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Search Balance and Product and Process Innovations

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Search Balance and Product and Process Innovations[1]

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Abstract

Firms' search for external knowledge is one aspect of knowledge integration in the innovation process. The literature has investigated innovation and the breadth of search in different information channels. We introduce the concept of search balance reflecting the heterogeneity of a firm's knowledge base. Results from German Community Innovation Survey data shows that search balance is positively connected to the introduction of product as well as process innovations. The connection is stronger for process innovations. The *relative* balance between all information sources used by firms is important for process innovations, but less so for product innovations. Product innovations rely on specific search directions where internal or market-based knowledge is found, offering an alternative to balanced search. Such an alternative does not exist for process innovations such that knowledge from specific information channels has to be accompanied by balanced search in other channels to be successfully used for process innovations.

Keywords: Openness; knowledge sources; innovative search; search balance; innovation; innovation performance

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1 Introduction

Innovation has an extraordinary value at a large scale: it helps coping with unemployment, climate change, and economic crises (OECD 2010). Therefore, science and policy makers are highly interested in the drivers of innovation at the firm level (see, e.g., Fagerberg *et al.* 2012). There is an ongoing shift within firms to focus not only on internal innovation efforts, but also on external knowledge, which is studied by many researchers. Firms' search for knowledge is one aspect of integrating external knowledge in the innovation process (Dahlander and Gann 2010), and has been covered by recent contributions to the empirical innovation literature (e.g., Laursen and Salter 2006; Leiponen 2012; Ebersberger *et al.* 2012).

Laursen and Salter (2006) use the concepts of search breadth and search depth to describe how firms use external information sources. Whereas breadth indicates how many different sources are used by firms, depth covers how many of the information sources used by firms are considered as highly important. Based on the notion of heterogeneity in the firm-internal knowledge base, we argue besides search breadth and depth there is a balance dimension of search. In this paper, balanced search is introduced as a new concept indicating how equal a firm's attention is attributed to the different information sources used in the innovation process. Search balance consists of an absolute effect of the number of information sources used by firms and a relative effect of balancing these sources in their importance. We propose there is a difference between firms using many information sources with equal importance and firms using the same number of information sources, but focusing on only a few information sources among them. Whereas the absolute effect is the same, the relative effect is larger for the former group of firs, as there is a higher balance between the sources in use.

The main contribution of this paper is the introduction of search balance in the literature on search and innovation. Search balance reflects heterogeneity in the firm internal knowledge base. Earlier empirical studies apply patent citations as measure for external search (e.g., Katila and Ahuja 2002). Later studies applying broader measures of codified and non-codified knowledge either analyze search strategies (e.g., Sofka and Grimpe 2010) or search breadth and depth (e.g., Laursen and Salter 2006). However, applying search breadth and depth separately does not reflect how balanced firms are searching for external knowledge. We therefore integrate these two dimensions into one measure of search balance in this paper. We use data of the Community Innovation Survey (CIS) 2009 for German firms to study search balance and innovativeness. The introductions of product and process innovations are applied as dependent variables in probit models. Number *and* importance of information sources are applied to compute a diversity index indicating search balance. We further analyze search balance for two subsets of firms using few and firms of using many information sources and include the importance of difference search directions in our model. In addition to most empirical papers on search and innovation, which solely focus on product innovations, we include both product *and* process innovations into the empirical analysis drawing a clearer picture on the relation of search and different innovation activities.[3]

We find a significantly positive relation between balanced search and the introduction of product and process innovations indicating that heterogeneity of the knowledge base is positively connected to the innovativeness of firms. The connection is found to be stronger for process innovations. Our results are robust to different measures of search balance. For process innovations, both the relative effect of balance between the information sources used and the absolute effect of the number of information sources is important, whereas for product innovations only the latter effect is found to be present. Firm internal and market-directed information sources such as customers and clients are found to be the most important search direction for product innovations. Focusing on these offers an alternative to balanced search. Such an alternative does not exist for process innovations: supplier-based knowledge is the most important search direction here. However it has to be accompanied by knowledge coming from balanced search in the other information sources.

The remainder of this paper is organized as follows: section 2 provides conceptual background on innovation and search, including the connection of search to the knowledge base of firms. Subsequently, the empirical literature on information sources and innovation is briefly reviewed, the concept of search balance is presented, and hypotheses are formulated. Section 3 contains the research design, data description, variables and statistical method applied in the analysis. In section 4, estimation results are presented including robustness checks and results for the subsamples of firms using few information sources and firms using many information sources. Further, results from a model with search balance as well as search direction are presented. Section 5 discusses the results and proposes directions for further research.

