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Search Patterns and Absorptive Capacity: A Comparison of Low- and High-Technology Firms from Thirteen European Countries

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Non-technical Summary

Searching for externally available knowledge has been characterised as a vital part of the innovation process. Previous research has, however, almost exclusively focused on high-technology environments, largely ignoring the substantial low- and medium-technology sectors of modern economies. We argue that low- and high-technology firms differ in their search patterns and that these moderate the relationship between innovation inputs and outputs. Our research aims at extending existing literature in two ways. First, we investigate whether different patterns of search strategies exist in high- and low-technology industries respectively. Second, we analyse the link between these search patterns and the payoffs from R&D investments with regard to market success. The empirical part of this research is based on the third Community Innovation Survey (CIS-3), providing insights to the innovation processes of 4,500 firms from 13 European countries using a latent class methodology. It enables us to derive targeted policy recommendations as we obtain fine-grained input-output relationships for different industries (high- versus low-technology) under different search patterns.

Our results paint a differentiated picture for optimised search patterns in high- and low-technology industries. This needs to be reflected in tailor-made policy development. We find that low-technology firms investing in R&D to develop absorptive capacity can achieve the highest returns if they direct their search behaviour towards customers. Competitor reconnaissance may be a less risky strategy but it is also associated with lower returns. With regards to policy implications, this implies that innovation performance can be strengthened by incorporating customer interaction into R&D funding and incentive schemes for these industries. This may imply preferential treatment or mandatory requirements for including customers in publicly funded project consortia. Besides, public R&D support schemes targeting low-technology sectors should be built around markets and customers instead of specific technologies. Moving from competitor centric search patterns to customer centred ones may be a promising but risky goal. However, even policy supported, gradual shifts towards more balanced search strategies would improve the efficiency of R&D investments with regard to market success.

In high-technology industries, though, supporting supplier centric search patterns that are built around suppliers of new equipment and materials is rewarding but appears to be a niche strategy. Instead, university knowledge is the major leverage point for a firm’s search pattern and hence policy intervention. Our results indicate that knowledge from universities play an important role for generating knowledge stocks inside high-technology firms. However, full market success can be realised once firms move away from a myopic focus on universities for their knowledge acquisition. The differences between these stages should be reflected in public R&D support. Hence, tailor-made policy instruments should encourage high-technolgy firms in applied, close-to-application fields to move away from a narrow focus in their search strategies on universities and develop a broader set of absorptive capacities.

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Abstract

Searching for externally available knowledge has been characterised as a vital part of the innovation process. Previous research has, however, almost exclusively focused on high-technology environments, largely ignoring the substantial low- and medium-technology sectors of modern economies. We argue that low- and high-technology firms differ in their search patterns and that these moderate the relationship between innovation inputs and outputs. Based on a sample of 4,500 firms from 13 European countries we find that search patterns in low-technology industries focus on market knowledge while they are built around differences in technology sourcing activities for high-technology industries.

Keywords: Absorptive capacity, search strategies, low-, medium- and high-technology sectors, open innovation

JEL-Classification: L60, O32

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1 Introduction

Innovation activities have frequently been shown to be a cornerstone for increasing the market share, market value as well as the long-term survival prospects of firms (e.g. Banbury and Mitchell, 1995; Brockhoff, 1997; Brockhoff, 1999). In order to sustain the ability to successfully introduce new products to the market, many firms have shifted to a model of "open innovation" that is characterised as involving a wide range of actors from the innovation system in the innovation process and exploiting their knowledge (Chesbrough, 2003). Such innovation impulses from external sources like customers, suppliers, competitors or universities can subsequently be conceptualised as the main elements of a firm's *search strategy,* which has been shown to have a substantial impact on innovative performance (Katila, 2002; Katila and Ahuja, 2002; Laursen and Salter, 2006). The search strategy can be defined as an "organisation's problem solving activities that involve the creation and recombination of technological ideas" (Katila and Ahuja, 2002: 1184). Problem solving activities hence occur in the spectrum from exploitation to exploration (March, 1991). The definition of an appropriate search strategy, however, critically depends on the ability to recognise the potential value of external knowledge sources. This ability has been summarised as the *absorptive capacity* of firms (Cohen and Levinthal, 1990).

Interestingly, there is almost an implicit assumption in the literature that search strategies for external knowledge are particularly beneficial for firms operating in those environments where research and development (R&D) is key to overall firm strategy, i.e. in high- or medium-high-technology (HMT). Shan et al. (1994) investigate the relationship between organisational learning through cooperation and innovative output in the biotechnology industry. Interorganisational collaboration and innovation in the same industry is studied by Powell et al. (1996). Rosenkopf and Nerkar (2001a) focus on the optical disc industry to examine boundary-spanning searches. Katila (2002) and Katila and Ahuja (2002) look into the search strategies of firms in the robotics industry. Generally speaking, the studies can substantiate a positive impact of search activities on innovation performance, although there are also hints for an "over-searching" that impedes innovation. Medium-low-technology and low-technology industries (LMT), however, have been ignored so far. Exploring the search strategies of LMT firms seems even more intriguing as these firms account for by far the largest share of modern economies in terms of value added and employment (OECD, 2006).

Besides, research on the nature of these search strategies has largely focused on the dimensions of breadth and depth (see for example Katila and Ahuja, 2002; Laursen and Salter, 2006), where breadth designates the diversity and depth the intensity of search activities. Very little is known about the complementary or contradicting effects of external knowledge from various sources. This is especially relevant as effective knowledge acquisition depends heavily on a firm's ability to transform it so that combinations become possible (Todorova and Durisin, 2007). Hence, we suggest that distinctive *search patterns* can be identified that reflect a firm's technology and market environment. In that sense, we propose that these search patterns vary between HMT and LMT industries. Moreover, we assume that there is not only one uniform association with innovation success but rather that the search patterns moderate the relationship between innovation input and output. Consequently, there are differences in the extent to which firms can appropriate external innovation impulses and hence generate returns on their absorptive capacities.

