External information sourcing and lead-time advantage in product innovation

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Abstract
* Purpose

Having a short throughput time for innovation projects, i.e. lead-time, can put firms in an advantageous position. The time that lapses between project start and project completion is influenced not only by the firm's internal capabilities but also by how the firm connects to external knowledge. In this paper, I study, this relation between external knowledge sourcing and lead-time advantage.

* Design/methodology/approach

In this paper, I empirically test the relation between external knowledge sourcing and lead-time advantage, based on firm level Community Innovation Survey (CIS) data I run limited dependent variable models, i.e. ordered probits.

* Findings

I find that breadth and depth of the external knowledge sourcing are positively relating to lead-time advantage, albeit with diminishing returns. Investment into absorptive capacity, i.e. internal R&D, mitigates the diminishing of returns. I find that firms directing their external knowledge sourcing strategy towards consumers, suppliers, and science are better able to capitalize on their innovations through lead-time advantages. I also assess the special case of collaboration for product development.

* Originality/value

The conceptual novelty of my research largely consists in empirically bringing together for the first time conceptualizations of external knowledge sourcing and the strategic use of lead-time. Given the prevalence of both concepts in the modern and fast changing economy, I think investigating this link is of great importance.

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1. INTRODUCTION

Lead-time advantage has been described as on avenue leading to better appropriation of the returns to innovation investment (Hall et al. 2014). This paper argues that lead-time advantage is a result of other upfront decisions made by the firm and that certain information sourcing strategies might be conducive for achieving an effective lead-time advantage for innovation projects.

It should be made clear from the outset that having a lead-time advantage does not necessarily correspond to being a first or early mover. Lead-time, as commonly defined in management literature, is the time that lapses between project start and project completion. With regard to innovation projects, having a short lead-time could both imply becoming a first or early mover (i.e. by introducing a market novelty), or it could imply that a firm out-imitates 'the rest of the pack' (i.e. by introducing an imitation to market in a timely way). By achieving an effective lead-time advantage over rivals' product development cycles, firms can enable better appropriation of the returns to their investments. I aim to contribute by using Belgian firm level Community Innovation Survey (CIS) data to answer the question: *"which external information sourcing strategies are most frequently observed to coincide with the build-up of effective lead-time advantages?"*

Although some inventions were come across haphazardly by a lone inventor, the canonical story of the lone genius inventor is largely, as Lemley (2012) puts it, a myth: *"...Edison didn't invent the lightbulb; he found a bamboo fiber that worked better as a filament in the lightbulb developed by Sawyer and Man, who in turn built on lighting work done by others..."* (also see Hargadon, 2003; Hargadon and Sutton, 1997; Singh and Fleming, 2010). Over the course of history, information became more widely available and knowledge sharing between partnering firms, universities, and customers became custom practice. Indeed, to bypass the constraints of own internal knowledge, firms are (increasingly) drawing upon external knowledge (Penrose, 1959; Teece, 1986; Barney, 1991; Grant, 1996). As such, external knowledge sourcing may be systematically used to promote information-enabled innovation (Reeves et al. 2017).

The perception that innovation is a network activity is not a new one. Efficient uptake and management of information are since long considered a prime attribute of successful innovators (Rothwell et al., 1974; Rothwell, 1977, 1992). More recent contributions argue that companies are increasingly sourcing knowledge from outside the firm to complement their own knowledge base. In addition, companies increasingly use external pathways to commercialization to monetize on innovation (cfr. e.g. Chesbrough, 2003).

One way to capture value from innovation is to become a first mover with regard to innovation and pre-empt the competition. Another is to enter the market at a later stage with an imitative offering and become a deliberate late mover. See Lieberman and Montgomery, 1988, for a literature review on the topic. At least since the 1980s when Japanese products challenged existing world markets, it is well known amongst scholars and practitioners that lead-time advantages are a crucial factor in competition. As a reason for the success of Japanese manufacturing companies in the 1980, typically the nowadays well-known business strategies such as just-in-time production and flexible manufacturing are quoted. In the literature, less attention has been paid to time-based innovation. Exceptionally, it has been argued that Japanese companies followed an innovation strategy that involved updating products in small steps but much more frequently than existing rivals (see Stalk, jr., 1988). Today, China is the new champion of accelerated innovation, leveraging concurrent engineering techniques to gain a time-to-market advantage for non-breakthrough innovations (Williamson and Yin, 2014).

A recent report by McKinsey & Company ranked ‘capturing external ideas’ among the top innovation management practices that differentiates the most from the least agile companies (Bazigos et al., 2015). In their meta-analysis, Cankurtaran et al. (2013), find that development speed is associated with increased new product success. Moreover, they also find in their analysis of the antecedents of development speed that integration with external partners, i.e. customers, suppliers and others, is positively contributing.

Chesbrough (2017) argues that managing the impact of open innovation on internal innovation is one of the main future challenges of open innovation. He also mentions that bringing in external knowledge into the organization could potentially slow down the innovation process if a company has not invested adequately in capacity to process the influx. Accordingly, in this paper, I study the nexus between external information sourcing and appropriation through lead-time advantage. In what follows I will consider three characteristics of the external sourcing strategy through which firms influence appropriation: 1) external knowledge sourcing breadth and depth, 2) use of specific external knowledge sources, 3) the special case of co-development.

I find that firms that are drawing information from consumers, suppliers, and science are more likely to enhance appropriation through lead-time advantages. The returns to breadth and depth of external sourcing are diminishing in nature. For depth of knowledge sourcing, I find that there exists an inflection point where returns get negative. As a special case, I further find that firms that developed their novelties or imitations with involvement of external parties benefit from better appropriation through lead-time advantages.

