Search Patterns in Transition Economies: A Comparison of Thirteen European Countries

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Abstract

Searching for externally available knowledge has been characterised as a vital part of the innovation process. The availability of such innovation impulses, however, critically depends on the environment a firm is operating in. Little is known on how national environments differ with respect to the munificence in providing innovation impulses. These differences may be particularly pronounced between transition economies and established market economies. We argue that firms from transition and established economies differ in their search pattern and that these search patterns moderate the relationship between innovation inputs and outputs. Based on a sample of almost 7,000 firms from 13 European countries we find strong support for open innovation strategies in both settings. However, performance differs in established and transition economy contexts.

Keywords: Absorptive capacity, search strategies, transition economies, open innovation

JEL-Classification: L60, O32

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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; 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, p. 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).

Most of the literature investigates open innovation strategies qualitatively (e.g. Chesbrough, 2003; Chesbrough and Appleyard, 2007) or in high-tech sectors often times based on patent statistics. Shan et al. (1994) investigate the relationship between organisational learning through cooperation and innovative output in the biotechnology industry. Rosenkopf and Nerkar (2001) 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. However, almost all of the empirical findings are limited to countries with stable, highly developed institutional environments, like the US, Japan or the UK. We question this implicit assumption and argue that dynamics in the institutional environment shape search strategies based on opportunities and challenges. We suggest that institutional transitions like the ones experienced by Eastern European countries after the collapse of the Soviet Union shape unique search strategies in the sense that existing knowledge pools run dry while new strategic opportunities emerge (Peng, 2003).

Research on the nature of 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 established and transition economies. 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 established and transition economies respectively. Secondly, 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. The harmonized dataset provides us with the unique opportunity to compare search strategies from the established market economies Belgium, Germany, Spain, Greece, Iceland, Norway and Portugal with the transition economies Latvia, Lithuania, Estonia, Hungary as well as the Czech and Slovak Republics. It enables us to derive targeted management and policy recommendations as we obtain fine-grained input-output relationships for different institutional environments (established and in transition) 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.

A BRIEF REVIEW ON ABSORPTIVE CAPACITY AND SEARCH STRATEGIES

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, 2001). 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 been best 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).

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 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. Hence, there is 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.

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 established and transition economies. This section develops hypotheses on expected search patterns. We use the distinction between established and transition economies and link it to possible sources of innovation impulses available to firms in these economic regimes.

After the collapse of the Berlin Wall and the fall of the Soviet empire, post-socialist economies in Central and Eastern Europe (CEE) have struggled mainly with problems of macroeconomic adjustment and privatisation. In this respect, an almost implicit assumption had been that industrial restructuring as well as technological change would immediately occur once the open market economy mechanism is in place (Radosevic, 1998). The perspective of national systems of innovation (for an overview e.g. Lundvall, 1992), though, stresses the notion that former socialist and capitalist innovation systems are rather far from each other in terms of underlying assumptions, guiding principles and instruments. Their adjustment might only happen over time and it takes more than just a market mechanism to make it change (Radosevic, 1998). One example for that is the system of Academies of Sciences in the CEE countries. Ideally, the Academies of Sciences would have maintained close collaboration with industry on a long-term basis to make prospective technologies available to the society. In reality, this collaboration was suffering heavily from a lack of economic incentives (which were not at all a characterising element of the socialist economies) (Meske, 1994). What is more, it turned out that technology development in CEE was generally far behind the Western standard, thus making innovation impulses from scientific institutions relatively unattractive for firms in such transition economies.

From this it follows that relationships with providers of external innovation impulses needed to be established first in transition economies while established economies could build upon existing relations. Moreover, economic incentives that were provided by the market once it had become operational had to be realised by the parties and transformed into actions. This process inevitably also required a cultural change towards acting in a market-oriented manner. Newly established firms in transition economies therefore presumably needed to spend much more attention to innovation impulses available internally than to those externally as these were scarce, not much focused towards a market application and hence not very helpful. Our overarching hypothesis thus centres around the assumption of a generally lower munificence of the environment in transition economies in terms of externally available innovation impulses.

According to the open innovation model, 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 established and transition economies 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 transition environments in terms of available knowledge spillovers. Extending the description by Radosevic (1998) we argue that innovation success in established market economies depends relatively more upon absorptive capacities that target technological knowledge than in transition economies. Moreover, markets can be regarded as relatively more saturated in established economies than in transition economies. In contrast to this, innovation success in transition economies should depend relatively more on market inputs than in established economies. As has been suggested before, technological knowledge should consequently be relatively less important in transition economies than in established market economies. 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 customers 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 Western standard 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.

Synthesising these arguments we conclude that the specific characteristics of technology and market sources available in the different economic systems 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 type of economy.

