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To what extent do external sources of knowledge affect the innovative performance of knowledge intensive entrepreneurial firms? The effects of depth and breadth of openness on manufacturing and service innovations

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Abstract

This paper examines the effects of breadth and depth of external knowledge sourcing on the innovativeness of a specific classification of organization, the knowledge intensive entrepreneurial (KIE) firm. This type of firm has been observed as being critically important to growth and development in modern economies, yet how it uses external knowledge sources for innovation has received little direct attention in the literature. Using data from the EU?s recent AEGIS project, investigating knowledge intensive entrepreneurship in Europe covering just over 4000 entrepreneurial firms, this paper uses fractional logit models, as well as an OLS model based on alternating least squares optimal scaling (ALSOS), to estimate the relationship between breadth and depth of external knowledge sourcing and that of innovative performance of the KIE firm. We find that breadth is curvi-linearly related to innovative performance in KIE firms, but that depth, while related to innovativeness, does not assume this functional form. Additionally, a principal components analysis reveals that non-industry sources of knowledge in the form of state, national, or regional research-based or academic entities, as well as knowledge in the form of academic and trade publications, are statistically significant/relevant as external sources of knowledge for innovation in KIE firms. Industry sources of knowledge such as clients, customers, and supplier are statistically significant sources only for innovation in goods, not in terms of innovation in services, or novelty of innovations produced. Recommendations for future research and policy implications are provided based on these findings.

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This paper examines the effects of breadth and depth of external knowledge sourcing on the innovativeness of a specific classification of organization, the knowledge intensive entrepreneurial (KIE) firm. This type of firm has been observed as being critically important to growth and development in modern economies, yet how it uses external knowledge sources for innovation has received little direct attention in the literature. Using data from the EU's recent AEGIS project, investigating knowledge intensive entrepreneurship in Europe covering just over 4000 entrepreneurial firms, this paper uses fractional logit models, as well as an OLS model based on alternating least squares optimal scaling (ALSOS), to estimate the relationship between breadth and depth of external knowledge sourcing and that of innovative performance of the KIE firm. We find that breadth is curvi-linearly related to innovative performance in KIE firms, but that depth, while related to innovativeness, does not assume this functional form. Additionally, a principal components analysis reveals that non-industry sources of knowledge in the form of state, national, or regional research-based or academic entities, as well as knowledge in the form of academic and trade publications, are statistically significant/relevant as external sources of knowledge for innovation in KIE firms. Industry sources of knowledge such as clients, customers, and supplier are statistically significant sources only for innovation in goods, not in terms of innovation in services, or novelty of innovations produced. Recommendations for future research and policy implications are provided based on these findings.

1. Introduction

External sources of knowledge are known to impact innovation within large manufacturing firms. Seminal papers based upon the Yale survey of R&D managers in different industries demonstrate not only that external knowledge sources were vital to R&D and innovation within firms, but also that the technological opportunities, the appropriability regimes, and the types of partners to access knowledge could differ by industry (Levin et al., 1987; Klevorick et al., 1995). More recently, the technology and innovation management literature proposes that firms use collaborations and networks in order to access different types of knowledge and in order to explore and exploit ideas as innovations for the market. Especially for large firms in manufacturing, this literature has long focused upon collaboration as a means for firms to access, and utilize, knowledge from a wide range of partners

(Dodgson et al., 2014). In recent years, one influential concept has been 'open innovation', which is "a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as [they] look to advance their technology" (Chesbrough, 2003:XXIV). Dahlander and Gann (2010) argue that the literature has focused upon the potential positive effects of open innovation, while pointing out the limitations and risks of open innovation to the firm. According to Gassmann et al. (2010:215-217), 'while most of the firms described in early works on open innovation were large multinational firms', trends for contemporary research are to start to understand openness in the context of small and medium firms (SMEs) and of service innovations. A few papers have begun to address openness in the context of SMEs (Keupp and Gassmann 2007; van de Vrande et al. 2010; Love et al. 2014), and the literature has identified differences between manufacturing and service innovations as well. This paper contributes to this emergent literature by analyzing the extent to which entrepreneurial SME firms' innovation performance is affected by their external search breadth and depth, that is, the number and importance of different types of external sources of knowledge used by the firm, in both manufacturing and in services.

Our focus is upon a particular type of entrepreneurial firms. The literature provides many concepts to categorize sub-sets of entrepreneurial firms. Indeed, although the importance of new and established small firms has been established for several decades as a vital component of economic growth and industrial change (Birch, 1979; Rothwell and Zegveld, 1982; Rothwell, 1989), this statement is a broad one, which includes small firms that have been established for many years as well as entrepreneurial ventures, associated with the start-up of new ventures.

Recent streams of research focus upon the particular importance of a sub-set of these start-ups, or entrepreneurial, firms that are argued to grow and impact the economy more than other types. The key conceptualization which underlies several of these streams of literature is that innovative entrepreneurial firms seem to contribute more to economic growth than other types of small firms.

Birch et al. (1995) defined 'gazelles' as high growth firms, which generate new jobs in the economy, and the literature on gazelles is reviewed in Henreksen and Johansson (2010). The 'born global' firm is another concept, capturing the idea of rapid international sales from an early stage in the development of the venture (Knight, 2010). The concept of 'technology based firms' captures firms in high-tech sectors reliant upon technology (Yli-Renko et al., 2001), whereas the roles of technology for competitiveness has also been stressed in the work by Audretsch and colleagues (Acs and Audretsch, 2003; Audretch et al., 2006). Another stream of literature calls these firms knowledge intensive entrepreneurial (KIE) ventures. The KIE venture concept is used to capture a population consisting of new firms, with significant knowledge intensity, who are innovative, and which exploit innovative opportunities across sectors from high tech to low tech and from manufacturing to services (Malerba et al., 2015; Malerba, 2010; McKelvey and Lassen 2013a; McKelvey and Lassen 2013b).

By focusing upon KIE ventures, this paper can use a large dataset. As part of the EU project AEGIS, a survey of 4004 firms fulfilling the criteria for the KIE venture definition was conducted, covering 22 sectors at the 2-digit NACE codes across 10 European countries. The KIE venture concept, used in this paper, has been developed to more specifically analyze how and why these entrepreneurial firms use knowledge and innovations to compete, across high tech and low tech sectors as well as across manufacturing and service innovations (Malerba and McKelvey, 2015). Following the tradition of innovation surveys to firms (Smith 2006:160), the AEGIS survey asks firms to describe innovation inputs as well as different types of outputs defined in terms of different innovations. Innovations can be classified into many types, although the most common are product innovations and process innovations (Fagerberg 2006:7). Hence, for the purposes of this paper, innovative processes are the development and sale of new or significantly improved products or services, while entrepreneurial processes are the identification and exploitation of new business opportunities.

Section 2 provides a literature overview focusing upon why external sources of knowledge may affect both manufacturing and service innovations in KIE ventures, which leads to 4 hypotheses for testing. Given that most of the literature refers to SMEs in general, rather than KIE ventures specifically, we will take that literature as our point of departure to understand why SMEs can use – or alternatively have trouble using – external sources of knowledge to innovate. Section 3 addresses the research design and methods, including details of the AEGIS study and the variables used to test the constructs. External sources of knowledge, which can be considered as indicators of openness, is analyzed in terms of breadth and depth of partners, based upon the AEGIS large scale survey data. This is followed by some descriptive statistics of the variables of interest. Section 4 provides the empirical results, using a fractional logit model, as well as standard OLS regression performed on rescaled dependent variables using alternating least squares optimal scaling (ALSOS) procedures. Section 5 provides some points of discussion regarding the results, and our conclusions, including also limitations and directions for future research.