The rest of this paper is structured as follows: Section 2 summarizes the relevant literature and develops the hypotheses. Section 3 describes the empirical setup. A description of the data and variables used is given and the estimation method is briefly explained. Section 4 summarizes the results from a regression analysis before they are subsequently discussed in section 5. Section 5 also concludes.

2. RELATED LITERATURE AND HYPTHESES DEVELOPMENT

Empirically, my analysis closely relates to the literature relating the use of external knowledge sources to innovation outcomes. The evidence points out that companies sourcing knowledge broadly (i.e. drawing from a diverse set of sources) and deeply (i.e. drawing extensively from the sources in use) have better innovation performance. Laursen and Salter (2006) find that searching widely and deeply is curvilinear related to innovative sales performance. Franz and Ietto-Gillies (2008) find that while own-generation, and bought-in R&D matter in innovation performance, the benefits of joint innovation efforts in the form of cooperation are less clear. Belderbos et al. (2010) confirm an inverted U-shape relationship between openness and the financial performance of the firm, while Salge et al. (2013) demonstrate that openness of knowledge sourcing and new product success also relate curvilinear at the project level. According to Leiponen and Helfat (2010), broader horizons with respect to innovation objectives and knowledge sources are associated with successful innovation. Zhu et al. (2019) look at the relation between external sourcing and new product development (NPD) speed and find positive effects of both external sourcing breadth and depth that are further moderated by business model innovation.

Theoretically, Koput's model of innovative search (1997) states, amongst other things, that within firms there may exist an 'attention allocation problem', i.e. only few ideas are given the required attention to bring them into implementation. In this respect, the attention-based theory of the firm (see also Simon, 1947 and Ocasio, 1997) argues that in allocating managerial attention to certain activities, firms are limited by their available attention pool. According to the theory, decision-makers need to ‘concentrate their energy, effort and mindfulness on a limited number of issues’ in order to achieve sustained strategic performance (Ocasio, 1997: p. 203).

Scanning a new source requires spending relatively little attention and finding an new interesting piece of knowledge can contribute to the quality of an innovation but also to the timeliness with which it can be introduced. However, benefits of ever-broader search might be diminishing in nature, because of a loss of (managerial) focus and decreasing additional usefulness of the marginal source. Therefore I hypothesize:

H1: The relationship between the broadness of knowledge sourcing and the degree to which companies can profit from lead-time advantage is positive but with diminishing marginal returns.

External search that explores too many sources deeply could lead to misallocation of the limited pool of attention that is available, which could lead to innovations that are of inferior interest to the market or it could delay the process of getting a useful invention to market. I hypothesise:

H2: The relationship between the deepness of knowledge sourcing and the degree to which companies can profit from lead-time advantage is positive but with diminishing marginal returns.

For deep search, ‘over-searching’ would tap into attention pool to a greater extent. Therefore, I expect that negative effects stemming from over-using deep search will be larger than the negative effects of merely over scanning the environment, i.e. over-using broad search.

The Yale survey (Klevorick et al., 1995) in the US and the PACE survey (Arundel et al., 1995) in Europe have documented a wide range of external information sources used by companies to complement their own knowledge base. These include: suppliers, clients, competitors in the same industry, consultants, and university and government research. These information sources can be divided into two broad categories: horizontally or vertically related. I define horizontal and vertical relations close to the definitions used in the mergers and acquisitions literature (Salinger et al., 1983; Salinger, 1989).

Vertically related sources pertain to institutions either upstream (suppliers) or downstream (clients) to the company. I also regard information from government and university research as vertically related because in a representative cross section of the economy it likely is positioned upstream, i.e. most firms do not have scientific research as their main business. Horizontally related sources pertain to institutions having similar product offerings (competitors). I regard information from consultants as horizontally related as it concerns information that is equally available amongst competitors and is not stemming from either up- or downstream entities in the value chain. For horizontally sourced information there is a trade-off taking place: i.e. more and better information could put firms at a speed-advantage, however insofar as information is disseminated multilaterally, the advantage might be mitigated because then competition is also better informed. Thus, horizontal related information may still be important to keep pace with the competition, but does not necessarily confer an advantage. Vertically sourced information however, I hypothesize, is acquired on the basis of an idiosyncratic relation with the up- or downstream entity and therefore does not entail direct information spill over to third party competition.

H3: External information sourcing from institutions that are vertically related to the focal company, i.e. suppliers, clients and science positively contribute to the degree to which the focal company profits from lead-time advantages.

Further, I will test how the effects of external knowledge sourcing on lead-time advantage are moderated by the internal R&D or absorptive capacity of the firm. I argue that firms making investments into absorptive capacity (see Cohen & Levinthal, 1990) are having a larger effective attention pool to be allocated over the different channels. Furthermore, these firms will make less 'misallocation' of attention. In line with existing research on the complementarity between external knowledge sourcing and internal R&D (Cassiman and Veugelers, 2006), I hypothesise:

H4: Companies that have a high absorptive capacity, in term of internal R&D intensity, suffer to a lesser extent from decreasing marginal returns to external information sourcing.

While companies can purposely use a certain external knowledge sourcing strategy, they also still have to decide on how to operationalize the innovation process. First, the company faces a make-or-buy decision (Veugelers and Cassiman, 1999). Second, if a company decides to 'make', the question arises of whether they will develop in relative isolation or would rather co-develop with others (as in e.g. Bossink, 2002). Co-operation can be regarded as a special case of information transmission in which the partners make (formal) ties. Also, proponents of open innovation argue extensively that an open innovation process contributes to the likelihood of innovation success (e.g. Chesbrough, 2003, 2017). I hypothesise:

H5: Companies that co-develop their product innovations profit to a higher degree from lead-time in innovation.

