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Local and firm-level influences on innovation performance: linkages, climate and externalities

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Abstract

Interest in the local dimension of economic development has intensified in recent years with changes in the English policy landscape emphasising local policy action. In this paper we use an augmented version of the UK Innovation Surveys 4-7 to explore firm-level and local area influences on firms' innovation performance. We find strong evidence of the value of external knowledge acquisition both through interactive collaboration and non-interactive contacts such as demonstration effects, copying or reverse engineering. Levels of knowledge search activity remain well below the private optimum, however, due perhaps to informational market failures. In terms of the effects of the local innovation eco-system on firms' innovation three results stand out. First, we find no significant relationship between either local labour quality or employment composition and innovative outputs. Second we find strong positive externalities of openness resulting from the intensity of local interactive knowledge search – a knowledge diffusion effect. Third, we find strong negative externalities result from the intensity of local non-interactive knowledge search - a competition effect. Our results provide support for local initiatives to support innovation partnering and counter illegal copying or counterfeiting.

Jelcodes:O30,O32

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Keywords: Innovation, local eco-system, UK, Local Enterprise Partnerships

JEL Codes: O30, 032, D62

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1. Introduction

Interest in the local dimension of economic development has intensified in recent years stimulated by discussion of creative cities, intelligent cities and agglomeration (Carney et al. 2011). This has led to an increasing focus on the role of local market and factor conditions on innovation performance with strategic implications as firms search to establish coherence between their organisational strategies and their context, and maximise the value of organisational assets and capabilities (Akgun, Keskin, and Byrne 2012; Vaccaro et al. 2012). Discussion of governments' ability to create advantage by shaping the framework conditions within which firms operate also focuses attention on the contextual influences on innovation (Asheim et al. 2007), and the interplay between these contextual influences and firms' own internal competencies (Cassiman and Veugelers 2002; Cassiman and Veugelers 2006). In England these broader debates have been paralleled by a move towards place-based policy structures oriented to addressing local development issues and stimulating local growth. In effect, this has created a new policy geography as Regional Development Agencies have been replaced with Local Enterprise Partnerships (LEPs) and other locally oriented business support mechanisms (Hildreth and Bailey 2013).[1]

In this paper we focus on how elements of the local business eco-system influence firms' innovation performance. Our analysis makes three main contributions to the developing literature on the role of contextual factors on innovation performance. First, we consider the impact on firm-level innovation of aspects of the local business environment linked to skills availability, occupational structure and the perceived barriers to innovation. Second, at firm level, we differentiate between the innovation benefits of collaborative or interactive knowledge search and non-interactive (e.g. copying, imitation) knowledge search strategies for innovation performance. We anticipate that at firm level both interactive and non-interactive knowledge search will raise anticipated post innovation returns, and therefore increase levels of innovation, by reducing development costs in collaborative projects and/or

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Some have argued that this approach is consistent with EU emphasis on smart specialisation, and the potential for local actors to create local advantage (Asheim et al. 2007). Others have suggested that at least outside the major UK cities 'many of the LEP areas are far too small for effective policymaking'. (Hildreth and Bailey 2013, p. 244).

providing access to otherwise inaccessible resources. Third, we explore the potential for local spillovers or externalities of openness to arise from the local intensity of firms' interactive and non-interactive knowledge search (Roper, Vahter, and Love 2013). Here, the anticipated effects are complex, with both types of search activity having the potential to generate knowledge diffusion effects which increase knowledge availability, reduce search costs and increase the returns to innovation. However, both types of knowledge search may also generate local competition effects intensifying market pressures and reducing the anticipated returns from innovation. For example, reflecting debates about the impact of counterfeiting on innovation (Qian 2014), in localities where copying or imitation are common it will be more difficult for firms to appropriate the full benefits of any innovation. These opposing (positive) knowledge diffusion and (negative) competition effects create the potential for either positive or negative local spillovers.

The remainder of the paper is organised as follows. In section 2 we outline our conceptual framework which considers how local business and market conditions may influence anticipated post innovation returns and hence firms' willingness to invest in innovation. Section 3 considers data and methods. Section 4 considers our key empirical results. Section 5 considers the implications.

2. Eco-system conditions and the innovation decision

A firm's decision to innovate in any given period will depend on the anticipated post-innovation returns. Where such returns are above some hurdle value or desired rate of return a firm will decide to innovate, and may choose to scale innovation inputs in line with anticipated rates of return (Levin and Reiss 1984). The scale of anticipated post-innovation returns will depend on appropriability conditions, market structure (Levin, Cohen, and Mowery 1985), and on the nature of the innovation itself. Product/service and process innovation may command very different returns depending on market conditions (Du, Love, and Roper 2007), with the returns to imitative and innovative product or service strategies also reflecting the context in which a firm is undertaking innovation (Naranjo-Valencia, Jimenez-Jimenez, and Sanz-Valle 2011; Schnaars 1994; Shenkar 2010; Ulhoi 2012).

Further choices relate to whether a firm innovates on the basis of proprietary knowledge developed purely within the firm, or adopts an open innovation strategy working with external innovation partners (Chesborough 2006; Chesbrough and Appleyard 2007). While independent or 'closed' technological development strategies have been linked to the success of some groups of firms, such as the 'hidden champions' of the German mittelstand (Simon 1996), such strategies are increasingly uncommon among innovative smaller firms (van de Vrande et al. 2009).

The relative costs and benefits of closed and open innovation strategies will depend on the strength of the internal resources of the business as well as the resources available externally. Smaller firms, for example, with weaker internal resources may gain more from adopting open innovation strategies than larger firms (Vahter, Love, and Roper 2015). Similarly, firms in more knowledge-rich environments – characterised perhaps by high levels of public R&D spending - may benefit more from developing external connections than those operating in knowledge poor environments (Toedtling, Lengauer, and Hoeglinger 2011). Moreover, firms' ability to develop and cost effectively implement appropriate search strategies will depend on their internal human (Roper and Love 2006) and technological resources (Griffith, Redding, and Van Reenan 2003).

2.1 Localised influences on innovation

Knowledge has a degree of geographical specificity. Despite the capacity of firms to tap into international knowledge networks, knowledge is still to some extent 'local': it has some dimension of spatial specificity which makes the pool of knowledge in any location different to that available elsewhere (Roper et al 2014). Some areas are simply more 'knowledge rich' than others with potentially important consequences for anticipated post-innovation returns and the potential for firms to innovate (van Beers and van der Panne 2011).

The richness of local knowledge – reflected in the capabilities of eco-system actors - and the nature of local knowledge networks and connectivity, will help shape the potential for firms to benefit from knowledge spillovers. For example, there is a strong geographical dimension to spillovers from universities, with the impact of university R&D being confined largely to the region in which the research takes place, (Audretsch and Feldman 1996; Anselin, Varga, and Acs 2000, 1997). To some extent, the spatial specificity of such effects is linked to the tacit nature of knowledge. In this sense, local knowledge may have the character of a (semi) public good, with properties of non-rivalry. In addition, local firms may be more willing to share knowledge with geographically close neighbours 'as a result of shared norms, values, and other formal and informal institutions that hold down misunderstanding and opportunism' (He and Wong, 2012, p. 542). To the extent that local knowledge influences innovation performance, variations in the specific characteristics of local knowledge have the potential to shape corresponding variations in innovation success at the spatial level (Toedtling, Lengauer, and Hoeglinger 2011; Jensen 2004).

Aside from the capabilities of individual actors, the accessibility or availability of knowledge in any locality will also depend on the density of local connections which facilitate knowledge sharing and diffusion. On the basis of an examination of technology diffusion in the flat-screen television sector, for example, Spencer (2003) suggests that high levels of network density are likely to be associated with higher levels of innovative activity and competitiveness, and that dense or strongly centralised networks are more likely to facilitate convergence on a dominant design than less dense networks. The suggestion is that network structure as well as the density of connections itself is important in shaping knowledge diffusion and, hence, innovation. In particular, Kesidou and Snijders (2012) find that gatekeeper firms, with strong external connections and extensive networks of linkages within the cluster play a particularly important role. Feldman (2003) and Agrawal and Cockburn (2002) call similar firms "anchor" companies, while Lorenzoni et al. (2010) also highlight the 'anchoring' role of multinational firms and universities.