In conclusion, our research aims at extending existing literature in two ways. First, we investigate whether different patterns of search strategies exist in HMT and LMT industries respectively. Second, we analyse the link between these search patterns and the payoffs from R&D investments with regard to market success. The empirical part of this research is based on the third Community Innovation Survey (CIS-3), providing insights to the innovation processes of firms from 13 European countries using a latent class methodology. It enables us to derive targeted policy recommendations as we obtain fine-grained input-output relationships for different industries (HMT versus LMT) and under different search patterns. Our paper is organised in six sections. Section 2 provides a brief review on absorptive capacities and search strategies while section 3 presents the research questions driving the analysis. Section 4 focuses on our empirical study, outlining data, variable measurement and estimation methodology. Section 5 follows, providing the results of the quantitative analysis. Based on the results, we discuss our findings in section 6. Section 7 closes with concluding remarks.

2 A brief review on absorptive capacity and search strategies

2.1 External knowledge and absorptive capacity

Unique knowledge, be it internal or external, is the most valuable asset of a firm for achieving competitive advantage (Liebeskind, 1996). Theoretically, this perspective has emerged from the resource and capability based view of the firm (Barney, 1991; Conner, 1991; Peteraf, 1993; Wernerfelt, 1984) and culminated in a knowledge-based view of the firm (Grant, 1996). Knowledge is crucial for a firm’s success as it provides a platform for decisions on what resources and capabilities to deploy, develop or discard as the environment changes (Ndofor and Levitas, 2004). However, building a competitive strategy around knowledge is challenging. Knowledge is by its very nature a public good (Jaffe, 1986) that could “spill over” to competitors and allow them to free-ride on a firm’s investments in knowledge production. Hence, firms have strong incentives to keep their knowledge proprietary (Porter Liebeskind, 1997). It is therefore not surprising that the traditional approach of producing knowledge through investments in R&D has been dominated by secretive and self-contained in-house processes. However, this negative perception of knowledge spillovers between firms and their environment is fading as recent literature has pointed towards the merits of acquiring external knowledge (Tsang, 2000) and moving from “research and develop” towards “connect and develop” (Huston and Sakkab, 2006).

The “open innovation” model by Chesbrough (2003) develops this new perspective on how firms innovate. Closed innovation, i.e. firms rely solely on their own resources for the complete R&D process, appears no longer to be a superior innovation strategy as important changes in the competitive and economic environment have occurred. Shorter product life cycles and the growing complexity of technologies and markets push firms towards using external sources of knowledge. External sources have also become more readily available, for example, information and communication technologies have improved. Chesbrough (2003) identifies four interconnected factors that propel a more open innovation process: the increasing availability and mobility of skilled workers, a venture capital market that endows entrepreneurs with the necessary capital to compete, external options for previously shelved ideas and, finally, the increased capabilities of external suppliers. Hence, firms have to reach out to actors beyond firm boundaries to maximise the benefits from inventions and ideas (Rosenkopf and Nerkar, 2001a). This openness materialises as a heightened demand for external knowledge and other external inputs in the innovation process (Fagerberg, 2005; Monjon and Waelbroeck, 2003; Peters, 2003). Several studies have identified positive performance effects from incorporating external knowledge at various levels. Such effects range from innovation success (Gemünden et al., 1992; Love and Roper, 2004) to an increased novelty of innovations (Landry and Amara, 2002) and higher returns on R&D investments (Nadiri, 1993).

External sources of knowledge need to be identified, activated and managed for success (Gottfredson et al., 2005; Stock and Tatikonda, 2004). A firm's capability to achieve this has probably best been summarised in the literature on absorptive capacity (Cohen and Levinthal, 1989, 1990). It has three major components: The identification of valuable knowledge in the environment, its assimilation with existing knowledge stocks and the final exploitation for successful innovation. These continuous learning engagements increase awareness for market and technology trends, which can be translated into pre-emptive actions. Absorptive capacities provide firms with a richer set of diverse knowledge which gives them more options for solving problems and reacting to environmental change (Bowman and Hurry, 1993; March, 1991). As a result, absorptive capacities enable firms to predict future developments more accurately (Cohen and Levinthal, 1994). This enables them to engage in exploratory innovation activities through unpredictable or rare combinations of resources (Jansen et al., 2006; Subramaniam and Youndt, 2005).

Absorptive capacities basically comprise a set of organisational routines and processes for this purpose (Zahra and George, 2002). Their roots, mechanisms and consequences have been major issues in recent scientific discussions (Lane et al. (2006) count 289 articles in their excellent review). They are generally developed as a by-product of R&D activities (Cohen and Levinthal, 1989). However, some authors have defined them more broadly as dynamic capabilities that refocus a firm's knowledge base through iterative learning processes (Szulanski, 1996; Zahra and George, 2002). In that sense, the effect of absorptive capacities varies across sources (Lane and Lubatkin, 1998) and is mediated by a firm's stable or turbulent knowledge environment (Van den Bosch et al., 1999). Absorptive capacities enable firms to find and recognise relevant external knowledge sources or require more resources to transform the knowledge so that it can be combined, i.e. assimilated, with existing knowledge stocks (Todorova and Durisin, 2007).

2.2 Search strategies

While investing in absorptive capacity is an important part of succeeding in an open innovation environment, it is not the only one. Firms need to identify the most promising external knowledge sources and align and optimise their absorptive capacities in accordingly. Hence, firms need search strategies that provide direction and priorities (Laursen and Salter, 2006). The search strategy should reflect the environment. Cohen and Levinthal (1990) have discussed the availability of technological opportunities, the turbulence of the environment as well as other firm's search activities in the industry. This means that investments in problem solving activities should result in a favourable combination and linkage of users, suppliers and other relevant actors in the innovation system (Laursen and Salter, 2006).

Laursen and Salter (2006) have developed the concepts of breadth and depth as the components of a firm's search strategy. On one hand, a broader set of external inputs reduces the risk from unforeseen development. On the other hand, it has to be considered that a company's information processing capacities are limited. There is hence a need to focus, as a vast amount of impulses would impede selection and in-depth exploitation processes (Koput, 1997). In contrast to breadth, search depth is defined as the extent to which firms draw deeply from the various external sources for innovation impulses (Laursen and Salter, 2006). Both breadth and depth can then be characterised as a firm's openness for external search processes (Chesbrough, 2003). In their study on the UK manufacturing sector, Laursen and Salter (2006) find that the relationship between searching widely and deeply and innovation performance takes on an inverted U-shape, i.e. although search efforts initially increase performance, firms may also "over-search" their environment, which in turn impedes performance.