To gauge to which extent my results are being driven by first-to-market innovators (capitalizing on first mover advantages) or imitators (capitalizing on late mover advantages), I will conduct a sample split analysis. As such the analysis is ran for firms having introduced market novelties in the last two years (first-to-market innovators) versus firms only having introduced products new to the firm in the last two years (imitations). For successfully imitation of an existing novelty, a firm might need a largely different knowledge sourcing strategy than when developing a market novelty.

3. EMPIRICAL SETUP

The data set used to conduct the analysis originates from Belgian part of the Community Innovation Survey[1], an inquiry about the innovative activities in the Flemish economy, carried out bi-annually since 1993. The CIS methodological standards comprise a stratified random sampling procedure to ensure representativeness of the sample for the whole economy. The data consists of one cross-section of the Flemish economy surveyed in 2013 about their activities in the period spanning 2010-2012. The sample covers firms in the manufacturing as well as services sector. 3871 firms responded to the survey. About 40 % of firms reported to have had at least one product innovation in the surveyed period. I restrict the sample to product innovators only as the interest lies in relating the effectiveness of using lead-time advantages for appropriation of innovation to the openness of the innovation process in general and the use of external information sources to innovate more specifically. The definition of an innovating firm follows the international guidelines for collecting innovation data from the business sector as described by the OSLO manual (OECD Publishing, 2005). Twenty firms were dropped from the analysis because of extreme sales productivity or extreme productivity growth. Considering item non-response on the variables used in our specifications, the final estimation samples count 852 observations.

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[1] This pan-european survey is conducted in Flanders by the Centre for Research & Development Monitoring (ECOOM) on behalf of the Flemish government.

3.1. Dependent Variable

The outcome variable in my analyses measures how effective the use of lead-time advantages in new product development was in sustaining or improving the competitive position of the firm. LEAD TIME is defined on a 4-point likert scale and indicates whether lead-time advantages were contributing to a large, medium, or small degree to competitive advantage build-up from innovation. Companies could also indicate they did not make use of lead-time advantages.

3.2. Regressors of Interest

The survey inquired firms about how intensely the following information sources were used in their innovation (knowledge sourcing) strategy:

a. Suppliers

b. Clients from the private sector

c. Clients from the public sector

d. Competitors

e. Consultants

f. Universities

g. Government institutions, research labs

h. Conferences, trade fairs, exhibitions

i. Scientific literature and professional publications

j. Professional and sectorial associations

k. Sources within the corporate group

On a 4-point likert scale companies could indicate whether the source had large (value 3), medium (value 2), or low (value 1) importance in their knowledge sourcing strategy, or that the source was not used (value 0). Knowledge sourcing BREATH and DEPTH are respectively defined as the total number of information sources used from the list and the number of sources with a large importance (having the maximum value of 3) (cfr. Laurson and Salter, 2006). Companies have an average knowledge sourcing BREADTH of about 7 and an average knowledge sourcing DEPTH of about 2.

I aggregate the list into logical categories by taking the maximum value from the relevant items from the list. Descriptively (a) SUPPLIERS appear with an average importance of 2.1, (b-c) CLIENTS with an average importance of 1.8, (d) COMPETITORS with an average importance of 1.5, (e) CONSULTANTS with an average importance of 1.1, and (f-j) SCIENCE – ACADEME with an average importance of 1.5.

The variable CO-DEVELOP is an indicator variable that is set to 1 when the company developed at least some of its innovations with third party involvement. 67 % of firms in the estimation sample co-developed, meaning that at least some of the innovations they launched in the survey period were developed in cooperation with other firms or institutions, or by subcontracting innovative activities.

3.3. Control Regressors

Patents are legal rights to exclude others from producing and selling an innovation, sometimes granted to the original inventor. As such, a first mover that obtained patent rights might be in a better position to monetize on its lead-time advantage. Patent stock for firm i in year t, was retrieved by from the PATSTAT database applying the following formula.

$$PS_{it} = (1 - \delta)\, PS_{it-1} + patent\ applications_{it}$$

Where δ, the constant knowledge depreciation rate, is set to 15%. PATENT INTENSITY further scales the patent stock per employee. The patent applications are aggregated on the family level to obtain unique inventions. To mitigate endogeneity concerns this variable enters my specification as measured in 2010, i.e. with a lag of 2 years. The PATENT INTENSITY varies between 0 and 1 and on average a firm has 1 patent per 50 employees. 77 % of the firms did not apply for patents in the past. The fact that the upper limit of the value range for this variable is 1 is purely due the coincidence that the most intensely patenting company seems to have exactly 1 patent per employee.

Internal R&D expenses could potentially confound the hypothesised effects. R&D heavy firms might both build lead-time advantages through their own internal research and development efforts and at the same time have more and better access to external information. I measure R&D INTENSITY as intramural R&D spending per employee in 2012. 30 % of the firms in the estimation sample realized their product innovations without spending on intramural R&D, whereas the most R&D intensive firm spent 231 thousand euro on internal R&D per employee.

Further general controls on firm size and age, EMPLOYMENT and AGE, are available. Large and established firms might more easily profit from lead-time advantages (due to market power) and more easily build external information networks or be in a better position to open up the innovation process. Therefore, these potential effects should be controlled for in the analysis.

Firms are between 3 and 179 years old and have between 2 and 4280 employees. Finally, sector dummies are available to be able to control for inter-sectorial differences.

Table I with the summary statistics shows a good amount of variation amongst the observations in the estimation sample. Because of the skewed distribution of age and size, their values will be log transformed for the regression analysis. The sectorial distribution of the sample, depicted in table II, shows quite some variation, but there is a substantial amount of observations in each sector. Table III depicts the pairwise correlations between the analysis variables.