2. Literature review and hypotheses

2.1 Why external sources of knowledge may matter for manufacturing innovations in entrepreneurial ventures

The technology and innovation management literature includes a series of contributions which examine the benefits to the firm of being able to collaborate with different types of partners, and how well the firm utilizes is position within a network (Carayannis and Alexander, 1999; Chesbrough, 2003; von Hippel, 1988; Uzzi 1999). Similarly across nations and countries, innovation systems literature examines the actors, the linkages and the role of collaboration and networks amongst firms, in order to explain the relative economic competitiveness of different nations and industries (Edquist, 2006). While the innovation management literature has focused upon networks and collaborations for the large firms, the entrepreneurship literature has focused upon how start-up ventures are dependent upon networks to access resources (see review in McKelvey and Lassen 2013a).

Therefore, a few recent papers have stressed the need to understand how and why networks and collaboration affects innovation within entrepreneurial ventures (Forsman and Ratanen, 2011; van de Vrande et al., 2008; Vanhaverbeke, 2012) [1]. Smaller firms can use networks and inter-organizational collaborations to increase their overall innovative capacity (Szeto, 2000; Caniels, 2005; Forsman, 2011). Moreover, collaborations around technologies may enhance the innovative capacity of firms (Alonso and Bressan, 2014), and achieving better innovative capacity has been argued to be of critical importance for the smallest of firms (Nieto and Santamaría, 2010). Smaller firms which "are aware of and use external information" (de Jong and Marsili, 2006: 221) were found in one study to be better off in terms of introducing successful innovations than those which do not. Likely, the learning capabilities of SMEs are enhanced through cooperative networks (Chell and Banes, 2000; Mäkinen, 2002; Reinl and Kelliher, 2010), and there are performance enhancing properties of learning from and interacting with larger organizations (Anderson and Lööf, 2012). Hence, there are likely positive effects of networks and collaboration on the ability of SMEs to gain improved knowledge, acquire new access to markets, and reduce research and development costs (Glaister and Buckley, 1996; Forsman, 2011).

However, SMEs will also face challenges in accessing external sources of knowledge. The literature suggests that most types of small firms will face challenges, like competition and limited resources, which limit their collaboration with external partners (Kotey and Sheridan, 2004; Franco and Haase, 2010; Thorgren et al., 2012; Alonso and Bressan, 2014). Reasons for their resource constraints range from management, labor skills, lack of finance and information (Cressy and Olofsson, 1997), to lack of owner-specific and organization-specific resources, all of which are crucial for performance and growth (Brush and Chaganti, 1999). Due to their periphery status in production chains, smaller enterprises often face steep challenges when attempting to use networks to increase their competitiveness (Forsman, 2009; 2011). Additional firm capabilities to manage interactions are required for reaping the benefits of a network. Thus, a firm without this capability, or a firm relying on too many sources of knowledge, may experience decreasing returns from collaborations.

[1] Ranging from 0-50 employees, with micro firms being those with 10 employees or less.

While the above benefits and challenges are specific to SMEs, we must also return to the question of why firms use external sources of knowledge to innovate at all – or what is known in the literature as firm search. A substantial body of literature has addressed how firms carry out technological search processes which span boundaries of technological classes and organizations, in the aim of attaining process and product innovation (Laursen, 2012). Indeed, much of the technology and innovation management literature deals with the idea that organization must search for new knowledge in order to innovate. Much of this research has differentiated between search processes which rely on sources that are internal to the firm, and those that rely upon external sources to the firm (Dodgson et al., 2014). An analytical category is also how far away this search is from the existing knowledge base of the firm, known as the difference between local and non-local search processes (Fleming, 2001; Laursen, 2012), and whether these search processes are used for explorative and exploitative aims (March, 1991).

Putting these elements together, the technology and innovation management literature argues that there is a tradeoff between internal and external search strategies in terms of what a firm can gain through search and what it can effectively take advantage of (Laursen, 2012). Search that is more explorative likely relies upon external sources of knowledge and is non-local, and hence it involves conscious steps to move beyond or away from current routines and knowledge, and into domains that are new to the firm (Katila and Ahuja, 2002; Laursen, 2012). In contrast, search that is more exploitative in terms of commercialization more likely relies upon utilizing in-house sources of knowledge, and hence that which lies within the current knowledge base as embodied within the firm (Helfat, 1994; Fleming and Sorenson, 2004).

Thus, in this paper, the extent to which the KIE ventures rely upon external sources of knowledge can be seen as openness. Openness is defined as, the degree to which firms are open to external sources of knowledge in their innovative and entrepreneurial processes. Following the definition in (Laursen and Salter, 2006: 134), search breadth is here defined as the "number of external sources or search channels that firms rely upon", where search depth is the "extent to which firms draw deeply from the different external sources or search channels". While their focus was on manufacturing firms, this paper focuses upon these concepts for KIE ventures.

In understanding why firms search by utilizing external sources of knowledge for innovations, the literature has also pointed out that the benefits to the firm of searching can be different under different conditions. The notion of over-search is exemplified in Katila and Ahuya's (2002) work on exploitative search processes within the firm in terms of depth and scope, and later in Laursen and Salter's (2006) work with explorative search processes. The idea of over-searching, in both instances, emphasizes that since search strategies are influenced by past managerial behavior and future expectations, the outcome of carrying out too many search processes could have diminishing returns for the firm and even lead to a detrimental outcome (Laursen and Salter, 2006, p. 136). The same rationale follows for the depth construct: That too deep reliance on partners could lead to decreasing marginal benefits. These constructs were operationalized by Laursen and Salter (2006) using a Community Innovation Survey (CIS) sample of UK manufacturing firms. They found that breadth and depth are curvi-linearly related to innovative performance.

Similar rationale can be applied to understanding KIE ventures, in terms of the impacts of external sources of knowledge. The literature on KIE ventures specifically proposes that they extensively use networks and external sources of knowledge to overcome resource limitations (Malerba et al., 2015). Still, due to the resource constraints specified above for SMEs in general, we would expect that an excessive breadth in sources of knowledge as well as excessive depth of collaboration with these sources should eventually result in a negative relationship. Therefore, we propose the same relationships hold as in the original Laursen and Salter (2006) paper, even though they focused upon larger manufacturing firms.

> Hypothesis 1a: Search breadth, in terms of the number of external sources of knowledge used by the firm, is curvi-linearly related to manufacturing innovation performance in KIE ventures.

In other words, if the KIE venture increases its search breadth, i.e. the number of external knowledge sources, it will eventually lead to diminishing returns for manufacturing innovation performance, producing an inverted U-shaped relationships as the number of partners increases.

> Hypothesis 1b: Search depth, in terms of the number of greatly important external sources of knowledge, is curvi-linearly related to manufacturing innovation performance in KIE ventures.

In other words, if the KIE venture has a large number of deep (or relatively highly important) external sources of knowledge, this search depth will eventually lead to diminishing returns in terms of manufacturing innovations, producing an inverted U-shaped relationships as the number of partners increases.