Katila and Ahuja (2002) apply a related approach to examine how firms search and solve problems by focusing on search depth, which they define as the extent to which a firm reuses existing knowledge, and on search scope, which is how widely a firm explores external knowledge. While the latter concept largely corresponds to search breadth, the former exhibits a different focus that is more centred on exploiting the established knowledge base. They also find an inverted U-shaped relationship between a firm's search behaviour and innovation performance, indicating the negative effects of overly extensive search activities (Katila and Ahuja, 2002). Moreover, they provide evidence that the interaction of search scope and depth is positively related with innovation performance as it increases the uniqueness of recombinations: A deep understanding of firm-specific knowledge assets that is extended towards a new application (scope) creates a unique combination that serves as a basis for commercialisation. Little, however, is known about how exactly this interaction takes place. Moreover, the concepts introduced by Katila and Ahuja (2002) as well as Laursen and Salter (2006) rather nonspecificially process the counts of patent citations or external information sources regardless of their meaning and significance for the innovation process. We argue that it depends on the actual combination of different external sources as there might also be contradictions and complementarities in the use of knowledge. Such combinations hence become manifest in the *search pattern* of a firm.

3 Analytical framework

As mentioned in the preceding text, the goal of this study is to move beyond broad and/or deep search strategies and identify characteristic search patterns that prove to be beneficial in the relationship between investments in R&D and market success. Hence, it is explorative in nature. Nevertheless, we argue that such search patterns may differ between the industries. This section hence develops hypotheses on what search patterns can be expected. Commonly used methodologies group firms into the high-technology, medium-high-technology, medium-low-technology and low-technology sectors (OECD, 2006). This classification breaks up the manufacturing sector into groups that are characterised by the basic nature of their technology and innovative patterns (Hall, 1994). In the high-technology group, technical change has been rapid and (R&D) activities are a major part of the overall firm strategy. As a consequence, the levels of knowledge spillovers that a firm could benefit from are higher. In the high-medium- and medium-low-technology sectors, technologies are relatively more stable, although exploiting technical change is still an important starting point for generating competitive advantage. Finally, R&D is supposed to be a rather unimportant part of firm strategies in general in the low-technology sector which also leads to rather low levels of knowledge spillovers. Obviously, these categories are somewhat coarse and innovative firms can be found in all sectors. Nevertheless, they have provided a useful reference for studying industry differences.

We split this conceptualisation into high- and medium-high-technology (HMT) as well as low- and medium-low-technology (LMT) industries and link their typical innovation behaviour to the benefits of knowledge from various sources. Typical sources for external knowledge are customers or lead users, suppliers and universities (von Hippel, 1988). Laursen and Salter (2006) include – among others – the competitors and Katila and Ahuja (2002) stress the importance of a firm's internal knowledge. We will focus on the external sources for linking search patterns to innovation success in LMT and HMT industries respectively. Moreover, following Katila and Ahuja (2002) we include the own company as an internal source of knowledge in our analysis to reflect the generally lower munificence of the LMT environment in terms of available knowledge spillovers. Extending the description by Hall (1994) we argue that innovation success in HMT industries depends predominantly upon absorptive capacities that target technological knowledge. In contrast to this, innovation success in technologically more stable environments (LMT industries) depends much more on market inputs. Technological expertise is typically associated with university research and specialised suppliers of equipment, materials and components (Laursen and Salter, 2006). Market inputs, though, stem from custumers and competitors. Literature has identified trade-offs between these inputs along several dimensions.

While customers in their function as lead users typically generate ideas and solutions that are tightly knit to an actual application (von Hippel, 1988), there may be a much greater distance from application in case of knowledge transfers from scientific research institutes (Siegel, 2004; Link et al., 2006). Customer knowledge, though, is more tacit in nature and challenging to access and evaluate. Customer needs are often unarticulated (Von Zedtwitz and Gassmann, 2002) and determined by idiosyncratic perspectives. Frosch (1996) suggests that customer impulses for innovation are therefore risky in the sense that they can be myopic, narrow and frequently wrong.

Furthermore, the novelty or degree of innovativeness of the knowledge obtained may vary. Knowledge from research institutes will presumably exhibit a higher degree of innovativeness than knowledge from competitors. Competitors provide rather visible impulses because of their market actions. They operate in a similar context and develop similar approaches (Dussauge et al., 2000). Reliance on knowledge from competitors would therefore hint more at an imitation strategy. Suppliers as an important source of knowledge correspond with the common perception that a large share of firms, e.g. in the automotive industry, rely on the suppliers to provide innovative components into the final product. Taking up the example of the automotive industry, the value chain is clearly dominated by high-technology or medium-high-technology firms like machinery and equipment, electrical machinery or automotive firms. In contrast to this, it is questionable whether suppliers are of equally high importance for LMT firms, particularly since LMT firms are often suppliers of high-technology components.

Synthesising these arguments we conclude that the specific characteristics of technology and market sources force firms to specialise their absorptive capacities. Absorptive capacities can be seen as learning routines that outline a stable model of organisational behaviour and reaction to internal or external stimuli. We argue that firms achieve the highest payoffs if they possess specialised search strategies, i.e. search patterns, designed for taking up technology or market knowledge. This specialisation may be superior to a general approach because external knowledge has to be transformed to fit into existing knowledge stocks (Todorova and Durisin, 2007). Hence, search patterns emerge that provide superior performance effects. We argue that these specialised patterns reflect the innovation behaviour of the industry.

Hypothesis I: Investments in R&D and subsequent absorptive capacity in LMT industries provide superior innovation success if they are combined with a search pattern that targets market knowledge (customers and competitors).

Hypothesis II: Investments in R&D and subsequent absorptive capacity in HMT industries provide superior innovation success if they are combined with a search pattern that targets technological knowledge (universities and suppliers).

