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Firms' knowledge search and local knowledge externalities in innovation performance

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ABSTRACT

We use an augmented version of the UK Innovation Surveys 4–7 to explore firm-level and local area openness externalities 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. We also find strong positive externalities of openness resulting from the intensity of local interactive knowledge search—a knowledge diffusion effect. However, there are strong negative externalities resulting 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. We find no significant relationship between either local labour quality or employment composition and innovative outputs.

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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 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 et al., 2012; Vaccaro et al., 2012). In England, for example, 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 knowledge context influence firms' innovation performance. It is now well established that the ability to access and absorb external knowledge is central to innovation for most firms (Chesbrough, 2006; Dahlander and Gann, 2010), and that the knowledge underlying innovation has some degree of spatial specificity (Storper and Venables, 2004; He and Wong, 2012; Toedtling et al., 2011). From both an academic and a policy perspective, there is therefore interest in considering how firms access and use external knowledge both from their own direct knowledge sourcing, and from the wider local context.

Our analysis makes three main contributions to the developing literature on the role of contextual factors on innovation performance. First, 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 providing access to otherwise inaccessible resources. Second, we explore the potential for local spillovers or externalities

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[1] 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).

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of openness to arise from the local intensity of firms' interactive and non-interactive knowledge search (Roper et al., 2013). Here, the anticipated effects are complex, with both types of knowledge 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. Third, we consider how the effects of both firm-level knowledge sourcing and externalities of openness may differ between larger and smaller enterprises. This is important because of the evidence that small firms access and use knowledge in the innovation process differently from larger enterprises (van de Vrande et al., 2009; Vahter et al., 2014). Throughout the analysis we allow for other relevant aspects the local environment on firms' innovation activity such as local occupational mix, labour quality, and the perceived barriers to innovation.

The remainder of the paper is organised as follows. In Section 2 we outline our conceptual framework which considers how local knowledge conditions may influence anticipated post innovation returns and hence firms' willingness to invest in innovation. Section 3 considers data and methods. Our analysis is based on data from the UK Innovation Surveys (UKIS) which cover the period 2002–2010 matched with other UK data which allows us to place UKIS observations in specific localities. Sections 4 and 5 consider our key empirical results. We conduct our analysis for two alternative levels of geographical disaggregation: Local Enterprise Areas (LEAs—the domain of Local Enterprise Partnerships), of which there are 39 in England, and more disaggregated Local Authority Areas (LAs) of which there are around 220. While the overall results from both levels of analysis prove very similar, there are subtle differences which suggest that the spatial scale over which knowledge externalities are influential varies between larger and smaller firms. Section 6 considers the implications.

2. Localised knowledge and 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, 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 et al., 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). 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 et al., 2011; Jensen and Tragardh, 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.[2] On the basis of an examination of technology diffusion in the flat-screen television sector, for example, Spencer (2003)[3] 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 Ferriani et al. (2016) also highlight the 'anchoring' role of multinational firms and universities.

This suggests that the knowledge-sourcing activities of individual firms, as well as the knowledge richness the areas in which they operate, will influence innovation at the firm level. It also suggests that firms may vary in their capacity both to engage in knowledge sourcing activities, and to take advantage of the local knowledge infrastructure. In the sections that follow we develop hypotheses which identify these possible effects.

2.1. 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 et al., 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.

[2] This is not to suggest – for the moment – that the extent or density of firms' own networks do or do not matter for innovation but rather that the extent of networking activity in the area in which a firm is located may be influential (Belussi et al., 2011; Spencer, 2003)

[3] Comparing the diverse experience of US and Japanese networks Spencer (2003) also suggests that cultural factors may also shape network structure: Corporatist countries are more likely to have greater network density than pluralist countries.

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 et al., 2013; Love et al., 2014). 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.[4] 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 et al., 2013). This leads to our first hypothesis:

Hypothesis 1. Interactive and non-interactive linkages are positively linked to innovation performance, but at a decreasing rate.

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. Thus, not only do managers learn to manage existing knowledge sources more efficiently (through the development of routines), they also learn to cope effectively with greater breadth of such linkages through time (via improvements in managerial cognition) (Powell et al., 1996; Love et al., 2014).

