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Heterogeneity, Information Sources, and the Introduction of Product and Process Innovations

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Abstract

Empirical studies on a firm's search for external knowledge and its innovativeness analyze the contribution of groups of information sources, such as market-based, competitor-based or public sources (e.g. Roper et al. 2008). However, analyzing groups of information sources does not reflect their heterogeneity. Using national Community Innovation Survey (CIS) data, Laursen and Salter (2006) as well as Ebersberger et al. (2010) study the number of information sources being used, indicating broad search in different information channels. We argue that a firm?s search behavior is positively connected to the heterogeneity of its knowledge base. In this context, a balanced use of information sources is best suitable to promote a higher heterogeneity of a firm's knowledge base. However, the empirical literature does not yet analyze the balance of search. We estimate the connection between a firm?s search for information and the introduction of product and process innovations, using data of the German CIS 2009 survey. Marginal effects are computed for two bivariate probit models for the full sample as well as for subsets of different firm sizes. Both the measures for broad and balanced search show a positive connection to the probabilities to introduce product as well as process innovations, whereas large firms profit more than small firms.

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Heterogeneity, Information Sources, and the Introduction of Product and Process Innovations[1]

Empirical Evidence for German firms

Martin Backfisch[2]

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Abstract

Empirical studies on a firm's search for external knowledge and its innovativeness analyze the contribution of groups of information sources, such as market-based, competitor-based or public sources (e.g. Roper et al. 2008). However, analyzing groups of information sources does not reflect their heterogeneity. Using national Community Innovation Survey (CIS) data, Laursen and Salter (2006) as well as Ebersberger et al. (2010) study the number of information sources being used, indicating broad search in different information channels. We argue that a firm's search behavior is positively connected to the heterogeneity of its knowledge base. In this context, a balanced use of information sources is best suitable to promote a higher heterogeneity of a firm's knowledge base. However, the empirical literature does not yet analyze the balance of search. We estimate the connection between a firm's search for information and the introduction of product and process innovations, using data of the German CIS 2009 survey. Marginal effects are computed for two bivariate probit models for the full sample as well as for subsets of different firm sizes. Both the measures for broad and balanced search show a positive connection to the probabilities to introduce product as well as process innovations, whereas large firms profit more than small firms.

1 Introduction

From the background of the economic crisis of 2008/09 and the ongoing public debt crisis in many developed countries – not only Europe, but also the USA – innovation can help firms to recover from economic downturn (OECD, 2010). At the same time, innovation serves economies to react to challenges like unemployment, climate change, and poverty. In a firms' innovation process, expenditures for research and development (R&D) is widely acknowledged as main driving force and regularly publicly reported for many developed and developing countries. However, there is an ongoing shift within firms, focusing not only on internal innovation efforts, but also on search for external knowledge. Ebersberger et al. (2010) state this is a phenomenon not only found in high technology firms but as well in companies from low tech manufacturing or service sectors.

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[2] Philipps-University Marburg (Chair for Economic Pollicy, Prof. Dr. Wolfgang Kerber) and DHBW Mannheim (Baden-Württemberg Cooperative State University). Financial support from these two institutions is gratefully acknowledged. Contact for correspondence: martin.backfisch@dhbw-mannheim.de

De Backer et al. (2008) empirically show that firms "open up" in the innovation process, as using technology from external sources is considered. However, the authors only use indicators based on codified knowledge such as patents and licenses. But most knowledge has an informal nature and is not codified (e.g., Sofka and Grimpe, 2010). As the OECD report further states, innovation policies should take into account innovation as it is practiced in firms and promote building networks and markets for information (OECD 2010). Mostly based on CIS data, empirical studies have analyzed the contribution of using information sources in search for external knowledge to the innovativeness of firms. These information sources can be argued to contain formal as well as informal knowledge. Some authors have analyzed the effects of searching knowledge in single information sources (Monjon and Waelbroeck, 2003; Belderbos et al., 2004) or groups of innovation sources (e.g., Roper et al., 2008). Contrary, Laursen and Salter (2006) as well as Ebersberger et al. (2010) focus on the number of information sources a firm uses in the innovation process. Whereas Laursen and Salter (2006) find evidence for a nonlinear, inversely-U-shaped effect of the number of information sources, Ebersberger et al. (2010) find a positive effect only in Denmark and Norway, whereas effects in Austria and Belgium are not significant.

The number of information sources can be interpreted as different information channels and therefore different pieces of knowledge being used. Therefore, it serves as a measure of variety of knowledge. We will argue that the number of information sources is an indicator for the heterogeneity of a firm's knowledge base. However, it does not reflect how balanced a firm is searching for external knowledge, leading to the proposing a different measure taking the balanced search for external knowledge into account. In using this measure, it is excluded that firms use a high number of information sources, indicating a high heterogeneity of its knowledge base, but strongly focuses only on a low number or only one information source.

This paper contributes to the literature threefold. First, the breadth *and* balance of a firms search process is analyzed considering its effect on firm innovativeness, whereas the previous literature only focuses on the breadth aspect. Second, the connection between search breadth (and balance) and process innovations has not yet been analyzed. Most of of the empirical literature focuses on product innovations or market novelties. The exceptions from this – Belderbos et al. (2004) and Roper et al. (2008) – apply measures for process innovations, however these studies do not measure the breadth (and balance) of search, but the effect of different groups of information sources. Third, analyzing different subsets of firms, namely large and small firms, has not yet been done as well.

A diversity index for information sources based on the inverted Herfindahl concentration index (HHI) is proposed to measure the balance of search and analyze its connection to the introduction of product and process innovations in a bivariate probit model. Data from the Mannheim Innovation Panel (MIP) wave of 2009 is applied, being the German part of the Community Innovation Survey (CIS) 2009. It is found that balanced search is positively connected to the introduction of product as well as process innovations. Results are robust to different model specifications and a different measure for broad and balanced search. Further, it is found that large firms obtain a higher effect from broad and balanced search than small firms.

The remainder of the paper is organized as follows: section 2 provides a conceptual background, including considerations about the costs and value of searching for external knowledge and its connection to the heterogeneity of a firm's knowledge base. Subsequently, the empirical literature on information sources and innovation is briefly reviewed and hypotheses are formulated. Section 3 contains data description, model building, estimation results and robustness checks. Section 4 discusses the results and proposes directions for future research.

2 Conceptual Background

2.1 Search for External Knowledge and a Firm's Knowledge Base

Studying determinants of innovativeness should acknowledge there are firm internal innovation efforts as well as activities of a firm to obtain and include external knowledge into the innovation process. As Laursen and Salter (2006: p. 133) emphasize that firm internal determinants *"need to be complemented by investigation into how differences in search strategy give rise to performance heterogeneity."*

Searching for knowledge imposes costs on firms. Gaining access to different information sources, such as lead users or suppliers, is accompanied by costly activities, e.g. by means of field service, sales departments and market research (von Hippel, 1988). Links to external knowledge providers may be contacts to employees of competing firms or researchers, making costly development and cultivation of a network of contacts on a personal and professional basis necessary. Parallel search activities for the same pieces of knowledge in different information sources best show the value and costs of broad search activities. Obviously, parallel search is more costly than searching only in one direction. However, under uncertainty a firm does not know where the information needed is contained. Parallel search promises a higher probability of finding adequate pieces of knowledge (and of finding them faster).[3] In an uncertain environment, firms are often not fast enough in developing solutions to given problems in innovating successfully. Reacting to this, firms build networks of contacts and build broad knowledge inventories (Levinthal and March, 1991), which can be reflected by its search strategies. Apart from this, broad and balanced search is also valuable considering the positive effect it has on the heterogeneity a firm's knowledge base. Broad search in many information sources makes the firm's future knowledge base more heterogeneous as knowledge from different sources is obtained. The value obtained from balanced search is similar. Here, not only the value of just using many sources is considered, but also that the information sources where knowledge is searched receive a balanced

[3]Kerber (2011: 180-182) illustrates this point at the industry level.

attention. Therefore, balanced search excludes that the firm uses many information sources, but focuses strongly on only a low number of specific information sources.