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

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

EMPIRICAL STUDY

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. 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. We obtain more than 3,600 firm observations from six transition economies in Eastern Europe and almost 8,000 observations from seven established European economies. Table 1 provides a detailed overview on the composition of the sample.

Table 1 goes about here

Due to missing values, not all cases available in the sample can be used for the estimation. After removing such cases we end up with 2,302 observations from transition economies and 4,636 observations from established market economies. CIS surveys are subjective assessments 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).

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, 2001). 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

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

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 contribution. More precisely, respondents are asked to evaluate the importance of the main sources for their innovation activities. We use five different sources: the own company, suppliers, customers, competitors and universities. We will use them to identify 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 innovation 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: innovation expenditure[2] (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. Besides, we add four industry control variables: Low-tech manufacturing, medium-tech manufacturing, high-tech manufacturing and services.

[2] Innovation activities/expenditures go beyond technological R&D investments and comprise also costs for market introduction, the establishment of sales channels, etc.

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:

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

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).

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. McLachlan and Peel (2000) suggest that the BIC criteria may be too rigid whereas AIC may be too liberal. Consequently, Andrews and Currim (2003) test multiple criteria and suggest AIC3[3] as the most

[3] AIC3 = LogLikelihood – 3 degrees of freedom

appropriate. Hence, we base our choices on an adequate number of classes on this criterion. In the following, we report the results for firms from transition economies before the results for the results for firms from established economies are presented.

We report all measurements of fit for a 1 to 5 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. We opt for a 4-class solution as it minimizes AIC3.

Table 2 provides the results for the recognition of search patterns. We will present its results separately from the tobit regression analysis in Table 3 although it should be mentioned that both were estimated simultaneously. Class 1 is the largest class covering 43% of the sample, followed by class 2 with 28% and class 3 with 25%. Class 4 is by far the smallest with 4% of all firms in the sample for transition economies. The coefficients in Table 2 can be interpreted as probabilities for class membership given a certain combination (i.e. pattern) of knowledge sourcing. The latent class methodology allows us to conduct Wald tests and obtain significance levels (p-value). Interestingly, supplier and customer knowledge show no significant impact. They should not be misinterpreted as having no effect. Instead, they do not differentiate classes of search patterns significantly. We find these significant differences from the company's own as well as competitor and university knowledge. Interestingly, the largest class of search patterns in transition economies (class 1) is predominantly influenced by competitor knowledge. This may be due to the fact that knowledge is often times embodied in new products or services. These impulses from competitors are immediately relevant for firms as they threaten established market positions and firms need to respond. In that sense, competition is the major channel for knowledge transfers in this class. We will subsequently refer to this search pattern as "competitive." Class 2 is different from the competitive pattern as it relies to a lesser degree on competitor impulses but combines it with internal knowledge. We will therefore refer to this pattern as "combinative-competitive." In contrast, class 3 is solely driven by a firm's own knowledge and can be characterized as a "closed" search pattern. Finally, the smallest class 4 is defined by knowledge stemming from universities. We will refer to this search pattern as "scientific."

Table 2 goes about here

The results of the tobit regression analysis presented in Table 3 provide links between innovation inputs and outputs under each class or search pattern.

Table 3 goes about here

The “Wald 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 “Wald 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 innovation (as a share of sales) have a significant, positive impact on market success and that its effect varies significantly by search pattern. It is most efficient in the scientific class, followed by a combinative approach (combinations of own and competitor knowledge). Innovation investments under closed search patterns yield still positive but substantially lower returns. As a result, we find support for the notion that firms with open innovation strategies can increase the efficiency of their investments in innovation (e.g. Chesbrough, 2003). Most strikingly, competitive search patterns lead to negative returns. 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. Interestingly, performing R&D activities continuously which is often associated with having a dedicated department has positive effects but these effects do not vary significantly across search patterns. With regard to control variables, we find significant effects for all variables except for the services industry dummy. Generally speaking, most effects are pronounced in the combinative-competitive class. In conclusion, our first hypothesis which stated that investments in R&D would be most effective with a market-oriented search pattern (customers and competitors) must be rejected.

Focusing on firms from established economies we identify again 4 classes of search patterns based on the AIC3 criterion (see Appendix B). Class 1 comprises 47% of all observations which makes it the largest class of search patterns. Class 2 and 3 are roughly equal in size with 24% of observations while class 4 is very small covering just 6%. While the number of classes is the same as in the transitions economics case, the knowledge sources that define these patterns significantly differ starkly. Table 4 provides probabilities (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 goes about here

Distinctive search patterns emerge based on internal and customer knowledge. Both are significant at the 99% level. Again, all other sources are not irrelevant but make no significant difference for the classification of search patterns. This is especially noteworthy as the importance of customers and the lack of explanatory power from competitor and university knowledge is in stark contrast to search patterns in transition economies.

