among firms with an analytical knowledge base (according to our classification), the introduction of product/service innovations was associated with investments in R&D and in IT, but not with investments in design or in branding and reputation. There is no effect of firm size, but young firms were less likely to have introduced a product/service innovation. Firms in the architecture/engineering consultancy sector were less likely to have introduced a product/service innovation than those in software / IT consultancy (i.e., the reference sector). The share of graduates in the workforce had no significant effect on the propensity to innovate.
- Among firms with a symbolic knowledge base (according to our classification), the introduction of product/service innovations was associated with investments in design and in IT, but not with investments in either R&D or branding and reputation. There is no effect of firm size, nor any significant sector effect, and nor were young firms significantly more or less likely to have introduced a product/service innovation. As with the analytical firms, the share of graduates in the workforce had no significant effect on the propensity to innovate.
- Among firms with a synthetic knowledge base (according to our classification), the introduction of product/service innovations was associated with investments in both R&D and design, as well as in IT, but not investments in branding and reputation. Again, there was no effect of firm size, and young firms were not significantly more or less

⁵ We also estimated the same model for the manufacturing firms (according to our classification), among which investments in design and IT were significantly associated with product/service innovation, while investments in R&D and branding and reputation were not. Firm size was also (weakly) significant and positive, meaning larger firms were more likely to introduce product/service innovations. This contrasts with the three types of KIBS, amongst which firm size was never found to be significant. There is also weak evidence that young firms are more likely to introduce product/service innovations.

likely to have introduced a product/service innovation. As before, the share of graduates in the workforce had no significant effect on the propensity to innovate, but firms in the architecture/engineering consultancy sector were more significantly less likely to have introduced a product/service innovation than those in software and IT services (from which specialist design firms did not differ significantly).

These estimations show very interesting difference. In particular, investments in R&D are associated with product/service innovation among firms with an analytical knowledge base, while investments in design are not important, but the opposite was the case among the firms with a symbolic knowledge base. Meanwhile, investments in both R&D and design are associated with product/service innovation among the firms with a synthetic knowledge base. Interesting also is that investments in IT were positively associated with product/service innovation in all three groups of KIBS firms, while investments in branding and reputation were never significant.

Also of note is the varying strengths of these models. The final model for the ‘analytical firms’ had a Nagelkerke pseudo R-square of 0.332. Because nearly three-quarters of these firms claimed to have introduced a product/service innovation, this model was more successful at identifying innovators than non-innovators, but overall it correctly identified 77% of the cases as innovators or non-innovators (based on a cut value of 0.5). The model for the ‘synthetic firms’ was also strong. With a Nagelkerke pseudo R-square of 0.471, this model correctly classified 70% of the non-innovators and 80% of the innovators. The model for the ‘symbolic firms’ was notably weaker, having a Nagelkerke pseudo R-square of 0.185; it correctly identified 69% of the non-innovators and 65% of the innovators.⁶

Note that as a robustness check we also estimated models in which we replaced the expenditures on R&D, Design, IT and Branding/Reputation with both dummy variables indicating whether or not the firm had invested in each of these activities and with the log of total expenditures without these being divided by employment. The results were fundamentally the same, particularly with regard to the investments associated (and not associated) with innovation.

⁶ The model for the manufacturing firms was also stronger, with a Nagelkerke pseudo R-square of 0.463; this correctly classified 80% of the non-innovators and 72% of the innovators.

4.2.1 Relating Knowledge Types to Process/Organisational Innovation: Findings

We then re-estimated the models this time with process/organisational innovation as the dependent variable (Table 9). In this case, we find:⁷

Insert Table 9 about here

- Among firms with an analytical knowledge base, the introduction of process/organisational innovations was associated with investments in R&D and in branding and reputation, but not investments in design or IT. There is no effect of firm size, and young firms were not more or less likely to have introduced process/organisational innovations. Again, the share of graduates in the workforce had no significant effect on the propensity to innovate, and no significant sector effect was found.
- Among firms with a symbolic knowledge base, the only factor significantly associated with the introduction of process/organisational innovations was investments in design, while investments in R&D were at 12%, marginally outside of the conventionally defined significance cut off of 10%. Similarly, there was some evidence that young firms were less likely to innovate, although this was significant only at 15%.
- Among firms with a synthetic knowledge base, the introduction of process/organisational innovations was associated with investments in design and (weakly) in R&D, but not investments in IT or branding and reputation. As with the result for product/service innovation among the same firms, firm size was positive and highly significant, but young firms were not significantly more or less likely to have introduced a process/organisational innovation. There is also no significant sector effect, and again the share of graduates in the workforce was not significant.