2.2 Openness & Service innovation[2]

Manufacturing and service innovations are thought to differ. Although studies of innovations have traditionally studied large firms in manufacturing industries, more recent work has also focused upon service innovations, and service industries, and the importance of collaborations (Tether, 2014). According to Tether (2014: 604-605,), four characteristics of classical services, which distinguish them from goods and manufacturing industries are: 1) Intangibility; 2) Inseparability between what is provided and who is providing it; 3) Temporal and perishable, that is, they exist in time; and 4) Heterogeneous depending upon the context of service deliverable, rather than standardized.

In terms of utilizing external sources of knowledge, Hipp and Grupp (2005) examined service-oriented firms in Germany. They categorized their results based on Pavitt's (1984) taxonomy**,** and emphasize the importance of knowledge intensive business services (KIBS) as a group which supplies a large number of economic actors with new knowledge. The OECD has also relied on this concept of KIBS to describe the drivers of service innovations in many knowledge-intensive organizations. These organizations tend towards generation of *ad hoc* and highly customized solutions to problems, with a high reliance on professional skills (Sundbo and Gallouj, 2000). Information regarding these innovations "may flow through professional networks and associations, or other communities of practice" (Miles, 2012: 11). External collaborations can thus generally be seen as beneficial for service-based innovation, especially for knowledge intensive business services. Den Hertog et al. (2010: 494) argue that service innovations are more and more the result of a realization of opportunities to create and appropriate value within a wide network of actors, including providers, value chain partners, and others, and that new and improved services are often generated within large communities through linked platforms and business relationships.

Hence, when developing service innovations, firms activities involve signaling user needs as ell as recognizing and sorting between technological options (den Hertog et al., 2010). Technological options provide opportunities for new paths of innovation, and the firm should remain open to external (as well as internal) sources of information, because that knowledge is crucial to translate potential technological options into innovations, including new service innovations (Teece, 2007; Wang and Ahmed, 2007; den Hertog et al., 2010). Bruni and Verona (2009: 107) similarly attribute these abilities to a firm's "dynamic marketing capabilities". A key variable in a firm's ability to generate innovations

[2] This paper assumes that "existing instruments will work effectively to describe the service economy" i.e. an *assimilative* approach (Miles, 2012: 11).

in services is thought to be user interaction as (Kindström et al., 2013), given the importance of co-creating services.

In terms of the degree of innovativeness, entrepreneurial firms may produce service innovations that are technological in nature or that are reliant on new business models which are based on a radical innovation. After a while, that firm may begin engaging in less radical forms and instead focus upon incremental and process improvements (Sundbo and Gallouj 2000).

Therefore, based on literature on service innovations, we can state that manufacturing and service innovations differ. However, because service innovations may rely extensively upon external sources of knowledge due to the inherent characteristics of services, the following hypotheses mirror those for manufacturing innovations.

> Hypothesis 2a: Search breadth, in terms of the number of external sources of knowledge used by the firm, is curvi-linearly related to service innovation performance in KIE ventures.
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> Hypothesis 2b: Search depth, in terms of the number of greatly important external sources of knowledge, is curvi-linearly related to service innovation performance in KIE ventures.

2.3 Openness & Degree of Novelty in Innovations

A final discussion, related to both manufacturing and service innovations, in the relative degree of novelty. In the literature, Innovations are classified according to their degree of radicalness as compared to the current standard of technology or as compared to the existing products (Freeman & Soete, 1997; Fagerberg, 2006). Continuous improvements are referred to as incremental innovations, while the introduction of something truly novel, new, or revolutionary in economic terms is called radical innovation (McKelvey, 1996). This distinction provides a more nuanced understanding of how and when external sources of knowledge impact innovative performance.

Although most studies focus upon large firms in manufacturing, a few studies address the degree of novelty in innovations for SMEs. Increased breadth of sources of knowledge could help the SME to increase the novelty of its innovation. Love et al. (2014) find that organizations that build off their prior innovation linkages in order to more effectively utilize their present day search breadth will tend to "experience higher innovation returns", and this may be characteristic of certain SMEs. Lee et al. (2010) argue that SMEs may be quite capable when it comes to invention, but lack the resources to properly innovate and commercialize invention. This notion of innovations requiring complementary assets (Teece, 1986) is not new, but it could be nonetheless relevant for explaining radicalness of innovations in small and micro firms. *Viz.*, this could mean that small and micro firms, while radical in their inventions, require extensive collaboration to properly reach innovation.

And that the more open an SME becomes, in terms of both breadth and depth, the more likely they are to realize the process of invention through radical innovations. Keupp and Gassmann (2013) find strong support for the hypothesis that knowledge constraints on a firm spur radical innovations (defined as new to the firm innovations), arguing that resource scarcity of firms can trigger an increased propensity towards explorative activities and recombining of resources both internal and external to the firm in order to innovate. Hence, utilizing external sources of knowledge can be seen as being a reactive attempt of SMEs to overcome their own resource constraints in order to seek out new combinations of their own resources as well as that of others.

Therefore, we expect the greater breadth and depth of external sources of knowledge that a KIE venture has, the more radical innovations that the firm will have, when we analyze manufacturing and service innovations together.

> Hypothesis 3: Search breadth, in terms of the number of external sources of knowledge used by the firm, is curvi-linearly related to the degree of novelty of innovations in KIE ventures.
>
> Hypothesis 4: Search depth, in terms of the number of greatly important external sources of knowledge, is curvi-linearly related to the degree of novelty of innovations in KIE ventures.

3. Research Design: Data and Methods

This paper is based upon the AEGIS survey. The AEGIS project was carried out to investigate knowledge intensive entrepreneurship in Europe given different national, sectoral and socio-economic contexts (Caloghirou et al., 2011; Malerba et al., 2015). Criteria for inclusion included: new firm; innovative, knowledge, and across different sectors, with operationalization explained below.

The sampling frame for the survey consisted of the Amadeus dataset, which is a pan-European database of public and private companies publishing financial statements which combines data from national sources. In addition there are supplemental country and sectoral level data obtained from the Dun and Bradstreet commercial database, the Kompass business directory, and select other sources in the specific industries. A benchmark sample of 4000 firms, broken up into three response size categories depending on the size of the national economies, was estimated. The sample is the firms interviewed (4004) out of this sampling frame approximating the benchmark. The survey captured results from 10 European countries[3], and focused on broad indicators such as: Information about the firm and founding team; the firm's formation process; the market environment; strategy; innovation and business models; and firm performance. The interviews were conducted using telephone interviews by 174 individual native language-speaking interviewers.

The survey samples firms in various sectors containing potentially knowledge intensive entrepreneurial firms, as shown in Table 1 below:

The AEGIS Survey: ***Selected Sectors***	***NACE rev. 1.1 code***
High-technology manufacturing sectors	
Aerospace	35.3
Computers and office machinery	30
Radio-television and communication equipment	32
Manufacture of medical, precision & optical instruments (scientific instruments)	33
Pharmaceuticals	24.4
Medium to high technology manufacturing sectors	
Manufacture of electrical machinery & apparatus	31
Manufacture of machinery and equipment	29
Chemical industry (excluding Pharmaceuticals)	24 (except 24.4)
Low technology manufacturing sectors	
Paper and printing	21, 22
Textiles and clothing	17, 18, 19
Food, beverages and tobacco	15, 16
Medium to low manufacturing sectors	
Wood/Furniture	36
Basic metals	27
Fabricated metal products	28
Knowledge intensive business service (KIBS) sectors	
Telecommunications	64.2
Computer and related activities	72
Research and experimental development	73
Other business service activities: (Legal/accounting; technical consulting incl. architectural and engineering activities; technical testing and analysis; labor recruitment and personnel provisioning; other misc. business activities.	74.1 – 74.4, 74.5, 74.8

Table 1: Selected sectors of the AEGIS survey (Caloghirou et al., 2011).