2.2. 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 et al., 2009; Storper and

[4] For example, in their analysis of university-business connections Hewitt-Dundas and Roper (2011) distinguish between knowledge connections 'characterised by a two-way flow of knowledge, e.g. through formal or informal joint ventures or collaborative R&D projects', and knowledge suppliers 'characterised by a more uni-directional transfer of knowledge'.

Venables, 2004), especially in the diffusion of tacit or un-codified knowledge (Asheim et al., 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'. 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.

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.

This leads to our second set of hypotheses:

Hypothesis 2a. Externalities of interactive openness are positively associated with firm-level innovation.

Hypothesis 2b. Externalities of non-interactive openness are negatively associated with firm-level innovation.

2.3. The role of firm size

There is now clear evidence that smaller firms can gain more than their larger counterparts from external knowledge sourcing, but that small firms experience the limits to 'openness' at lower levels of openness than larger plants (Vahter et al., 2014). Weaker internal knowledge resources and ability to invest in in-house knowledge creation make external sourcing of knowledge especially important for small firms (Leiponen and Byma, 2009). As small firms start, on average, with lower overall levels of knowledge resources, adding more or new sources of innovation knowledge is likely to have a larger proportionate effect on them. However, due to their smaller top management teams and therefore potentially lower capacity to organise and manage large sets of external linkages, Vahter et al. (2014) find that the limit to benefit from additional knowledge sources is reached more quickly among small firms than larger ones.

This firm size effect may have parallels with respect to the externalities of openness. The richness of local knowledge environment is more likely to be of benefit to smaller enterprises. They have the more to benefit from local knowledge as a result of limited internal capacity, and they are more likely than larger enterprises to have a predominantly local knowledge environment, especially in the diffusion of tacit or un-codified knowledge (Asheim et al., 2007; He and Wong, 2012). By contrast, by virtue of their greater absorptive capacity, larger firms can access and use knowledge from a much larger hinterland and typically have a larger and more intensive network of knowledge sourcing linkages than smaller enterprises (Love et al., 2014), and are therefore less likely to be limited to local knowledge sources. As a result, we might expect smaller firms to be more affected by the localised openness externalities discussed above.

Hypothesis 3. Externalities of openness effects on innovation are stronger for smaller enterprises.

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 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:

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

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 (largely) rational and we regard

$$\pi_i = \beta_0 + \beta_1 RBASE_i + \beta_2 ITECH_k + \eta_i \quad (2)$$

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

$$RD_i = \theta_{10} + \theta_{12} RBASE_i + \gamma_{13} LK_j + \theta_{14} ITECH_k + \lambda_1$$
$$IKS_i = \theta_{20} + \theta_{22} RBASE_i + \gamma_{23} LK_j + \theta_{24} ITECH_k + \lambda_2 \quad (3)$$
$$NKS_i = \theta_{30} + \theta_{32} RBASE_i + \gamma_{33} LK_j + \theta_{34} ITECH_k + \lambda_3$$

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 et al., 2008):

$$INNOV_i = \phi_0 + \phi_1 RD_i + \phi_2 IKS_i + \phi_3 NKS_i + \chi_1 RBASE + \chi_2 LK + \chi_3 ITECH + \mu_i \quad (4)$$

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%.[5]

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 Authority District (LAD) 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.[6] Once each UKIS respondent had been allocated a postcode these were then matched into LADs and these, in turn, were matched into the larger LEA areas.

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.

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 et al., 2008; Love et al., 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% 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 and Helfat (2010). Unsurprisingly perhaps our two innovation output indicators are relatively strongly and positively related having a correlation coefficient of 0.70 (Table 2). The Tobit estimator is used in all estimations.

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).[7] 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 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.

[5] 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.

[6] 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.

[7] 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).

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.