2 Theoretical Background

2.1 Innovation and External Search

Analyzing determinants of innovation 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. Laursen and Salter (2006) emphasize not only R&D expenditures of firms should be studied, but search activities and strategies as well. Different streams of literature identify the value of external knowledge for innovation. Innovation can be interpreted as combinations of different pieces of existing knowledge and the exploration of new knowledge (e.g., Nelson and Winter 1982; Fleming and Sorenson 2001). Knowledge for the innovation process is obtained by search activities. The open innovation literature states innovative firms should be open to use different external information channels (Chesbrough 2006). Using information sources can be described as sourcing knowledge for

[3] A notable exception is Roper *et al.* (2008), using both product and process innovations as well.

inbound innovation activities (Dahlander and Gann 2010). Searching in one information channel is promoting learning in other channels as well. Moreover, not only knowledge from different sources, but also searching in each channel as activity itself proves valuable to firms. The number of different information sources reflects the *"(…) type and number of pathways of exchange between a firm and its environment"* (Laursen and Salter 2006, p. 133). Firms need different competences and search behavior and develop source-specific means to obtain knowledge for each *pathway*. Therefore, not only the knowledge retrieved from searching, but also the capabilities of a firm's employees searching for external knowledge become more heterogeneous. Combining these heterogeneous capabilities increases the success probability of innovation projects (Sakakibara 1997).

However, searching in different information sources, such as lead users or suppliers is accompanied by costly activities as well, e.g. by expenditures for field services, sales departments or market research (von Hippel 1988). Further, firms have to balance exploration and exploitation implying exploration is costly while exploitation secures the financial capabilities needed for exploration (March 1991). By costly search activities new knowledge is explored, which in turn has to be exploited in the innovation process to gain financial returns. In an uncertain environment, firms tend to build broad networks of contacts and knowledge inventories, implying maintenance costs as well (Levinthal and March 1993). Parallel search activities for the same pieces of knowledge in different information sources illustrate the value and costs of search. Obviously, parallel search is more costly than searching only in one source. However, under uncertainty a firm does not know which sources contain the necessary piece of information. Parallel search therefore promises a higher probability of finding adequate pieces of knowledge and of finding them faster (Kerber 2011)[4].

2.2 External Search and the Knowledge Base of Firms

Using external knowledge from different sources is valuable considering its contribution to the heterogeneity of firms' knowledge bases. The use of different information sources makes future knowledge more heterogeneous as the knowledge obtained from each source is differing in content, type or actor it is coming from (Laursen and Salter 2006).

In addition, the connection between search and the knowledge base may also work in the opposite direction, i.e. a heterogeneous knowledge base leads to using more different information sources. In evolutionary economic, firms are characterized by bounded knowledge. To reduce knowledge boundaries, firms develop routines, e.g. searching for knowledge (Nelson and Winter 1982). These routines are firm-specific. 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. In this respect, we argue the value and the

[4] Kerber (2011) describes this point at the industry level whereas we focus on the firm level here.

costs of using information sources are firm-specific. The value of search differs across firms as it is dependent on firms' absorptive capacities (Cohen and Levinthal 1990; Zahra and George 2002; Todorova and Durisin 2007). These abilities to search and detect relevant knowledge and to integrate it into the internal knowledge base are higher in fields where a firm has already developed competences (Cohen and Levinthal 1990). Moreover, *"(…), a diverse background provides the prospect that incoming information will relate to what is already known."* (ibid., p. 131). Therefore, firms with a heterogeneous knowledge base receive a higher value from searching as it is easier to use and integrate the external knowledge from different sources. Observing a firm using information from different information sources implies these firms receive a higher value from searching based on its already existing heterogeneous knowledge base. Further, interacting with different groups of actors implies that a firm has diverse internal resources and structures (Ebersberger and Herstad 2011).

To conclude, the relation of search balance and the heterogeneity of firms' knowledge bases is twofold. First, using different information sources contributes to build a more heterogeneous knowledge base in the future. Second, an already existent heterogeneous knowledge base increases the value of searching different information channels as new pieces of knowledge can be found and evaluated more easily when firms already have sufficient competencies in various fields.

2.3 Empirical Literature on Search and Innovation

Studies analyzing external knowledge and innovativeness apply different indicators to measure search. (Katila and Ahuja 2002) include external knowledge by patent citations. However, one of the main challenges in measuring knowledge flows is that *"they leave no paper trail"* (Sofka and Grimpe 2010, p. 315), i.e., most knowledge is not patented or else codified. The European Community Innovation Surveys (CIS) contain questions on firms' use and importance of information sources they use in the innovation process, include both codified and non-codified knowledge. Table 1 gives an overview of the use of different information sources in our data of German innovators. The most important information sources are sources inside the firm of within the firm group. Nearly all firms use this information source.[5] Clients, suppliers, competitors and suppliers are used as information sources in more than 4 out of 5 firms. Among information sources not bound to specific actors we find trade fairs, conferences and exhibitions as well as scientific and specialist journals to be the sources used with highest frequency.