To the extent that local innovation eco-systems do influence firms' innovation decisions, variations in the specific characteristics of local eco-systems (both in terms of content and richness) have the potential to shape matching variations in innovation success (Toedtling, Lengauer, and Hoeglinger 2011; Jensen 2004). This also suggests the potential for local, regional or urban strategies to influence the characteristics of local knowledge as a means of driving competitiveness (Asheim et al. 2007; Hewitt-Dundas and Roper 2011). However, as Wolfe (2009, p. 186) comments on Canada: 'The mere presence, or absence, of key institutional elements of the local or regional innovation system also affects their innovative capacity and their potential to serve as nodes for cluster development. Many clusters enjoy the knowledge assets and research infrastructure that are necessary for the development of an innovation-based development strategy, but they differ dramatically in their capacity to mobilize these assets in the pursuit of such a strategy'. This emphasises the potential importance of local policy initiatives which can: 'address systemic failures that block the functioning of innovation systems, hinder the flow of knowledge and technology and, consequently, reduce the overall efficiency of R&D efforts. Such systemic failures can emerge from mismatches between the different components of an innovation system, such as conflicting incentives for market and non-market institutions (e.g. enterprises and the public research sector), or from institutional rigidities based on narrow specialisation, asymmetric information and communication gaps, and lack of networking or mobility of personnel' (OECD 1999, p. 10).

2.2 Interactive and non-interactive knowledge search

When a firm positively assesses the anticipated post-innovation returns and does decide to innovate based on knowledge developed fully or partially outside its boundaries, the organisation faces further choices relating to its knowledge acquisition strategies. For example, should the firm develop collaborative or interactive connections with partners to jointly develop new knowledge? These might be partnerships, network linkages or contractually-based agreements entered into on either a formal or informal basis. This type of connection is characterised by strategic intent and mutual engagement of both parties, and will be characterised by interactive learning (Glückler 2013). Such strategies may generate new-to-the-world knowledge but may also involve significant commercial, technical and managerial risks (Astebro and Michela 2005), as well as high management and co-ordination costs (Crone and Roper 2003). Alternatively, should the firm adopt non-interactive, imitation or copying strategies focussed on the exploitation of knowledge previously implemented by others (Glückler 2013)? Here, the technical risks and management and co-ordination costs will be lower but the firm may forego the potential first mover advantages associated with more interactive knowledge search strategies (Xin, Yeung, and Cheng 2010). The choice of one of these knowledge search strategies, or the combination of both, will reflect both the nature of firms' evaluations of the post-innovation returns from different types of innovation and the anticipated cost-benefit of each type of search strategy.

Interactive search strategies involve a purposive decision by firms to build links or connections with other firms and economic actors (e.g. research institutes, universities and government departments) to capitalise on the knowledge of the linked parties, co-operate with the linked parties, and/or to exploit their joint knowledge together (Borgatti and Halgin 2011). Three characteristics seem important in measuring the potential cost-benefits of interactive learning: the number of connections the firm has; the mode of interaction adopted; and the nature of the embeddedness of the networks in which firms are involved (Borgatti and Halgin 2011; Glückler 2013). At its simplest, the benefits of interactive knowledge search will be positively affected by a firm's number of connections. In purely statistical terms, since the payoff from any given innovation connection is unknown in advance, the chances of obtaining benefit from any connection in a given distribution of payoffs increases as the number of connections increases (Love et al, 2014). Having more connections increases the probability of obtaining useful external knowledge that can be combined with the firm's internal knowledge to produce innovation (Leiponen and Helfat 2010). The extent or breadth of a firm's portfolio of external connections may also have significant network benefits, reducing the risk of "lock-in" where firms are either less open to knowledge from outside its own region (Boschma 2005), or where firms in a region are highly specialised in certain industries, which lowers their ability to keep up with new technology and market development (Camagni 1991). The benefits of firms' interactive knowledge search activity are, however, unlikely always to be proportional to the number of connections. Instead, as the cognitive capacity of management is limited (Simon 1947), firms may reach a point at which an additional connection actually serves to diminish the innovation returns of interactive search (Laursen and Salter 2006; Leiponen and Helfat 2010; Grimpe and Sofka 2009; Garriga, von Krogh, and Spaeth 2013). The co-ordination, management and participation costs involved in structuring interactive knowledge search may also be significant, particularly where outcomes are uncertain and a firm is working with a large and potentially diverse portfolio of external partners.

The alternative to an interactive knowledge search strategy is non-interactive search. Here, firms search for external knowledge deliberately but without the direct engagement of another party. Non-interactive search is therefore characterised by the absence of reciprocal knowledge and/or resource transfers between actors. The most frequently discussed modes of non-interactive learning are: imitation, where a firm absorbs the knowledge of other actors through observation of the actions/behaviour of the source actor; reverse engineering, where a firm derives knowledge from the final product of another firm, obtained from the market or through supply chain interaction; and the codification of knowledge, where a firm obtains knowledge through knowledge which is a public good such as news, patents and regulations etc. (Glückler 2013). As with interactive search, the chances of obtaining useful knowledge from any non-interactive search will increase as the number of non-interactive contacts increases. Or, put another way, having more non-interactive contacts will increase the probability of obtaining useful external knowledge. As with interactive search, however, limits to managerial cognition may mean that the marginal benefits to extending interactive search fall as the number of non-interactive contacts increases (Laursen and Salter 2006; Leiponen and Helfat 2010; Grimpe and Sofka 2009; Garriga, von Krogh, and Spaeth 2013).

The contrasting nature of interactive and non-interactive knowledge search, and consequent differences in their cost-benefit profiles, suggests the potential for a complementary relationship. Two groups of alternative explanations for this complementarity are possible relating to the contrasting knowledge generated by each type of search and/or their management and co-ordination costs. First, in terms of content, the different types of learning processes - exploratory and exploitative – implicit in interactive and non-interactive search generates knowledge which plays a complementary role in firms' innovation activity. Collaborative connections with universities or research centres, for example, may facilitate exploratory activity, while non-interactive contacts with customers or equipment suppliers may contribute more directly to exploitation (Faems et al. 2010; Lavie and Rosenkopf 2006). Second, there may be economies of scope as firms learn how to better manage and co-ordinate their external connections and contacts whether interactive or non-interactive (Love, Roper, and Vahter 2014).

2.3 Local knowledge spillovers: externalities of openness

Recently, Roper et al. (2013) have added to the literature on knowledge spillovers by identifying and quantifying another form of knowledge externality: externalities of openness. These are externalities which arise not simply from the quasi-public good nature of 'local' knowledge, but from the open innovation process itself, reflecting the social benefits of firms' adoption of external linkages and knowledge sourcing in their innovation activity. They argue that even where, for example, the average level of R&D or other knowledge-creation investment remains unchanged, an increase in the degree of 'openness' in an area may result in beneficial externalities which can – indirectly - raise the average level of innovation productivity. Ultimately, therefore, ‘the social benefits of widespread adoption of openness in innovation may be considerably greater than the sum of the achieved private benefits.’ (Roper et al 2013, page 1544). In their empirical analysis Roper et al (2013) find strong evidence of externalities of openness in Irish manufacturing over the period 1994-2008. Although in their analysis the identified externalities are sectoral rather than geographic, there are good reasons to suppose that such spillover effects may also manifest themselves spatially. Reflecting the earlier discussion of interactive and non-interactive knowledge sourcing by individual firms, we might also anticipate that both knowledge search activities may generate potential externality of openness effects.

Three potential sources of externalities of openness may be envisaged: increased knowledge diffusion in a (quasi) public good environment; imitation or demonstration effects; and knowledge competition effects (Bloom et al 2012). For example, knowledge which has the characteristics of a quasi-public good is of little value unless there are mechanisms which allow it to spread. These may include social interaction or inter-personal networks, trade publications and professional associations, or through firms’ direct links with knowledge brokers such as consultants or intermediary institutions (Roper et al 2013). Knowledge diffusion may also be greater where spatially bounded or concentrated networks facilitate intensive face-to-face interaction between network members (Breschi and Lissoni 2009; Ibrahim, Fallah, and Reilly 2009; Storper and Venables 2004), especially in the diffusion of tacit or un-codified knowledge (Asheim, Coenen, and Vang 2007; He and Wong 2012). These types of interactive mechanisms may be 'particularly powerful in generating positive externalities of openness, raising firms’ innovation productivity above that suggested by their private investments in knowledge creation and external search' (Roper et al 2013, page 1545).