Moreover, the search process itself proves valuable to a firm. The number of different information channels a firm searches reflects the *"type and number of pathways of exchange between a firm and its environment",* yielding *"innovative opportunities"* (Laursen and Salter, 2006: p. 133): in a trial and error process, firms develop means to obtain knowledge from each information source, whereas these means are likely to differ by source. Getting knowledge from public research institutions, for example, involves different mechanisms of search than obtaining knowledge from competitors. Therefore, not only the knowledge base, but also the organizational structures and capabilities of the divisions searching for external knowledge become more heterogeneous. For this reason, a firm is more flexible and better able to react to unforeseeable changes by means of innovating (Laursen and Salter, 2006). Further, combining heterogeneous capabilities contained in different information sources, may increase the success probability of innovation projects (Sakakibara, 1997).

There is reason to assume the value of search is not the same to each firm. In evolutionary economics, firms are characterized by limited knowledge, especially about the organization of the market process (Nelson and Winter, 1982). To overcome this, firms develop routines, including search, being specific to each firm. Search processes, understood in a broader sense of detection, acquisition, and integration of knowledge into the firm's own knowledge base can be subsumed by the term of absorptive capacity, which Cohen and Levinthal (1990) argue to be higher in fields where a firm has already developed competences. In these fields it is easier for firms to assess and use new knowledge. Interacting with different groups of actors implies that different internal resources and knowledge systems are existent within a firm (Ebersberger and Herstad, 2010). When a firm is using information from a wide range of sources, it is probable that its knowledge base is broad as well. The same considerations apply for the balance of search. Balanced search necessitates a firm's knowledge base to be balanced, as well, implying larger heterogeneity.

Especially when potentially many sources of external knowledge have to be considered and assessed under uncertainty, it is important to confront different views, compare them and assess which pieces of knowledge are most valuable. As Laursen and Salter (2006) note, variety of knowledge gives opportunities to choose from different technological paths, a concept proposed by Metcalfe (1994). Eventually, according to Fleming and Sorenson (2001), inventions are created by the recombination of already existing and new knowledge. In this interpretation, broad and balanced search increases the probability to find and recombine suited pieces of knowledge therefore increasing the probability of successful innovation.

To subsume, the connection between searching for external knowledge and the heterogeneity of a firm's knowledge base is twofold. First, different sources contribute to build a heterogeneous knowledge base in the future. Second, an already heterogeneous knowledge base increases the value of searching for information in different information sources. If therefore, it is observed that a firm searches for information from a wide range of different sources, it receives a higher return from broadly searching for knowledge, either in contributing strongly to a more heterogeneous future knowledge base or through a more heterogeneous existing knowledge base. Similar considerations have been made for the balance of using information sources. A larger balance implies the incoming knowledge is balanced as well as the firm does not focus on a low number of sources, and is best suitable for contributing to a more heterogeneous knowledge base in the future. Conversely, a balanced search for external knowledge implies the firm's knowledge base is already highly heterogeneous. While the direction of connection between search and knowledge base is not clear per se, in both cases a positive connection between a firm's use of information sources is positively connected to the heterogeneity of its knowledge base. From the considerations above, it also emerges that broad and balanced search for external information as indicator for a heterogeneous knowledge base may be positively connected to a firm's innovativeness.

2.2 Empirical Literature

Katila and Ahuja (2002) measure a firm's search for external knowledge sby patent citations. Therefore, only codified knowledge can be analyzed. However, one of the main challenges in measuring knowledge flows is that *"they leave no paper trail"* (Sofka and Grimpe, 2010, p. 315): most knowledge is not patented or else codified. A convenient feature of the Community Innovation Surveys within the European Union is that it asks a firm directly about the information sources it uses in the innovation process. The obtained variable includes both codified and non-codified knowledge. The information sources in the questionnaire are summarized in Table 1. Note that information within a firm or firm group may represent external search as well, coming from different firm sites or subsidiaries as *"listening posts"* (Ebersberger et al. 2010: p. 4). The empirical literature on information sources and innovation, mostly based on CIS data, will be reviewed in the following.

Effects of Single Information Sources

Three major groups of empirical literature can be distinguished. The first strand of papers analyzes the effects of some or each of the single information sources on the introduction or turnover share of innovations (the latter being referred to as *"innovation performance")*. It provides results on which information sources are most promising in the innovation process. In a data set on French manufacturing firms covering 1994-1996, Monjon and Waelbroeck (2003) find knowledge from

Table 1: Information Sources

Information Source
1. Sources inside the firm or within the firm group
2. Clients
3. Suppliers
4. Competitors, other firms of the same sector
5. Consultancy firms, private research establishments
6. Universities and other higher education institutions
7. Public research institutions
8. Trade fairs, conferences, and exhibitions
9. Scientific and specialist journals and literature
10. Professional associations
11. Patent specifications
12. Standardization panels and documents

Source: Mannheim Innovation Panel (ZEW) 2009; table by the author

competitors, universities, and public research institutions to be significantly negative for the introduction of market novelties. These sources therefore seem to be used rather for product imitations. The authors interpret the negative effect of knowledge from universities such that informally available knowledge is used for imitation, whereas formal collaboration with universities promotes the degree of innovation novelty. Additionally, knowledge from suppliers, consultants, and other firms of the group as well as from patents and trade fairs has a significantly positive effect on the introduction of market novelties. Belderbos et al. (2004) use data on Dutch firms and find only universities as information source have a significantly positive effect on the growth in labor productivity (being interpreted as an indicator for process innovation performance). For the turnover share of market novelties, information from customers and from universities has a significantly positive effect. Other information sources are not found to be significant.

Groups of Information Sources

The second group of literature aggregates information sources into broader categories Here, results can be interpreted as which search strategy or focus (i.e. group of information sources) performs best for innovativeness. Sofka and Grimpe (2010), for example, use CIS data from Belgium, Germany, Greece, Portugal, and Spain covering the period 1998 to 2000. The authors perform factor analysis to identify three factors interpreted as search directions: market-driven (customers, competitors), technology-driven (universities, public research institutions), and supply-driven (suppliers, conferences, trade fairs) and find evidence for a significantly positive effect on the turnover share of market novelties for science-driven and supply-driven information search. Further examples are Spithoven et al. (2010), for Belgian firms and Mention (2011) for Luxembourgish service firms.

The literature above analyzes the effect of on product innovations and their turnover share, neglecting effects on process innovations. An exception is the growth in labor productivity applied by Belderbos et al. (2004), being interpreted as improvements in the production process obtained by process innovations. Roper et al. (2008) use Irish data from 1991 to 2002 to investigate the effects of four groups of external knowledge sources on product *and* process innovations. The authors distinguish between four different groups of information sources: Forward knowledge linkages where information is coming from customers, backward (suppliers and consultancy firms), horizontal (competitors), and public knowledge linkages (universities or public and non-profit research centers). The authors find significantly positive effects of forward, backward, and horizontal knowledge sources on the introduction of process innovations. For the introduction process innovations, only information from suppliers and consultants as well as from competitors has a positive effect. The study points to differences in the effects when different kinds of innovation are considered.