Then again, we also find a “closed” search pattern in established economies as firms in class 1 rely predominantly on their own knowledge. Class 2 differs strongly as it has the most negative probability for using internal knowledge. Instead, this search pattern is mildly influenced by customer impulses. We will refer to this search pattern as “market influenced.” Class 3 can be considered a derivation of class 2 as this search pattern is not as strong in rejecting internal knowledge but much more clearly defined by customer inputs. We will therefore use the term “market driven” for this search pattern.

Finally, in the comparatively small class 4 of search patterns the firms are able to combine both their own knowledge with customer impulses. Hence, the term “market combinative” appears appropriate.

However, success can only be judged based on the inputs that are necessary to achieve innovation success given a certain search pattern. Table 5 provides these estimation results.

Table 5 goes about here

As in the transition economies 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). Again, we find that the returns from investments in innovation activities differ significantly depending on the search pattern. Similarly, closed search patterns are outperformed by open ones. However, important differences between search patterns remain. Interestingly, search patterns that are only mildly influenced by customers and the ones that combine internal with customer knowledge perform best. The market driven approach has comparatively lower performance effects. This may be due to the fact that customer impulses have been found to be often unarticulated, myopic or unreliable (Frosch, 1996). Hence, search patterns that rely heavily on them may be prone to more frequent errors. Focusing on control variables, we find significant results only for the export intensity, the sales in 1998, the high- and low-technology manufacturing dummies as well as the country share R&D expenditure over GDP. These effects tend to be pronounced in the market combinative class. In conclusion, our second hypothesis which stated that R&D investments would be most effective under technology-driven search patterns has to be rejected.

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 depend upon the institutional environment, most prominently in transition economies. We explore both research questions empirically through separate latent class tobit regression analyses for six transition and seven established economies in Europe based on a harmonized dataset. Hence, our findings are not confined to a single country context. Most strikingly, we find strong support for open innovation strategies in both settings. However, performance differs in established and transition economy contexts.

Most firms in transition economies rely on search patterns that are determined by competitor behaviour. These largely reactive engagements do not reward investments in innovation engagements. Instead, performance can be increased if firms are able to generate combinations of knowledge. This could be internal knowledge or even more promising scientific inputs from universities. By comparison, the knowledge landscape in established economies is much more determined by customer knowledge. We suspect that customers in these countries are both highly demanding but also willing to pay for innovative products or services. In that sense, success depends upon a firm’s capability for finding, absorbing and exploiting customer impulses. However, search patterns that rely exclusively on customer impulses are not the most promising ones. Firms need to be able to assess them and/or combine them with internal knowledge for maximum innovation success.

In conclusion, we find generally strong support for the merits of open innovation strategies. Then again, tailor made search strategies that reflect the institutional environment outperform oversimplified approaches. In that sense, we find support for going beyond breadth and depth when defining search strategies in both established and transition economies. Put simply, too many firms in transition economies appear to be just reacting to competitor moves, which in turn hurts their performance. The most promising solution lies in redirecting their search patterns towards scientific inputs. For firms in established economies, though, customers and firms' capabilities for responding to their needs are the defining driver. However, we find that smart approaches that follow market leads selectively or in combination with internal knowledge perform best.

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 dynamic relationships, 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.

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APPENDIX

Appendix A: Model goodness of fit for transition economies

	LL	BIC(LL)	AIC(LL)	AIC3(LL)	No. of param.	R^2
1-Class Regression	-989.28	2071.46	2002.56	2014.56	12	0.06
2-Class Regression	-765.65	1763.55	1591.30	1621.30	30	0.57
3-Class Regression	-726.43	1824.46	1548.87	1596.87	48	0.65
4-Class Regression	-698.07	1907.08	1528.13	1594.13	66	0.68
5-Class Regression	-677.19	2004.68	1522.39	1606.39	84	0.81

Appendix B: Model goodness of fit for established economies

	LL	BIC(LL)	AIC(LL)	AIC3(LL)	No. of param.	R^2
1-Class Regression	-1698.15	3497.59	3420.29	3432.29	12	0.05
2-Class Regression	-1227.14	2707.53	2514.28	2544.28	30	0.45
3-Class Regression	-1118.24	2641.68	2332.48	2380.48	48	0.53
4-Class Regression	-1090.09	2737.33	2312.18	2378.18	66	0.59
5-Class Regression	-1066.47	2842.04	2300.95	2384.95	84	0.65

TABLES

Table 1: Number of observations

Transition economies		Established market economies	
Czech Republic	1,284	Belgium	706
Estonia	767	Germany	1,656
Hungary	256	Spain	3,169
Lithuania	585	Greece	342
Latvia	433	Iceland	125
Slovak Republic	363	Norway	1,190
		Portugal	780
Total	3,688		7,968