Micro firms constitute the majority of the firms sampled in the AEGIS survey (64%). This study covers firms ranging mainly from micro to small sized (0-50 employees)[4] according the OECD definition of small enterprises. In this study we focus only on those firms which are less than 51 employees in size. In terms of formulation of survey questions regarding innovation processes and knowledge sources, much of the AEGIS survey was originally modelled after the CIS, including similarly subject oriented data and questions.

[3] Croatia, Czech Republic, Denmark, France, Germany, Greece, Italy, Portugal, Sweden and the UK constituted the sampled EU countries.
[4] A handful of medium sized and large firms occur in the dataset.

Since the CIS is known to exclude firms with personnel amounting to less than 10 employees (de Jong & Marsili, 2006), this survey presented an opportunity to assess a population of firms that has received considerably less attention from innovation surveys and surveyors.

There are of course limitations with this approach. It should be noted that using self-reported data-driven questionnaires in survey data imposes various limitations on the analysis, as well as does the use of large scale databases in general, especially when quantifying this material.

3.1 Descriptive results

In the survey, firms were asked to rate the relative important of 11 different sources of knowledge for exploring new business opportunities, ranging from *1* being not important and *5* being extremely important. Table 2 presents the results of the (*n = 4004*) firms on this indicator in terms of percentage of the sample:

Table 2: Sources of knowledge used to build independent variables

Source of Knowledge	**Not important**	**2**	**3**	**4**	**Extremely important**
Clients or customers	2%	2	10	24	62%
Suppliers	13%	13	23	25	26%
Competitors	9%	15	33	26	17%
Public research institutes	44%	22	20	9	5%
Universities	47%	20	18	10	5%
External commercial labs/R&D firms/technical institutes	48%	20	18	10	4%
In house (know how, R&D laboratories)	24%	7	16	25	28%
Trades fairs, conferences, and exhibitions	18%	18	30	21	13%
Scientific journals and other trade or technical publications	20%	18	29	21	12%
Participation in nationally funded research programs	58%	16	13	9	5%
Participation in EU funded research programs (Framework Programs)	62%	13	11	8	6%

The following tables present the number of firms sampled in each sector, the degree of radicalness of innovation, average R&D intensity of the sector, and the calculated means of the breadth and depth indicators. Lastly, the percentage of innovative goods and innovative services as a proportion of total sales by sector is displayed (explanations of derivation of these independent variables in the section to follow).

Table 3: Radical innovation, R&D intensity and openness by sector

SAMPLE SECTOR [5]	# Of Firms	% No Innovation	% New to Firm	% New to Mkt	% New to World	Average R&D intensity	Breadth mean	Depth mean
ICT manufacturing	150	26.67	42.00	18.67	12.67	19.24	7.57	3.78
Manufacture of machinery and equipment	184	38.04	39.13	15.76	7.07	11.40	7.02	3.14
Chemical industry (including pharmaceuticals)	43	23.26	51.16	16.28	9.30	19.37	7.67	4.00
Paper and printing	518	39.19	39.38	16.22	5.21	10.71	6.69	3.26
Textile and clothing	176	45.45	32.95	14.20	7.39	10.78	6.76	3.50
Food, beverages, and tobacco	233	39.06	37.77	16.31	6.87	8.16	7.10	3.58
Wood and furniture	203	41.87	36.45	13.30	8.37	9.44	6.87	3.29
Telecommunications	20	30.00	55.00	10.00	5.00	14.00	7.35	3.35
Computer and related activities	451	29.05	38.80	24.17	7.98	18.22	6.61	2.84
Research and experimental development	57	31.58	28.07	21.05	19.30	41.45	8.14	3.91
Other business service activities	1175	46.64	32.85	16.34	4.17	10.40	6.52	2.98
Mfg. of metals	219	37.44	42.01	15.98	4.57	9.73	7.04	2.98

Table 4: Goods and service innovation turnover by sector

SAMPLE SECTOR	% of Innovative Goods/Sales	% of Innovative Services/Sales
ICT manufacturing	32.23	16.59
Manufacture of machinery and equipment	23.69	9.91
Chemical industry (including pharmaceuticals)	26.77	12.81
Paper and printing	17.11	17.59
Textile and clothing	23.87	9.06
Food, beverages, and tobacco	19.11	8.21
Wood and furniture	23.61	8.74
Telecommunications	13.20	32.95
Computer and related activities	19.27	24.75
Research and experimental development	25.58	23.82
Other business service activities	9.79	19.16
Manufacture of metals	17.67	12.88

3.2 Measures

3.2.1 Dependent variables

Innovative performance has commonly been measured through turnover of new or substantially improved products or services over a relatively recent time period, usually three years (Caloghirou et al., 2004; Jantunen, 2005). Laursen and Salter (2006) measured innovative performance in terms of ability to produce radical and incremental innovations in terms of turnover. This paper takes a combinative approach in order to measure innovative performance:

[5] The sector Aerospace was not part of the sample following list-wise deletion of so-called "*Don't know*" values regarding the dependent variable(s) of interest.

In terms of research design, the concept of interest is *innovativeness,* the conceptualized construct of which is *innovative performance* at the firm level. This dependent variable is measured by 3 indicator variables, or measures on the construct: Thus, The latent dependent variable, *INNP*,* or innovative performance of the firm, is captured/approximated by 3 dependent variables, built using the following questions from the AEGIS survey: First, the respondent was asked if their company introduced any new or significantly improved (i.e. innovative) goods or services in the past three years; if yes, they were asked to estimate the share of both innovative goods and innovative services within total sales. They were also asked if the innovative goods *or* services were new to the firm, new to the market, or new to the world.

The first and second dependent variables combined uses the proportion of innovative sales of goods/services to the total sales generated by the firm over the past three years, approximating the amount of sales generated by this recent innovation activity

1. *INNGOODS:* The proportion of innovative (new or improved) goods to that of total sales.
2. *INNSERV:* The proportion of innovative (new or improved) services to that of total sales

The third dependent variable measures the degree of radicalness/novelty of the innovation practices of the firm during the past three years, approximating the degree of radicalness/novelty of innovation in that firm in general. Originally the respondent was given the opportunity to indicate up to three different products or services that were new or significantly improved, and rank them according to the provided scale. In order to construct a meaningful model from the data, a new variable was constructed using conditional indicators of the highest *achieved* level of novelty for each firm:

3. *RADINN:* The Degree of Radicalness of innovations (goods or services) introduced to the market by the firm over the past 3 years.
   - 0 = No new innovations introduced.
   - 1 = Up to the “new to the firm” level innovations introduced.
   - 2 = Up to and including “new to the market” level innovations introduced.
   - 3 = Up to and including “new to the world” level innovations introduced.