Monjon and Waelbroeck (2003) as well as Belderbos *et al.* (2004) analyze which single information sources are linked to innovation. Other authors aggregate sources into broader categories and present evidence which search strategies – or directions – are most promising in the innovation process. Sofka

[5] Note that knowledge from sources within a firm or firm group represent external search as well, coming from different firm sites or (foreign) subsidiaries, considered as *"listening posts"* (Ebersberger *et al.* 2012, p. 4).

and Grimpe (2010) find evidence for a significantly positive effect of using science-driven and supply-driven information sources on the turnover share of market novelties. Further examples in this line are Henttonen *et al.* (2011), Mention (2011), and Köhler *et al.* (2012).

Table 1: Information Sources

Information Source		Percentage of use
1.	Sources inside the firm or within the firm group	96.95
2.	Customers or clients	95.61
3.	Suppliers	83.73
4.	Competitors, other firms of the same industry	89.90
5.	Consultancy firms, private research service firms	54.97
6.	Universities and other higher education institutions	60.94
7.	Public research institutions	45.63
8.	Trade fairs, conferences, and exhibitions	82.91
9.	Scientific and specialist journals and literature	84.26
10.	Professional associations and chambers	63.02
11.	Patent specifications	44.91
12.	Standardization panels and documents	54.16

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

All these studies analyze the effect of search strategies on product innovations and do not regard effects on process innovations.[6] Contrary, Roper *et al.* (2008) as well as Criscuolo *et al.* (2011) include process innovations into their studies. Roper *et al.* (2008) distinguish between four different groups of information sources in the innovation process. *Forward linkages* contain information from customers; *backward linkages* contain information from suppliers and consultancy firms. *Horizontal knowledge* is coming from competitors while *public knowledge* is obtained from universities, public and non-profit research centers. The authors find significantly positive effects of forward, backward, and horizontal knowledge linkages on the introduction of product innovations. For process innovations, only backward linkages and horizontal knowledge have a positive effect. The results of Criscuolo *et al.* (2011) indicate that combinations with information from suppliers are more important for process innovations while combinations with knowledge from customers are rather promoting product innovations. Both studies point to differences in the effects of search, depending on whether product or process innovations are regarded. Empirical studies should therefore take into account these two kinds of innovation.

Whereas the literature described above studies single information sources or groups of information sources, (Laursen and Salter 2006) follow a different approach in analyzing the number of information sources used by firms. This measure is interpreted as search breadth indicating how many different information channels firms use. Based on the notion of search scope and depth (Katila and Ahuja 2002), Laursen and Salter (2006) broaden the concept of search breadth and depth to non-codified

[6] 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.

knowledge. They find an inversely u-shaped effect of search breadth on innovation performance. Search depth, measured as the number of important information sources, shows an inversely u-shaped effect as well. The study provides insights in the effects of these two search dimensions and led to further studies analyzing search breadth and depth for different countries, sectors, and firm size classes, e.g. Ebersberger *et al.* (2012), Leiponen (2012), Leiponen and Helfat (2010), Cosh and Zhang (2012), Hwang and Lee (2010), and Chiang and Hung (2010) (see Table 2) . Generally, they confirm the Laursen and Salter's results of a positive effect of breadth and depth on innovation performance. However, not all authors find an inversely u-shaped effect of search breadth and depth.

Table 2: Empirical Studies on Search Breadth and Depth

Authors (year)	Country	Sector/Industry	Main Findings
Laursen and Salter (2006)	UK	Manufacturing	Search breadth and depth have an inversely u-shaped relation to innovation performance both for radical and incremental innovations
Chiang and Hung (2010)	Taiwan	Electronic product manufacturers	Search breadth has positive effect on radical innovations; Search depth has positive effect on incremental innovations
Hwang and Lee (2010)	Korea	ICT sector	Search breadth has inversely u-shaped effect on innovation performance, but only for incremental innovations; breadth shows negative, diminishing effect on productivity increases, whereas depth shows an inversely u-shaped effect
Leiponen and Helfat (2010)	Finland	Manufacturing	Search breadth has positive effect on introduction of innovations as well as on turnover share with innovations
Criscuolo *et al.* (2011)	UK	Manufacturing and services	Combinations with information from suppliers are more important for process innovations while combinations with knowledge from customers are rather promoting product innovations.
Cosh and Zhang (2012)	USA	Manufacturing and knowledge intensive business services (KIBS); small and large (>100 empl.) firms	Manufacturing: large firms have inversely u-shaped effect; small firms have linear positive effect; KIBS: both large firms and small firms: inversely u-shaped; but higher effects for large firms
Ebersberger *et al.* (2012)	Austria, Belgium, Denmark, Norway	Manufacturing and knowledge intensive service sectors	Search breadth: positive effect on the introduction of market novelties in 2 of 4 countries; Search depth: positive for the introduction of market novelties in 1 of 4 countries
Leiponen (2012)	Finland	Manufacturing and services	Search breadth has positive effect on innovation performance

Search breadth is measured as the number of information sources firms use. Search depth is the number of important information sources firms use.
Source: Table by the author