Insert Tables 1, 2 and 3 about here

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4. RESULTS

In the regression analysis, I study an ordered outcome variable indicating the effectiveness of lead-time advantages in the appropriation strategy of firms. I relate it to characteristics of the external knowledge sourcing strategy and a measure of co-development. I run ordered probit models in order to take into account the nature of the dependent variable.

4.1. Knowledge Sourcing Breadth and Depth (H1, H2)

Table IV contains the results from ordered response models assessing the relation between the effectiveness of lead-time advantage (LEAD TIME EFFICIENCY) for appropriation of innovation and knowledge sourcing BREATH and DEPTH. The initial specification only includes the variables of interest. To allow for non-linearity I include also the squares of the variables. In line with H1 and H2 I find that knowledge sourcing BREATH and DEPTH have diminishing marginal returns on the effectiveness of using lead-time advantage in the competitive strategy, all coefficients being significant at least at the 5% level. Stacking PATENT and R&D INTENSITY into the specification, I find that innovation input is positively related to the outcome variable. The coefficients on the variables of interest do not change much and remain significant at the same significance level. Further adding general firm level controls also does not change the effects on the variables of interest. I find that bigger firms (LNEMP) are more effectively using lead-time advantages. The coefficient on LNAGE is insignificant. A test on the joint significance of the sector dummies indicates that the effectiveness of lead-time advantages is sector specific, the F-test being significant at the 5% level.

To further gauge the diminishing marginal returns to knowledge sourcing breadth and depth, I plot the linear predictions of LEAD TIME EFFICIENCY relative to the values taken by breadth (figure I) and depth (figure II). Since the cut-off points in the estimation are ordered along this linear prediction, higher values of the linear prediction correspond to higher values of estimated LEAD TIME EFFICIENCY.

Insert Figures 1 and 2

From figure I we can read that the positive returns to knowledge sourcing breath are diminishing in nature. There is no clear point of inflection where the returns become negative. Figure II indicates that the (initially positive) returns to knowledge sourcing depth are diminishing in nature. However, at around the value of 5 the predicted latent probability start to decrease, indicating that at higher values of depth the returns become negative.

Insert Table 4 about here

4.2. Specific Sources of External Information (H3)

Table V contains the results from ordered response models assessing the relation between the effectiveness of use of lead-time advantages and the types of external information channels in use. The initial specification only includes the variables of interest. In line with H3, I find that vertically related information sources (CLIENTS, SUPPLIERS and SCIENCE) are positively impacting LEAD TIME, the coefficients being significant at least at the 5% level. The coefficients on horizontally related sources (COMPETITORS and CONSULTANTS) are at most marginally significant. Stacking PATENT and R&D INTENSITY into the specification, I find that innovation input is positively related to the outcome variable. The coefficients on the variables of interest do not change much and remain significant at the same significance levels. Further adding general firm level controls also does not change the effects on the variables of interest. I find that bigger firms (LNEMP) are more effectively using lead-time advantages. The coefficient on LNAGE is insignificant. A test on the joint significance of the sector dummies indicates that the effectiveness of lead-time advantages is sector specific, the F-test being significant at the 5% level.

Insert Table 5 about here

4.3. Complementarity between external sourcing and internal capacity (H4)

Next, I estimate separate coefficients for breadth, depth and their squares by interacting with a dummy variable that splits the sample at the mean of R&D Intensity (see table VI). By plotting the linear predictions at the mean of all other regressors (see Figures III and IV) one can see that firms having an R&D intensity above the mean are not estimated to be confronted with substantially diminishing marginal returns. Neither for breadth nor for depth. Firms with R&D intensities below the mean do exhibit substantial diminishing marginal returns.

Insert Table 6 about here

Insert Figures 3 and 4 about here

4.4. Co-operation for New Product Development (H5)

Throughout the empirical analysis, I find a robust effect of firms that CO-DEVELOP to be more likely to have a high LEAD TIME EFFICIENCY. All effects in this regard are significant at the 1 pct. level. This result is in line with H5.

4.5. *Sample split new-to-market vs. new-to-firm*

Based on the survey response I split the sample into firms having introduced an entire new product as first to the market and firms not having done so. See table VII for descriptive statistics by subsample. In table VIII I find that both knowledge sourcing breadth and depth matter with regard to having had effective benefit from lead-time advantage for first-to-market product innovators. For firms only having had new-to-firm innovations (imitations) only knowledge sourcing breadth seems to matter. In the regressions with the specific external information channels included as regressors, the coefficients are only significant when estimating for first-to-market innovators.

Insert Tables 7 and 8

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5. DISCUSSION AND CONCLUSION

This paper, based on an analysis of Community Innovation Survey data, aimed to find out if certain innovation strategies might be conducive for achieving an effective lead-time advantage with respect to innovation. In particular, external knowledge sources were studied as catalysts of innovation appropriation by means of obtaining a lead-time advantage over rivals' product development cycles.

I find firms drawing information from vertically related information sources, consumers, suppliers, and science are benefiting from more effective appropriation from lead-time advantages. Returns to knowledge sourcing breadth, I find, are diminishing in nature. Further, I find an inverted-U relation between the efficiency of using lead-time advantage for appropriation on the one hand and depth of the external knowledge sourcing strategy on the other. Lead-time advantages can thus seemingly be created through diverse and deep knowledge sourcing, although there are diminishing returns. Furthermore, I find that co-developing firms, i.e. indicating they realized their innovations or imitations with active involvement of external parties, are more likely to profit from lead-time advantages. The results are mainly driven by first-to-market innovators, however, new-to-firm innovators are seemingly still benefiting from a broader external knowledge sourcing strategy, possibly reflecting that effective imitation requires firms to have a bird's eye view of the innovative landscape to out-imitate their competition. Apart from the information sourcing strategy, also cooperation during the development process seems to matter, as firms that co-develop are more likely to profit from lead-time advantages.