The second group of mechanisms through which search externalities might occur can arise as the result of both interactive and non-interactive knowledge sourcing. These are demonstration or learning effects, where externalities of openness arise as firms respond to observed openness by becoming more open themselves. Firms in the proximity of open innovators, for example, may observe the innovation value of openness, and therefore be more inclined to increase their own level of openness. Labour mobility may also play a role. There is clear evidence, for example, that knowledge spillovers via labour mobility has a spatial dimension: mobility of highly skilled labour has been shown to significantly increase knowledge spillovers among firms in clusters and in the same region, significantly improving innovation success (Almeida and Kogut 1999; Breschi and Lissoni 2009). Labour mobility may also spread an awareness of the benefits of openness as employees move between firms or establish new companies: this type of demonstration or adoption effect is likely to be stronger where firms are strongly networked and geographically proximate (Roper et al 2013).

The proximity of open innovators may also have externality effects through competition (Bloom et al. 2012). The competition effect itself can be divided into two elements, reflecting the dichotomy between interactive and non-interactive knowledge search strategies described earlier. The first is a negative 'market stealing' effect, in which there is competition for available network linkages. Here, firms located in areas where innovation partner networks are dense may lose out if other firms are more strongly networked and therefore find it cheaper and easier to acquire suitable external knowledge. This suggests the potential for negative (competition) externalities from interactive openness where levels of openness are high, and therefore in which it might be difficult to establish new network linkages or break into existing knowledge networks – a case of 'lock-out'.

The negative competition effects of openness might be even greater in the case of non-interactive knowledge activity. Activities such as imitation, reverse engineering and codification of public knowledge do little to add to the density of knowledge networks, and do not themselves generate new knowledge: indeed the last of these is designed to capture privately some of the benefits of the existing public stock of knowledge. In geographical areas in which imitation and copying are commonplace potential innovators may downgrade their expectations of post-innovation returns, reducing the incentive to invest in innovation inputs including investment in knowledge generating and sourcing activities. This in turn is likely to reduce the level of innovation at the firm and regional level below what would otherwise be the case, suggesting that the competition effect of non-interactive forms of knowledge sourcing is likely to be overwhelmingly negative.

Because of these different mechanisms – both positive and negative – through which openness may generate externalities at the local level, it is impossible to be definitive about the likely size, or even direction, of the net effect. Empirically, Roper et al (2013) identify net positive externalities of openness in Ireland, and conclude that in the Irish context demonstration effects have little part to play in the process. However, their analysis is restricted to the consideration of interactive knowledge linkages: the potential externality effects which may arise from non-interactive knowledge search remain untested.

3. Data and Methods

3.1 Empirical Model

Following the general line of argument in the innovation production function literature stemming from Griliches (1995), firms will invest in knowledge sourcing through each activity only if the expected returns are positive, with the scale of any investment varying positively with the expected rate of return. Decision-theoretic models of the choice of research intensity by firms, for example Levin and Reiss (1984), therefore relate the intensity of knowledge sourcing activity to the expected post innovation margins, the structure of the industry within which the firm is operating, the market position of the firm itself, and a range of other firm and industry specific factors. We adapt this basic model to reflect the local knowledge climate in which firms are located, and the nature of the firm's knowledge sourcing activity. This suggests that investments by firm i in R&D (RD_i), interactive knowledge sourcing (IKS_i) and non-interactive knowledge sourcing (NKS_i) may be represented by equations of the form:

$$
\begin{aligned}
RD_i &= \gamma_{10} + \gamma_{11}\pi_i^e + \gamma_{12}RBASE_i + \gamma_{13}LK_j + \gamma_{14}ITECH_k + \varepsilon_1 \\
IKS_i &= \gamma_{20} + \gamma_{21}\pi_i^e + \gamma_{22}RBASE_i + \gamma_{23}LK_j + \gamma_{24}ITECH_k + \varepsilon_2 \qquad (1) \\
NKS_i &= \gamma_{30} + \gamma_{22}\pi_i^e + \gamma_{32}RBASE_i + \gamma_{33}LK_j + \gamma_{32}ITECH_k + \varepsilon_3
\end{aligned}
$$

where π^e_{ijk} is the expected level of post innovation returns for the firm in local area j and industry k, $RBASE_i$ is a group of variables reflecting the strength of the firm's internal resource base, LK_j is group of variables reflecting the strength of the local knowledge climate within which the firm is located, and $ITECH_k$ is reflects the character of technology in the industry in which the firm is operating.

If firms' expectations about post-innovation returns are rational and we regard

$$\pi_i = \beta_0 + \beta_1 \text{RBASE}_i + \beta_2 \text{ITECH}_k + \eta_i \qquad (2)$$

We can substitute for expected post-innovation returns in equation (1) to obtain reduced form knowledge sourcing equations:

$$\begin{aligned} \text{RD}_i &= \theta_{10} + \theta_{12}\text{RBASE}_i + \gamma_{13}\text{LK}_j + \theta_{14}\text{ITECH}_k + \lambda_1 \\ \text{IKS}_i &= \theta_{20} + \theta_{22}\text{RBASE}_i + \gamma_{23}\text{LK}_j + \theta_{24}\text{ITECH}_k + \lambda_2 \\ \text{NKS}_i &= \theta_{30} + \theta_{32}\text{RBASE}_i + \gamma_{33}\text{LK}_j + \theta_{34}\text{ITECH}_k + \lambda_3 \end{aligned} \qquad (3)$$

where: $\theta_{12}=\gamma_{12}+\gamma_{11}\beta_1$ and $\lambda_1=\varepsilon+\eta$.

Knowledge sourced through R&D or external knowledge sourcing will then be combined into a form which can be commercially exploited through innovations. Locational and industry-specific factors may also be important – along with the resource base of the firm – in determining the efficiency with which knowledge acquired is translated into commercially exploitable outputs or innovations (INNOV_i). The potential for such effects suggests a general form of innovation production function (Geroski 1990; Roper, Du, and Love 2008):

$$\text{INNOV}_i = \varphi_0 + \varphi_1\text{RD}_i + \varphi_2\text{IKS}_i + \varphi_3\text{NKS}_i + \chi_1\text{RBASE} + \chi_2\text{LK} + \chi_3\text{ITECH} + \mu_i \qquad (4)$$

which is our reduced form estimating equation.

3.2 Data

The principal dataset used in our analysis is the UK Innovation Survey (UKIS). This is an official survey conducted every two years by the Office for National Statistics on behalf of the Department of Business Innovation & Skills (BIS), and is part of the EU Community Innovation Survey (CIS). We use data from waves four to seven of the UKIS, covering the periods 2002-04, 2004-06, 2006-08 and 2008-10. In each case the UKIS survey instrument was sent to around 28,000 enterprises with 10 or more employees, with response rates ranging from 50 to 58%[2].

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2 Details of the UKIS sampling methodology and response rates can be found at: https://www.gov.uk/government/statistics/uk-innovation-survey-2011-statistical-annex-revised

UKIS data used for this study was made available via the UK Secure Data Service with limited geographical reference data to preserve confidentiality. In order to match the UKIS data with relevant spatial data at both Local District Authority (LDA) and Local Enterprise Area (LEA) area level, a data matching exercise was undertaken. Each observation in the UKIS has a common reference number which allows it to be linked anonymously to other government surveys and datasets. Using these common reference numbers, UKIS observations were matched with postcode data mainly derived from the Business Structures Database (BSD), itself derived from the Inter-Departmental Business Register (IDBR), which is a live register of data collected by HM Revenue and Customs via tax and employment records[3]. Once each UKIS respondent had been allocated a postcode these were then matched into LDAs and these, in turn, were matched into the larger LEA areas.

The UKIS provides a number of indicators of firms' innovation outputs and we focus on two measures here. First, we use a measure of innovative sales defined as the proportion of firms' sales at the time of the survey derived from products or services newly introduced during the previous three years. This variable has been widely used as an indicator of firms' innovation output (Laursen and Salter 2006; Roper, Du, and Love 2008; Love, Roper, and Du 2009), and reflects not only firms' ability to introduce new products or services to the market but also their short-term commercial success. Across those elements of the UKIS used in the current analysis, 5.6 per cent of firms' sales were derived from newly introduced products or services (Table 1). Our second measure of innovation outputs reflects the (log) scale of firms' sales of products or services newly introduced during the previous three years as used by Leiponen et al (2010). Unsurprisingly perhaps our two innovation output indicators are relatively strongly and positively related having a correlation coefficient of 0.70 (Table 2).