Number of Information Sources

Laursen and Salter (2006) as well as Ebersberger et al. (2010) do not study effects of single information sources or groups of information sources. Instead, the number of information sources being used by firms in the innovation process is analyzed. This measure is interpreted as information breadth indicating how broadly firms are searching for external knowledge, i.e., in how many information channels a firm searches. As Ebersberger et al. (2010: p. 7) note, the number of information sources *"gives the variety of information channels"* being used in a firms innovation process. Relating to Stirling (2007), this can be viewed as the variety aspect of diversity. A higher number of information sources implies their variety to be larger, as the different search spaces vary in its content and type of knowledge.

Laursen and Salter (2006) analyze a cross-section of UK firms provided by CIS data from 1998-2000. The authors distinguish between the introduction of product innovations new to the world, new to the firm, and significantly improved products as dependent variables and find an inversely U-shaped effect of the number of information sources on innovation performance. Ebersberger et al. (2011) analyze both the introduction of market novelties and their performance measured by turnover share. With CIS data for Austria (1998-2000), Belgium, Denmark, and Norway (2002-2004), the number of information sources is significantly positive for the introduction of market novelties only in Denmark and Norway, but not significant in any model for innovative performance in terms of turnover share.

2.3 Balance of Information Sources and Hypotheses

The interpretation in these two studies is that broad search for external knowledge shows how broad firms search and how different the incoming knowledge is (Laursen and Salter, 2006). As argued above, a firm's use of information sources is an indicator for the heterogeneity of its knowledge base. However, using only the number of information sources could be misleading. For example a firm using 3 information sources may give them equal attention; or it may be focusing on one information source while assigning lower importance to the other two sources. The number of information sources neglects the importance relations of the information sources. We propose measuring the balance of all information sources as it reflects not only how many information sources a firm uses, but also how equal the importance is divided to the information sources in use. A heterogeneous knowledge base can best be built if the incoming knowledge obtained by search differs as much as possible. This is the case when a firm does not focus strongly on one or a low number of information sources, but distributes its search efforts equally to many sources. Conversely, balanced search for knowledge indicates that a firm may already have a balanced, heterogeneous knowledge base, leading to a higher value it receives from balanced search for external knowledge. Measuring the balance of information sources also takes into account whether a firm focuses on one or a low number of information sources or uses information sources equally.

To subsume, a broad and balanced search for external knowledge is potentially valuable to firms as it contributes to either building a heterogeneous knowledge base. The theoretical as well as the empirical literature describes the value of broad search for knowledge and a heterogeneous knowledge base, not neglecting there are also costs of a heterogeneous knowledge base. A heterogeneous knowledge base could, however, as well lower the innovativeness as a sufficient level of knowledge has to be built in many fields. High expenditures in searching and connecting to different actors and information sources could then lead to a lower budget devoted to the development and introduction of innovations itself, leading to a lower innovativeness. Therefore I want to empirically test the following hypothesis on a firm's search for external knowledge and its innovativeness:

Hypothesis 1: The number of information sources a firm uses (search breadth) is positively connected to its innovativeness.

Whereas hypothesis 1 would confirm the existing literature (Laursen and Salter 2006; Ebersberger et al. 2010), hypothesis 2 extends to balanced search:

Hypothesis 2: A balanced use of information sources (search balance) is positively connected to a firm's innovativeness.

An interesting question is the relation of a heterogeneous knowledge base and firm size. Large firms may have better capabilities to to transform the obtained knowledge from search in innovation output, leading to hypotheses 3 and 4:

Hypothesis 3: The connection between using many information sources and innovativeness is stronger for large firms than for small firms.

Hypothesis 4: The connection between a balanced use of information sources) and innovativeness is stronger for large firms than for small firms.

3 Research Design

3.1 Data

For the empirical analysis, data of the Mannheim Innovation Panel (MIP) of the 2009 survey is used. MIP data is annually gathered as representative random sample from the population of all firms in Germany in each manufacturing and some service industries.[6] From the MIP dataset, we take the innovation active firms as only these firms report their use of information. These firms have at least introduced either a product or process innovation in the period 2006-2008, or they had innovation projects which were delayed or canceled, or they still have innovation projects under development without having yet introduced an innovation in the surveyed period.

3.2 Measuring Innovativeness

In the reviewed empirical studies, measures of innovation are mostly based on product innovations. Analyzing the effect of broad and balanced search for external knowledge on process therefore complements the existing literature.

Table 2: Occurrences of Product and Process Innovations

Variable		Introduction of Product Innovations No (PD=0)	Introduction of Product Innovations Yes (PD=1)	Total Process Innov.
Introduction of Process Innovations	No (PZ=0)	284 (0.1135)	696 (0.2782)	980 (0.3917)
	Yes (PZ = 1)	446 (0.1783)	1,076 (0.4301)	1,522 (0.6083)
Total Product Innov.		730 (0.2918)	1,772 (0.7082)	2,502 (1.000)

N = 2,502 observations of innovation active firms; Shares in parentheses.
Source: Mannheim Innovation Panel (ZEW) 2009; calculations by the author

We follow Roper et al. (2008), using the introduction of product innovations and process innovations respectively to measure innovativeness. The definition of innovation in the MIP surveys is based on the Oslo Manual (Eurostat and OECD, 2005). A product innovation is defined as introducing a new or significantly improved good or service to the market. The introduction of process innovations is defined as implementing new or significantly improved production or delivery methods for goods and services. It is noteworthy that the innovation need not be new to the market, but new to the firm. From this perspective, the innovation variables are firm-subjective as judgment is left to the firm whether a product or process is new or significantly improved. However, the Oslo Manual requires introduction to the market or implementation in the firm's production process or methods of service provision.

[6] For a description of the 2009 survey of the MIP, see Rammer and Pesau (2011).

These criteria require an innovation to be economically profitable or at least expected to be profitable for a firm. New products are introduced only if the firm expects to generate positive net returns Process innovations, similarly, are implemented if the expected decrease in production offset the costs of its implementation.

The share of product innovating firms in the period 2006-2008 is 70.8 percent on all innovation active firms whereas the share of process innovating firms is 10 percentage points lower at 60.8 percent (see Table 2). It can also be seen that product and process innovations may not be independent from each other. It shows the shares of joint probabilities are not independently distributed, but the share of introducing both product and process innovations (P11) is 43 percent such that the two innovation types occur jointly with the largest sample probability. However, there is also a considerable share of 27.8 percent introducing only product innovations. There may be factors influencing both product and process innovations either positively or factors that lead to a decision to only introduce product innovations.

To account for the possibility that product and process innovations are determined by the same, unobserved variables, a bivariate probit model is applied in the empirical analysis. The underlying notion is that there are two latent variables, product and process innovation propensity (PD* and PZ*). These latent variables cannot be observed. The introduction of product and process innovations (PD and PZ) is observed when the latent variable is larger than 0. In both equations, we use the same explanatory and control variables:

$$PD^* = X'\beta_1 + \varepsilon_1, \qquad PD = 1 \text{ if } PD^* > 0 \qquad (1)$$

$$PZ^* = X'\beta_2 + \varepsilon_2, \qquad PZ = 1 \text{ if } PZ^* > 0 \qquad (2)$$

$$\text{with } \begin{pmatrix}\varepsilon_1\\ \varepsilon_2\end{pmatrix} \sim N\left[\begin{pmatrix}0\\ 0\end{pmatrix}\begin{pmatrix}1 & \rho\\ \rho & 1\end{pmatrix}\right] \qquad (3)$$

The error terms of both equations is allowed to be correlated. The respective correlation coefficient in (3) is ρ. When estimating two probit models for the introduction of product and process innovations separately, $\rho = 0$. Coefficients for the explanatory variables ($\beta 1$ and $\beta 2$) and the correlation of error terms (ρ) are obtained by maximum likelihood estimation (MLE). Using coefficient estimations, marginal effects on the probability to introduce product innovations, process innovations as well as on joint probabilities of the introduction of both innovation types can be computed.