These results are especially relevant in the light of recent literature on open innovation (e.g. Chesbrough, 2017) which states that managing the impact of open innovation on internal innovation is one of the main future challenges of open innovation. The results are also in line with

Laursen and Salter (2006), who find an inverse-U relation between breadth and depth of knowledge sourcing and innovation sales performance. If one considers that timeliness is an important dimension of successful innovation, one could argue that my results reflect that broad and deep information sourcing is inverse-U related to successful innovation. The diminishing returns that I find are thus in line with existing empirical work. Chesbrough's (2017) argument that innovation could be slowed down if companies do not invest properly into the capacity to handle the influx of external information can probably partly explain why firms are confronted with decreasing marginal retuns. Additional evidence for this argument – i.e. complementarity between external information sourcing and internal absorptive capacity – was found , i.e. firms having a higher absorptive capacity, as proxied by a high R&D intensity, do not exhibit a significant decrease in their marginal returns to both breadth and depth. This result is in line with the complementarity between internal R&D and external knowledge acquisition as found by Cassiman and Veugelers (2006).

The digital revolution, being a main contributor by the increasing information storage, processing, and retrieval capacity (Hilbert & López, 2011), enabled firms to become ever more agile (Overby et al., 2006) and thereby, most likely, contributed to the rise of superstar firms in concentrated industries (cf. e.g. Mcafee & Brynjolfsson, 2008) . One interesting avenue for future research would be to find out how the relation between external knowledge sourcing strategy and lead-time advantage is moderated by investments in ICT capacity. ICT concerns general-purpose technology (GPT). As Pisano (2017) argues and later elaborated upon by Helfat (2018), building GPT capabilities, and by extension competitive lead-time advantages, might require drawing on substantially different types of knowledge sources than those underpinning market or application specific capabilities. As a first effort in this regard I re-considered the models from the previous section while estimating separate coefficients for NACE[2] sectors 62 (design and programming of computer software, computer consultancy and related activities; 109 observations) and 63 (information services; 8 observations) of the sample. The results (not reported) indicate an asymmetric importance of different knowledge sourcing types with regard to lead-time. GPT industries mainly leverage scientific knowledge in combination with information retrieval from clients (e.g. for the determination of customer needs). Other industries leverage a combination of supply side and demand side information.

Interpreting my results requires adequate caution by considering it as correlational evidence since I did not establish a clean identification of causal effects. Good instruments for the information sourcing variables would be hard to come by given that the knowledge sourcing strategy decisions are potentially highly interrelated with other (measurable) company characteristics. Natural experiments that influence the companies' knowledge sourcing profile are, to my knowledge, non-existent. Panel data on the subject could resolve the issue to some extent but it is currently impossible to plausibly build a representative panel from Flemish CIS cross sections.

Keeping this in mind, my results inform firms' management when establishing an external search strategy and government when subsidising specific projects. The type of innovations prevalent in the firm – general purpose vs. application specific, new-to-firm vs. new-to-market – seems to prescribe distinct knowledge sourcing strategies. Another factor to take into consideration in tandem are the investments in absorptive capacity a firm makes. Leveraging external knowledge

[2] NACE Rev. 2: Statistical classification of economic activities in the European Community. https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

efficiently might require simultaneous internal R&D efforts to offset potential diminishing returns.

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Table 1. Descriptive Statistics[2]

VARIABLE	DESCRIPTION	N	μ	σ	MIN	MAX
LEADTIME	4-point likert indication of how efficient lead-time was with regard to appropriation.	852	1.16	1.18	0	3
BREADTH	Total number of external information sources used.	852	7.53	3.06	0	11
DEPTH	Total number of external information sources for which the company indicated the maximum importance.	852	2.07	1.68	0	11
SUPPLIERS	Indicates on a 4 point scale how intensively the company used suppliers as a source of information.	852	2.12	0.90	0	3
CLIENTS	Indicates on a 4 point scale how intensively the company used clients as a source of information.	852	1.83	1.09	0	3
COMPETITORS	Indicates on a 4 point scale how intensively the company used competitors as a source of information.	852	1.52	0.95	0	3
CONSULTANTS	Indicates on a 4 point scale how intensively the company used consultants as a source of information.	852	1.11	1.00	0	3
SCIENCE	Indicates on a 4 point scale how intensively the company used science/academia as a source of information.	852	1.47	1.00	0	3

Table 1. Descriptive Statistics Cnt'd[3]

VARIABLE	DESCRIPTION	N	μ	σ	MIN	MAX
CO-DEVELOP	Indicates whether the company realized its innovation with third party involvement.	852	0.67	0.47	0.00	1
PATENT INTENSITY	Depreciated patent stock per employee	852	0.02	0.07	0.00	1
R&D INTENSITY	R&D expenditures (2012) per employee	852	12.00	27.02	0.00	231.5
AGE	Age of the firm	852	26.56	18.70	3.00	179
EMP	Number of employees	852	140.84	378.58	2.00	4280

[3] From the sample, 20 companies were dropped due to a suspiciously high sales product (>15mio per employee) or productivity growth (x2), indicating there might be some error in the response (i.e. the unit which was reported for might not be identified since there is a 'mismatch' between 2 measures of size, employment and turnover).