4 Empirical study

4.1 Data

For the empirical part of this analysis we use cross-sectional data from the third *Community Innovation Survey* (CIS-3), a survey conducted under the coordination of Eurostat in 2001 on the innovation activities of enterprises in the EU member states (including all ascending and some neighbouring states) with at least ten employees. For the 2001 survey, data was collected on the innovation activities of enterprises during the three-year period from 1998 to 2000. CIS data represents an important source of information, since it offers representative firm data for all EU-27 member states. Thus the CIS provides a wealth of information that is particularly relevant to the research questions covered here. Micro data contains information on the NACE 2-sector a firm belongs to and thus allows the identification of firms in LMT and HMT sectors. CIS-3 data has only recently been released by Eurostat. It is important to note that this micro data has been released in the form of anonymised data. The CIS-3 anonymisation method developed by Eurostat is based on a micro-aggregation process which modifies the firm level data in such a way that individual firms can no longer be identified, i.e. it is not possible to match a firm with its exact responses. The process is divided into several stages: pre-processing of the data, micro-aggregation, global recoding, evaluation of the disclosure risk, data suppression and release of the micro-data file (Eurostat, 2005). Nevertheless, the usefulness of CIS can be evaluated based on a comparison of anonymised and non-anonymised micro-data. A comparison using German non-anonymised micro-data yielded a satisfactory performance, so that the data can consistently be used to reveal structural relationships among the survey variables (Gottschalk and Peters, 2007).

Although CIS-3 was performed in each EU member state, country data availability is restricted. For CIS-3, micro-aggregated data is only available for 13 of the EU countries. The sample of innovating firms comprises 11,656 observations and is composed of firms from Belgium (706 firms), the Czech Republic (1,284 firms), Estonia (767 firms), Germany (1,656 firms), Greece (342 firms), Hungary (256 firms), Iceland (125 firms), Latvia (433 firms), Lithuania (585 firms), Norway (1,190 firms), Portugal (780 firms), Slovakia (363 firms) and Spain (3,169 firms). Industries were identified based on the NACE 2-digit classification and grouped according to the standard industry aggregation by technology level (OECD, 2006). Table 1 provides details on the industries represented in our analysis.

Table 1: Industry breakdown

Industry	NACE Code	Industry Group
Food and tobacco	15 – 16	Low-technology
Textiles and leather	17 – 19	Low-technology
Wood / paper / publishing	20 – 22	Low-technology
Chemicals and pharmaceuticals	24	High-/medium-high-technology
Plastics / rubber	25	Medium-low-technology
Glass / ceramics	26	Medium-low-technology
Metals	27 – 28	Medium-low-technology
Machinery and equipment	29	Medium-high-technology
Office and computing machinery	30	High-technology
Electrical machinery and apparatus	31	Medium-high-technology
Radio, TV and communication equipment	32	High-technology
Medical, precision and optical equipment	33	High-technology
Motor vehicles and trailers	34	Medium-high-technology
Transport equipment	35	Medium-high-technology
Manufacturing n.e.c. (e.g. furniture, jewellery, sports equipment and toys)	36 – 37	Low-technology

CIS surveys are self-reported and largely qualitative which raises quality issues with regard to administration, non-response and response accuracy (for a recent discussion see Criscuolo et al., 2005). However, the surveys have a number of features designed to limit possible negative effects. First, CIS-3 was administered via mail which prevents certain shortcomings and biases of telephone interviews (for a discussion see Bertrand and Mullainathan, 2001).

The multinational application of CIS adds extra layers of quality management and assurance. The survey is subject to extensive pre-testing and piloting in various countries, industries and firms with regard to interpretability, reliability and validity (Laursen and Salter, 2006). Second, the questionnaire contains detailed definitions and examples to increase response accuracy.

A major advantage of CIS data is that they provide direct, importance-weighted measures for a comprehensive set of sources (Criscuolo et al., 2005). On the downside, this information is self-reported. Heads of R&D departments or innovation management are asked directly if and how they are able to generate innovations. Overall, this immediate information on processes and outputs can complement traditional measures for innovation such as patents (Kaiser, 2002; Laursen and Salter, 2006).

4.2 Measures

Measuring innovation success

Several concepts have been discussed in the literature for capturing innovation success (for an overview see OECD, 2005). Some focus on innovation inputs (R&D expenditure), while others point towards the consequences of innovation activities, e.g. patents, new processes and products. We choose the latter perspective. While each new product may be valuable in itself, firm success heavily depends on its market acceptance. Hence, we conceptualise innovation success as the share of turnover achieved with new products. Finally, new products vary with regard to their degree of novelty. Some products may be new only to the firm while others may be new for the market as a whole. The former may be more related to imitative behaviour whereas the latter is more closely related to radical innovation success. As a result, we choose the share of turnover with market novelties[1] as our dependent variable in line with several other studies in the field (see for example Laursen and Salter, 2006).

Capturing search strategies

Measuring knowledge spillovers is a challenging task since they leave no paper trail. Therefore, several studies in the field have relied on patent statistics and subsequent citations to capture them (see for example Galunic and Rodan, 1998; Rosenkopf and Nerkar, 2001b). This approach has several disadvantages. Most importantly, “not all inventions are patentable, not all inventions are patented” (Griliches, 1979: p.1669). What is more, the distribution of patenting firms is heavily skewed. Bloom and van Reenen (2002) illustrate this, with 72 per cent of their sample of almost 60,000 patents by UK firms stemming from just 12 companies. Patenting implies the disclosure and codification of knowledge in exchange for protection (Gallini, 2002). The majority of valuable knowledge may therefore never be patented. Most importantly for this study, patent citation statistics cannot reveal the relationship between two firms (e.g. whether they are customers or competitors). Thus, the opportunities for pattern recognition are limited. Consequently, we rely on survey questions to identify the sources of external knowledge and receive importance-weighted answers on the value of their

[1] By definition this is a novelty on a firm’s relevant market and not necessarily a “new to the world” innovation.

contribution. More precisely, respondents are asked to evaluate the importance of the main sources for their innovation activities on a 4-point Likert scale ranging from "not used" to "high". We use five different sources: the own company, suppliers, customers, competitors and universities. We will use these rankings to estimate search patterns.

Measuring absorptive capacity

Absorptive capacities are not a tangible construct. Managers cannot simply be surveyed to judge their existence or extent. They are typically assumed to be a by-product of performing R&D activities. In line with the literature (Cohen and Levinthal, 1990; Rothwell and Dodgson, 1991) we capture absorptive capacities through variables on the two major inputs for innovation activities: R&D expenditure (as a share of turnover) and the expertise of employees (employees with college education). Van den Bosch et al. (1999) suggest that absorptive capacities are accumulated over time as part of an iterative process. We therefore add an additional dummy variable indicating whether R&D activities are performed on a continuous basis.