3.3 Measures of Broad and Balanced Search

In section 2 it has been argued that using a larger number of information sources reflects a higher variety of incoming knowledge and is positively connected to the heterogeneity of a firm's knowledge base. points to a more heterogeneous knowledge base of a firm. In model 1, I therefore use the number of information sources a firm uses, ranging from 0 to 12 (see Table 3).

If the respective information source has been used by a firm, the firm was subsequently asked in the CIS survey to rate its importance as low (1), intermediate (2), or high (3). We use these importance ratings to calculate a measure of balanced search for external knowledge., As has been pointed out, assigning equal importance to many information sources either requires the firm to already have a sufficient level of knowledge in many fields or is best suitable to build a heterogeneous knowledge base in the future. Therefore, the measure has to distinguish between cases, where a firm uses many information sources, but is focusing on a low number of sources, and cases where a assigns equal importance to most of the information sources.

Table 3: Descriptive Statistics of Explanatory Variables

Variables	Mean	Standard Dev.	Min.	Max.
Number of Information Sources	8.5755	2.8248	0.0000	12.0000
(1 – info-HHI)	0.8376	0.1115	0.0000	0.9167
(1 – info-CR1)	0.7895	0.1056	0.0000	1.0000

N = 2,502 observations of innovation active firms.
Source: Mannheim Innovation Panel (ZEW) 2009; calculations by the author.

To measure the balance in using information sources, we propose applying an indicator based on a well-known measure in competition policy, the Herfindahl index (HHI). The HHI is used to analyze firm concentration in markets, summing up squared market shares of all firms (e.g. Motta, 2004). The index is lowest when all firms have the same market share. The Herfindahl index can be as well transformed in a diversity index, rewriting it as (1-HHI). Note that the index is also increasing when the number of information sources increases. Therefore, (1-HHI) can be considered to be an integrative measure of the variety and balance of information sources (Stirling, 2007).

Instead of using market shares of firms, we calculate the index as the sum of squared importance "shares" of all information sources used by a firm. To clarify the calculation of the HHI, consider the following example: Three information sources are used by a firm. Information source 1 is assigned low importance by the firm (value = 1), information source 2 gets medium importance (2); information source 3 is assigned high importance (3). The sum of all importance ratings is 1 + 2 + 3 = 6. The HHI is computed as $(1/6)^2 + (2/6)^2 + (3/6)^2 = 0.389$. Note that (1-HHI) is maximized if all information sources are assigned equal importance.

As importance ratings are of ordinal scale, a quasi-metric scale has to be assumed in calculating (1-HHI). Interpretation should therefore not strongly focus on the numerical values, but on the index' indication of how balanced the use of information sources of each firm is. It indicates a lower deviation from an even distribution of the importance each firm assigns to its information sources.[7]

In the example with three information sources, (1-HHI) is maximized in three cases: when all information sources are rated as being of little importance, all information sources are of intermediate importance, or all sources are rated to be very important. It can be objected that no difference is made between these three cases. However, as we want to measure how balanced the importance of the information sources is, no difference can be made between these three as each information source is rated as being as important as the other sources.

The importance of information sources does not perfectly reflect the intensity of using information sources. It could be the case that a firm regularly uses a certain information source, yet it is of only minor importance in the innovation process and would, therefore receive a lower importance rating. On the other hand, when an information source is rated to be very important, it is plausible that a firm uses more resources for this source and searches more deeply and intensely. The interpretation of Laursen and Salter (2006) and Ebersberger et al. (2010) is similar, when the authors use the number of highly important information sources to indicate how deeply and intensely a firm is searching for external knowledge in different information sources.

To the best of my knowledge, there is no empirical literature analyzing how a balanced use of information sources is connected to product and process innovations. Cassiman and Veugelers (2002) provide an integrative measure of number and importance of information sources as determinant of cooperation with other firms. However, the authors add up the importance ratings for each firm and normalize the obtained score to lie between 0 and 1. This is done by dividing the score of each firm by the maximum possible score, which is the same to each firm. This does not reflect how balanced search is.

The firms in the sample use many information sources as the mean is 8.6 information sources (see Table 3). The high average is expected as the sample only contains innovation active firms combining information from different sources in their innovation projects. Ebersberger et al. (2010) report a comparable use of information sources for Austria, Belgium, Denmark and Norway. As has been noted above, the diversity index (1–HHI) is increasing in the number of information sources just as the Herfindahl Index is decreasing in the number of competitors in a market. As a consequence of the high number of information sources that is used in average, the diversity index of information sources is large as well, with a mean of 0.84.

[7] Using the Herfindahl index to measure market concentration can be criticizes for similar reasons, as market shares based on quantities sold or turnover shares are used to indicate market power. However, market power is not undoubtedly connected to market shares.

3.4 Control Variables

Firm Size and Internal R&D Intensity

Previous studies find that innovation determinants may be dependent on firm size as well as R&D (Acs and Audretsch, 1988; Bhattacharya and Bloch, 2004). Large firms have an advantage in using new technology and exploit it (Schumpeter, 1976). The reduction of unit costs by process innovations has a larger scale effect in large firm, also pointing to a positive relation between firm size and process innovations (Aschhoff et al., 2007). However, small firms are characterized by a higher flexibility considering management of innovation projects and hiring R&D workers. Further, the correlation matrix – containing Pearson correlation coefficients of all independent variables – shows there is a significantly positive relation between the number (0.2) as well as with the diversity index of information sources (0.17, see Table 5). We use the logarithm of the number of employees to account for firm size (for a detailed description of control variables, see Table 4).[10]

R&D expenditures divided by sales (R&D intensity) is included as control variable for the firm's internal R&D effort. I only include internal R&D, as external R&D is likely to be covered by one or more information sources, confounding the effect of information sources on innovativeness.[11] Firms' internal R&D intensity is expected to be positively connected at least with product innovations. The correlation matrix shows a weak, but significantly positive link between internal R&D intensity and the number of information sources and the diversity index. Firms' internal R&D intensity is on average 4.3 percent of turnover. We further include the share of employees with higher education as indication of a firm's knowledge utilization capabilities (Roper et al., 2008). A higher average qualification of a firm's workforce may facilitate the use of external knowledge as well as the introduction of product and process innovations. On average, the share of employees with higher education on a firm's total workforce is 23.1 percent. The correlation matrix shows small but significant correlation of this variable with the number and diversity index of information sources (see Table 5).

International Acitivities

Many CIS studies on firms' innovation activities apply the share of exports on turnover (export intensity) to account for international activities (e.g. Müller and Peters 2010). Contrary, we suggest including a firm's presence on different geographical markets (Germany, Europe, and others) as a more general measure of international activities. 40.1 percent of the firms in the sample have activities in all three areas, whereas 17.9 percent are active in Germany and Europe. 35.8 percent of the firms

[10] Different specifications of firm size have been tried as well, such as the number of employees and its squared not leading to substantial changes in the other estimated coefficients.

[11] The total R&D intensity (internal and external R&D) have been tested in one specification as well, leading only to minor reductions of coefficients of the information sources variables.