2.4 Balanced Search

In section 2.2, we argue a firm's search behavior is reflecting the heterogeneity of its knowledge base. To empirically study search and heterogeneity of firm-internal knowledge, it is necessary to specify which kind of search behavior is reflecting heterogeneous knowledge best. A heterogeneous knowledge base can best be built (1) if many information sources are used (*absolute* effect) and (2) if the incoming knowledge obtained by using several information sources differs as much as possible (*relative* effect). The latter case is given when different search channels obtain an equal attention and firms do not focus on specific information channels, building a diverse mix of incoming knowledge. Focusing on specific information sources like customers or suppliers while attributing less attention to others would not yield the same diversity. Especially when search balance is high, sufficient absorptive capacities as well as different internal structures are necessary in different fields. Only when their own knowledge base is sufficiently heterogeneous, firms receive a value from balanced search large enough to outweigh the larger search costs compared to focused search.

Laursen and Salter (2006) and the related literature do not consider the relative effect of balance, neglecting the importance relations between information sources. Although the number of information sources measures the absolute effect, applying the number of information sources (search breadth) and the number of very important information sources (search depth) separately could be misleading as the relative effect is not measured. For example, consider a firm using three information sources. It may consider all three to be of equal importance, searching in all three directions with the same intensity. However, it may as well be the case that the firm focuses on only one information source with high importance while the importance of the two other sources is low. Measuring only the number of information sources ignores these differences. For search depth, similar considerations can be made. For instance, when a firm uses three information sources it can consider all three to be very important. We then know that the firm assigns equal importance to these three sources. However, we do not know anything about the importance of other information sources in use. These may, e.g., be all of intermediate importance or all of low importance. In the first case, the balance between the very important sources and the other sources can be considered to be higher than in the second case.

The empirical literature does not yet consider the balance dimension of search, especially the relative effect of balance. With regard to the firm internal knowledge base, we argue this is a relevant dimension of using information sources. Our concept of balanced search does not separately consider search breadth and depth, but integrates both dimensions in regarding the number information channels the firm is using as well as the importance relations between these information channels. An integrative measure of the absolute and the relative effect of search balance is presented in the subsequent empirical part of this paper (section 3.2).

2.5 Hypotheses

Balanced search for external knowledge is potentially positively connected to innovation as it contributes to either building a heterogeneous knowledge base or indicates an already heterogeneous knowledge base. A more heterogeneous knowledge base not only facilitates the assessment and integration of external knowledge into the own knowledge base, but has also a beneficial effect on the innovation process itself as new combinations of knowledge are possible (Cohen and Levinthal 1990). Combining heterogeneous capabilities has a positive effect on the success of innovation projects (Sakakibara 1997) and more diverse search processes yield a larger probability to find problem solutions (Fleming and Sorenson 2004). We therefore test the following hypotheses:

Hypothesis 1a: Balanced search is positively related to the product innovativeness of firms.

Hypothesis 1b: Balanced search is positively related to the process innovativeness of firms.

Our concept of search balance includes both the *absolute* and the *relative* effect of search balance: higher search balance can either be obtained in using more information sources (absolute effect) or increasing the balance between the sources already in use (relative effect). As the reviewed literature already considers the absolute effect, but not the relative effect, we want to show that the latter is as well important with respect to innovativeness. We therefore analyze firms using a lower number of information sources and firms using a higher number of information sources in two separate samples. Distinguishing firms by search breadth disentangles absolute and relative effect of search balance to some degree. We argue the absolute effect is lower when many sources are used: when the number of information sources is low, a firm only covers a small search space and using an additional information source substantially broadens this space. Contrary, when already many sources are used, a broad search space is covered and searching an additional source would potentially yield less additional insights. If we observe that search balance is significantly positive when a low number of information sources is used this is argued to be driven rather by the absolute effect. Contrary, when a high number of information sources is used, a significantly positive search balance would be driven by the relative effect of balancing the many information sources in use. We expect both absolute and relative effect contributing to the positive relation between search balance and information sources, leading to the following hypotheses:

Hypothesis 2a: The relation of balanced search and product innovativeness is positive both when few and when many information sources are used by firms.

Hypothesis 2b: The relation of balanced search and process innovativeness is positive both when few and when many information sources are used by firms.

The empirical literature on search strategies find evidence that strategic search in specific information sources is promoting innovation performance (e.g., Sofka and Grimpe 2010; Roper *et al.* 2008). We follow this conjecture in additionally including the importance of the different search directions w*ithin firm or firm group*, *market-based knowledge*, *supplier-based knowledge*, and *science-based knowledge*. These search directions are not mutually exclusive, i.e. firms can assign a high importance to one, two, three or four search directions. Results on these measures indicate which search directions are important for product and for process innovativeness, but also give an idea about their relation to balanced search, i.e. how knowledge from these specific directions interacts with knowledge from other sources. We argue it can well be the case that only one search direction is of high importance for innovativeness, but has to be accompanied by balanced search within other information sources to successfully integrate knowledge from this direction into the own knowledge base. Then, both search balance and specific search directions are significantly connected to innovativeness, leading to hypotheses 3a and 3b:

Hypothesis 3a: Both search balance and the importance of specific search directions are significantly related to product innovativeness.