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.[8] 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 et al., 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 et al., 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 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/LAD we take a simple average of the intensity of interactive knowledge search firms among firms in each area (Roper et al., 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'

[8] Inevitably there may be forms of knowledge gathering that will be at the boundaries of this distinction. For example, contract research and in-licensing are methods of acquiring external knowledge with relatively little interaction. However, they do consciously engage two parties, and clearly have two-way resource transfer (payment one way and knowledge the other). We deliberately restrict our components of non-interactive search in the way described above, as it makes the interactive/non-interactive distinction very explicit empirically.

own intensity of interactive search is already included as a separate variable in Eq. (4). We follow a similar procedure to define a similar measure for average non-interactive search intensity in each local area.

To reflect the potential impact of other aspects the local environment 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.[9] 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.[10] 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.[11]

4. Empirical results

Tables 3 and 4 show the results of estimating the innovation production function (Eq. (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 (Crépon et al., 1998; Jordan and O'Leary, 2007; Moultrie and Livesey, 2014), 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 of 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 et al., 2014). Hypothesis 1 is therefore supported.

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 firms and smallest for large firms (columns 4, 5 and 6 respectively). This is illustrated in Figs. 1 and 2, in which the coefficients on the search variables are used to plot the relationship between interactive and non-interactive search and innovation performance (percentage of sales). This finding is consistent with that of Vahter et al. (2014) 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.

There is also 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. Hypotheses 2a and 2b are therefore partly supported, for large firms and manufacturing only. By contrast, there is no support for Hypothesis 3 on firm size and openness externalities: indeed, the LEA results suggest the reverse effect.

Turning to the other 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

[9] 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.

[10] 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.

[11] 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.

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	8441	17,700	14,877	7230	6690

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.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

medium-sized enterprises, skills at LEA level appear not to matter for innovation outputs.

5. Robustness tests

We carry out a number of 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 et al., 2003; Shefer and Frenkel, 1998)? Finally, we allow for the effect of local R&D intensity and for interactions between firm-level search and local economic conditions.

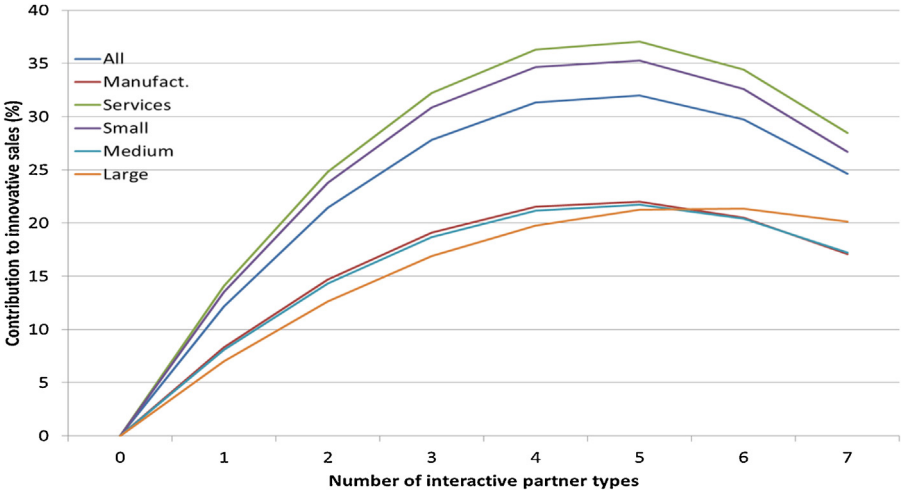

Fig. 1. Relationship between number of different types of interactive partners and innovation performance.

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	8729	18,806	15,850	7515	6972

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.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

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. 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