Table 4: Descriptive Statistics of Control Variables

Variable	Explanation	Mean	St.Dev.	Min.	Max.
Firm Size (ln(empl.))	Logarithm of number of Employees	4.0960	1.6922	0.0000	12.5523
Internal R&D Intensity (%) (fueints)	Expenditures for internal research and development (R&D) divided by sales	4.3172	19.1423	0.0000	444.0000
East Germany (east)[d]	Firm is located in East Germany (former GDR)	0.2930	0.4552	0.0000	1.0000
Market Uncertainty (mkt_uncert)[d]	Firm fully agrees to *"Activities of Competitors are difficult to foresee."* or *"Development of demand is difficult to foresee."*(5 point Likert scale)	0.2206	0.4148	0.0000	1.0000
Market Competitiveness (mkt_comp)[d]	Firm fully agrees to "*High threat due to new competitors*" or *"Products can easily be substituted by products of competitors"* or *"Strong competition by foreign firms"* (5 point Likert scale)	0.3038	0.4600	0.0000	1.0000
Market Dynamics (mkt_dyn)[d]	Firm fully agrees to *"Products/Services are outdated rapidly."*(5 point Likert scale)	0.0420	0.2006	0.0000	1.0000
Geogr. Markets: All 3 Areas (geom_all_3)[d]	Firm is active in all three broader geographical areas (Germany, Europe, Others).	0.4005	0.4901	0.0000	1.0000
Geogr. Markets: Germany and Europe (geom_d_eu)[d]	Firm is active in Germany and in Europe	0.1791	0.3835	0.0000	1.0000
Geogr. Markets: Only Germany (geom_d)[d]	Firm is only active in Germany	0.3577	0.4794	0.0000	1.0000
Distance to Technological Frontier (dist_tf_n3)	1– (Firm Labor Prod./95th percentile of Labor Prod. of Nace 3 industry); set to 0 if result < 0 (firm is on the technological frontier); labor prod. is measured as sales per employee	0.5980	0.2651	0.0000	0.9937
Share of Employees with Higher Education (%) (hes)	Share of employees with higher education (high school degree)	22.9424	25.3150	0.0000	100.0000

N = 2,509 Observations

[d]: denotes indicator variable (taking the value 0 or 1)

Source: Mannheim Innovation Panel (ZEW); calculations by the author.

Table 5: Correlation Matrix

Model 1 (No. of information sources – info_use)	ln(empl.)	fueints	east	mkt_uncert	mkt_comp	mkt_dyn	geom_all_3	geom_d	geom_d_eu	dist_tf_n3	hes	info_use
ln(empl.)	1											
fueints	-0.09	1										
	(0.00)											
east	-0.20	0.09	1									
	(0.00)	(0.00)										
mkt_uncert	-0.03	0.00	-0.01	1								
	(0.11)	(0.87)	(0.69)									
mkt_comp	0.06	-0.02	-0.07	0.57	1							
	(0.00)	-0.43	(0.00)	(0.00)								
mkt_dyn	-0.02	0.04	0.01	0.03	0.09	1						
	(0.24)	(0.07)	(0.48)	(0.10)	(0.00)							
geom_all_3	0.30	0.04	-0.12	-0.11	0.00	-0.02	1					
	(0.00)	(0.06)	(0.00)	(0.00)	(0.96)	(0.30)						
geom_d	-0.25	-0.06	0.11	0.09	-0.01	0.00	-0.61	1				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.73)	(0.93)	(0.00)					
geom_d_eu	-0.06	-0.01	0.02	0.03	0	0.01	-0.38	-0.35	1			
	(0.00)	(0.47)	(0.32)	(0.10)	(0.83)	(0.76)	(0.00)	(0.00)				
dist_tf_n3	-0.15	0.10	0.15	0.01	-0.02	-0.03	-0.16	0.18	0	1		
	(0.00)	(0.00)	(0.00)	(0.67)	(0.29)	(0.20)	(0.00)	(0.00)	(0.95)			
hes	-0.22	0.20	0.15	-0.10	-0.12	0.07	0.00	0.00	-0.05	-0.05	1	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.82)	(0.83)	(0.01)	(0.01)		
info_use	0.26	0.09	0.01	-0.08	-0.01	0	0.25	-0.23	-0.03	-0.09	0.07	1
	(0.00)	(0.00)	(0.61)	(0.00)	(0.49)	(0.99)	(0.00)	(0.00)	(0.16)	(0.00)	(0.00)	
Model 2 (Diversity Index of Information Source – 1-HHI)												
Control Variables	Same Correlations as above											
(1-info-HHI)	0.17	0.06	0.01	-0.02	0.02	0.01	0.15	-0.16	0.00	-0.05	0.06	
	(0.00)	(0.00)	(0.46)	(0.21)	(0.23)	(0.73)	(0.00)	(0.00)	(0.93)	(0.01)	(0.00)	

N = 2,509 Observations; Pearson correlation coefficients (p-values in parantheses).

Source: Mannheim Innovation Panel (ZEW); calculations by the author.

are only active on a domestic level. As Hitt et al. (1997) argue international diversification can be positive for innovation as presence on many markets yields greater returns from innovating. Further, the authors argue that firms, by diversification, can access knowledge from different market and cultural perspectives. Supporting this argument, being active in all three geographical areas is significantly positively correlated to the number of information sources as well as to the balance of information sources measured by the diversity index (see Table 5). Firms only present in Germany tend to use less information sources and have a lower balance of information sources.

Market Environment

As Bhattacharya and Bloch (2004) note, besides firm size, market characteristics are considered to be of relevance explaining innovation performance. Silverberg et al. (1988) model the diffusion of new technologies – which indicates the implementation of product and process innovations – in a dynamic model, taking the changing competitive positions of a adopting vs. non-adopting firms and uncertainty into account. We include these dimensions in the model, indicating strong uncertainty, competitiveness, or dynamics in a firm's market environment (see Table 4 for details).

Distance to Technological Frontier

The distance of a firm to the technological frontier of an industry is used as well. The technological frontier can be defined as the most efficient technology in an industry, measured by labor productivity (see, e.g. Amable et al. 2009). This measure can be transferred to the firm level. A firm's distance to the technological frontier is computed as the difference between its labor productivity and the 95th percentile of labor productivity within its NACE three-digit industry.[13] As Aghion et al. (2006) point out innovation behavior of firms is different for laggard and advanced industries. Further, an objection to the positive relation of a heterogeneous knowledge base and external search could be made such that firms with already highly heterogeneous knowledge may consider it to be not necessary to search externally. A firm already having a heterogeneous knowledge base and finding it not necessary to search externally is also likely to be close or on the technological frontier of its industry. Then, the expected knowledge gains from searching are not large enough to invest in costly search.

Eventually, an indicator variable for the firm's location in Eastern Germany is included as well as industry affiliation measured by NACE two-digit industry classification covering additional influences of the firms' environment, strategic opportunities and demand structure, as far as they are not observed by the other variables included. Note that a variable controlling for cooperation or the number of different collaboration partners is not included in the model. As is noted by the Oslo-Manual, it is important to clearly distinguish between information sources and cooperation partners. Cooperation in innovation is defined as active participation on joint projects with other firms or organizations.

Labor productivity has been tried as well in a different specification, being not significant and not substantially changing coefficient estimates.

Information sources 1 to 7 are identical to the 7 cooperation partners. A cooperation partner is therefore most likely to be considered as an information source by the firm as well, as is discussed in the Oslo Manual (see Eurostat and OECD 2005: 83).