Control variables

We add control variables for several other factors that may influence the estimation results. Firms may suffer from a liability of size or smallness. We capture these factors by including a firm's turnover from the start of the reporting period (1998) in logs. In addition, we control for a firm's degree of internationalisation by incorporating the ratio of exports to total turnover. Our observations stem from various European countries. It is necessary to control for the strength of each domestic innovation system. We do so by adding a variable capturing the total national R&D expenditure as a share of each country's GDP (GERD) for 2003, as provided by the European Union. Finally, we add a dummy variable to control for the fact that a firm is part of a group, which would imply that it has the possibility to spread certain functions across subsidiaries or draw from their resources.

4.3 Estimation strategy and method

Our research question has two major components. First, we suggest that subpopulations of firms with distinctive search patterns exist in our dataset. Secondly, relationships between innovation inputs and outputs differ significantly between subpopulations. While the former issue is traditionally addressed through cluster analytical methods, the latter would typically require regression analysis. We rely on latent class analysis that allows us to cover both aspects simultaneously. It was introduced by Lazarsfeld (1950) for identifying patterns in survey responses. Latent classes are unobservable (latent) subgroups or segments. The goal of latent class analysis is to identify subgroups of observations that are similar to other subgroup members, in terms of predefined variables, but dissimilar to members of other subgroups. In that sense, latent class analysis differs from other continuous latent variable approaches (like random-effects regression) in the identification of groups (or categories) as the primary goal. It therefore follows a finite mixture model rationale of disentangling a dataset into a finite mixture from a finite number of distinctly different populations. It is superior to traditional cluster analysis as it is based on a statistical model which allows for significance tests and measurements of fit (Jensen et al., 2007; for a detailed discussion see Hagenaars and McCutcheon, 2002).

Latent class analysis can be combined with regression analysis by specifying a set of variables (so called covariates) that influence the conditional probability of a certain observation belonging to a certain class, as well as variables that influence the dependent variable (so called predictors). Put simply, the problem of assigning observations to latent classes and obtaining separate regression results for each class is solved in one optimisation step. Latent class regression analysis can therefore be considered more general than traditional regression analysis that assumes that all observations are homogeneous.

The general probability structure is:

$$f(y_i \left| z_i^{\text{cov}}, z_i^{pred} \right.) = \sum_{x=1}^{K} P(x \left| z_i^{\text{cov}} \right.) \prod_{t=1}^{T_i} f(y_{it} \left| x, z_{it}^{pred} \right.)$$

where the probability of outcome y for observation i depends upon the conditional probability of belonging to one of K latent classes (with x as the latent variable) based on a vector z of covariate variables and a vector z of predictors and T replications of a single dependent variable. This method reflects our research question perfectly. We assume that a firm's search behaviour can be condensed into a finite number of patterns (latent classes) depending upon their usage of external knowledge sources (covariates). Besides, we can test at the same time whether differences exist between the effects of the various innovation inputs (predictors) on innovation outputs given that firms follow a certain type of search pattern (i.e. are part of a particular latent class).

One more issue has to be addressed methodologically. Our dependent variable is the share of turnover with market novelties. While all firms in our sample are successful innovators, it cannot be assumed that all of their innovations were not just new to the firm but new to the market as a whole. This demanding standard for formulating the dependent variable implies that many more zeros will appear than can be expected based on a univariate normal distribution. Hence, we adjust our empirical strategy by estimating a tobit model as part of the latent class regression model. These estimations are carried out by relying on the algorithm provided by Vermunt and Magidson (2005).

5 Results

Choosing the correct number of classes is an important step of the analysis because each additional class increases the fit of the model by capturing more heterogeneity. Then again, choosing too many classes makes it difficult to achieve meaningful interpretations for each class and the system as a whole. Hence, a parsimonious approach is required that balances both interests. This decision is typically based upon two key figures: the Bayesian information criteria BIC and the Akaike information criteria AIC. Both should be minimised to indicate an appropriate number of classes. In the following, we report the results for the group of LMT firms before the results for the group of HMT firms are presented.

We report all measurements of fit for a 1 to 4 class solution in Appendix A. First of all, looking at the sharp increase in R^2 values between a 1-class and 2-class solution it becomes apparent that a conventional regression analysis assuming one homogeneous class of observations would hardly have been adequate for the available dataset. The BIC criterion reaches its minimum for the 2-class solution while AIC points towards a 3-class approach. McLachlan and Peel (2000) suggest that the BIC criteria may be too rigid whereas AIC may be too liberal. After all, it depends on the interpretability of the solution (Jensen et al., 2007). We opt for a 3-class solution.

Table 2 provides the results for the recognition of search patterns. We will present its results separately from the regression analysis in Table 3 although it should be mentioned that both were estimated simultaneously. Appendix B provides mean profiles for the 3 classes. Class 1 and class 2 are roughly equal in size, covering 39% and 37% of the sample respectively. Class 3 is smaller, with 24%. A closer look at the averages presented in Appendix B provides an indication for the appropriateness of latent class analysis. The own company is the most important source for knowledge and receives an average rating of 2 (medium) out of a maximum of 3 (high). However, Table 2 reveals that it makes no difference across companies and therefore has no significant influence on class generation. The same is true for the impulses from suppliers and universities. The former may be less surprising because suppliers may transfer most of their knowledge in the form of the supplied product or service. As this is available to all firms, it is not a differentiating factor. In a similar way, university knowledge embodied in publications may be equally available. Again, this does not imply that inputs from universities are not important. They are just not a factor that sets firms apart in their search strategies.

Table 2: Model for latent classes (LMT firms)

Model for classes	Class1	Class2	Class3	Wald (p-value)
Covariates				
Own company	-0.014	-0.095	0.109	3.984
				(0.140)
Suppliers	0.042	0.004	-0.046	0.888
				(0.640)
Customers	-0.136	-0.029	0.165	8.986
				(0.011)
Competitors	0.193	-0.060	-0.133	11.187
				(0.004)
Universities	0.054	-0.088	0.034	2.206
				(0.330)
Intercept	0.086	0.496	-0.582	8.744
				(0.013)

Customer and competitor knowledge can be shown as decisive factors for establishing search patterns. A trade-off between the two emerges. While the importance of impulses from competitors dominates class 1, customer impulses have a highly negative impact. Exactly the opposite relationship holds true for class 3. We find that both sources of external knowledge require unique approaches. Competitors provide rather visible impulses because of their market actions. They operate in a similar context and develop similar approaches (Dussauge et al., 2000). Customer knowledge, though, is more tacit in nature and challenging to access and evaluate. Moreover, customer needs are often unarticulated (Gassmann and von Zedtwitz, 1998) and determined by idiosyncratic perspectives. Frosch (1996) suggests that customer impulses for innovation are therefore risky in the sense that they are myopic, narrow and frequently wrong. Interestingly, class 2 appears to represent the middle ground between both perspectives, being negatively influenced by both, but only very mildly. We conclude that class 1 represents competitor driven search patterns and class 3 customer driven ones. Class 2 however seems to follow a balanced pattern somewhere in between. To simplify the argumentation in subsequent parts of the analysis, we will refer to class 1 as “competitor centric”, class 2 as “balanced” and class 3 as “customer centric”. Hence, Hypothesis I is supported.