3.2.2 Independent variables

Breadth and Depth of External Search are used to approximate the construct of *Openness* (Laursen & Salter, 2006), which indicates characteristics of external search for knowledge:

BREADTH***:*** This represents the combination of the 10 external sources of knowledge (see Table 2) expressed in regards to exploring new business opportunities in the AEGIS survey questionnaire (while omitting the response representing in-house R&D activities). The value 0 is assigned if the observation indicated the source was not important (a score of 1), the value 1 is assigned if the observation indicated that it was anything greater than not important (a score between 2 and 5). The number external sources are then summed for each firm to create the BREADTH variable (min = 0, max = 10; Cronbach's alpha coefficient = 0.81).

DEPTH: This variable represents the deepness of collaboration of the sources of knowledge from the questionnaire. Built from the summated rating scale also used to construct BREADTH, it was coded 0 if the observation was coded 1, 2 or 3; assigning a 1 if the observation was coded 4 or 5 (Thus only those sources ranked 4 or 5 are deemed to be very or extremely important). As BREADTH**,** this variable takes on values between 0 and 10, where firms getting a score of 10 deeply collaborate with all external sources of knowledge listed in the questionnaire (Cronbach's alpha coefficient = 0.69) This binary coding approximates the method employed by Laursen and Salter (2006).

These two variables are also used to test the hypothesis that there is also a curvilinear, or inverse quadratic, relationship between the concepts of interest. This is done by including the quadratic interaction effect of both variables in the regressions.

Additionally, principal components were extracted from the external knowledge sources conveyed in the survey question, and run in separate models. Measuring openness via a company's breadth and depth of external knowledge sourcing has become a fairly well established construct in the literature by the time this study was carried out. Nonetheless, the summation of binary outcomes used to construct the BREADTH and DEPTH variables may fail to capture the more nuanced underlying variance conveyed by the summated rating scale for openness to different external sources of knowledge and degrees of reliance on them. To counteract this, and in a more exploratory attempt to account for more of the variance in the summated rating scale used to derive the BREADTH and DEPTH variables, a principal components analysis (PCA) of this summated rating scale was carried out and its interpretable components run as independent variables in additional models. Three principal components were derived (see appendix for more details):

- PCA1*: External, non-industry sources of knowledge* (or specialized knowledge providers (Tether and Tajar, 2008)).
- PCA2*: Business and operations-based relationships* (made up of clients, customers, and suppliers)
- PCA3*: Sources of knowledge stemming directly from academia and related communities.*

In addition to Models I, II, and III, which utilize the breadth and depth constructs as the main independent variables, these three components constitute the main independent variables of interest in Models IV, V and VI below.

3.2.3. Control variables:

We also include a set of control variables:

STARTYEAR*:* The year the venture was established (screened for change in legal status of existing firm).

INTLSALES*:* Percentage of international sales estimated by survey respondents.

USER: Binary variable specifying whether the firm saw implicated users in their sources of knowledge as important (values 2 – 5) or not (value of 1). This is included to control for the presence of 'lead users' in the innovation process, shown to affect innovative performance in firms (von Hippel, 1988).

R&DINT: R&D intensity (by % of sales invested) estimated by survey respondents, in order to control for the effect of R&D on our variables of interest (Hagedoorn & Cloodt, 2003) and the effect of absorptive capacity of the firm (Cohen & Levinthal, 1990; Tsai, 2001).

LOGEMP*:* The number of employees (full + part-time) is used to control for the size of the firm. By using this measure in our controls, we also indirectly account for other measures related to firm size.

Industry: HTMS (High-tech manufacturing sectors)¸ LTMS (Low-tech manufacturing sectors); KIBS (Knowledge intensive business services); OBS (Other business services). These were constructed based on the sector selection of the AEGIS survey itself (see Table 1).

SAMPLESECTOR: Additionally, country of origin was included in the regression to control for national differences.

The following tables give an overview of the variables of interest in descriptive terms:

Table 5: Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
INNGOODS	3429	.1704	.2553	0.00	1.00
INNSERV	3429	.1685	.2448	0.00	1.00
RADINN	3429	0.90	0.90	0.00	3.00
RADINN_OS	3429	0.90	0.90	-0.08	2.98
BREADTH	3429	6.78	2.53	0.00	10.00
DEPTH	3429	3.16	2.10	0.00	10.00
STARTYEAR	3429	2003	2.1614	2000	2007
INTLSALES	3429	14.01	25.99	0.00	100.00
R&DINT	3429	12.34	19.13	0.00	100.00
USER	3429	0.86	0.35	0.00	1.00
LOGEMP	3429	1.86	1.03	0.00	7.26

Table 6: Correlation matrix

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. INNGOODS	1											
2. INNSERV	0.1141	1										
3. RADINN_OS	0.5209	0.4852	1									
4. BREADTH	0.1353	0.09	0.2014	1								
5. DEPTH	0.1354	0.0861	0.1701	0.5631	1							
6. STARTYEAR	0.015	0.0359	-0.0044	-0.0284	0.0014	1						
7. USER	0.0259	0.0318	0.0611	0.1498	0.3142	0.0146	1					
8. LOGEMP	0.1556	0.0302	0.1752	0.1973	0.0976	-0.0638	0.0247	1				
9. R&DINT	0.1487	0.0073	0.1231	0.0748	0.0588	-0.0501	0.0207	0.1393	1			
10. INTLSALES	0.2872	0.2078	0.2364	0.2061	0.1915	0.025	0.0087	0.0698	0.1655	1		
11. SECTOR	-0.1818	0.0876	-0.0663	-0.0634	-0.0923	0.08	-0.0072	-0.0806	-0.0593	-0.019	1	
12. COUNTRY	-0.0187	0.024	0.034	0.0528	0.0239	-0.0247	0.1092	0.0106	-0.024	-0.0043	0.0362	1
All correlations above 0.04 significant (p< 0.01)												

3.3 Statistical method

In the AEGIS questionnaire, respondents where provided with the option of indicating that they don't know what proportion of innovative goods or services are representative of the firm's total sales during the past 3 years. A substantive interpretation of these answers is difficult, due to the fact that in this situation, don't know gives no indication of the true ratio of goods or services to sales. As *don't know* answers are difficult to interpret when the question asked requires specific knowledge and/or not interpretable via any underlying continuum (here the latent variable *INNP**), these cases were subject to listwise deletion in accordance with the recommended missing value analysis literature (Acock, 2005; Little & Rubin, 2002). As a result the number of cases drops from 4004 to 3429 firms[6].