As with the estimations for product/service innovations, the estimations for process/organisational innovations show interesting differences in the factors associated with innovating. Also notable is the varying strengths of these models. The final model for the ‘analytical firms’ had a Nagelkerke pseudo R-square of 0.190. It correctly predicted just over half of the non-innovators and 80% of the innovators (based on a cut value of 0.5). The

⁷ We also estimated the same model for the manufacturing firms. This found significant and positive effects for investments in design and IT, but not in R&D or in branding and reputation. Firm size was also significant and positive, while there was not effect of firm age, sector, or the share of graduates in the workforce.

model for the ‘synthetic firms’ was of similar strength. With a Nagelkerke pseudo R-square of 0.221; this correctly classified 69% of the non-innovators and 75% of the innovators. The model for the ‘symbolic firms’ was again notably weaker, having a Nagelkerke pseudo R-square of just 0.109. This was much more effective at correctly identifying non-innovators (80% of which were correctly classified) than innovators (42%).⁸

Again, as a robustness check we also estimated models in which we replaced the expenditures on R&D, Design, IT and Branding/Reputation with both dummy variables indicating whether or not the firm had invested in each of these activities and with the log of total expenditures without these being divided by employment. The results were again fundamentally the same, particularly with regard to the investments associated (and not associated) with innovation.

5. Discussion

The conviction underlying this study is that KIBS (and indeed other firms) are differentiated in their knowledge bases, and moreover that firms with different knowledge bases are likely to have different characteristics and to behave differently. To this end, we applied the conceptual model of three knowledge types developed by Asheim and colleagues (2005). Specifically, we drew on information publicly available in firms’ websites and were able to first manually classify firms using web-sites to identify their primary knowledge base, and to do this with a high level of inter-rater agreement. It is worth noting that aside from their word content, the websites for different ‘types’ of firms typically present information in very different ways. Creative design agencies, for instance, typically present themselves through very colourful, graphics rich, and fun websites. Key people are usually names, but often only their first names are given, indicating a very friendly, informal approach. By contrast ‘analytical firms’ tend to emphasise what they (do as a firm), and names of key individuals are very often not provided. When they are, the websites tend to provide full names in a formal fashion, with supporting credentials, like degrees from specific universities, or membership of important organisations. ‘Synthetic firms’ tend to be closer to analytical firms in presentation, but with greater emphasis on problem solving and solutions.

We were then able to extract specific words and successfully identify a set of words strongly associated with each of a ‘symbolic knowledge base’ and an ‘analytical knowledge

⁸ The model for the manufacturing firms was also reasonably strong, with a Nagelkerke pseudo R-square of 0.344; it correctly classified 62% of the non-innovators and 86% of the innovators.

base'. Our success with the former is particularly notable, because hitherto a challenge with this conceptual model was identifying 'symbolic knowledge' and firms based on this (without simply relying on SIC codes). Our failure to identify a set of words associated with 'synthetic knowledge' is also notable. As our work progressed, we increasingly took the view that synthetic knowledge lies between analytical and symbolic knowledge, which are more extreme types. Indeed, arguably all firms exploit considerable synthetic knowledge, but some also exploit analytical, symbolic or some other knowledge type which when present, tends to be more prominent in company websites.