Using descriptive statistics based on the success of each class, measured in terms of their share of turnover with market novelties, one would be tempted to say that class 2 is the most successful, followed by class 3. However, these descriptive results do not take into account the inputs that were necessary to achieve the innovation output. The results of the tobit regression analysis presented in Table 3 provide these links between inputs and outputs under each class or search pattern.

Table 3: Tobit regression for the share of turnover with market novelties (LMT firms)

Tobit model (n=2,782)	**Class1**	**Class2**	**Class3**	**Overall**	**Comparison**
Class focus	**Competitor centric**	**Balanced**	**Customer centric**		
R-squared	0.205	0.125	0.207	0.409	

	Class1	**Class2**	**Class3**	**Wald (p-value)**	**Wald (=) (p-value)**
	Coeff.	Coeff.	Coeff.		
Intercept	-0.110	1.245	0.247	68.636	63.072
				(0.000)	(0.000)
Predictors					
Continuous R&D (dummy)	0.048	0.103	0.015	40.181	5.516
				(0.000)	(0.063)
R&D intensity	0.580	1.384	2.373	28.459	8.828
				(0.000)	(0.012)
No of employees with graduate education (in logs)	0.017	0.032	0.001	23.049	5.070
				(0.000)	(0.079)
Controls					
Export share of turnover	-0.014	0.123	-0.007	5.212	5.192
				(0.160)	(0.075)
Share of total country R&D expenditures of GDP (%)	-0.010	-0.139	-0.010	27.986	12.402
				(0.000)	(0.002)
Turnover 1998 (in logs)	0.002	-0.077	-0.011	44.161	31.792
				(0.000)	(0.000)
Part of company group (dummy)	0.010	0.008	0.005	1.227	0.078
				(0.750)	(0.960)

The "overall" column of Table 3 provides significance tests (Wald statistics and significance levels) for the overall impact of a variable on the success with market novelties given a certain search pattern (i.e. class). The "comparison" column provides equivalent significance tests on the hypothesis that the coefficients differ across classes.

Focusing on the main topic of this investigation we find that investments in R&D (as a share of turnover) have a significant, positive impact on market success and that its effect varies significantly by search pattern. It is most efficient in the customer centric class, followed by a balanced approach. Apparently, investments in R&D and subsequent absorptive capacities are most rewarding if they are distinctively directed at customer inputs. In that sense we provide empirical evidence for the merits of "market driven" organisations (Day, 1994) in an LMT environment. For a balanced search pattern investments in R&D are still highly rewarding whereas competitor centric search patterns yield the lowest return. This would indicate that the latter are generally more reactive or defensive types of absorptive capacities that are built around adaptation and imitation which makes it difficult to generate radical innovation that is new to the whole market. However, when it comes to continuous R&D engagements, it is most rewarding in a balanced search pattern followed by competitor centric approach. It appears that customer centric patterns induce higher levels of dynamism that reward flexibility over stable routines. This relationship is also reflected in the number of skilled employees which are closely connected to continuous R&D engagements.

With regard to control variables, we find no significant effects from a company's export activity and whether it is part of a company group. Company size (measured as turnover in 1998) has a positive effect on market success under competitor centric search patterns while it is disadvantageous in the other classes. Large companies may be better prepared to sustain adaptation or imitation strategies reflected in competitor centric search patterns as they typically have a richer set of resources to compete with. Interestingly, the home country R&D intensity (share of R&D expenditures on GDP) has a negative impact across all search patterns, being most pronounced at the balanced search pattern. This may indicate that a lack of external knowledge opportunities in the domestic innovation system is most severely felt in search patterns that are not clearly defined (neither focusing on competitors or costumers).

Focusing on HMT industries we find the same trade-off between the exploratory power of our model and parsimony when it comes to choosing the number of latent classes. The BIC points towards a 2-class solution while the AIC favours a 3-class choice (see Appendix C). Again, we select the 3-class option. Appendix D provides a descriptive overview for these classes. Class 1 and 2 are roughly equal in size comprising 42% and 41% of all observations respectively. Class 3 is significantly smaller with 17%. As in the LMT case knowledge from inside the company is the most important source followed by customer knowledge. The latter is on average more important for HMT than for LMT industries. The same is true for university inputs. However, they have the lowest average importance rating within HMT firms across classes. The question remains which sources of external knowledge make a significant difference for the identification of classes (and hence search patterns) among HMT industries. Table 4 provides these results (it should be noted that the latent class analysis is simultaneously conducted with the tobit regression for which results are presented in Table 5).

Table 4: Model for latent classes (HMT firms)

Model for classes	Class1	Class2	Class3	Wald (p-value)
Covariates				
Own company	-0.135	0.081	0.054	3.308 (0.190)
Suppliers	-0.176	0.061	0.115	4.976 (0.083)
Customers	-0.059	-0.100	0.159	2.430 (0.300)
Competitors	0.095	0.002	-0.097	1.399 (0.500)
Universities	0.162	-0.176	0.015	7.279 (0.026)
Intercept	0.721	0.382	-1.103	7.801 (0.020)

Distinctive search patterns emerge based on supplier and university knowledge. They make a significant difference at the 92% and 97% level respectively. This does not indicate that the other sources have no merits. It indicates that they make no significant difference for search strategies of HMT firms. However, latent classes of search patterns in the HMT sector are based on significant differences in the usage of technological knowledge from suppliers and/or universities. Hence, Hypothesis II receives support.