Commonly, when two of the variables of interest are cornered, or censored, Tobit's model of censored regression may be used in subsequent analyses (Long, 1997). However, since in this dataset, these depending variables which are fractions between 0 and 1 do not have a pileup effect at both ends of the spectrum (Wooldridge, 2002/2012), as well as the conceptual mismatch between the variables being defined as, rather than limited to, lying between 0 and 1 (Cook, et al., 2008), the Tobit was not an appropriate choice. In the modelling of the dependent variables INNGOODS and INNSERV, which have a large percentage of values clustered at 0, we have applied the Bernoulli quasi-maximum likelihood estimation (QMLE) fractional logit model as developed by Papke and Wooldridge (1996). The third variable, RADINN was originally intended for use in an ordered logit model. However, due to

[6] Additionally, firms that introduced no innovations in the last 3 years were given the value of 0 for the dependent variables *INNGOODS, INNSERV,* and *RADINN*

violations of the parallel regression assumptions of that particular model using a Brant (1990) test[7], an alternating least squares optimal scaling (ALSOS) routine was conducted using the `optiscale` package in the *R* statistical computing environment, and the optimally scaled variable was then modelled using OLS regression (cf. Young, 1981; Jacoby, 1999; Jacoby, forthcoming). The resultant variable RADINN_OS, is proposed to also represent the latent variable *INNP**. Tables 5-6 document the results of the analysis. ALSOS is commonly used in order to test the measurement assumptions of a variable, and through it, empirical transformations of variable values may give insights about the appropriate level of measurement for that variable (Jacoby, 1999). The technique, commonly used in psychometric analysis, optimally scales the variable to find the maximized goodness of fit between the analytical model and empirical observations (Young, 1981), by relaxing the assumption that the measurement scale of the variable is fixed. Using this, we have rescaled the dependent variable RADINN, which is assumed to be interval level data, into an ordinal variable which minimizes the sum of squared residuals (For a more comprehensive discussion of the ALSOS method, see Young, 1981 and Jacoby, 1999). Once this is done the optimally scaled variable lends itself very well to standard OLS regression (See appendix for variable transformations).

[7] In the ordered logit model, the cumulative probability curves, that is, the probability that the unit being analyzed falls into one of the ordered categories of the dependent variable, are assumed to be parallel. The Brant (1990) test is used to test if any variables violate this. In this case, several variables were in violation, thus an alternative model was needed.

Table 7: Results - Marginal effects at the mean using Fractional Logit (Models 1,2,4, & 5) and OLS coefficients (Models 3 &6)

VARIABLES	(1) Fr. Logit INNGOODS	(2) Fr. Logit INNSERV	(3) ALSOS OLS RADINN_OS	(4) Fr. Logit INNGOODS	(5) Fr. Logit INNSERV	(6) ALSOS OLS RADINN_OS
breadth	0.0362***	0.0336***	0.157***			
	(0.0111)	(0.0113)	(0.0339)			
breadth2	-0.00249***	-0.00231***	-0.00997***			
	(0.000807)	(0.000821)	(0.00255)			
depth	0.0171**	0.00233	0.0448*			
	(0.00705)	(0.00689)	(0.0255)			
depth2	-0.00113	0.000289	-0.00193			
	(0.000728)	(0.000672)	(0.00266)			
pca1				0.00895***	0.00790***	0.0496***
				(0.00229)	(0.00224)	(0.00834)
pca2				0.0119***	-0.00252	0.00955
				(0.00457)	(0.00445)	(0.0159)
pca3				0.0128***	0.00753*	0.0741***
				(0.00431)	(0.00427)	(0.0153)
startyear	0.00309	0.00173	-0.00168	0.00302	0.00170	-0.00240
	(0.00192)	(0.00190)	(0.00691)	(0.00193)	(0.00191)	(0.00691)
user	-0.00964	0.00682	0.0128	-0.00768	0.0216	0.0936*
	(0.0137)	(0.0140)	(0.0473)	(0.0154)	(0.0162)	(0.0541)
logemp	0.0283***	0.00962**	0.125***	0.0294***	0.0102**	0.132***
	(0.00470)	(0.00483)	(0.0177)	(0.00471)	(0.00480)	(0.0176)
r&dint	0.000646***	-0.000242	0.00216***	0.000626***	-0.000254	0.00204***
	(0.000151)	(0.000175)	(0.000592)	(0.000152)	(0.000176)	(0.000592)
Intlsales	0.00234***	0.00172***	0.00803***	0.00241***	0.00169***	0.00811***
	(0.000216)	(0.000207)	(0.000814)	(0.000218)	(0.000209)	(0.000818)
Constant			2.961			4.969
			(13.85)			(13.84)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,327	3,327	3,327	3,327	3,327	3,327
R-squared	0.1502	0.0747	0.132	0.1490	0.0733	0.132

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4. Results

Looking at the results in Table 7, BREADTH can be seen as strongly statistically significant and positive across all three dependent variables, thus confirming H1a, H2a, and H3. In our estimations, Breadth has a slightly larger marginal effect at its mean on innovative goods than on innovative services, though the two results are quite similar. For all three dependent variables BREADTH2 is statistically significant and negative, confirming its curvi-linear relationship to innovative performance of knowledge intensive entrepreneurial firms as captured in the sample.

The results regarding DEPTH of external search are less robust, providing no support for the hypotheses H1b, H2b, or H4. For INNGOODS, the model returns a statistically significant value at the 5% level for DEPTH, but DEPTH2 is insignificant; additionally, neither DEPTH nor DEPTH2 are found to be statistically significant ($p<0.05$) for INNSERV or RADINN_OS, indicating an ambiguous relationship between depth of external search, as it has thus far been derived, and innovative performance[8].

Substituting the variables BREADTH and DEPTH with the three principle components returns some interesting results[9]: PCA1, representing *non-industry sources of knowledge,* is significant in all three of the PCA models. This suggests that the relationship between non-industry sources of knowledge has a statistically significant and positive effect on innovative performance. Its strongest effect is on that of services, followed by goods, and lastly by degree of radicalness: This suggests that these particular sources of knowledge may exhibit stronger ties to innovativeness in terms of sales than to novelty of goods or services offered. PCA2 has a statistically significant positive effect on only innovative goods as a proportion of total sales. Finally, PCA3 has a statistically significant positive effect on all dependent variables representing our latent dependent variable.

In summary, hypotheses regarding the role of breadth in innovative performance of KIE entrepreneurial firms are confirmed in this study, but those regarding depth are not supported. However, a more nuanced view of the summated rating scale by which breadth and depth were constructed reveals that the underlying principle components are uniquely correlated with certain groupings of knowledge sources, which have their own relationships with innovative performance.

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[8] Note: When running the models without the DEPTH2 term, DEPTH became positive and significant in all analyses, potentially indicating that while non-linearly related to the dependent variable(s), the quadratic form does not give us a representative model for depth.

[9] We see this approximation of breadth and depth as a summarizing measure of the rating scale employed, and it does not take into account the values of breadth and depth across multiple sources of knowledge and sum them, as was done in the previous regressions (I – III). Therefore, interpretation of these principal components as being directly related to the breadth or depth variables employed earlier in the study would be insubstantive. It is measuring the summated average of depth across all respondents, which is the main function of principal component analysis (Dunteman, 1989).

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5. Discussion and Conclusions

Research in recent years has focused on a subset of simultaneously innovative and entrepreneurial firms, due to their importance in economic growth. Therefore, stimulating small and micro firms to be more knowledge intensive and more innovative has been on the top of the policy agenda for many years. The OECD (2008), as well as the European Commission (2013) has argued that micro firms are some of the most important firms driving global economic growth, and that using policy as a tool to help them overcome challenges to their size, networking potential, and competitiveness could be a strong recipe for strengthening entrepreneurship. Prescriptions constitute the broadening of support programs; including better-tailored network building, greater policy awareness, and not least, encouraging more collaborative measures among these firms regarding innovation in order to become more internationally competitive (OECD, 2008; OECD, 2013). This paper contributes to the understanding of this type of firms, and as such may offer some new suggestions for policy.