We then related these knowledge types to firm choices and strategies, first in relation to investing in R&D, design, branding and reputation, and IT, and second to the introduction of innovations. With regard to the former, it must be conceded that the models were not particularly strong, however, in each case the addition of the variables relating to the 'knowledge types' significantly strengthened the model beyond the explanatory power provided by characteristics including size and (SIC) sector, with at least one of the knowledge types being associated with significantly different behaviour. For example, we found, as expected, that after controlling for size and sector firms with an analytical knowledge base were significantly more likely to invest in both R&D and design, while firms with a symbolic knowledge base were significantly less likely to do the same. This indicates that the identification of 'knowledge types' has explanatory power, and moreover, that this categorisation complements rather than replaces the established Standard Industrial Classification.⁹

Our modelling of the 'drivers' of innovation among these different types of firms also found substantial differences in both: 1. The strength of the models, and; 2. The particular factors associated with innovation within each group. With regard to the first, it is notable but perhaps unsurprising that the models for firms with a symbolic knowledge base were significantly weaker than those for firms with an analytical or synthetic knowledge base. We consider that this reflects much less understanding of innovation in symbolic activities and the key drivers. Essentially, both the concept of 'technological product and process' (TPP) innovation in the form of distinctly new or changed products and/or processes and its key drivers (e.g., size, sector, R&D, etc.) has been derived studies of manufacturing firms where analytical and synthetic knowledge tends to be most prevalent; much less is known about

⁹ Note here that this is after the 'cleaning' of categorisation of firms to SIC codes. We were surprised, indeed somewhat alarmed, by the sizable share of firms which appear to have been classified to the wrong SIC code. This was particularly commonplace among the architecture and engineering consultancy firms, but was also found among firms in the other sectors as well.

innovation in contexts heavily dependent on symbolic knowledge, or symbolic manipulation, and about the key activities and investments underlying this. With regard to the second, we do however reach findings that broadly reflect our prior expectations. Investing in R&D, for instance, is strongly associated with product/service innovation in firms with an analytical knowledge base, and those with a synthetic knowledge base, but has no effect among those with a symbolic knowledge base (who are in any case much less likely to engage in R&D).

Four other things are worth highlighting:

First, that recent investments in information technologies were associated with product/service innovation (but not process/organisational innovation) among KIBS of all three knowledge types. This reinforces the notion that IT investments are particularly important among (innovating) KIBS.

Second, and by contrast, none of our models of innovation find any significant effect for the share of graduates in the workforce. In other words, firms with a low share of graduates were just as likely to innovate as those with a high share. This is interesting, because it is assumed that one of the reasons why KIBS are highly innovative is because they are ‘knowledge intensive’, and ‘knowledge intensity’ is typically measured by the share of graduates in the workforce. However, we find 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. This begs the question why not? It may be that the measures of innovation used overlook how graduates contribute. For example, firms with a high share of graduates might provide a more flexible, customised service, while those with fewer graduates might provide narrower, more standardised services (Tether et al., 2001) – the relationship between customisation and innovation being that more of the former can lead to less of the latter (Hipp et al., 2000).

Third is the finding that investment in branding and reputation is significantly associated with process/organisational innovation among firms with an analytical knowledge base (but not other firms). We conjecture that this may be related to increased standardisation of the service provided, such that they are less relational (or personal) and more transactional (and impersonal). Investments in branding and reputation build the status of the firm as a whole, rather than be reliant on the relational capital of individuals within it.

Fourth is the significance of design. We find that investments in design are associated with both product/service and process/organisational innovation among both the symbolic and synthetic firms, but not the analytical firms. This is intriguing, and partially fits with the observation in Pavitt (1984) that design is a key driver of innovation amongst ‘specialist

suppliers' as distinct from science based firms. More generally, we find that all three types of firms were more likely to invest in design than R&D, which indicates this is an important activity. We suspect, however, that design covers a variety of activities (e.g., identification of customer needs; ideation and creativity, selecting ideas for products/services; implementing products/services; form giving etc.) rather than a specific activity. This finding further reinforces the need to explore deeper what design is, and how it contributes to both competitiveness and innovation, especially in contexts of high symbolic content (c.f., Ravasi and Stigliani, 2012; Eisenman, 2013; D'Ippolito, 2014)