3.5 Estimation Results

Subsequently, the results of two bivariate probit models will be presented. In model 1, the number of information sources is used as indicator for a heterogeneous knowledge base of a firm, whereas in model 2 the diversity index of information sources (1– info-HHI) is applied, indicating variety and balance of searching for external knowledge. Control variables are the same as well for product and process innovations and for model 1 and model 2. Heteroscedasticity robust standard errors have been used.

Table 6: Model Statistics

Model Statistics	Model 1	Model 2
Rho	0.0141	0.0148
S.E. of Rho	(0.0356)	(0.0356)
Wald Chi2 (70)	422.9***	422.9***
P(Chi2)	0.0000	0.0000

N = 2,509 observations; model statistics for coefficient estimations of bivariate probit models for dep. var. introduction of product innovations and introduction of process innovations.; ***/**/* denotes significance at the 1/5/10 percent level.
Source: Mannheim Innovation Panel (ZEW); calculations by the author.

As the Wald test shows, both models are overall significant (see Table 6). Rho is the estimated correlation coefficient between the error terms of the product and process innovation equation. As can be seen, Rho is not found to be significant in both models. However, as we want to analyze joint probabilities on the combinations of the introduction of both innovations, the bivariate probit approach is nevertheless chosen to compute the respective marginal effects on joint probabilities. Overall, model 1 predicts 73.4 percent and model 2 predicts 73.3 percent of the sample cases correctly (see Table 7). For obtaining these shares, predicted probabilities of introducing neither innovation type (P00), only process innovations (P01), only product innovations (P10), and both innovation types (P11) are estimated. Subsequently, the value of the combination of product and process innovations with the largest predicted probability is set to 1, the remaining three occurrences are set to 0. Confronting the model predictions with the naïve prediction is a further indicator of model fit (Rouvinen, 2002). The naïve prediction identifies the combination of product and process innovations in the sample having the highest fraction and sets it to 1 for every observation. In our sample, this is P11 (the introduction of both innovation types). Not surprising, it predicts all cases where P00, P01, and P10 is equal to 0 correctly, however at the cost of not predicting any of the occurrences where these combinations are equal to 1. For P11, 43 percent of cases are predicted correctly, which is just the sample fraction of

Table 7: Shares of Correct Predictions

	Joint Probability				
Share of Correct Predictions	P(PD=0, PZ=0)	P(PD=0, PZ=1)	P(PD=1, PZ=0)	P(PD=1, PZ=1)	P(PD=0, PZ=0)
Model 1 (No. of Info Sources)	88.13%	80.78%	70.10%	54.52%	73.38%
Model 2 (1 – info-HHI)	88.05%	81.14%	70.34%	53.52%	73.26%
Naïve Prediction	88.65%	82.17%	72.18%	43.01%	71.50%

N = 2,502 Observations;
P00 denotes the probability to neither introduce product nor process innovations; P01 denotes the probability of only introducing process innovations, P10 denotes the probability of only introducing product innovations, and P11 denotes the probability of introducing both innovation types.
Source: Mannheim Innovation Panel (ZEW), calculations by the author.

Table 8: Average Marginal Effects, Model 1

			Predicted Probabilities			
Marginal Effect of…	P(PD=1)	P(PZ=1)	P(PD=0, PZ=0) (P00)	P(PD=0, PZ=1) P(01)	P(PD=1, PZ=0) (P10)	P(PD=1, PZ=1) (P11)
ln(empl.)	0.0006	0.0519***	-0.0154***	0.0148***	-0.0365***	0.0371***
	(0.0059)	(0.0067)	(0.0031)	(0.0040)	(0.0052)	(0.0061)
fueints	0.0018*	0.0000	-0.0007	-0.0011*	0.0007	0.0011
	(0.0009)	(0.0005)	(0.0004)	(0.0006)	(0.0005)	(0.0008)
east	0.0107	-0.0136	-0.0002	-0.0105	0.0139	-0.0032
	(0.0201)	(0.0218)	(0.0102)	(0.0137)	(0.0173)	(0.0197)
mkt_uncert	-0.0347	-0.0240	0.0207	0.0140	0.0033	-0.0380
	(0.0257)	(0.0280)	(0.0131)	(0.0174)	(0.0220)	(0.0254)
mkt_comp	-0.0028	0.0118	-0.0024	0.0052	-0.0095	0.0067
	(0.0236)	(0.0250)	(0.0121)	(0.0158)	(0.0196)	(0.0233)
mkt_dyn	0.1133**	0.0224	-0.0512**	-0.0621**	0.0288	0.0845*
	(0.0471)	(0.0477)	(0.0243)	(0.0306)	(0.0368)	(0.0463)
geom_all_3	0.0934**	0.0813**	-0.0606***	-0.0329	-0.0207	0.1141***
	(0.0377)	(0.0403)	(0.0194)	(0.0254)	(0.0317)	(0.0370)
geom_d	-0.0592	0.1229***	-0.0126	0.0718***	-0.1103***	0.0511
	(0.0381)	(0.0416)	(0.0193)	(0.0262)	(0.0331)	(0.0374)
geom_d_eu	-0.0224	0.1189***	-0.0259	0.0484*	-0.0929***	0.0705*
	(0.0399)	(0.0435)	(0.0204)	(0.0272)	(0.0344)	(0.0394)
dist_tf_n3	-0.0784**	0.0048	0.0295*	0.0489**	-0.0343	-0.0441
	(0.0352)	(0.0384)	(0.0178)	(0.0242)	(0.0306)	(0.0343)
hes	0.0013***	-0.0008*	-0.0003	-0.0010***	0.0011***	0.0002
	(0.0005)	(0.0005)	(0.0002)	(0.0003)	(0.0004)	(0.0004)
info_use	0.0087***	0.0187***	-0.0089***	0.0002	-0.0098***	0.0185***
	(0.0033)	(0.0036)	(0.0017)	(0.0023)	(0.0029)	(0.0033)

N = 2,509 observations; standard errors are given in parentheses; ***/**/* denotes significance at the 1/5/10 percent level; indicator variables for industry affiliation based on aggregated NACE 2-digits have been applied as well (not reported here); [d] marginal effects of indicator variables are for discrete change from 0 to 1.
Source: Mannheim Innovation Panel (ZEW), calculations by the author.