The paper focused only upon one aspect, namely how and why external sources of knowledge, impact innovativeness, by analyzing the impact of open innovation on the innovative performance of knowledge intensive start-ups, in terms of manufacturing innovations, service innovations, and degree of radicalness. It did so by focusing on one sub-set of small and micro firms, that we call knowledge intensive entrepreneurial firms, by analyzing a sample of 4004 such firms. In doing so, the paper and its results provide the following two contributions. The first relates to whether and how these firms search externally for new knowledge and the influence of this search on their innovation performance and the second is proposing some directions for future research based on the results of this study. The following table is a summary of our empirical results:

Table 8: Main empirical results

Dependent Variables representing innovative performance	***Main independent Variables***		
	Depth	***Breadth***	***Channels for external search (as shown by the PCA)***
Goods innovation	Significantly positive but non-curvilinear	Significantly positive and curvilinear	All sources (non-industry, business & academic) positive and significant
Service innovation	Not significant and non-curvilinear	Significantly positive and curvilinear	Only non-industry (p<0.01) and academic (p<0.10) sources significant
Degree of novelty in both good and service innovation	Positive (p<0.10) but non-curvilinear.	Significantly positive and curvilinear	Only non-industry (p<0.01) and academic (p<0.01) sources significant.

Goods

Our results indicated a curvilinear relationship between both breadth and depth and the sale of innovative goods, while only a curvilinear relationship between breadth (no relationship at the 5% level was found regarding depth) and sales of innovative services and novelty of innovations produced: Much like larger firms involved in manufacturing activities, small new manufacturing firms benefit initially from involving themselves in external networks of information, and deeper collaborations yield higher innovative returns. However excessive breadth could yield negative marginal benefits[10], though effects of depth as constructed by Laursen and Salter (2006) are here found to be inconclusive for KIE entrepreneurial firms. Through principal components analysis, external sources of information from all three components - representing research, business, and published knowledge - were all found to be significant for innovative performance measure by goods.

Services

For innovative services, the depth component was not significant. Due to the intangibility of services in many industries, an organization might rely more deeply on non-industry sources of knowledge through the form of applied research, academia, and public sector initiatives, especially when the firm is new, and has not adequately forged relationships with its business partners and competitors to rely on knowledge from these sources for innovation and new business opportunities. The newness of the firm also may limit the amount of external knowledge that can even be absorbed into the firm. Indeed, using principal components analysis, the component explaining most of the variance in the scale, with high correlation to *non-industry sources of knowledge in the form of business and operations-based relationships*, was found to be statistically significant with proportion of innovative services to that of sales.

Degree of novelty

Concerning radicalness of innovation, our results are in line with the expectations regarding breadth, though not with that of Laursen and Salter's (2006) depth. This could mean that a new knowledge intensive small or micro-firm, again perhaps due to resource constraints and liability of newness, may need to set a greater focus on its explorative capabilities, that is, seeking out external information for innovative and entrepreneurial opportunities (Cf. Katila and Ahuja (2002)) than multiple deep collaborative efforts (which they consequentially may lack the resources to enact and maintain). Thus,

[10] A fitted model of residuals indicates that the predicted breadth ”tipping point” lies between 8 and 9 sources for Models I and II, between 9 and 10 sources for Model III. For depth's tipping point in Model I, between 7 and 9 sources.

it is likely that exploration in March's (1991) sense is an important factor for new small firms in increasing the degree of radicalness in innovations realized. Again, radicalness of innovations was positively associated with the first and third principal components, suggesting that depth in terms of *non-industry and academic* sources of knowledge may be positively related to radicalness of innovations, while depth of *industrial, business, and operations-based sources of knowledge* may not be possible for KIE firms to achieve at this snapshotted level of development as represented by the survey**.**

The second contribution is that our results can lead to proposition and ideas for future research.

Most surprising are the almost counter-intuitive results of the effects of depth of search on innovative services. Our PCA analysis does not find a significant relationship between clients, customers, competitors and suppliers as knowledge sources, with that of innovative services as a proportion of sales. This is surprising, since the literature detailed above in the theoretical section points towards the importance of user communities, business networks, etc., in the innovation process of services. However, this reliance on these sources of knowledge, especially for services and for producing more radical as opposed to incremental innovation, could be strong *regardless* of overall innovative performance. Depth of collaboration could be important for all small service firms, so the measure may not capture the sought-after relationships when applied to firms relying on these sources of knowledge regardless of their innovativeness. Also, given the theoretical reasoning, it seems that constraints of size and newness have a real effect on what sources successful service innovations may be drawn from and how deep collaborations need be (or can be) in the initial phases of firm development.

Hence, a more parsimonious approach to explaining the outcomes of collaborative depth with these types of knowledge sources for these small KIE firms is recommended for future research. An alternative model could better capture the relationship between depth of search and innovative performance for small entrepreneurial firms. For the small new KIE firms captured in the sample, it is possible that constraints of networks and of resources as outlined in the literature prevents firms from establishing deeper search relationships and hence curvi-linearity might not appropriately characterize the effect

There are also a number of more detailed issues, related to research design. One interpretation of our results is that researchers should be wary of summarizing all outside sources of knowledge into a single construction representing firm openness, as the underlying clusters of knowledge sources seem to have varying degrees of effects on this latent variable. Therefore, further investigating the linkages between innovative performance and depth in business relationships as opposed to non-corporate, publically, academically, or scientifically driven relationships with outside sources of knowledge is encouraged.

Most crucial is perhaps that work is done to try and understand how newness affects a firm's ability to innovate in diverse sectors and in different national contexts. This survey has included a variety of industries (both goods and services) as well as 10 different EU countries that differ on a number of indicators (including the macro-economic landscape, science policy, and demography). More work should be directed towards exploring the confines placed on new firms in different national contexts in regards to fulfilling the innovative potential of the firm and the availability of sources of external knowledge from the different channels analyzed here.

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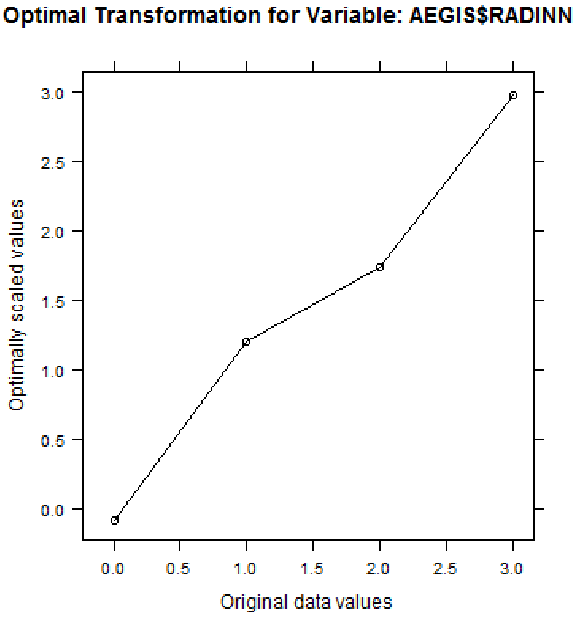
Appendix:

Alternating Least Squares Optimal scaling transformation:



Original value	0	1	2	3
Scaled value	-0.07893	1.20908	1.74038	2.98457
# of obs.	1364	1261	588	216