6. Conclusions

While knowledge intensive business services are increasingly recognised as being among the most dynamic sectors of advanced economies, not only achieving high rates of innovation but also helping others to innovate, there is relatively little research that sought to examine variety within KIBS, other than through using standard industrial codes or applying broad distinctions between professional and technical KIBS. In this paper we have sought to advance understanding by seeking to identify the primary knowledge type associated with KIBS active in three sectors: architecture and engineering consultancy, software and IT consultancy, and specialist design. We have developed a method which successfully draws on information available on company websites to distinguish between 'analytical' and 'symbolic' knowledge orientations. Furthermore, we have shown that the categorisation contributes to understanding differences in behaviour among KIBS, including their investments in R&D and design. And that there are substantial and significant differences between the investments that firms with different knowledge bases make that are associated with their introduction of innovations.

Further work needs to be done. Aside from examining further the role(s) of design, as discussed above, we suggest that further work is needed to:

1. Identify a synthetic knowledge base. While we were able to do this manually, we were not able to find a set of words on websites clearly associated with synthetic knowledge.
2. To extent the conceptualisation to other 'types of knowledge'. In this paper we applied Asheim's three knowledge types model to three sectors for which we thought it particularly appropriate. But what of other sectors such as accountancy and legal services. It is not so clear that the model would fit these well, where other types of knowledge – of procedures, jurisprudence, etc. – are more important. There may well be other 'types of knowledge' and work is needed to define these.

3. To reconsider measures of innovation. In essence, we ask whether the standard measures are more appropriate to firms with some knowledge bases (analytical or synthetic) than others (synthetic).

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Tables

Table 1: The Initial Sample and Analysed Sample of KIBS Firms

Sector	Initial Sample	Names not provided	Excluded as Manufacturing or other Non-KIBS activity	Analysed Sample of KIBS firms
Architecture & Engineering Consultancy	217	18	111	88
Software and IT Services	189	19	27	143
Specialist Design	185	26	28	131
Combined Sample	591	63	166	362

Table 2: UCINET 6 Clustering of Analytical and Symbolic Words into Clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Initial proportion correct	Final proportion correct
Two clusters	15 symbolic words - all words selected as symbolic	16 analytical words - all words selected as analytical	-	-	0.916	0.972
Three clusters	13 symbolic words – all except ‘creativity’ and ‘studio’	6 analytical words – plus 2 symbolic words (‘creativity’ & ‘studio’)	10 analytical words	-	0.9464	0.994
Four clusters	11 symbolic words – plus 1 analytical word (‘optimisation’)	6 analytical words – plus 1 symbolic word (‘illustrator’)	4 analytical words – plus 2 symbolic words (‘designer’ and ‘studio’)	5 analytical words – plus 1 symbolic word (‘creativity’)	0.955	0.998

Table 3: Classification of Firms by Primary ‘Knowledge Type’

	Initial Manual Coding	Computer-based Coding	Final classification
Analytical	62	96	73
Synthetic	138	0	169
Symbolic	115	105	120
Multiple Types	47	0	0
Not classified	0	112	0
Total sample	362	362	362

These were the firms for which none of the specified words occurred at least 6 times

Table 4: Primary ‘Knowledge Types’ by Sector among KIBS

	All	Analytical	Synthetic	Symbolic
Whole Sample	362	73	169	120
Architecture & Engineering Consultancy	88	28	51	9
Software and IT Services	143	44	96	3
Specialist Design	131	1	22	108