Table 9: Average Marginal Effects, Model 2

Marginal Effect of…	P(PD=1)	P(PZ=1)	Predicted Probabilities P(PD=0, PZ=0) (P00)	P(PD=0, PZ=1) P(01)	P(PD=1, PZ=0) (P10)	P(PD=1, PZ=1) (P11)
ln(empl.)	0.0015	0.0560***	-0.0169***	0.0154***	-0.0391***	0.0406***
	(0.0058)	(0.0066)	(0.0031)	(0.0039)	(0.0052)	(0.0060)
fueints	0.0018*	0.0001	-0.0007*	-0.0011*	0.0006	0.0012
	(0.0010)	(0.0005)	(0.0004)	(0.0006)	(0.0004)	(0.0008)
east	0.0110	-0.0100	-0.0014	-0.0096	0.0114	-0.0004
	(0.0200)	(0.0219)	(0.0102)	(0.0137)	(0.0173)	(0.0198)
mkt_uncert	-0.0355	-0.0261	0.0216	0.0140	0.0045	-0.0401
	(0.0256)	(0.0280)	(0.0131)	(0.0174)	(0.0220)	(0.0255)
mkt_comp	-0.0049	0.0090	-0.0007	0.0056	-0.0083	0.0034
	(0.0236)	(0.0250)	(0.0121)	(0.0157)	(0.0196)	(0.0233)
mkt_dyn	0.1132**	0.0249	-0.0517**	-0.0615**	0.0268	0.0864*
	(0.0471)	(0.0478)	(0.0244)	(0.0306)	(0.0368)	(0.0466)
geom_all_3	0.0960**	0.0880**	-0.0633***	-0.0326	-0.0247	0.1206***
	(0.0376)	(0.0401)	(0.0193)	(0.0253)	(0.0316)	(0.0370)
geom_d	-0.0584	0.1235***	-0.0131	0.0714***	-0.1104***	0.0520
	(0.0380)	(0.0415)	(0.0192)	(0.0262)	(0.0330)	(0.0374)
geom_d_eu	-0.0223	0.1202***	-0.0263	0.0485*	-0.0939***	0.0716*
	(0.0398)	(0.0434)	(0.0203)	(0.0271)	(0.0343)	(0.0395)
dist_tf_n3	-0.0813**	-0.0021	0.0325*	0.0487**	-0.0304	-0.0508
	(0.0352)	(0.0385)	(0.0178)	(0.0242)	(0.0307)	(0.0345)
hes	0.0013***	-0.0007	-0.0003	-0.0010***	0.0010***	0.0003
	(0.0005)	(0.0005)	(0.0002)	(0.0003)	(0.0004)	(0.0004)
eins_info_HHI	0.2288***	0.3237***	-0.1842***	-0.0446	-0.1396*	0.3683***
	(0.0777)	(0.0921)	(0.0390)	(0.0565)	(0.0748)	(0.0770)

N = 2,509 observations; standard errors are given in parentheses; ***/**/* denotes significance at the 1/5/10 percent level; indicator variables for industry affiliation based on aggregated NACE 2-digits have been applied as well (not reported here); [d]marginal effects of indicator variables are for discrete change from 0 to 1.
Source: Mannheim Innovation Panel (ZEW), calculations by the author.

firms introducing both product and process innovations Overall, the naïve prediction only predicts 71.5 percent of cases correctly.

From the coefficients estimation in the bivariate probit model, we cannot obtain directly marginal effects. Therefore, marginal effects have been computed to analyze the partial effect a change in an independent variable has on the probabilities to introduce product and process innovations and on joint probabilities of combinations of product and process innovations. Average marginal effects have been computed, first calculating marginal effects for each firm, taking the values of control variables as observed. Averaging over the firm-specific marginal effects yields average marginal effects (AME, see Table 8 and Table 9).

In model 1, it can be seen that both the introduction of product innovations as well as the introduction of process innovations are positively connected to the number of information sources a firm uses. Using one more information source is connected to a 0.9 percentage point increase in the probability to introduce product innovations and an increase in the probability to introduce process innovations by 1.9 percentage points. In model 2, the diversity index of information sources (1-HHI) is also significantly positive for product as well as for process innovations. As the diversity index ranges from 0 to 0.9147, interpreting an increase by one unit is meaningless. We rather describe the effect of an increase of the index by 0.1 points. Such a rise in balance is connected to a 2.3 percentage point increase in the probability to introduce product innovations and a 3.2 percentage point increase to introduce process innovations. Note. However, that interpreting this way should be done with caution, as the importance ratings of firms are originating from an ordinal scale. Nevertheless, a significantly positive connection between a higher number and balance of using information sources is found.

Considering joint probabilities, using a larger number of information sources and conducting broad and balanced search is therefore valuable to obtain a high innovativeness and introduce both innovation types, but it also prevents from not introducing innovations at all. For the probability to introduce only product innovations (P10) there is a difference between model 1 and model 2. The number of information sources has a negative effect on the probability of only introducing product innovations, which is significant at the 1 percent level. In model 2, the diversity of information sources only has a weakly significant effect on this joint probability. The inclusion of balance in measuring external search seems to offset the negative effect variety (i.e., the number of information sources) has on the probability to follow a strategy of only introducing product innovations.

Overall, results of both models strongly support hypothesis 1 as well as hypothesis 2. Using a larger number of information sources is positively connected to a firm's ability to introduce product and process innovations. Including the balance aspect of using information sources leads to a positive connection to a firm's innovativeness as well. Broad and balanced search for external knowledge are therefore positively connected to the innovativeness of a firm. Moreover, applying the diversity index in model 2 takes into account whether firms just use a large number of information sources, but focus on one or a low number of sources. As the balance of search is positively connected to a heterogeneous knowledge base, results show a positive connection of increasing the heterogeneity of knowledge has on a firm's innovativeness. As the diversity index (1-info-HHI) is an integrative measure of variety and balance (Stirling, 2007), it can be argued that both aspects of heterogeneity are likely to increase innovativeness. Otherwise it would be the case that the positive and significant effect of the number of information sources would be driven to insignificance or even be negative. As has been shown, this is only the case for a strategy of only introducing product innovations.

Coming to control variables, we find only small differences between average marginal effects of the two models. Therefore, marginal effects for model 2 are commented. Firm size is only significant in the equation for process innovation, indicating a positive effect. As pointed out above, this may be due to the fact that effects of improving production processes may especially be valuable for larger firms (scale effect). On the other hand, the number of employees seems to be a weak indicator of a diversified product portfolio; if it had been a strong indicator we would have expected a positive relation as well. The connection of firm size to process innovations can be seen by the reduction of the probability to introduce product innovations only, as well as by increasing the introduction of process innovations only. All effects are significant at the 1 percent level. In line with Roper et al. (2008), we find positive effects of the log number of employees on the introduction of process innovations, but not on product innovations. Internal R&D intensity and the share of highly educated personnel are both significantly positive for product innovations, but not for process innovations. These two measures of innovation efforts or innovative capabilities matter especially for product innovations. However, internal R&D intensity is only weakly significant at the 10 percent level and shows only small marginal effects. Firms with a higher share of high skilled employees are less likely to follow a process innovations only strategy connected to the probability to introduce only process innovations (P01). These firms rather follow a strategy of only introducing product innovations.

A dynamic market environment is clearly connected to product innovations, being significantly positive for the introduction of product innovations (11.3 percentage points). This finding is not surprising as a firm's dynamic market environment is characterized by products to be outdated rapidly, making a continuous introduction of new products necessary. The missing significance in the process innovation can be interpreted such that a dynamic market environment not necessarily means to change production processes rapidly. It might rather be the case that the product innovations introduced in a dynamic market environment are often incremental innovations or improvements of existing products.

Being near to the technological frontier is significantly positive for the probability to introduce product innovations. A firm close to the technological frontier is using the most productive technology available in its industry (Amable et al., 2010). As the firm is already close to the technological frontier, there is only little possibility of further improving production technology, making the introduction of process innovations less attractive. A larger distance to the technological frontier, conversely, is positively connected to a strategy of only introducing process innovations. As a firm then is a technological laggard , improvements in production technology are more easily obtained by imitating and "catching up".[14]

3.6 Robustness Checks

Nonlinear Effect of Information Sources

Using too many information sources could be detrimental to innovation. There may be too many ideas to choose between, these ideas may come to the wrong time or only few ideas can be exploited appropriately. Laursen and Salter (2006) include a squared term of the number of information sources and find a nonlinear, inversely U-shaped effect on innovation performance, pointing to an optimal

[14] The mechanism described here may be present at one point in time (and therefore in cross-sectional data). However, in a dynamic setting, one would expect that also firms near the technological frontier invest in process innovations to keep their front position.

number of information sources. We also include the square term of the number of information sources, not finding any evidence for a nonlinear effect to be present for product as well as process innovations. The reason may be that in our sample of innovative firms, using more information sources is mostly better, as it yields additional insights outweighing the additional costs. The high number of information sources firms use on average (8.5 out of 12 sources) supports this consideration.