Table 2. Sector Distribution for N=852

Sectors	SECTOR DESCRIPTION	N	R. Freq
Sector 1	Food, beverage, tobacco	116	0.14
Sector 2	Textile, clothing and leather industry	37	0.04
Sector 3	Manufacture of cokes, chemicals, pharmaceuticals, rubber and plastic	91	0.1
Sector 4	Manufacture of non-ferro minerals, metals and metal products (no machinery and equipment)	82	0.1
Sector 5	Manufacture of electrical equipment, IT-products, electronic and optical products	54	0.06
Sector 6	Manufacture of machinery, equipment, tools and transport	74	0.08
Sector 7	Wholesale	72	0.09
Sector 8	Telecomunication, software design and programming, computer-consultancy, information services, architects and engineering, R&D	217	0.26
Sector 9	Remaining sub-sectors	109	0.13

Table 3. Bivariate correlations

Pairwise correlation	1	2	3	4	5	6	7	8	9	10	11	12
1. LEADTIME	1											
2. BREADTH	0.28	1										
3. DEPTH	0.22	0.45	1									
4. SUPPLIERS	0.17	0.48	0.48	1								
5. CLIENTS	0.24	0.57	0.48	0.23	1							
6. COMPETITORS	0.17	0.64	0.54	0.38	0.46	1						
7. CONSULTANTS	0.19	0.62	0.46	0.24	0.28	0.35	1					
8. SCIENCE	0.23	0.68	0.52	0.35	0.29	0.47	0.45	1				
9. CO-DEVELOP	0.17	0.15	0.12	0.18	0.04	0.12	0.18	0.09	1			
10. PAT. INTENSITY	0.07	0.11	0.06	-0.02	0.09	-0.01	0.16	0.12	-0.00	1		
11. R&D INTENSITY	0.18	0.22	0.21	-0.02	0.19	0.13	0.26	0.22	0.03	0.34	1	
12. LNAGE	-0.01	0.02	0.02	0.10	0.03	0.01	-0.02	-0.01	0.07	-0.16	-0.19	1
13.LNEMP	0.17	0.28	0.16	0.14	0.16	0.17	0.18	0.18	0.22	-0.08	-0.03	0.36

Table 4. Breadth and Depth of Knowledge
Ordered Probit Regressions

b/se	LEAD TIME	LEAD TIME	LEAD TIME
BREADTH	0.217***	0.198***	0.202***
	(0.063)	(0.066)	(0.066)
BREADTH_SQUARED	-0.009**	-0.009*	-0.011**
	(0.005)	(0.005)	(0.005)
DEPTH	0.301***	0.284***	0.287***
	(0.065)	(0.066)	(0.066)
DEPTH_SQUARED	-0.031***	-0.031***	-0.030***
	(0.009)	(0.009)	(0.009)
CLOSED		-.322***	0.307***
		(0.086)	(0.088)
PATENT INTENSITY		0.039	0.132
		(0.623)	(0.642)
R&DINTENSITY		0.005***	0.005***
		(0.002)	(0.002)
LNAGE			-0.049
			(0.064)
LNEMP			0.064**
			(0.032)
Sectors			Incl.**
cut1	1.285***	1.414***	1.532***
_cons	(0.211)	(0.214)	(0.299)
cut2	1.673***	1.809***	1.936***
_cons	(0.213)	(0.216)	(0.301)
cut3	2.387***	2.535***	2.674***
_cons	(0.216)	(0.219)	(0.303)
Pseudo R2	0.049	0.061	0.073
#obs	852	852	852
Wald	107.96	133.61	159.64
Sig	0.000	0.000	0.000

*(Notes: Significance levels: *** 1 pct. or less; ** less than 5 pct. , * less than 10 pct.)*

Figure 1. Returns to BREADTH

Linear Prediction for LEADTIME in Relation to Knowledge Sourcing BREADTH Derived From the Ordered Probit Estimation.

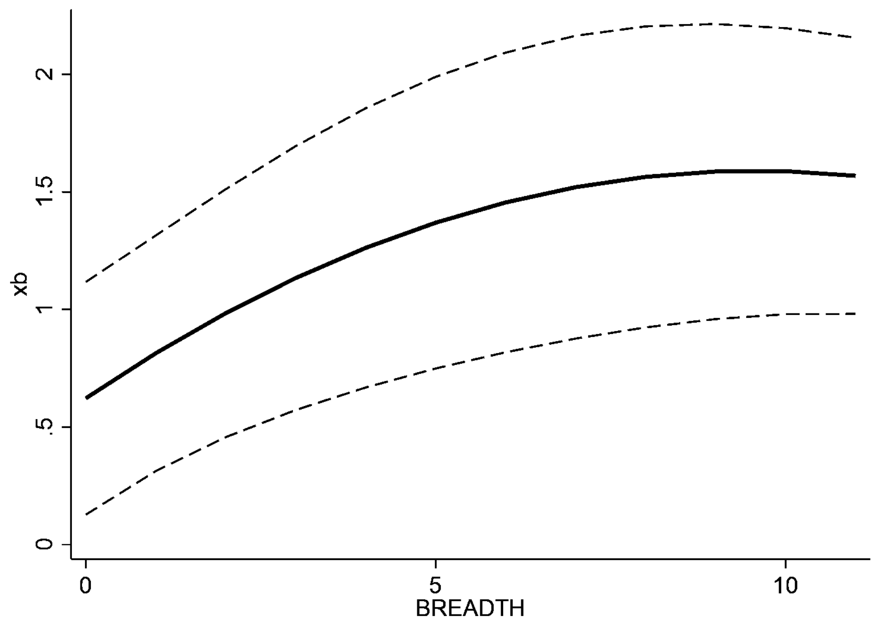

Figure 2. Returns to DEPTH

Linear Prediction for LEADTIME in Relation to Knowledge Sourcing DEPTH Derived From the Ordered Probit Estimation.