Iteration	R-squared	Improvement
1	0.1238525	0.12385
2	0.1274784	0.00362
3	0.1279307	0.00045

R Code for ALSOS transformation

```
library(foreign)
AEGIS<- read.dta(file.choose())
head(AEGIS)

library(optiscale)
help(opscale)
summary(lm(AEGIS$RADINN ~ AEGIS$breadth + AEGIS$depth + AEGIS$breadth2 + AEGIS$depth2 +
AEGIS$user + AEGIS$logemp + AEGIS$Q16_3 + AEGIS$Q32 +
AEGIS$HTMS + AEGIS$LTMS + AEGIS$KIBS + AEGIS$OBS + AEGIS$COUNTRYID))

previous.rsquared <- 0
niter <- 0
rsquared.differ <- 1.0
record <- c()

dvar.os <-AEGIS$RADINN
while (rsquared.differ > .001 && niter <= 30) {
  niter <- niter + 1
  reg.os <- lm(dvar.os ~ AEGIS$breadth + AEGIS$depth + AEGIS$breadth2 + AEGIS$depth2 +
                 AEGIS$user + AEGIS$logemp + AEGIS$Q16_3 + AEGIS$Q32 +
                 AEGIS$HTMS + AEGIS$LTMS + AEGIS$KIBS + AEGIS$OBS + AEGIS$COUNTRYID)

rsquared.differ <- summary(reg.os)$r.squared - previous.rsquared
previous.rsquared <- summary(reg.os)$r.squared
record <- c(record, niter, summary(reg.os)$r.squared, rsquared.differ)

if (rsquared.differ > .001) {

dvar.pred <- predict(reg.os)
opscaled.dvar <- opscale(AEGIS$RADINN, dvar.pred, level = 2, process = 1)
dvar.os <- opscaled.dvar$os  }}

record <- matrix(data = record, ncol = 3, byrow = T)
colnames(record) <- c("Iteration", "R-squared", "Improvement")

record

summary(reg.os)

summary(lm(dvar.os ~ AEGIS$breadth + AEGIS$depth + AEGIS$breadth2 + AEGIS$depth2 +
     AEGIS$user + AEGIS$logemp + AEGIS$Q16_3 + AEGIS$Q32 +
     AEGIS$HTMS + AEGIS$LTMS + AEGIS$KIBS + AEGIS$OBS + AEGIS$COUNTRYID))

plot(opscaled.dvar)
opRADINN <- opscale(x.qual=AEGIS$RADINN, x.quant=AEGIS$Q27B_1, level=2, process=1, rescale =
FALSE)

table(AEGIS$RADINN)
table(dvar.os)
AEGIS$RADINN.OS <- dvar.os
summary(AEGIS)
library(foreign)
write.dta(AEGIS, "AEGIS_OP.dta")
```

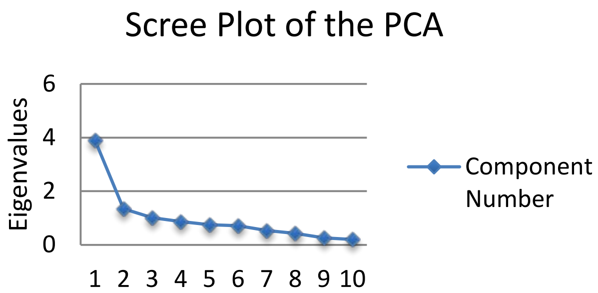
Principal Components of External Sources of Knowledge

PCA is "a statistical technique that linearly transforms an original set of variables that represents most of the information in the original set of variables [in order to] reduce the dimensionality of the original data set", for use in subsequent analyses (Dunteman, 1989: 7). These derived variables are orthogonal with one another, and maximize the variance accounted for in the original set of variables (ibid.). This technique can be extremely useful in understanding the underlying dimensions which account for the variation in a set of correlated variables. Here, it is of interest to model the preceding regressions with principal components added in.

Principal components/correlation — Number of obs = 3429; Number of comp. = 10; Trace = 10

Rotation: (unrotated = principal) — Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.90152	2.55169	0.3902	0.3902
Comp2	1.34983	.33532	0.1350	0.5251
Comp3	1.01451	.148535	0.1015	0.6266
Comp4	.865975	.124222	0.0866	0.7132
Comp5	.741752	.0305962	0.0742	0.7874
Comp6	.711156	.177545	0.0711	0.8585
Comp7	.533611	.112775	0.0534	0.9118
Comp8	.420836	.158731	0.0421	0.9539
Comp9	.262105	.0634007	0.0262	0.9801
Comp10	.198704	.	0.0199	1.0000



The fact that the components are per-construction orthogonal with one another facilitates their interpretation as regression coefficients. Using the scree plot comparing the Eigenvalues generated by the PCA with the number of components, it can be seen that 3 principal components account for a cumulative 62.6 percent of the total variance of the 10 variables used to estimate DEPTH. Following the Kaiser-Guttman criterion (Kaiser, 1960; Guttman, 1954) commonly applied to PCA, only those with an eigenvalue of $\Lambda > 1$ are retained for analysis.[11] Upon closer inspection through a bivariate correlation matrix comparing the components with the original variables, a pattern begins to emerge (see next page):

[11] OLS regressions on the dependent variables were also carried out using all 10 components, and while a few of the lower order components were significant in the regressions, they were not substantively interpretable.

Bivariate correlations of principal components of external knowledge sources:

	PCA1	PCA2	PCA3
PCA1	1.0000		
PCA2	-0.0000	1.0000	
PCA3	-0.0000	-0.0000	1.0000
Q24_1	0.2138	**0.6733**	-0.2551
Q24_2	0.3698	**0.6270**	-0.1422
Q24_3	0.3816	**0.5403**	-0.0087
Q24_4	**0.8007**	-0.1415	-0.1468
Q24_5	**0.7939**	-0.1785	-0.1566
Q24_6	**0.7485**	-0.1157	-0.1447
Q24_8	0.5298	0.2003	**0.6318**
Q24_9	0.5432	0.0090	**0.6472**
Q24_10	**0.7835**	-0.2451	-0.1389
Q24_11	**0.7430**	-0.2144	-0.1573

How high PCA bivariate correlations must be in order to be interpretable by the researcher is highly discretionary, as no reliable guidelines exist. Though it is generally thought that patterns in the correlations must be readily identifiable in order for substantive interpretation of the components to follow (Dunteman, 1989). Hence, of most interest are the correlations of components with certain variables relative to the other components. The first principle component seems to be most highly correlated with Q24_4, Q24_5, Q24_6, Q24_10, and Q24_11. Comparing this coding with the labels assigned to the questions by the AEGIS survey, one can see that the first principal component (PCA1) is highly correlated with these *external, non-industry sources of knowledge,* mainly related to the collaboration with state, national, or regional research-based or academic entities: Roughly equivalent to Tether and Tajar's (2008) specialist knowledge providers (SKPs). Conversely, the second principal component is most correlated with Q24_1 - Q24_3: Representing clients or customers; suppliers; and competitors. This second component (PCA2) can thus be interpreted as explaining the shared variation of sources of knowledge through *business and operations-based relationships*. The third principal component is most correlated with Q24_8 and Q24_9: Trade fairs, conferences and exhibitions; and scientific journals and other trade or technical publications. This last component (PCA3) can be seen as *sources of knowledge stemming directly from academia and related communities.*