Hypothesis 3b: Both search balance and the importance of specific search directions are significantly related to process innovativeness.

Altogether, the hypotheses comprehensive review balanced search as a new concept integrating the breadth and depth dimensions of search and guide the way for our subsequent empirical analysis.

3 Research Design

3.1 Data

We use data of the Mannheim Innovation Panel (MIP) from the 2009 survey wave. This survey is the German part of the Community Innovation Survey (CIS) 2008.[7] We take the subsample of innovation active firms as only these firms report the use of information sources. Innovation active firms have at least introduced either a product innovation or a 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 survey period.

3.2 Variables and Methods

Dependent Variables

As argued in section 2.3, both product and process innovativeness should be included in the empirical analysis. We follow (Roper *et al.* 2008) to measure product innovativeness by the introduction of product innovations and process innovativeness by the introduction of process innovations. The share of product innovating firms on all innovation active firms is 70.2 percent, whereas the share of process innovating firms lies at 60.8 percent (see Table 3). The share of firms combining the introduction of

[7] For a detailed description of the survey wave of 2009, see Rammer and Pesau (2011).

both product and process innovations is high (43.1 percent), however, there is also a considerable share of 27.9 percent of firms introducing product innovations only.

Table 3: Introduction of Product and Process Innovations

Variable		Introduction of Product Innovations		Total Process Innovations
		No	Yes	
Introduction of Process Innovations	No	287 (0.1137)	703 (0.2785)	990 (0.3922)
	Yes	447 (0.1771)	1,087 (0.4306)	1,534 (0.6078)
Total Product Innovations.		734 (0.2908)	1,790 (0.7019)	2,524 (1.000)

N = 2,524 observations of innovation active firms; shares are given in parentheses.
Source: Mannheim Innovation Panel (ZEW) 2009; calculations by the author

Statistical Methods

We estimate two probit models, one for product innovations and a second for process innovations.[8] Our model consists of two latent variables, product and process innovation propensity *PD** and *PZ**. The introduction of product innovations is observed when PD* is positive, the introduction of process innovations is observed when PZ* is positive. For both equations, we use the same explanatory and control variables, denoted as *Search Balance* and *X*:

$$PD^* = \alpha_1 + \beta_1 \cdot \text{Search Balance} + X'\gamma_1 + \varepsilon_1, \qquad PD = 1 \text{ if } PD^* > 0;\ PD = 0 \text{ else} \tag{1}$$

$$PZ^* = \alpha_2 + \beta_2 \cdot \text{Search Balance} + X'\gamma_2 + \varepsilon_2, \qquad PD = 1 \text{ if } PZ^* > 0;\ PZ = 0 \text{ else} \tag{2}$$

Coefficients β_1, β_2, γ_1, and γ_2 are estimated by maximum likelihood. Heteroskedasticity robust standard errors are used. Subsequently, marginal effects on the probability to introduce product innovations and process innovations are computed based on coefficient estimates.

Explanatory Variables

We use survey questions on the use of each of the 12 information sources given by Table 1 to measure search balance. When a firm uses an information source, it is also asked to rate the importance of the respective source as low, intermediate, or high. The measure for balance has to recognize the *absolute* and the *relative* effect of balance, i.e. the measure's value is higher either when the number of information sources increases or when the information sources in use receive a more equal attention (see section 2.4). A measure based on the Herfindahl index (HHI) fulfils these requirements. The HHI is usually used to analyze firm concentration in markets, summing up squared market shares of firms

[8] We also tried a bivariate probit model, allowing correlation between the error terms of the two equations measured by the tetrachoric correlation coefficient ρ linking both equations. However, maximum likelihood estimation yielded ρ not being significantly different from 0, leading to the choice of the standard probit approach instead.

(see, e.g., Motta 2004). The index is lowest when all firms have the same market share. The Herfindahl index can be as well transformed from a concentration index into a diversity index (1 – HHI).[9] We calculate the index of search balance as

$$(1 - infoHHI) = 1 - \sum_{j=1}^{12} \left(s_j\right)^2 \qquad (3)$$

For each firm, the importance share of information source j (s_j) is calculated by dividing the importance rating of this source by the sum of importance ratings of all information sources. Consider the following example: Three information sources are used by a firm. Information source 1 is rated to be of low importance (and receives a value of 1), information source 2 gets intermediate importance (2), and information source 3 is rated as highly important (3). The sum of all importance ratings is 6. (1-HHI) is calculated as $1 - [(1/6)^2 + (2/6)^2 + (3/6)^2] = 0.611$. Note that (1 – HHI) is maximized if all information sources are of equal importance, given the number of information sources is constant. Subsequently, when the maximum of 12 information sources is used, the absolute maximum value of (1 – HHI) is given by 1 – 1/12 = 0.917.