To measure the extent of firms' interactive knowledge search activity we define a measure which relates to the number of innovation partner types with which each firm was working (wherever they were located)[4]. In the UK Innovation Survey we find the following question: 'Which types of cooperation partner did you use and where were they located?'. Seven partner types are identified: other enterprises within the group; suppliers of equipment, materials, services or software; clients or customers; competitors within the industry or

3 This matching was possible where firms were single plants. In the relatively small number of cases where multi-plants were recorded we matched using Business Enterprise Research and Development (BERD) data.
4 This measure of the 'breadth' of search activity has been used extensively in studies of the determinants of innovation (Laursen and Salter 2006) and in prior studies of the determinants of 'openness' (Moon 2011).

elsewhere; consultants, commercial labs or private R&D institutes; universities or other higher education institutions; government or public research institutes. Our indicator of the extent of firms' interactive knowledge search therefore takes values between 0, where firms had no innovation collaboration, and 7 where firms were collaborating with all partner types identified. On average firms were working with an average of 0.67 interactive types (Table 1).

We measure the extent of firms' non-interactive knowledge search in a similar way using information from a question which asks: 'How important to your firm's innovation were each of the following data sources?' Here, we focus on four non-interactive knowledge contacts: conferences, trade fairs, exhibitions; scientific journals and trade/technical publications; professional and industry associations; technical, industry or service standards. Our indicator of non-interactive knowledge search therefore takes values between 0, where the firm is not engaging in any non-interactive knowledge search activity, and 4 where it has non-interactive contacts of each type. On average firms had 0.87 non-interactive contacts (Table 1).

The UKIS also provides information on a number of other firm characteristics which previous studies have linked to innovation outputs (Annex 1). For example, plants' in-house R&D activities are routinely linked to innovation performance in econometric studies with suggestions that the innovation-R&D relationship reflects both knowledge creation (Harris and Trainor 1995) and absorptive capacity effects (Griffith, Redding, and Van Reenan 2003). Design spending has also been linked to innovative outputs and we therefore include a dummy variable which takes value 1 where a firm was investing in design (Love, Roper, and Bryson 2011). We also include in the analysis as controls a group of variables which give an indication of the quality of firms' in-house knowledge base – e.g. skills, plant size, and whether or not a firm was exporting. Skill levels are reflected in the proportion of each plant's workforce which have a degree level qualification (in science or another subject) to reflect potential labour quality impacts on innovation or absorptive capacity (Freel 2005; Leiponen 2005).

To reflect the potential impact of the local innovation eco-system on firms' innovation we include three indicators related to local occupational mix, labour quality, and the perceived barriers to innovation. High local labour quality – reflected both by the representation of high level occupations and qualification levels – may have supply-side advantages by enabling firms to recruit skilled employees, and sell-side advantages by creating a more sophisticated local market for innovative products. Both are likely to increase anticipated post-innovation returns (Roper and Love 2006). To reflect occupational mix in each area we define a variable which measures the percentage of all employment that is categorised into SOC (2010) groups 7-9 (i.e. Sales and Customer Service Occupations; Process, Plant and Machine Operatives; and Elementary Occupations). Labour quality is reflected in a variable which measures the percentage of all in employees in the LEA which are qualified to apprenticeship level or equivalent (i.e. NVQ level 3) or above[5]. Finally, to reflect the local barriers to innovation we constructed a measure for the average number of barriers to innovation faced by firms in each local area. Data on the perceived barriers to innovation is available from the UK Innovation Surveys which generally identify ten specific barriers[6]. For each one a dummy variable was created at firm level equal to 1 if the barrier was coded as of medium or high importance, and equal to 0 if the barrier was coded as of low importance or was not experienced. The dummy variables were summed per firm to provide a total score for the number of barriers faced, and then an average barrier score was calculated per wave for each local area[7].

To capture potential externalities from the local intensity of interactive knowledge search and/or firms non-interactive innovation contacts we construct two variables which reflect the local intensity of each activity. For interactive knowledge search in each LEA/LDA we take a simple average of the intensity of interactive knowledge search firms among firms in each area (Roper, Vahter, and Love 2013). Note, however, that for each firm we then exclude the intensity of its own interactive knowledge search from the calculation of local area search intensity among its peers. In this way we have a more direct test of potential spillovers: we do not double-count the own-firm effect of interactive knowledge search, as the firms' own intensity of interactive search is already included as a separate variable in Equation (4). We

[5] Data for both labour quality variables was sourced from NOMIS. For the occupational mix variable the 3 SOC categories were combined to produce one overall percentage for each LEA/LAD at the start year of the reference period for each wave of the UK Innovation Survey. The labour quality variable was sourced directly from NOMIS again for each LEA/LAD at the start year of the reference period for each wave of the UK Innovation Survey.

[6] The ten barriers identified in most waves of the UKIS are: Excessive perceived economic risks Direct innovation costs too high; Cost of finance; Availability of finance; Lack of qualified personnel; Lack of information on technology; Lack of information on markets; Market dominated by established enterprises; Uncertain demand for innovative goods or services; Need to meet UK Government and EU regulations.

[7] The LAD variables were generally calculated in the same manner as the LEA variables except for the Northern Ireland Local Authorities where the number of observations was too small to produce reliable statistics. Instead, the Northern Ireland totals were used for each of the Local Authorities. There were also no SOC statistics available for the City of London Local Authority due to small sample sizes.

follow a similar procedure to define a similar measure for average non-interactive search intensity in each local area.

4. Empirical Results

Tables 3 and 4 show the results of estimating the innovation production function (equation 4) including spatial variables defined at the LEA level. For both dependent variables the relatively large number of observations in the pooled UKIS dataset permits separate estimations for manufacturing and services firms, and for small (<50 employees), medium (50-249) and large (250+) firms respectively. In addition to the variables reported all models include sectoral and wave dummies.

The basic firm-level variables perform largely as expected in the innovation production function: investment in knowledge production (R&D) and design have a positive and significant association with innovation outputs (Crepon et al. 1998; Jordan and O'Leary 2007; Moultrie and Livesey 2013), as do skills in the form of both science and non-science graduate employment (Freel 2005; Leiponen 2005). As expected, exporting is also positively linked to innovation, although we make no inference about causal links from this association (Love and Roper 2015). The positive association between exporting and innovation is least strong for large firms, almost certainly because almost all such firms (250+ employees) are active in export markets.

Of more interest here are the firm-level interactive and non-interactive knowledge search variables. In common with the recent literature (Laursen and Salter 2006; Love et al 2014) we use both levels and the square of the search variables to allow for possible quadratic effects. For both dependent variables, and for all types of firms, both interactive and non-interactive knowledge search have a positive impact on innovative output, albeit at a decreasing rate (Tables 3 and 4). This reflects the findings other studies which identify an inverted-U shape relationship between knowledge inputs and innovation outputs and which generally attribute the decreasing returns to knowledge inputs to the cognitive limits of management (Laursen and Salter 2006; Love, Roper, and Vahter 2014).

Two other regularities are also evident in the firm level determinants of innovation. First, the innovation effects of both interactive and non-interactive knowledge search are markedly stronger in services than in manufacturing, suggesting that external knowledge sourcing is more important in services. Second, while the coefficients on each type of search are of similar sizes in the case of the first dependent variable (log of innovative sales), in the case of the percentage of new products sold there is a clearly monotonic effect with firm size: the effect of both interactive and non-interactive search is greatest for small firms, followed by medium-sized firm and smallest for large firms (columns 4, 5 and 6 respectively. This finding is consistent with that of Vahter et al (2013) who found that in Irish manufacturing small firms benefitted most from interactive knowledge links on innovation performance, but that small plants also reach the limits to benefitting from 'breadth' of such linkages at lower levels of openness than larger firms.

Turning to the LEA-level effects, the most striking result is perhaps the lack of significant effects. Certainly with respect to the LEA skill level variables (SOC7-9 and NVQ3+ qualifications) there is little evidence of significant effects, suggesting that, in general, there is little or no disadvantage to a firm's innovation from being located in a LEA with a low average skillset. The only exception to this is for large firms, who do obtain some benefit from being located in relatively high-skills area. However for small and medium-sized enterprises, skills at LEA level appear not to matter for innovation outputs.