Table 5: Descriptive Statistics

Variables	KIBS – Final Classification			Non-KIBS	
	Analytical	Symbolic	Synthetic	Manuf.	Others
Firms (Number of Observations)	73	120	169	134	32
Sector = “Architecture & Eng. Consultancy”	38%	8%	30%	80%	13%
Sector = “Specialist Design”	1%	90%	13%	10%	44%
Sector = “Software and IT Services”	60%	3%	57%	10%	44%
Size = Small firms (5 to 19 employees)	32%	76%	42%	31%	44%
Size = Medium firms (20 to 99 employees)	32%	23%	34%	34%	34%
Size = Large firms (100+ employees)	37%	2%	24%	34%	22%
Age = Young firms (less than 10 years old)	29%	28%	19%	16%	22%
Graduates in Workforce = none to 5%	1%	7%	10%	41%	16%
Graduates in Workforce = 6 to 20%	5%	4%	15%	32%	6%
Graduates in Workforce = 21 to 50%	16%	19%	21%	13%	28%
Graduates in Workforce = over 50%	77%	70%	54%	13%	50%
Engaged in Research & Development?	42%	14%	28%	37%	16%
--- median R&D/emp. spend (when >£0)	£2,500	£1,430	£7,570	£2,000	£2,000
Engaged in design activities?	52%	25%	41%	41%	41%
--- median design/emp. spend (when >£0)	£2,500	£1,040	£3,950	£1,250	£830
Invested in IT?	47%	65%	64%	55%	53%
--- median IT/emp. spend (when >£0)	£975	£1,000	£835	£509	£660
Invested in reputation or branding?	53%	63%	48%	45%	63%
--- median brand/emp. spend (when >£0)	£630	£1,200	£835	£400	£720
Introduced product/services innovations	75%	48%	59%	56%	63%
Introduced process &/ or org innovations	68%	50%	53%	58%	56%

Table 6: Multinomial Logistic Regressions for Engaging in R&D, Design or Both

	Model 1: Excludes Knowledge Types			Model 2 Includes Knowledge Types		
	R&D Only	Design Only	Both R&D & Design	R&D Only	Design Only	Both R&D & Design
	B (S.E)	B (S.E)	B (S.E)	B (S.E)	B (S.E)	B (S.E)
Constant	-1.998***	-0.637	-1.829***	-2.040***	-0.635	-1.760***
Size (Ln_Emp)	0.247** (0.126)	0.091 (0.105)	0.322*** (0.104)	0.222* (0.130)	0.071 (0.107)	0.254** (0.107)
Young firm (D)	0.732*	0.433	0.993***	0.689 ^(12%)	0.407	0.888**
S_ArchEng (D)	-0.950**	-1.000***	-0.962**	-0.967**	-0.997***	-0.920**
S_Design (D)	-1.060**	-1.006***	-1.081***	-1.113	-0.922*	0.098
KT_Analytical (D)	Not Incl.	Not Incl.	Not Incl.	0.443	0.273	0.668*
KT_Symbolic (D)	Not Incl.	Not Incl.	Not Incl.	0.197	-0.038	-1.474**
N.		362			362	
Model Chi-square		42.3***			52.63***	
-2LL		595.2			656.7	
McFadden pseudo R ²		0.049			0.061	

Note, 118 firms engaged in neither R&D nor design (reference case); 36 only in R&D, 78 only in design, and 60 in both R&D and design. (D) indicates a dummy variable. *** indicates significant at 1%; ** indicates significant at 5%; * indicates significant at 10%. [Note to self – these models have been double checked]

Table 7: Binary Logistic Regressions for Investing in (i) Branding, and (ii) IT

	(i) Investing in Brand/Reputation			(ii) Investing in IT Networks/Software		
	B (S.E)	B (S.E)	B (S.E) [#]	B (S.E)	B (S.E)	B (S.E)
Constant	-1.23***	-1.33***	-1.33***	-0.01	0.07	0.51***
Size (Ln_Emp)	0.34*** (0.09)	0.36*** (0.09)	0.36*** (0.09)	0.03 (0.08)	0.08 (0.08)	Deleted
Young firm (D)	-0.01	0.01	Deleted	0.07	0.17	Deleted
S_ArchEng (D)	0.01	-0.04	Deleted	0.53*	0.55*	0.43 ^(11%)
S_Design (D)	0.94***	0.50	0.52 ^(16%)	0.56**	0.46	Deleted
KT_Analytical (D)	Not Incl.	0.04	Deleted	Not Incl.	-0.79***	-0.81***
KT_Symbolic (D)	Not Incl.	0.58 ^(13%)	0.57 ^(13%)	Not Incl.	-0.12	Deleted
N.	362	362	362	362	362	362
% Yes	53.9%	53.9%	53.9%	60.8%	60.8%	60.8%
Correct No %	52.1%	54.5%	53.9%	0%	21.8%	21.1%
Correct Yes %	69.7%	67.7%	68.2%	100%	93.2%	93.2%
Model Chi-square	23.5***	25.9***	25.8***	5.99 n.s.	13.0**	10.3***
-2LL	476.1	473.8	473.8	478.9	471.9	474.6
Nagelkerke Psudo R ²	0.084	0.092	0.092	0.022	0.048	0.038