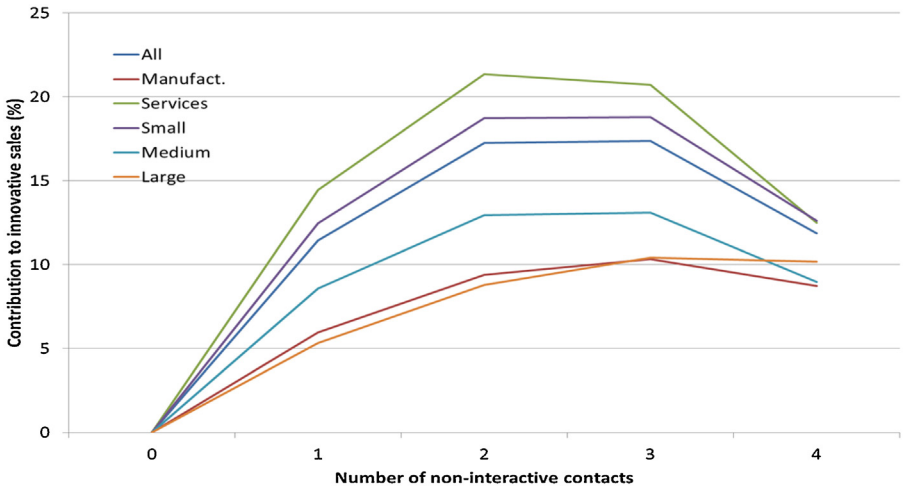

Fig. 2. Relationship between number of different types of non-interactive knowledge sources and innovation performance.

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	9968	20,113	17,377	8658	7322

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.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

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 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: indeed, at LAD level openness externality effects are generally greater for small enterprises than for their large counterparts. 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, suggesting support for Hypothesis 3 at the very local level

Our second robustness test relates to the potential endogeneity of firm location and its potential influence on the modelled relationships. Here, the potential issue is that firms might select to locate in areas with 'good' local innovation ecosystems. We therefore 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.[12] Of these the vast majority 83.9% (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 5000 firms which changed their postcode around 3000 stayed within an individual LAD, 2000 firms (6.4%) moved postcode and LAD, and 900 (2.9%) 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.

Finally, we make allowance for the average level of R&D intensity in the local area and for interactions between firm-level search and local economic conditions. Local R&D intensity could be regarded as another indicator of a favourable economic environment (Sofka and Grimpe, 2010). In additional estimations, measures of R&D intensity proved to be wholly insignificant in all estimations at both the LEA and LAD levels. We also tested for the

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

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	9005	7619

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.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

possibility that interactive and non-interactive knowledge search is more productive where local economic conditions are favourable by interacting both firm-level search variables with the indicators of local economic conditions. In all cases these interactions proved to have statistically insignificant coefficients, and there was no systematic change in any of the other coefficients.

6. 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 how elements of the local knowledge context (at both LEA and LAD level) and firms' own knowledge gathering activities influence their 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 et al., 2003). Second, increments to skill levels will also benefit innovation output alongside any related gains in productivity (Jacobs et al., 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 (Chesbrough, 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, interactive search involved 0.7 partners (Table 1), well below the optimal level of around 5 partners suggested by our estimation (Fig. 1). Similarly, non-interactive search involved an average of 0.9 contacts, again well below the estimated optimum of around 2.5 (Fig. 2). 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.[13] 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 et al., 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.

Our other main 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 et al., 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.

In terms of other local effects on firms' innovation 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 results provide some guidance for local policy-makers seeking to boost local innovation outputs, over and above efforts which might be made to strengthen local firms' internal innovation capabilities. In particular, our results emphasise the value of local policy interventions to build interactive or collaborative partnerships between firms. Not only do these relationships benefit the participating firms but they generate wider local benefits by stimulating knowledge creation and diffusion. Moreover, these relationships particularly benefit smaller firms. Greater care appears necessary in terms of the potential negative impacts which can arise from local non-interactive search. Here, it seems more beneficial to encourage firms to search for knowledge for innovation more widely than their immediate locality to avoid intensifying local competition between innovations. Trade missions, attending national or international trade fairs or national benchmarking initiatives would all maximise the search benefit while minimising any risk of intensified local competition.

Finally, it is worth noting some of the limitations of our analysis, and possible areas for future research. 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 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. A more comprehensive treatment of local area influences might also involve the use of, for example, a multilevel modelling approach which allows for the decomposition of the multiple levels of heterogeneity in firm-level innovation performance. 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.

[13] 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).

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The statistical data used here is from the Office of National Statistics (ONS) and is Crown copyright and reproduced with the permission of the controller of HMSO and Queens Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. The analysis upon which this paper is based uses research datasets which may not exactly reproduce National Statistics aggregates. We are grateful for the thoughtful comments of three referees and the editor.

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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