There is, however, some evidence of externalities of openness, i.e. benefits to firms from locating in areas rich in interactive or non-interactive search activity. However, effects are restricted to large firms and manufacturing firms only, and then only with respect to interactive search. There is some evidence of negative externalities of openness with respect to non-interactive search, again restricted to large and manufacturing firms. This appears to suggest that such enterprises are good at harnessing the benefits of interactive search spillovers at LEA level, while suffering most from location in an imitation-rich environment, a form of environment from which large firms may have most to lose. More tellingly, SMEs and firms in services appear to experience no form of (positive or negative) spillovers from operating in a spatial environment that is rich in knowledge search activity.

Robustness tests

We considered two robustness tests. First we consider the extent to which our choice of geographical unit of analysis was influencing the results. Second, we consider the potential for endogeneity in firms' locational choice: to what extent do firms move between LEAs to take advantage of local economic conditions or more conducive environments for innovation (Shefer, Frenkel, and Roper 2003; Shefer and Frenkel 1998).

The choice of geographical unit of analysis might be important as small firms, and perhaps firms in some service activities, may have a more localised focus both in terms of their business activity and external knowledge search than larger firms and those involved in manufacturing (REFS?) In order to examine whether the spatial level of the local knowledge environment markedly affects the results on firm-level innovation, we repeat the analysis reported in Tables 3 and 4 at a lower level of geographic aggregation, the Local Authority District (LAD) level (Tables 5 and 6). While the overall results from analysis at the LEA and smaller LAD areas prove very similar, there are some subtle differences. For example, as with the LEA-level analysis, there is ceteris paribus no evidence that being in a LAD characterised by lower skill levels acts as a disadvantage in terms of firm-level innovation among smaller firms. Here, any locational skills effect is relatively unimportant compared to the strong positive effect on innovation of the quality of firms' own workforce (Tables 5 and 6). There is, however, some evidence that large firms benefit from being in a high-skill environment, although the size of this effect is noticeably smaller than at LEA level.

Some differences are evident between the LEA and LAD analyses in terms of the externalities of openness effects, with these effects generally stronger at the more local level (Tables 5 and 6). More specifically, the overall positive effect of interactive openness is much stronger at LAD than LEA level for all firms (compare column 1 in Tables 5 and 6 with the corresponding column in Tables 3 and 4). The sectoral pattern of externality effects also differs somewhat between the LEA and LAD levels of analysis. At LAD level only services exhibit positive interactive spillovers and negative non-interactive spillovers, while at LEA level only manufacturing exhibits this this combination of effects. Also, at LAD level, small firms (as well as large) show evidence of interactive and non-interactive spillover effects, an effect restricted to large firms in the LEA-level analysis. Overall, and perhaps unsurprisingly, this suggest that externalities of openness – both positive and negative – impact more strongly on small firms and services businesses at the very local (LAD) level.

Our second robustness test relates to the potential endogeneity of firm location and its potential influence on the modelled relationships. Here, we focus on the extent of mobility among firms in the UKIS based on a comparison of their location at the start and end of each wave of the survey. More specifically, we compare respondents' postcodes at the time of the survey and three years earlier to determine what proportion of firms have moved between postcodes, LED and LEA. We focus our attention on the 31,000 single workplace firms for which we were able to identify full post codes at the time of each wave of the UKIS and three years earlier.[8] Of these the vast majority 83.9 per cent (26,000) had the same postcode in both years, i.e. they either remained in the same property or had moved to an adjacent property sharing the same local postcode. Of the 5,000 firms which changed their postcode around 3,000 stayed within an individual LAD, 2,000 firms (6.4 per cent) moved postcode and LAD, and 900 (2.9 per cent) firms moved postcode and LEA. Both proportions are sufficiently small to suggest that any endogeneity effect linked to firm mobility is likely to be minimal.

5. Discussion and conclusions

More localised policy frameworks in England have focussed attention on the effect of local influences on firm growth and performance. Innovation, a key contributor to firm productivity and growth, is of obvious interest. Here, using data from the UKIS we examine the influence of both firm-level and local (LEA and LAD level) factors on firms' innovation performance. At the level of the firm our results provide confirmatory evidence of the importance for innovation of investments in R&D and design, the skill level of firms' workforces and engagement with export markets. Each has a strong and positive association with innovation outputs. We also find strong evidence to firms' innovation of the value of external knowledge acquisition both through interactive collaboration and non-interactive contacts such as demonstration effects, copying or reverse engineering. However, both interactive and non-interactive knowledge acquisition are subject to diminishing returns as the number of collaborative partners or non-interactive contacts increases.

At the level of the individual firm our results therefore suggest a number of clear strategic messages where organisations are keen to increase their innovation success. First, investing in R&D and design have significant innovation benefits, potentially increasing firms' stock of proprietary intellectual property and also their absorptive capacity (Griffith, Redding, and Van Reenan 2003). Second, increments to skill levels will also benefit innovation output

[8] These accounted for 51.7 per cent of the overall number of observations (59,940) in the combined UKIS dataset

alongside any related gains in productivity (Jacobs 2002). Third, using external knowledge will also benefit firms' innovation outputs, augmenting and perhaps complementing firms' proprietary knowledge (Artz et al. 2010). Here, our results suggest that up to some limit firms may gain from both collaborative innovation and also from more non-interactive knowledge acquisition. In this sense our results reinforce the messages implicit in much of the literature on open and interactive innovation (Chesborough 2006, 2003) inter alia emphasising the importance of firms' ability to identify and access appropriate external knowledge.

Our results also suggest, however, that for the majority of firms the intensity of both interactive and non-interactive knowledge search remain well below the optimum. Or, in other words firms are failing to capture the maximum benefit for innovation from external knowledge search. On average, average interactive search involved 0.7 partners (Table 1), well below the optimal level of around 5 partners suggested by our estimation. Similarly, small firms non-interactive search involved an average of 0.9 contacts, again well below the estimated optimum of around 2.5. Essentially similar comparisons could be made for larger firms and those in both manufacturing and services. Three informational failures may account for the relatively low level of knowledge search activity. First, there may be information failures which mean that firms are unaware of the potential benefits of more extensive knowledge search, or are unable to predict the likely (private) returns[9]. Either market failure may mean that firms either fail to engage in knowledge search activity or, where they do engage in such activity they under-invest in forming partnerships or developing contacts (Spithoven, Clarysse, and Knockaert 2011). Two other market failures relate primarily to firms interactive knowledge search. Firms may, for example, have incomplete or asymmetric information on potential partners' functional capabilities which may lead either to a failure to identify appropriate partners or the establishment of partnerships with the wrong partners. Even where firms do have complete information on the functional capabilities of potential partners, asymmetric information in terms of potential partners' strategic aspirations or trustworthiness may result in the establishment of relationships with inappropriate or inadequate governance mechanisms.

[9] Here there may be an element of learning-by-using as firms which undertake open innovation – or observe others undertaking open innovation learn to appreciate the potential benefits and are better able to predict the private returns (McWilliams and Zilbermanfr 1996).

In terms of the effects of the local innovation eco-system on firms' innovation three results stand out. First, and ceteris paribus, we find no significant relationship between either local labour quality or employment composition and innovative outputs. This is not to say that skills do not matter: skills inside the firm matter greatly, but local labour quality and employment composition do not. Two implications follow. First, improving labour quality in an area will, of itself, do little to promote innovation activity until those skills are engaged. Second, and again ceteris paribus, our results suggest that firms located in areas where the skill base is weak are at no particular disadvantage in terms of innovation compared to firms in areas with a stronger skills base. What matters is not the skills base in an area but the skills within the business. In terms of policy action this suggests a rather targeted approach which emphasises the importance of ensuring that firms are able to access the skills they require for innovation but places less emphasis on local labour quality.

Our other main local eco-system results relate to the externalities of openness resulting from the intensity of local knowledge search. Interactive search intensity generates positive 'externalities of openness' contributing positively to local innovation outputs. The implication is that interactive search generates both private and localised social benefits perhaps by promoting local knowledge diffusion. These positive externalities imply that the socially optimal level of interactive search intensity is greater than the private optimum. However, as we have already noted, informational market failures mean that private levels of interactive knowledge search are well below the private optimum, and therefore even further below the (greater social) optimum. The existence of these market failures, and the potential for social benefits from more intensive interactive knowledge search and diffusion, provide a strong rationale for local policy intervention to promote more intensive interactive search and hence innovation. Relevant activities are likely to include promoting the benefits of open innovation, brokering innovation partnerships (with partners inside and outside the local area) and/or supporting the development of relevant boundary spanning capabilities in local firms and potential innovation partners (Roper, Vahter, and Love 2013).