(D) indicates a dummy variable. *** indicates significant at 1%; ** indicates significant at 5%; * indicates significant at 10%. [Note to self – these models have been double checked]

Branding Model with only size and Symbolic knowledge (D): Model Chi-sq. 23.8, Nagekerke R² = 0.085

Branding Model with only size and Design Sector (D): Model Chi-sq. 23.5, Nagekerke R² = 0.084

Table 8: Binary Logistic Regressions for Introduction of Product / Service Innovation among the Three Sub-samples of KIBS and Manufacturing Firms

	Analytical KIBS	Symbolic KIBS	Synthetic KIBS	Manufacturing
Constant	1.113**	-1.051***	-1.934***	-2.316***
Young Firm (D)	-1.231*	Deleted	Deleted	Deleted
Ln(Emp)	Deleted	Deleted	0.257** (0.131)	0.383** (0.159)
Sector_ArchEng (D)	-1.861**	Deleted	-0.925**	Deleted
Ln(R&D/Emp)	0.258** (0.109)	Deleted	0.213*** (0.069)	Deleted
Ln(Design/Emp)	Deleted	0.144** (0.065)	0.216*** (0.056)	0.340*** (0.071)
Ln(IT/Emp)	0.234** (0.119)	0.155*** (0.060)	0.183*** (0.059)	0.129* (0.070)
N observations	73	119	167	134
% Innovating	75%	48%	59%	55%
Correct No %	56%	69%	68%	83%
Correct Yes %	93%	63%	79%	69%
Model χ^2	18.3***	14.9***	70.6***	51.5***
-2 Log-LL	63.2	149.8	155.8	131.1
Nagelkerke R ²	0.330	0.157	0.464	0.430

(D) indicates a dummy variable. *** indicates significance at 1%; ** at 5%; *at 10%.

Insignificant variables have been deleted.

Insignificant variables have been deleted. Other deleted (insignificant) variables not shown above are: dummy variable for the Specialist Design Sector; categorical variables for the share of graduates in the workforce.

[Note to self – these models have been double checked]

Table 9: Binary Logistic Regressions for Introduction of Process/Organisational Innovations among the Three Sub-samples of KIBS and Manufacturing Firms

	Analytical KIBS	Symbolic KIBS	Synthetic KIBS	Manufacturing
Constant	-0.204	-0.162	-2.205***	-2.529***
Young Firm (D)	Deleted	-0.630 ^(15%)	Deleted	Deleted
Ln(Emp)	Deleted	Deleted	0.460*** (0.124)	0.508*** (0.171)
Ln(R&D/Emp)	0.182** (0.079)	0.128 ^(12%) (0.082)	0.087** (0.046)	Deleted
Ln(Design/Emp)	Deleted	0.123* (0.065)	0.071 ^(11%) (0.044)	0.110* (0.060)
Ln(IT/Emp)	Deleted	Deleted	0.088* (0.050)	0.265*** (0.067)
Ln(Brand/Emp)	0.165** (0.086)	Deleted	Deleted	Deleted
N observations	73	120	169	133
% Innovating	68%	50%	53%	58%
Correct No %	52%	80%	69%	62%
Correct Yes %	80%	42%	75%	86%
Model χ^2	10.6***	10.3**	30.5***	39.4***
-2 Log-LL	80.3	156.1	203.3	141.7
Nagelkerke R ²	0.190	0.109	0.221	0.344

(D) indicates a dummy variable. *** indicates significance at 1%; ** at 5%; *at 10%.

Insignificant variables have been deleted. Other deleted (insignificant) variables not shown above are: dummy variables for sectors; categorical variables for the share of graduates in the workforce.

[Note to self – these models have been double checked]

Appendix 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 et al. (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.