Different Measure of Diversity

To check robustness of the results of the inverted Herfindahl index, a different concentration measure is applied. We use the "importance share" of the most important information source on the sum of all importance ratings. Consider, again, the case of three information sources, where information source 1 is rated as highly important (value = 3), information source 2 is of intermediate importance (2) and source 3 is of low importance (1). The measure of concentration is obtained to be 3 / (3+2+1) = 0.5. The measure is related to the concentration ratio in competition policy, being the market share of the largest firm in a market (CR1). To obtain a diversity measure, we use the inverted concentration (1-CR1).[15] This measure is easier to interpret than (1-HHI), as it does not compute an abstract value of diversity, but can be traced back to the relative importance the most important information source of a firm.[17] Coefficient estimation yields only minor changes for the control variables. Therefore, only average marginal effects results for (1-CR1) are reported (see Table 10).

Table 10: Average Marginal Effects for (1-CR1)

	Predicted Probabilities					
Marginal Effect of…	P(PD=1)	P(PZ=1)	P(PD=0, PZ=0) (P00)	P(PD=0, PZ=1) P(01)	P(PD=1, PZ=0) (P10)	P(PD=1, PZ=1) (P11)
(1-CR1)	0.2775***	0.2529***	-0.1829***	-0.0945	-0.0699	0.3474***
	(0.0813)	(0.0959)	(0.0418)	(0.0581)	(0.0766)	(0.0819)

N = 2,509 observations; standard errors are given in parentheses; ***/**/* denotes significance at the 1/5/10 percent level;.
Source: Mannheim Innovation Panel (ZEW), calculations by the author.

The alternative measure of diversity is significant both for product and process innovations as well. It yields similar results as the diversity measure based on the Herfindahl index. It shows similar effects for the probability to introduce product and process innovations as well as on joint probabilities. Whereas in the model with (1-HHI), the effect on P10 was only weakly significant, it is not significant for (1-CR1). Effects on joint probabilities P00 and P11 are almost identical in magnitude than in model 2. Overall, the robustness check further confirms the findings on a higher balance of searching for external knowledge.

[15] Pearson's correlation coefficient between 1-HHI and 1-CR1 is 0.72, being significant at the 1% level.

[17] If two or more sources were equally important as most important sources, only one of these has been used to calculate the concentration ratio.

3.7 Marginal Effects by Firm Size

Small and large firms might differ in how they are able to use external information obtained by searching. Smaller firms may have less capabilities of using external knowledge, implying the number of information sources or the balance of search for information is more valuable to large firms. To analyze this, the sample has been divided according to firms smaller than the median firm and firms larger than the median firm, obtaining two equally large samples of 1,251 firms. Overall, large firms profit from balanced search such that the marginal effects are double as large (in absolute value) than for smaller firms. Comparing the number of information sources with the diversity indices (1-HHI) and (1-CR1), it shows there are differences. For the introduction of product innovations, the number of information sources is not significant for smaller, but for larger firms, whereas balanced search is least weakly significant for smaller firms as well Further, considering the probability of only introducing product innovations (P10), the number of information sources yields a significantly negative effect for smaller firms. However, this effect is only significant at 10 percent. The effect of the diversity index (1-HHI) is not significant for small firms. Large firms show to have a significantly negative connection between the number and balance of information sources. Therefore, for larger firms, a strategy of introducing product innovations only is discourages. Either, broad and balanced search increase the probability of introducing both innovation types, i.e., to obtain the highest innovativeness.

Table 11: Marginal Effects for Small and Large Firms

Average Marginal Effects	P(PD=1)	P(PZ=1)	P(PD=0, PZ=0)	P(PD=0, PZ=1)	P(PD=1, PZ=0)	P(PD=1, PZ=1)
			Ln(empl.) < 3.9415 (p50) (N=1,251 obs.)			
Model 1: Info_use	0.0051	0.0140***	-0.0067**	0.0017	*-0.0073**	0.0124***
	(0.0046)	(0.0052)	(0.0027)	(0.0029)	.0041178	(0.0044)
Model 2: (1-info-HHI)	*0.1705**	0.2514**	-0.1579***	-0.0126	-0.0935	0.2639***
	(0.0987)	(0.1203)	.0582354	.0659128	(0.0972)	(0.0960)
			Ln(empl.) > 3.9415 (p50) (N=1,251 obs.)			
Model 1: Info_use	0.0113**	0.0235***	-0.0101***	-0.0012	-0.0134***	0.0247***
	(0.0047)	(0.0050)	(0.0022)	(0.0034)	0.0039	(0.004938)
Model: (1-info-HHI)	0.3204**	0.4640***	-0.2278***	-0.0925	-0.2361**	0.5564***
	(0.1270)	(0.1368)	(0.0501)	(0.1014)	(0.1152)	(0.1181)

N = 2,509 observations; standard errors are given in parentheses; ***/**/* denotes significance at the 1/5/10 percent level;.
Source: Mannheim Innovation Panel (ZEW), calculations by the author.

4 Discussion and Conclusion

This paper has studied whether broad and balanced search for external knowledge positively connected to a firm's innovativeness. Two measures for searching have been applied in two bivariate probit models on the introduction of product and process innovations. The measures have been argued to indicate the heterogeneity of a firm's knowledge base. Both measures show a positive connection to the introduction of product and process innovations, supporting the hypotheses that broad and balanced search is positively connected to a firm's innovativeness. Moreover, a heterogeneous knowledge base can be argued to be positively connected to innovativeness. Some robustness checks, considering different specifications of control variables, a nonlinear effect of the number of information sources as well as an alternative measure of balanced search proved the estimated model to be robust.

The study is the first to analyze breadth *and* balance of information sources by firms and its connection to product as well as to process innovations. Prior empirical research on information sources and innovation does not include the balance dimension of heterogeneity. Including this dimension of heterogeneity should therefore be considered in subsequent analyses. Further, process innovations are only rarely analyzed in the empirical literature in this context. The analysis is, however, limited as it is based on cross-sectional data and exhibits problems of simultaneously determined control and dependent variables. Constructing and analyzing a panel data set could provide further insights and confirm the results of this paper. Panel estimation techniques would allow controlling for unobserved firm-specific effects. Further, the simultaneity issue could be addressed at least to a certain degree by including control variables with time-lag.

Further, the breadth and balance of search for external knowledge is only a rough indicator on a firm's knowledge base. To study the heterogeneity of a firm's knowledge base and its interaction with external information in the innovation process would be desirable and provide further insights. Therefore, more sophisticated measures of knowledge heterogeneity within a firm would be necessary. However, such a study would impose rather detailed, firm-internal data, which is possibly not available for large-scale analysis.

Keeping in mind there is room for further research, some policy implications can be drawn. Innovation policy should try to support innovation processes as they occur within firms (OECD 2010). It should therefore acknowledge that searching for external knowledge is considerably positive for to innovativeness. Innovation policy may therefore try to promote and facilitate a firm's search for external knowledge. Obviously, this is difficult in cases where obtaining external knowledge is bound to personal networks and contacts. However, policy could try to bring relevant actors, be it of universities or public research institutions, and firms, together on a local basis. Policy could try promoting broad and balanced search by larger firms, as the connection to innovativeness shows to be especially strong there. On the other hand, however, facilitating search for information sources targeted especially on small firms could be considered as well as these firms seem to receive a lower value from broad and balanced search.

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