Table 4 gives stylized computations for the value of (1-HHI) in a case with up to 5 information sources. Two aspects are shown: first, the balance measure increases when the number of information sources a firm uses increases (*absolute* effect, Panel A). Second, given the same number of information sources, the measure increases when the balance between sources increases (*relative* effect, Panel B). The lowest diversity is measured when all but one information sources receive low importance and one source receives high importance, i.e. the firm focuses strongly on this one source. The second lowest value is measured when only one info source receives high importance, but a second source at least receives intermediate importance. In the subsequent lines of the table in panel B, either the number of sources the firm focuses on with high importance increases or the discrepancy between sources receiving high importance and the sources receiving lower importance decreases, leading to a higher value of the diversity index. Therefore, the diversity index (1-HHI) is suitable to measure both the absolute and relative effect of search balance.

Firm ratings on the importance of information sources are of ordinal scale. Firms order each information source they use into one of the categories high, intermediate, or low importance. However, to calculate the diversity index (1 – info-HHI) a metric scale has to be assumed. The interpretation of results should therefore not focus on numerical values, but on the index' rough indication of how balanced the use of information sources of each firm is.[10]

The *importance* of information sources does not perfectly reflect the *intensity* of their use. It could be the case that a firm regularly uses a certain information source, yet it is of only minor importance to

[9] (1-HHI) is also known as *Blau's index*, see, e.g., Salter *et al.* (2009) who apply this measure in a different context

[10] Using the Herfindahl index to measure market concentration can be criticized 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.

the firm and receives a lower rating. However, when an information source is rated to be very important, it is likely that firms invest more resources for deep and intense search in this information channel. Laursen and Salter (2006) use the number of very important information sources to indicate search depth, which is also based on the idea that search effort can be reflected by the importance rating.

Table 4: Examples for the Calculation of (1 – info-HHI)

Panel A						
Number of Sources Used	Importance Rating of Information Sources					(1 – info-HHI)
	Info 1	Info 2	Info 3	Info 4	Info 5	
1	3	0	0	0	0	0.000
2	3	3	0	0	0	0.500
3	3	3	3	0	0	0.667
4	3	3	3	3	0	0.750
5	3	3	3	3	3	0.800
Panel B						
Case Number	**Importance Rating of Information Sources**					**(1 – info-HHI)**
	Info 1	Info 2	Info 3	Info 4	Info 5	
1	3	1	1	1	1	0.735
2	3	2	1	1	1	0.750
3	3	3	2	1	1	0.760
4	3	3	2	2	1	0.777
5	3	3	3	2	1	0.778
6	3	3	3	2	2	0.793
7	3	3	3	3	2	0.796
8	3	3	3	3	3	0.800

Source: author's calculations

To the best of our knowledge, there is no empirical literature analyzing the connection between balanced search and product and process innovativeness. Cassiman and Veugelers (2002) provide an integrative measure of number and importance of information sources as a determinant of cooperation with other firms. For each firm, the authors add up their importance ratings and normalize the obtained score to range 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. Kang and Kang (2009) as well as Varis and Littunen (2010) simply add up the importance ratings of all information sources for each firm. These approaches do not reflect balanced search. For example, a value of 6 for the latter measure can be either obtained by (a) three information sources with intermediate importance (the rating of each source being 2) or (b) by one information source with high importance (3), one with intermediate (2), and one with low importance (1). The diversity index applied in our analysis assigns a higher value to (a) than to (b), reflecting the higher balance between information sources in this case.

The average firm in the sample uses 8.6 information sources. The high average is not surprising as the sample only contains innovation active firms combining knowledge from information sources in their innovation process. Ebersberger *et al.* (2012) report comparable numbers for the use of information sources for Austria, Belgium, Denmark and Norway. As a consequence of the high average number of information sources being used, (1 – info-HHI) is high on average as well, with a mean of 0.837 (see Table 5).

Control Variables

Firm Size as well as *R&D* have an effect on the innovativeness of firms in earlier studies (Acs and Audretsch 1988; Bhattacharya and Bloch 2004). The reduction of unit costs by process innovations has a larger scale effect for large firms, pointing to a positive relation between firm size and process innovations (Aschhoff *et al.* 2007). We therefore use the logarithm of the number of employees to account for firm size (for a detailed description of control variables, see Table 5).

Internal R&D expenditures divided by sales are included as control variable (*R&D intensity*) indicating firm internal R&D efforts. We only include internal R&D, as external R&D may be considered to be prevalent in the information sources as well, confounding the effect of information sources on innovativeness. Internal R&D intensity is expected to be positively connected with product innovations. Following Sofka and Grimpe (2010), we also control whether a firm *regularly or temporarily Performs R&D* compared to the alternative of not performing R&D at all.[11]

We further include the *Share of Employees with Higher Education* as measure for the knowledge utilization capabilities of firms (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.