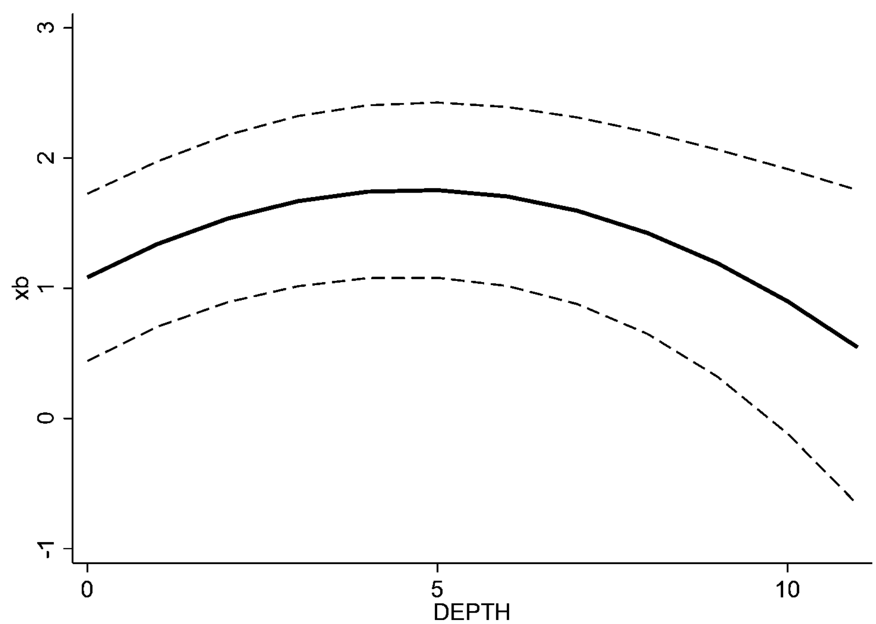

Table 5. Intensity of Use of Specific of Knowledge Sources
Ordered Probit Regressions

b/se	LEADTIME	LEADTIME	LEADTIME
SUPPLIERS	0.127**	0.125**	0.130**
	(0.050)	(0.051)	(0.052)
CLIENTS	0.206***	0.200***	0.191***
	(0.042)	(0.042)	(0.042)
COMPETITORS	-0.028	-0.034	-0.042
	(0.052)	(0.053)	(0.053)
CONSULTANTS	0.079*	0.023	0.018
	(0.045)	(0.046)	(0.047)
SCIENCE	0.160***	0.148***	0.113**
	(0.048)	(0.048)	(0.049)
CLOSED		0.359***	0.340***
		(0.087)	(0.089)
PATENT INTENSITY		-0.01	0.113
		(0.630)	(0.647)
R&D INTENSITY		0.005***	0.005***
		(0.002)	(0.002)
LNAGE			-0.059
			(0.064)
LNEMP			0.070**
			(0.032)
Sectors			Incl. **
cut1	0.784***	0.622***	0.613**
_cons	(0.123)	(0.133)	(0.257)
cut2	1.167***	1.013***	1.014***
_cons	(0.126)	(0.134)	(0.258)
cut3	1.880***	1.739***	1.751***
_cons	(0.131)	(0.139)	(0.260)
Pseudo_R2	0.042	0.056	0.068
#obs	852	852	852
Wald	92.419	121.986	148.858
Sig	0.000	0.000	0.000

*(Notes: Significance levels: *** 1 pct. or less; ** less than 5 pct. , * less than 10 pct.)*

Table 6. Complementarity Between External Sourcing and Internal Capacity

CMLTAD	**b/se**
BREADTH	0.28***
Breadth_squared	-0.02***
Depth	0.37***
Depth_squared	-0.04***
I(>μ(R&DINTENSITY))	1.32***
BREADTH* I(>μ(R&DINTENSITY))	-0.28**
Breadth_squared* I(>μ(R&DINTENSITY))	0.02**
Depth* I(>μ(R&DINTENSITY	-0.20
Depth_squared* I(>μ(R&DINTENSITY))	0.03
Patent intensity	0.04
R&Dintensity	0.00**
LNAGE	-0.04
LNEMP	0.08***
Sector dummies	Incl.
/cut1	1.72
/cut2	2.13
/cut3	2.87

Figure 3. Complementarity Between External Sourcing and Internal Capacity (BREADTH)

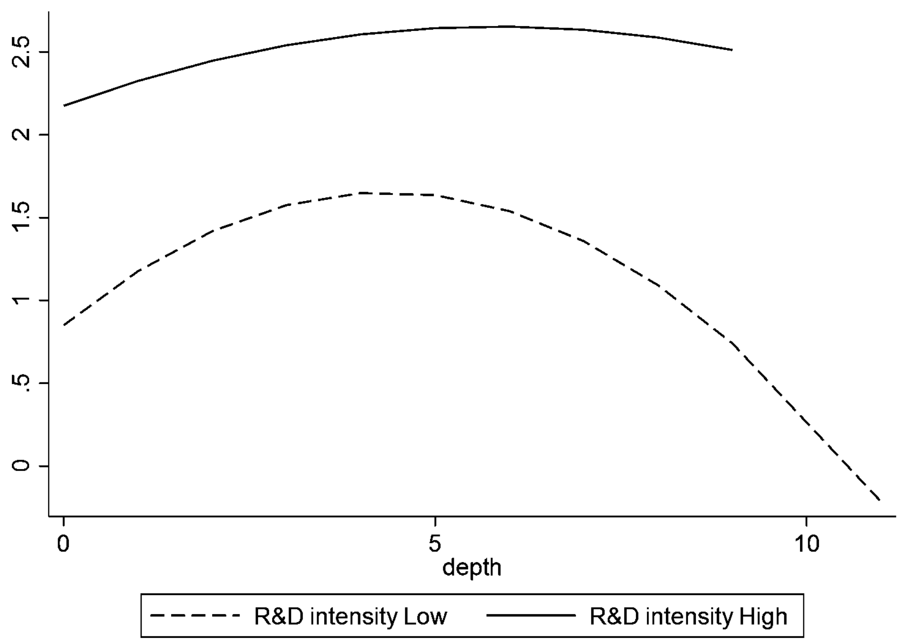

Figure 4. Complementarity Between External Sourcing and Internal Capacity (DEPTH)