The probability of a firm to be assigned to class 1 is determined by intensive knowledge acquisition from universities. Apparently, this search pattern is accompanied by an explicit disregard for supplier knowledge. Hence, we term this class "university centric". Class 3, though, the smallest class in our sample, shows the opposite constellation. It benefits extensively from supplier knowledge while university impulses are significant but close to zero. As a result, we call this a "supplier centric" class (and hence search pattern). Finally, class 2 exhibits the most interesting pattern. It has the highest positive impact from internal knowledge although this variable is only significant at the 81% level. Firms following this search pattern benefit from supplier knowledge but the influence is weaker than for the supplier centric class. Most strikingly, though, is the pronounced negative impact of university knowledge. In that sense, it is the only search pattern among HMT firms that neglects university impulses. We will therefore refer to it as a "university averse" search pattern. Descriptive statistics (Appendix D) point towards the university averse search pattern as the one with the highest market success, followed by the supplier centric and the university centric pattern. However, success can only be judged based on the inputs that are necessary to achieve it. Table 5 provides these estimation results.

Table 5: Tobit regression for the share of turnover with market novelties (HMT firms)

Tobit model (n=1,719)	**Class1**	**Class2**	**Class3**	**Overall**	**Comparison**
Class focus	**University centric**	**University averse**	**Supplier centric**		
R-squared	0.173	0.095	0.517	0.390	

	Class1	**Class2**	**Class3**	**Wald (p-value)**	**Wald (=) (p-value)**
	Coeff.	Coeff.	Coeff.		
Intercept	-0.114	0.694	0.359	20.110	14.808
				(0.000)	(0.001)
Predictors					
Continuous R&D (dummy)	0.065	0.101	-0.003	26.520	5.543
				(0.000)	(0.063)
R&D intensity	-0.109	1.112	0.580	9.937	8.596
				0.019	0.014
No of employees with graduate education (in logs)	0.013	0.046	-0.016	13.625	11.564
				(0.004)	(0.003)
Controls					
Export share of turnover	-0.036	0.014	0.123	14.413	13.004
				(0.002)	(0.002)
Share of total country R&D expenditures of GDP (%)	0.020	-0.142	0.027	24.117	23.412
				(0.000)	(0.000)
Turnover 1998 (in logs)	0.000	-0.040	-0.018	13.083	5.356
				(0.005)	(0.069)
Part of company group (dummy)	0.022	0.072	-0.046	8.623	8.239
				(0.035)	(0.016)

As in the LMT case, the “overall” column provides statistics on the significance of the coefficient of a particular variable while the “comparison” column provides significance tests on whether these differ between classes (and hence search patterns). In contrast to the LMT industries estimation all variables have significant impacts (at least at the 95% level) and all significant variables vary across search patterns. The coefficients on R&D intensity (R&D expenditures as a share of turnover) support the descriptive results on the merits of different search patterns. R&D expenditures in a university averse search pattern provide the highest payoffs with regard to market success and there is an additional positive effect from engaging in R&D continuously. The latter is also positive but weaker for a university centric search pattern. Most interestingly, though, R&D expenditures within a university centric search pattern have a negative impact. This seems counterintuitive at first glance. However, we use market success (turnover with market novelties) as dependent variable. Knowledge from research institutions is generally more distant from application stages (Link et al., 2006; Siegel, 2004) and one cannot expect immediate market success. We suspect that firms with a university centric search pattern are primarily interested in absorbing technological knowledge which can be exploited later on. The university averse search pattern may exactly reflect this second phase which translates previously acquired knowledge into turnover with new products. Interestingly enough, both classes of search patterns are roughly equal in size (42%). The smaller class of supplier centric high-tech firms also achieves positive returns on their investments in R&D. However, continuous R&D engagements do not pay off. We suggest that the absorptive capacities of these firms are primarily directed at selecting and engaging specialised suppliers that trigger innovations by supplying new equipment, components or materials. Hence, the results of this search pattern reflect the “supplier dominated” classification of innovation behaviour by Pavitt (1984) and support the findings of Laursen and Salter (2006) for this particular class. The previously outlined trends are also reflected in the merits of skilled employees. They provide no additional benefits within a supplier centric search pattern and are most meaningful for university averse search patterns. A moderate positive effect emerges for university centric search patterns.

Focusing on control variables, we find that the internationalisation of turnover has a negative impact in university centric search patterns while it is positive for the two other classes. A country’s R&D intensity is positively related in university and supplier centric search patterns, indicating that opportunities for knowledge sourcing may be more abundant in these environments. Less munificent environments, though, coincide with university averse search patterns. Company size has a negative effect in university averse and supplier centric search patterns while being part of a company group is positively related to market success for university centric and averse search patterns.

6 Discussion

This study is designed to connect the concepts of R&D investments and derived absorptive capacity with explicit patterns of search behaviour. We develop a conceptual argumentation that goes beyond the general assertion that firms need external knowledge to succeed in their innovation engagements and that the search for these valuable items of information should be broad and/or deep. Instead, we extend existing research that focuses on differences between various sources and the knowledge they provide (see for example Szulanski, 1996). We argue that these differences in the access, reliability and transferability of knowledge materialise as trade-offs. Search patterns emerge that reflect these complementarities and contradictions. The first goal of this study is to identify these patterns. Additionally, we propose that these search patterns are reflected in the efficiency of innovation investments with regard to their market success because different combinations of external knowledge require specific absorptive capacities to transform and combine them with existing knowledge stocks. What is more, we argue that these patterns will appear among technological sources (suppliers and universities) in HMT industries and among market sources (customers and competitors) in LMT industries. We explore both research questions empirically through separate latent class tobit regression analyses for 4,500 firms in LMT and HMT industries and their innovation activities from 13 European countries. Hence, our findings are not confined to a single country. Most strikingly, we find that search patterns in LMT industries are mostly determined by the market side while HMT industry search patterns emerge because of differences in technology sourcing. Hence, our hypotheses are supported.

Focusing on search patterns in LMT industries, internal sources for information and impulses from suppliers or universities have their merits but they are no significant source of heterogeneity in search patterns among firms. Trade-offs emerge as firms have to centre their search strategies on competitor or customer impulses. Roughly 60% of the firms in our sample settle for one or the other but not a combination of both. The rest follows a balanced search pattern. We argue that the tradeoffs between competitor and customer knowledge emerges because of the different demands they put on knowledge acquisition and transformation which leads to specialisation patterns in search behaviour. Competitor impulses are typically easier to identify and interpret because they operate in a comparable context and serve the same market (Dussauge et al., 2000). However, once they emerge the firm has very little time to react and may be forced to engage in adaptive and imitative behaviour. Customer knowledge, though, is often unarticulated, tacit and unreliable (Frosch, 1996). Then again, firms that discover unique needs early may benefit from sustained competitive advantages (Von Zedtwitz and Gassmann, 2002). These search patterns shape the payoffs from investments into R&D. R&D investments are most efficient with regard to market success of market novelties if they are combined with customer centric search patterns followed by balanced search patterns. Competitor centred search patterns, though, provide the lowest levels of efficiency as they may be limited to adaptations. Contrary to this, continuous R&D engagements are least rewarding if they coincide with customer centric search patterns. For the latter flexibility may be more important than stable trajectories.