Many CIS studies on innovation activities apply the share of exports on turnover to account for *International Activities* (e.g. Leiponen 2012). Contrary, we suggest including firms' presence on different geographical markets as a more general measure. These markets are Germany, Europe, and other geographical regions. 39.9 percent of firms have activities in all three geographical areas, whereas 17.9 percent are active both in Germany and Europe. 35.8 percent of the firms only serve the domestic German market. Hitt *et al.* (1997) argue international diversification can be positive for innovation as the presence on many markets yields larger innovation returns. The authors also show that *Market Characteristics* are determinants of innovation performance. Silverberg *et al.* (1988) model the diffusion of new technologies and take into account the changing competitive positions of technology adopting vs. non-adopting firms as well as uncertainty. We include these dimensions in the model, controlling uncertainty, competitiveness, and dynamics of the market environment.

[11] There is a considerable share of innovative firms not performing R&D at all (Rammer et al. (2011).

Table 5: Descriptive Statistics of Independent Variables

Variable	Explanation	Mean	St. Dev.	Min.	Max.
(1 – info-HHI)	Search balance measure (1 – Herfindahl Index of information sources)	0.8372	0.1126	0.0000	0.9167
Firm Size	Logarithm of number of Employees	4.0806	1.6980	0.0000	12.5523
Internal R&D Intensity	Expenditures for internal research and development (R&D) divided by sales (in percent)	4.6717	25.6888	0.0000	867.000
Continuous R&D[d]	Firm has continuous R&D activities (base group: no R&D activities)	0.4406	0.4966	0.0000	1.0000
Temporary R&D[d]	Firm has temporary R&D activities (base group: no R&D activities)	0.1977	0.3983	0.0000	1.0000
East Germany[d]	Firm is located in eastern part of Germany (former GDR)	0.2940	0.4557	0.0000	1.0000
Market Uncertainty[d]	Firm fully agrees to *"Activities of Competitors are difficult to foresee."* or *"Development of demand is difficult to foresee."*(5 point Likert scale)	0.2425	0.4287	0.0000	1.0000
Market Competitiveness[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)	0.3035	0.4599	0.0000	1.0000
Market Dynamics[d]	Firm fully agrees to *"Products/Services are outdated rapidly."*(5 point Likert scale)	0.0420	0.2006	0.0000	1.0000
All 3 Georgraphical Areas[d]	Firm is active in all three broader geographical areas (Germany, Europe, Others).	0.3986	0.2006	0.0000	1.0000
Germany and Europe[d]	Firm is active in Germany and in Europe	0.1791	0.3835	0.0000	1.0000
Only Germany [d]	Firm is only active in Germany	0.3597	0.4800	0.0000	1.0000
Distance to Technological Frontier	1– (Firm Labor Prod. divided by 95th percentile of Labor Prod. in industry); based on 25 aggregated NACE 2 industries set to 0 if result < 0 (firm is at the technological frontier)	0.6524	0.2506	0.0000	0.9940
Labor Productivity	Labor Productivity as sales per employee	0.4642	2.1018	0.0059	94.2140
Higher Education	Share of employees with higher education (high school degree)	23.0474	25.4150	0.0000	100.000

N = 2,524 observations; [d] indicator variable (being either 0 or 1)
Source: Mannheim Innovation Panel (ZEW); calculations by the author.

The *Technological Frontier* of an industry can be defined as the most efficient production technology available, measured by labor productivity (e.g. Amable et al. 2010). A firm's distance to the technological frontier is calculated as the difference between its labor productivity and the 95th percentile of labor productivity within its three-digit NACE industry. The innovation behavior of firms is different for laggard and advanced industries (Acemoglu et al. 2006). The same may be true for advanced and laggard firms within an industry. 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 not consider it to be necessary anymore to perform balanced search. This would indicate a *negative* relation between heterogeneity of the knowledge base and search. Firms which already have a heterogeneous knowledge base and find it is not necessary to perform balanced search are likely to be close to the technological frontier of their industry. This effect can therefore be controlled by including the distance to the frontier in the model. Besides the distance to the most efficient production technology, the production technology of firms itself included in the model, indicated by *Labor Productivity*. A specification with squared term is chosen as there may be an inversely u-shaped relation between innovation and productivity. For highly productive firms, it may not be necessary to increase productivity by means of process innovation in the short-run, leading to a weaker connection between these two variables at the right tail of the firm productivity distribution. Finally, indicator variables for *Location in East Germany* and *Industry Affiliation* measured by aggregated two-digit NACE industry classification are included in the model.[12]

4 Results

4.1 Search Balance and Innovation

Subsequently, we present estimation results of the probit models described by (1) and (2) in section 3.2. Coefficients are estimated by maximum likelihood using Stata 12. Heteroskedasticity robust standard errors are applied. Variance inflation factors do not indicate any collinearity problems.