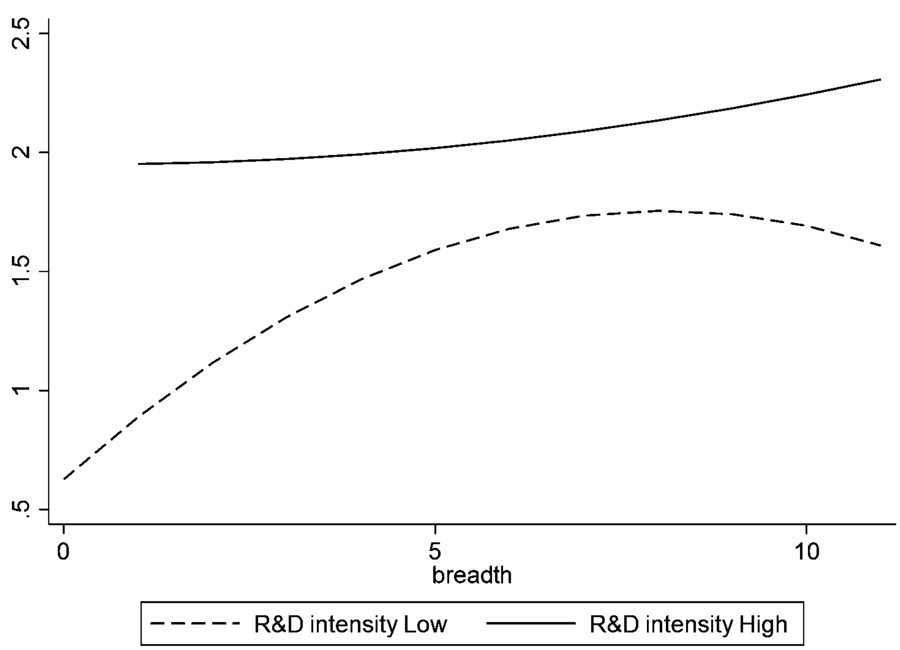

Table 7. Descriptive Statistics for Split Sample

VARIABLE	DESCRIPTION	NOVELTIES	NO NOVELTIES	T-TEST
LEADTIME	4-point likert indication of how efficient lead-time was with regard to appropriation.	1.31	0.85	***
BREADTH	Total number of external information sources used.	7.97	6.38	***
DEPTH	Total number of external information sources for which the company indicated the maximum importance.	2.23	1.72	***
SUPPLIERS	Indicates on a 4 point scale how intensively the company used suppliers as a source of information.	2.12	2.1	
CLIENTS	Indicates on a 4 point scale how intensively the company used clients as a source of information.	2.05	1.40	***
COMPETITORS	Indicates on a 4 point scale how intensively the company used competitors as a source of information.	1.60	1.38	***
CONSULTANTS	Indicates on a 4 point scale how intensively the company used consultants as a source of information.	1.23	0.89	***
SCIENCE	Indicates on a 4 point scale how intensively the company used science/academia as a source of information.	1.31	0.85	***

CLOSED	Indicates whether the company realized its innovation without third party involvement.	0.31	0.37	
PATENT INTENSITY	Depreciated patent stock per employee	0.018	0.0078	**
AGE	Natural logarithm of age of the firm	15	5.08	**
EMP	Natural logarithm of number of employees	26.37	26.7	

*(Notes: Significance levels: *** 1 pct. or less; ** less than 5 pct. , * less than 10 pct.)*

Table 8.
Sample Split on Having a Market Novelty
Ordered Probit Regressions of Efficiency of Using Lead-Time Advantages for Appropriation on External Knowledge Sourcing Variables.

	FIRMS HAVING MARKET NOVELTIES		**FIRMS HAVING NO MARKET NOVELTIES**	
b/se	**LEAD TIME**	**LEAD TIME**	**LEAD TIME**	**LEAD TIME**
BREADTH	0.179** (0.087)		0.299*** (0.103)	
BREADTH_SQUARED	-0.008 (0.006)		-0.022*** (0.008)	
DEPTH	0.339*** (0.080)		0.142 (0.121)	
DEPTH_SQUARED	-0.035*** (0.010)		-0.015 (0.019)	
CO-DEVELOP	0.323*** (0.107)	0.343*** (0.110)	0.275* (0.156)	-0.312** (0.159)
SUPPLIERS		0.164** (0.065)		0.119 (0.087)
CLIENTS		0.172*** (0.054)		0.133* (0.074)
COMPETITORS		-0.048 (0.065)		0.010 (0.097)
CONSULTANTS		0.008 (0.058)		0.000 (0.085)
SCIENCE		0.153** (0.060)		0.006 (0.092)
general Firm Level controls & Sector dummies	Included	Included	Included	Included
Pseudo R2	0.074	0.068	0.06	0.049
#obs	576	568	296	284
Wald	113.712	103.893	39.564	31.274
Sig	0.000	0.000	0.001	0.027

*(Notes: Significance levels: *** 1 pct. or less; ** less than 5 pct. , * less than 10 pct.)*