Table 2: Model for latent classes for transition economies: Probabilities for class membership

	Class1	Class2	Class3	Class4	Wald	p-value
Search pattern	**competitive**	**combinative-competitive**	**closed**	**scientific**		
Own company	-0.18	0.30	0.50	-0.62	7.21	0.07
Supplier	-0.15	-0.10	-0.11	0.36	1.09	0.78
Customer	-0.01	-0.15	0.42	-0.27	4.55	0.21
Competitor	0.37	0.07	-0.42	-0.02	10.83	0.01
University	-0.91	-1.62	-0.57	3.10	13.54	0.00
Intercept	1.34	1.21	0.72	-3.27	8.52	0.04

Table 3: Tobit regression for the share of turnover with market novelties in transition economies

Search pattern	Class1 competitive	Class2 combinative-competitive	Class3 closed	Class4 scientific	Wald Overall (p-value)	Wald(=) Comparison (p-value)
Innovation exp. as share of sales (ratio)	-0.21	0.43	0.06	0.89	22.04 (0.00)	21.97 (0.00)
Continuous R&D activities (dummy)	0.08	0.11	0.06	0.04	86.90 (0.00)	1.50 (0.47)
Exports as share of sales (ratio)	-0.07	0.19	0.01	0.30	30.53 (0.00)	26.70 (0.00)
Empl. with college educ. (no.)	0.01	0.04	-0.01	0.06	10.56 (0.01)	7.96 (0.02)
Sales 1998 (logs)	0.00	-0.06	-0.01	-0.09	20.80 (0.00)	18.29 (0.00)
High-tech manuf. (dummy)	-0.02	0.22	0.12	-0.22	731.93 (0.00)	549.40 (0.00)
Medium-tech manuf. (dummy)	0.01	0.07	0.13	-0.81	725.61 (0.00)	512.49 (0.00)
Low-tech manuf. (dummy)	-0.01	0.06	0.13	-0.53	1400.52 (0.00)	990.20 (0.00)
Services (dummy)	-0.01	0.10	0.11	0.00	4.54 (0.21)	1.99 (0.37)
Country share R&D exp. of GDP (ratio)	-0.16	-0.17	-0.07	-0.65	98.99 (0.00)	5.30 (0.07)
Intercept	0.08	0.96	0.13	2.28	54.30 (0.00)	34.51 (0.00)
R^2	0.31	0.19	0.19	0.94		

Table 4: Model for latent classes for established economies: Probabilities for class membership

	Class1	Class2	Class3	Class4	Wald	p-value
Search pattern	closed	market influenced	market driven	market combinative		
Own company	0.33	-0.45	-0.08	0.20	14.65	0.00
Supplier	0.15	0.15	-0.04	-0.26	4.11	0.25
Customer	-0.35	0.02	0.16	0.17	20.39	0.00
Competitor	-0.03	0.15	-0.09	-0.03	2.36	0.50
University	-0.04	-0.19	0.14	0.10	3.62	0.31
Intercept	1.01	0.15	0.14	-1.29	62.56	0.00

Table 5: Tobit regression for the share of turnover with market novelties in established economies

Search pattern	Class1 closed	Class2 market influenced	Class3 market driven	Class4 market combinative	Wald Overall (p-value)	Wald(=) Comparison (p-value)
Innovation exp. as share of sales (ratio)	0.00	0.71	0.11	0.37	72.71 (0.00)	71.41 (0.00)
Continuous R&D activities (dummy)	0.06	0.12	0.04	0.04	110.99 (0.00)	7.20 (0.07)
Exports as share of sales (ratio)	0.01	0.00	0.00	0.05	47.36 (0.00)	35.87 (0.00)
Empl. with college educ. (no.)	0.00	0.06	0.01	-0.01	1.62 (0.81)	1.26 (0.74)
Sales 1998 (logs)	0.01	-0.03	0.00	-0.06	100.55 (0.00)	92.31 (0.00)
High-tech manuf. (dummy)	0.03	0.05	0.05	0.33	55.95 (0.00)	28.11 (0.00)
Medium-tech manuf. (dummy)	0.02	0.07	0.02	-0.22	4.51 (0.34)	3.01 (0.39)
Low-tech manuf. (dummy)	0.01	-0.03	-0.05	0.16	14.31 (0.01)	14.31 (0.00)
Services (dummy)	0.00	0.07	-0.02	0.04	1.63 (0.80)	1.63 (0.65)
Country share R&D exp. of GDP (ratio)	0.01	-0.18	-0.01	0.03	63.25 (0.00)	62.05 (0.00)
Intercept	-0.22	0.82	0.19	0.78	136.42	136.38
R^2	0.31	0.16	0.33	0.92		