With regard to search patterns in HMT industries, we find that all types of internal and external knowledge have their merits but the usage of university and supplier knowledge differentiates search strategies and patterns emerge. A minority of HMT firms (17%) build their search strategies around supplier knowledge which may propel their innovation engagements through new equipment, materials and components (Laursen and Salter, 2006). Apparently, this is much less reflected in long-term in-house R&D engagements (continuous R&D, high number of skilled employees) but still rewarding with regard to market success. However, absorptive capacities within a supplier centric search pattern may be concentrated on identifying specialised suppliers and integrating their inputs into the final product. The vast majority of HMT firms (roughly 80%) develop search strategies that depend upon knowledge acquisition from universities. Half of them rely heavily on university inputs (university centric) at the expense of supplier inputs, the other half moves its search pattern distinctively away from university knowledge (university averse). Interestingly, the latter is more successful with turnover of new products than the latter. We argue that university centric search patterns are primarily directed at knowledge acquisition for subsequent exploitation even if this application stage may develop the future (Link et al., 2006; Siegel, 2004). Hence, a lack of market success should not come as a surprise. Firms with university averse search patterns may have already made that step from acquisition and assimilation phases towards exploitation. At this point, absorptive capacities have shifted away from university inputs.

In conclusion, our results paint a differentiated picture for optimised search patterns in LMT and HMT industries. This needs to be reflected in tailor-made policy development. We find that LMT firms investing in R&D to develop absorptive capacity can achieve the highest returns if they direct their search behaviour towards customers. Competitor reconnaissance may be a less risky strategy but it is also associated with lower returns. With regards to policy implications, this implies that innovation performance can be strengthened by incorporating customer interaction into R&D funding and incentive schemes for LMT industries. This may imply preferential treatment or mandatory requirements for including customers in publicly funded project consortia. Besides, public R&D support schemes targeting LMT sectors should be built around markets and customers instead of specific technologies. Moving from competitor centric search patterns to customer centred ones may be a promising but risky goal. However, even policy supported, gradual shifts towards more balanced search strategies would improve the efficiency of R&D investments with regard to market success.

In HMT industries, though, supporting supplier centric search patterns that are built around suppliers of new equipment and materials is rewarding but appears to be a niche strategy. Instead, university knowledge is the major leverage point for a firm's search pattern and hence policy intervention. Our results indicate that knowledge from universities play an important role for generating knowledge stocks inside HMT firms. However, full market success can be realised once firms move away from a myopic focus on universities for their knowledge acquisition. The differences between these stages should be reflected in public R&D support. Hence, tailor-made policy instruments should encourage HMT firms in applied, close-to-application fields to move away from a narrow focus in their search strategies on universities and develop a broader set of absorptive capacities.

7 Concluding remarks

Our analysis benefits from the unique opportunity to assemble innovation survey data across national and industry boundaries. There are, however, also some shortcomings of our study regarding country coverage and dynamic relationships. First, the availability of country data for all EU member states that participated in CIS-3 is limited. This applies particularly to large economies like France, Italy or the Netherlands. Adding observations from these countries would provide an improved basis for our reasoning. It depends on the member states to provide access to the micro-data that needs to be treated subsequently by Eurostat in order to be released. Second, it would be most interesting to study the dynamic relationship, i.e. changes in the search behaviour of firms. Although results from CIS-4 are already available in a tabulated form there is no possibility to merge two or more waves of CIS to yield a panel structure of the data without violating the data confidentiality requirements that have to be implemented by Eurostat. An alternative approach could hence be to focus just on a few countries for which micro-data is available as a panel, e.g. Germany. This could provide some interesting results regarding the evolution of search patterns in relation to certain company characteristics. Besides the focus on European countries it would also be interesting to compare results with other major economies like the U.S. or Japan. Different administrative, cultural and historical backgrounds would enhance our understanding of how firms interact with their environment and what differentiates actual from best practices.

8 Appendix

Appendix A. Model goodness of fit (LMT firms)

No. of classes	LL	BIC(LL)	AIC(LL)	No. of parameters	R^2
1-Class Regression	-1,053.827	2,179.032	2,134.654	9	0.051
2-Class Regression	-794.681	1,779.703	1,661.361	24	0.368
3-Class Regression	-750.989	1,811.283	1,618.977	39	0.409
4-Class Regression	-733.753	1,895.775	1,629.505	54	0.534

Note: AIC(LL) = LL − 3 df

Appendix B. Mean class profiles (LMT firms)

	Class1	Class2	Class3
Class size	0.388	0.368	0.244
Dependent variable			
Share of turnover with market novelties	0.016	0.178	0.099
Covariate variables			
Own company	2.061	1.932	2.172
Suppliers	1.749	1.623	1.653
Customers	1.673	1.608	1.862
Competitors	1.409	1.128	1.195
Universities	0.721	0.546	0.677

Appendix C. Model goodness of fit (HMT firms)

No. of classes	LL	BIC(LL)	AIC(LL)	No. of parameters	R^2
1-Class Regression	-591.548	1250.142	1210.097	9	0.024
2-Class Regression	-440.305	1059.397	952.609	24	0.307
3-Class Regression	-415.786	1122.103	948.572	39	0.390
4-Class Regression	-395.515	1193.304	953.031	54	0.462

Note: AIC(LL) = LL − 3 df

Appendix D. Mean class profiles (HMT firms)

	Class1	Class2	Class3
Class size	0.420	0.411	0.170
Dependent variable			
Share of turnover with market novelties	0.040	0.198	0.106
Covariate variables			
Own company	2.107	2.251	2.300
Suppliers	1.483	1.677	1.771
Customers	2.025	1.942	2.205
Competitors	1.498	1.373	1.442
Universities	1.067	0.781	0.999

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