While more intensive interactive search activity by local firms generates positive externalities augmenting firms' innovative outputs, we find that more intensive non-interactive search instead generates negative externalities (Tables 3-6). Here, it seems the competition effect dominates any benefit from increased knowledge diffusion or use. The implication is that the socially optimal level of non-interactive local search intensity is below the private optimum, perhaps more akin to the naturally occurring intensity of non-interactive local search intensity. Policy implications here are perhaps less obvious, but the negative effects of non-interactive search – i.e. copying, imitation, reverse engineering – do suggest the potentially damaging social impacts of counterfeiting, for example, and the value of the enforcement of intellectual property regulations, trading standards etc.

Finally, it is worth noting some of the limitations of our analysis. First, and perhaps most important, our analysis remains essentially cross-sectional limiting our ability to make causal statements. Future analysis might usefully exploit the increasing panel data component within the UKIS both with a view to establishing causality and examining the longer term effects of the externalities identified here. Second, the range of local eco-system characteristics we consider here is relatively narrow. The availability of finance locally, the characteristics and influence of local markets and the impacts of population density, for example, remain as yet unexplored. Third, limitations to the UKIS itself mean that our analysis of the importance of firms' own external knowledge search and the resulting externalities takes on a rather special character. More specifically, while we are able to identify the intensity of knowledge search – interactive and non-interactive – by firms located in each area we are unable to say where their partners or contacts are located. Our results therefore provide little insight into the value of local innovation partnerships but relate instead to the engagement of local firms in innovation partnerships wherever their contacts or partners are located. This limits our ability to contribute to debates about the value of local clusters or networks, although in general terms our results do suggest the general value of innovation partnering or openness.

Table 1: Descriptives

Variable	Obs	Mean	Std. Dev.
Revenue new prods (Log)	33357	1.584	3.050
Rev. new & imp. prods (Log)	33228	1.821	3.334
Sales new prods (%)	35140	5.593	15.653
Sales new & imp. prods (%)	35011	9.213	22.226
Employment (Log)	35140	4.084	1.501
R&D Investment	35140	0.332	0.471
Design investment	35140	0.197	0.398
Science Graduates	35140	6.136	15.520
Other Graduates	35140	8.822	18.526
Exporter	35140	0.362	0.480
Interactive search	35140	0.666	1.557
Interactive search sqrd.	35140	2.868	8.804
Non-interactive search	35140	0.869	1.294
Non-interactive search sqrd.	35140	2.428	4.583
LEA SOC 7-9	29669	26.626	4.241
LEA NVQ3+	29669	47.750	4.493
LEA interactive	29669	0.590	0.160
LEA non-interactive	29669	0.785	0.281
LEA barriers (avg.)	29669	2.274	0.425
LAD SOC 7-9	35140	26.895	6.413
LAD NVQ3+	35140	48.312	7.951
LAD interactive	35140	0.589	0.298
LAD non-interactive	35140	0.786	0.344
LAD barriers (avg.)	35140	2.291	0.625

Sources: Combined data from UKIS 4-7, see annex for variable definitions.

Table 2: Correlation matrix

(a) LEA variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Revenue new prods (Log)	1																		
2	Rev. new & imp. prods (Log)	0.94	1																	
3	Sales new prods (%)	0.7	0.64	1																
4	Sales new & imp. prods (%)	0.71	0.77	0.86	1															
5	Employment (Log)	0.16	0.17	-0.02	0.01	1														
6	R&D Investment	0.45	0.46	0.31	0.37	0.12	1													
7	Design investment	0.39	0.4	0.28	0.33	0.1	0.49	1												
8	Science Graduates	0.18	0.19	0.18	0.21	0.01	0.22	0.16	1											
9	Other Graduates	0.07	0.07	0.07	0.08	0.06	0.09	0.07	0.14	1										
10	Exporter	0.26	0.26	0.15	0.17	0.14	0.31	0.24	0.23	0.09	1									
11	Interactive search	0.39	0.4	0.28	0.32	0.12	0.35	0.32	0.2	0.05	0.19	1								
12	Interactive search sqrd.	0.32	0.33	0.24	0.27	0.11	0.28	0.27	0.18	0.04	0.15	0.94	1							
13	Non-interactive search	0.32	0.33	0.22	0.27	0.14	0.34	0.29	0.19	0.09	0.17	0.34	0.3	1						
14	Non-interactive search sqrd.	0.28	0.29	0.2	0.23	0.13	0.29	0.25	0.17	0.09	0.15	0.31	0.28	0.96	1					
15	LEA SOC 7-9	-0.02	-0.02	0.01	-0.02	-0.1	-0.02	0.01	-0.09	-0.14	-0.05	-0.04	-0.03	-0.01	-0.01	1				
16	LEA NVQ3+	0.02	0.03	0.01	0.02	0.06	0.01	0.01	0.09	0.09	0.02	0.06	0.04	-0.02	-0.01	-0.73	1			
17	LEA interactive	-0.01	-0.02	-0.01	-0.02	0.04	0.03	0.03	0.03	-0.05	0.07	0.08	0.06	-0.09	-0.07	-0.15	0.2	1		
18	LEA non-interactive	0.06	0.06	0.06	0.07	0.01	0.05	0.01	0.01	0.01	-0.02	-0.1	-0.06	0.19	0.15	0.05	-0.21	-0.34	1	
19	LEA barriers (avg.)	0.03	0.03	0.04	0.05	0.01	0.07	0.03	-0.01	-0.08	0.04	-0.03	0.01	0.09	0.08	0.18	-0.33	0.3	0.55	1

(b) LAD Variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Revenue new prods (Log)	1																		
2	Rev. new & imp. prods (Log)	0.94	1																	
3	Sales new prods (%)	0.7	0.64	1																
4	Sales new & imp. prods (%)	0.71	0.77	0.86	1															
5	Employment (Log)	0.16	0.17	-0.02	0.01	1														
6	R&D Investment	0.45	0.46	0.31	0.37	0.12	1													
7	Design investment	0.39	0.4	0.28	0.33	0.1	0.49	1												
8	Science Graduates	0.18	0.19	0.18	0.21	0.01	0.22	0.16	1											
9	Other Graduates	0.07	0.07	0.07	0.08	0.06	0.09	0.07	0.14	1										
10	Exporter	0.26	0.26	0.15	0.17	0.14	0.31	0.24	0.23	0.09	1									
11	Interactive search	0.39	0.4	0.28	0.32	0.12	0.35	0.32	0.2	0.05	0.19	1								
12	Interactive search sqrd.	0.32	0.33	0.24	0.27	0.11	0.28	0.27	0.18	0.04	0.15	0.94	1							
13	Non-interactive search	0.32	0.33	0.22	0.27	0.14	0.34	0.29	0.19	0.09	0.17	0.34	0.3	1						
14	Non-interactive search sqrd.	0.28	0.29	0.2	0.23	0.13	0.29	0.25	0.17	0.09	0.15	0.31	0.28	0.96	1					
15	LAD SOC 7-9	-0.01	-0.01	-0.01	-0.02	-0.05	-0.02	0.01	-0.1	-0.14	-0.04	-0.02	-0.02	-0.01	-0.02	1				
16	LAD NVQ3+	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.1	0.13	0.02	0.03	0.02	-0.01	0.01	-0.74	1			
17	LAD interactive	0.01	0.01	0.01	0.01	0.03	0.03	0.03	0.03	-0.02	0.05	0.06	0.04	-0.03	-0.02	-0.05	0.03	1		
18	LAD non-interactive	0.05	0.06	0.05	0.06	0.02	0.05	0.01	0.02	0.01	-0.01	-0.07	-0.04	0.16	0.14	0.01	-0.1	0.07	1	
19	LAD barriers (avg.)	0.05	0.05	0.05	0.05	0.01	0.08	0.05	0.01	-0.06	0.04	0.01	0.03	0.1	0.09	0.11	-0.2	0.29	0.45	1

Sources: Combined data from UKIS 4-7, see annex for variable definitions.

Table 3: Sales revenue from new products by LEA (Log)

VARIABLES	(1) All	(2) Manufact.	(3) Services	(4) Small	(5) Medium	(6) Large
Employment (Log)	0.112*	0.350***	-0.00285	-0.321	0.423	0.570***
	(0.0625)	(0.0854)	(0.0867)	(0.204)	(0.318)	(0.0189)
R&D Investment	4.938***	4.625***	4.819***	4.789***	5.090***	5.356***
	(0.190)	(0.249)	(0.261)	(0.224)	(0.336)	(0.109)
Design investment	2.727***	2.732***	2.710***	2.757***	2.520***	2.955***
	(0.187)	(0.225)	(0.269)	(0.225)	(0.327)	(0.0987)
Science Graduates	0.00610	0.0136*	0.00630	0.00247	0.0151	0.0428***
	(0.00503)	(0.00708)	(0.00619)	(0.00573)	(0.00935)	(0.00253)
Other Graduates	0.0167***	0.0105	0.0199***	0.0152***	0.0192**	0.0216***
	(0.00466)	(0.00787)	(0.00565)	(0.00538)	(0.00859)	(0.00193)
Exporter	1.149***	1.207***	0.997***	1.043***	1.723***	0.890***
	(0.192)	(0.240)	(0.263)	(0.224)	(0.361)	(0.103)
Interactive search	2.257***	1.889***	2.403***	2.188***	2.406***	2.632***
	(0.142)	(0.158)	(0.199)	(0.173)	(0.221)	(0.0257)
Interactive search sqrd.	-0.247***	-0.208***	-0.261***	-0.240***	-0.274***	-0.262***
	(0.0245)	(0.0272)	(0.0339)	(0.0301)	(0.0370)	(0.00386)
Non-interactive search	2.265***	1.439***	2.643***	2.234***	2.496***	2.148***
	(0.211)	(0.239)	(0.298)	(0.254)	(0.339)	(0.0386)
Non-interactive search sqrd.	-0.456***	-0.270***	-0.553***	-0.457***	-0.516***	-0.357***
	(0.0547)	(0.0622)	(0.0771)	(0.0674)	(0.0863)	(0.00929)
LEA SOC 7-9	0.0438	-0.0386	0.0692*	0.0508	0.0165	0.00409
	(0.0288)	(0.0380)	(0.0392)	(0.0339)	(0.0498)	(0.00455)
LEA NVQ3+	0.0386	-0.0495	0.0716*	0.0292	0.0708	0.0555***
	(0.0277)	(0.0341)	(0.0388)	(0.0319)	(0.0483)	(0.00253)
LEA interactive	1.365	2.542**	0.541	1.117	2.314	1.024***
	(0.989)	(1.144)	(1.427)	(1.152)	(1.635)	(0.196)
LEA non-interactive	-1.482	-2.887**	-0.445	-1.412	-1.841	-0.503***
	(1.212)	(1.423)	(1.746)	(1.407)	(2.090)	(0.127)
LEA barriers (avg.)	-0.0940	-0.208	0.114	-0.334	1.094	0.0414
	(0.450)	(0.553)	(0.652)	(0.522)	(0.774)	(0.0515)
Constant	-8.359**	-4.026	-15.86***	-6.165*	-11.90**	-54.98***
	(3.322)	(3.254)	(3.401)	(3.730)	(5.368)	(0.124)
Observations	28,797	8,441	17,700	14,877	7,230	6,690

Notes and sources: Combined data from UKIS 4-7, see annex for variable definitions. Coefficients are reported. Robust standard errors in parentheses control for possible cluster of reporting units belonging to the same enterprise. *****p<0.01, **p<0.05, *p<0.1.

Table 4: Sales from new products by LEA (%)

VARIABLES	(1) All	(2) Manufact.	(3) Services	(4) Small	(5) Medium	(6) Large
Employment (Log)	-3.789***	-2.832***	-4.254***	-7.068***	-0.362	-0.0886
	(0.474)	(0.508)	(0.706)	(1.610)	(1.424)	(0.0737)
R&D Investment	30.94***	25.27***	32.50***	33.58***	21.55***	18.77***
	(1.403)	(1.584)	(2.037)	(1.783)	(1.806)	(0.404)
Design investment	17.50***	15.72***	18.46***	19.25***	12.90***	10.91***
	(1.331)	(1.409)	(2.032)	(1.742)	(1.647)	(0.368)
Science Graduates	0.0986***	0.166***	0.0994**	0.0919**	0.0878*	0.156***
	(0.0369)	(0.0510)	(0.0474)	(0.0457)	(0.0472)	(0.00978)
Other Graduates	0.144***	0.0844*	0.172***	0.154***	0.0822*	0.0888***
	(0.0315)	(0.0497)	(0.0400)	(0.0392)	(0.0443)	(0.00733)
Exporter	5.796***	4.958***	5.477***	5.840***	7.056***	1.392***
	(1.384)	(1.393)	(2.004)	(1.764)	(1.785)	(0.398)
Interactive search	13.60***	9.307***	15.76***	15.14***	9.058***	7.691***
	(1.112)	(0.997)	(1.666)	(1.464)	(1.125)	(0.0997)
Interactive search sqrd.	-1.440***	-0.981***	-1.670***	-1.618***	-0.942***	-0.688***
	(0.184)	(0.170)	(0.272)	(0.243)	(0.194)	(0.0150)
Non-interactive search	14.28***	7.210***	18.24***	15.59***	10.71***	6.250***
	(1.468)	(1.444)	(2.190)	(1.922)	(1.603)	(0.147)
Non-interactive search sqrd.	-2.828***	-1.257***	-3.779***	-3.109***	-2.116***	-0.926***
	(0.379)	(0.381)	(0.563)	(0.506)	(0.416)	(0.0354)
LEA SOC 7-9	0.340*	-0.161	0.561**	0.405	0.195	0.312***
	(0.198)	(0.233)	(0.282)	(0.252)	(0.234)	(0.0177)
LEA NVQ3+	0.219	-0.271	0.463	0.181	0.319	0.422***
	(0.193)	(0.200)	(0.288)	(0.242)	(0.223)	(0.00987)
LEA interactive	11.55*	17.97**	6.719	12.38	7.132	5.881***
	(6.732)	(6.985)	(10.24)	(8.592)	(7.260)	(0.764)
LEA non-interactive	-6.039	-18.73**	1.723	-5.731	-6.249	-5.850***
	(8.417)	(8.461)	(12.90)	(10.67)	(9.670)	(0.489)
LEA barriers (avg.)	-3.129	-2.620	-2.641	-5.117	3.866	-2.429***
	(2.997)	(3.300)	(4.585)	(3.811)	(3.530)	(0.200)
Constant	-21.60	-11.15	-100.1***	-11.84	-45.79*	-198.3***
	(26.00)	(18.93)	(24.95)	(31.40)	(24.13)	(0.483)
Observations	30,337	8,729	18,806	15,850	7,515	6,972

Notes and sources: Combined data from UKIS 4-7, see annex for variable definitions. Coefficients are reported. Robust standard errors in parentheses control for possible cluster of reporting units belonging to the same enterprise. *******p<0.01, **p<0.05, *p<0.1.

Table 5: Sales revenue from new products by LAD (Log)

VARIABLES	(1) All	(2) Manufact.	(3) Services	(4) Small	(5) Medium	(6) Large
Employment (Log)	0.112*	0.342***	-0.0158	-0.370*	0.448	0.680***
	(0.0589)	(0.0784)	(0.0834)	(0.192)	(0.296)	(0.0181)
R&D Investment	4.897***	4.677***	4.778***	4.732***	5.067***	5.406***
	(0.178)	(0.230)	(0.246)	(0.208)	(0.310)	(0.106)
Design investment	2.727***	2.649***	2.763***	2.746***	2.581***	2.890***
	(0.175)	(0.210)	(0.254)	(0.211)	(0.300)	(0.0966)
Science Graduates	0.00702	0.0121*	0.00762	0.00433	0.0104	0.0399***
	(0.00478)	(0.00681)	(0.00588)	(0.00542)	(0.00873)	(0.00254)
Other Graduates	0.0162***	0.0109	0.0194***	0.0143***	0.0198**	0.0222***
	(0.00455)	(0.00747)	(0.00557)	(0.00531)	(0.00818)	(0.00192)
Exporter	1.172***	1.151***	1.040***	1.062***	1.755***	0.757***
	(0.181)	(0.225)	(0.250)	(0.212)	(0.336)	(0.101)
Interactive search	2.279***	1.888***	2.380***	2.229***	2.311***	2.650***
	(0.133)	(0.147)	(0.189)	(0.163)	(0.203)	(0.0252)
Interactive search sqrd.	-0.252***	-0.206***	-0.258***	-0.249***	-0.257***	-0.267***
	(0.0229)	(0.0253)	(0.0320)	(0.0283)	(0.0339)	(0.00378)
Non-interactive search	2.273***	1.469***	2.679***	2.233***	2.456***	2.208***
	(0.197)	(0.223)	(0.281)	(0.238)	(0.313)	(0.0374)
Non-interactive search sqrd.	-0.446***	-0.281***	-0.543***	-0.442***	-0.501***	-0.362***
	(0.0511)	(0.0576)	(0.0731)	(0.0632)	(0.0794)	(0.00903)
LAD SOC 7-9	0.00919	-0.00825	0.0141	0.0176	-0.0256	-0.0246***
	(0.0164)	(0.0215)	(0.0224)	(0.0194)	(0.0284)	(0.00399)
LAD NVQ3+	-0.000866	-0.00441	-0.00353	-0.00213	0.00383	-0.00746***
	(0.0130)	(0.0169)	(0.0181)	(0.0153)	(0.0234)	(0.00234)
LAD interactive	0.822**	0.306	1.104**	0.945**	-0.0353	1.417***
	(0.322)	(0.369)	(0.467)	(0.370)	(0.515)	(0.148)
LAD non-interactive	-1.233***	-1.064**	-1.118**	-1.315***	-0.980	-0.151
	(0.392)	(0.507)	(0.555)	(0.457)	(0.660)	(0.114)
LAD barriers (avg.)	0.411***	0.253	0.414*	0.477***	0.107	0.0260
	(0.157)	(0.185)	(0.230)	(0.183)	(0.260)	(0.0467)
Constant	-7.574***	-8.307***	-11.93***	-6.487**	-5.190	-51.87***
	(2.441)	(1.831)	(1.938)	(2.684)	(3.908)	(0.119)
Observations	33,357	9,968	20,113	17,377	8,658	7,322

Notes and sources: Combined data from UKIS 4-7, see annex for variable definitions. Coefficients are reported. Robust standard errors in parentheses control for possible cluster of reporting units belonging to the same enterprise. *****p<0.01, **p<0.05, *p<0.1.

Table 6: Sales from new products by LAD (%)

VARIABLES	(1) All	(2) Manufact.	(3) Services	(4) Small	(5) Medium	(6) Large
Employment (Log)	-3.699***	-2.697***	-4.315***	-7.159***	-0.257	0.305***
	(0.444)	(0.461)	(0.684)	(1.517)	(1.345)	(0.0694)
R&D Investment	30.78***	25.34***	32.61***	33.32***	21.97***	18.72***
	(1.304)	(1.459)	(1.922)	(1.658)	(1.685)	(0.384)
Design investment	17.46***	15.13***	18.92***	19.25***	12.96***	9.777***
	(1.248)	(1.306)	(1.937)	(1.638)	(1.526)	(0.354)
Science Graduates	0.109***	0.160***	0.113**	0.107**	0.0709	0.144***
	(0.0351)	(0.0486)	(0.0453)	(0.0434)	(0.0448)	(0.00957)
Other Graduates	0.138***	0.0855*	0.165***	0.146***	0.0850**	0.0836***
	(0.0306)	(0.0468)	(0.0393)	(0.0383)	(0.0422)	(0.00714)
Exporter	5.901***	4.639***	5.722***	6.040***	6.943***	0.817**
	(1.314)	(1.294)	(1.934)	(1.679)	(1.665)	(0.382)
Interactive search	13.74***	9.024***	15.80***	15.49***	8.499***	7.635***
	(1.040)	(0.917)	(1.580)	(1.379)	(1.035)	(0.0952)
Interactive search sqrd.	-1.476***	-0.939***	-1.678***	-1.696***	-0.819***	-0.695***
	(0.172)	(0.158)	(0.258)	(0.229)	(0.179)	(0.0143)
Non-interactive search	14.24***	7.414***	18.52***	15.47***	10.82***	6.772***
	(1.376)	(1.337)	(2.092)	(1.810)	(1.493)	(0.140)
Non-interactive search sqrd.	-2.750***	-1.325***	-3.748***	-2.989***	-2.136***	-0.989***
	(0.355)	(0.351)	(0.539)	(0.477)	(0.386)	(0.0337)
LAD SOC 7-9	0.107	0.0128	0.148	0.163	-0.0899	0.0277*
	(0.115)	(0.128)	(0.168)	(0.149)	(0.133)	(0.0153)
LAD NVQ3+	0.0321	0.0208	0.0149	0.0348	0.0126	0.0476***
	(0.0883)	(0.0991)	(0.131)	(0.113)	(0.108)	(0.00894)
LAD interactive	6.319***	2.214	8.753**	7.796**	0.130	5.214***
	(2.427)	(2.158)	(3.781)	(3.049)	(2.425)	(0.562)
LAD non-interactive	-5.579**	-5.443*	-4.889	-5.987*	-4.343	-4.167***
	(2.726)	(3.224)	(4.061)	(3.449)	(3.229)	(0.432)
LAD barriers (avg.)	1.488	0.870	1.366	1.826	0.509	0.510***
	(1.063)	(1.090)	(1.654)	(1.362)	(1.231)	(0.178)
Constant	-22.91	-39.63***	-77.99***	-20.77	-15.35	-181.4***
	(19.89)	(10.33)	(13.86)	(23.42)	(18.08)	(0.454)
Observations	35,140	10,309	21,377	18,516	9,005	7,619

Notes and sources: Combined data from UKIS 4-7, see annex for variable definitions. Coefficients are reported. Robust standard errors in parentheses control for possible cluster of reporting units belonging to the same enterprise. ***p<0.01, **p<0.05, *p<0.1.

Annex 1: Variable definitions

Revenue new prods (Log)	Log of sales revenue from new products. Sales revenue from new products is calculated as the product of the proportion of firms' sales from new products and turnover at the end of the survey reference period. Source: UKIS
Rev. new & imp. prods (Log)	As above using the proportion of firms' sales derived from new or improved products. Source: UKIS
Sales new prods (%)	The proportion of firms' sales derived from new products at the end of each survey reference period. Source: UKIS
Sales new & imp. prods (%)	The proportion of firms' sales derived from new and improved products at the end of each survey reference period. Source: UKIS
Employment (Log)	Log of employment at the start of the survey reference period. Source: UKIS
R&D Investment	Binary variable taking value 1 where a firm engages in either intra-mural or extra-mural R&D. Source: UKIS
Design investment	Binary variable taking value 1 where a firm invests in design as part of its innovation activity. Source: UKIS
Science Graduates	Proportion of the firm's workforce which have a science, engineering or technology degree or equivalent. Source: UKIS
Other Graduates	Proportion of the firm's workforce which have a degree or equivalent in a non-technical discipline. Source: UKIS
Exporter	Binary variable taking value 1 if the firm is exporting. Source: UKIS
Interactive search	Count variable taking values 0 to 7 depending on the number of partner types with which the firm is collaborating as part of its innovation activity. Source: UKIS
Non-interactive search	Count variable taking values 0 to 4 depending on the number of partner types with which the firm is collaborating as part of its innovation activity. Source: UKIS
LEA SOC 7-9	The percentage of all employment that is categorised into SOC (2010) groups 7-9 (i.e. Sales and Customer Service Occupations; Process, Plant and Machine Operatives; and Elementary Occupations). Source: NOMIS
LEA NVQ3+	The percentage of all in employees in the LEA which are qualified to apprenticeship level or equivalent (i.e. NVQ level 3) or above. Source: NOMIS
LEA interactive	For each firm, the mean level of interactive search among all other firms in the LEA in which the firm is located. Source: UKIS
LEA non-interactive	For each firm, the mean level of non-interactive search among all other firms in the LEA in which the firm is located. Source: UKIS
LEA barriers (avg.)	For each firm, the average number of barriers to innovation which other firms in the LEA are indicated was of 'medium' or 'high' importance. Source: UKIS

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