The values of Pseudo R-squared are comparable to other innovation studies applying probit models.[13] Overall, the models predict 73.8 percent of the occurrences of product innovations and 64.1 percent of process innovations correctly (see Table 6). Confronting model predictions with the naïve prediction can be used as indicator of model fit (e.g., Rouvinen 2002). The naïve prediction identifies whether the share of firms introducing product innovations in the sample is larger than 0.5. If so, the predicted occurrence of product innovations is set to 1 for all observations. For process innovations, the same is done. As in our sample, both product and process innovations exceed the share of 0.5 (see Table 3), both predictions are set to 1 for all observations. The naïve prediction classifies 70.2 percent of product innovation cases correctly, whereas for process innovations, prediction is correct in 60.8 percent of cases. The naïve prediction performs well when there is an imbalance of firms introducing innovations and firms not introducing innovations (Rouvinen 2002), which is the case in our sample. However, both estimated models yield an improvement compared to the naïve prediction (see Table 6).

[12] For details on the aggregated industries, see Table A 1 (Appendix).

[13] e.g., Ebersberger *et al.* (2012), report values between 0.09 and 0.12. MIP studies with the introduction of product *or* process innovations (i.e., innovating at all) as dependent variable report values of Pseudo R-squared of 0.15 to 0.16, see Aschhoff *et al.* (2007).

Table 6: Model Statistics

Model Statistics	Product Innovation	Process Innovation
Log Likelihood	-1,338	-1,602
Pseudo R-squared	0.119	0.055
Wald Chi2 (41 degrees of freedom)	348.0**	174.9**
Correctly classified (percent)[1]	73.1	64.1
Correctly classified by naïve prediction	70.2	60.7

N = 2,524 observations; model statistics for probit models for introduction of product innovations and introduction of process innovations; ** denotes significance at the 1 percent level. [1]correctly classified: a prediction of PD = 1 (PZ = 1) is assumed if the predicted probability of introducing product innovations (process innovations) is larger than 0.5.
Source: Mannheim Innovation Panel (ZEW); calculations by the author.

Based on coefficient estimates we calculate marginal effects of the independent variables on the probabilities to introduce product and process innovations. [14,15] Marginal effects cannot be interpreted as causal effects here since we apply cross sectional data and have no suitable instruments or identification strategy. When interpreting average marginal *effects* we should keep this in mind.

We find a significantly positive relation between balanced search and innovativeness (see Table 7). The diversity index (1 – info-HHI) is positively related to both the introduction of product and process innovations. An increase in the index by 0.1 points is connected to a 1.7 percentage points increase in the probability to introduce product innovations and a 3.2 percentage points increase in process innovations. Both effects are statistically significant and support hypotheses 1a and 1b. Search balance is positively connected to a firm's innovativeness with respect to both innovation types. As search balance indicates the heterogeneity of a firm's knowledge base, our results suggest that heterogeneity in knowledge is positive for the innovativeness of firms.[16] Note that the relation of search balance and the innovativeness is stronger for process innovations.

To check robustness of results with respect to the measure of search balance, we apply two further diversity measures.[17] First, we use the share of the most important information source on the sum of all importance ratings. This measure is based on the concentration ratio (CR1). To obtain a diversity measure, we use (1-CR1). Consider the case of three information sources, where information source 1 is rated as highly important, i.e., receives a value of 3, information source 2 is of intermediate importance (2) and information source 3 is of low importance (1). The measure of diversity is obtained

[14] Average marginal effects are calculated by the following procedure: First, marginal effects for each firm are calculated taking the values of control variables as observed in the sample. Second, averages of the firm-specific marginal effects are computed, yielding the average marginal effect (AME) of each variable.

[15] Coefficient estimation results can be found in Table A 4 (Appendix). Note that the quadratic terms of labor productivity and the share of highly qualified personnel are significant for product innovations confirming this approach in model specification.

[16] In one model specification, we also included the square of (1 – info-HHI), however, as this term showed no significance, there is no evidence for an inversely u-shaped effect of search balance on innovativeness and there is no "over-searching" in the sense of Laursen and Salter (2006).

[17] Descriptive statistics on these measures are given in Table A 2 (Appendix).

by 1 – [3 / (3+2+1)] = 0.5. If two or more sources at the top of the rating are equally important only one of these is used to calculate the ratio.

Table 7: Average Marginal Effects of Probit Models

Variable	Dependent Variable: Introduction of Product Innovations	Process Innovations
Search Balance (1 – Info-HHI)	0.1689*	0.3237**
	(0.0749)	(0.0913)
Ln(Firm Size)	-0.0120*	0.0549**
	(0.0058)	(0.0068)
Internal R&D Intensity	-0.0002	-0.0003
	(0.0003)	(0.0004)
Continuous R&D Activities[d]	0.2283**	0.0344
	(0.0220)	(0.0257)
Temporary R&D Activities[d]	0.0922**	0.0094
	(0.0207)	(0.0271)
Market Uncertainty[d]	-0.0287	-0.0066
	(0.0206)	(0.0228)
Market Competitiveness[d]	-0.0151	-0.0031
	(0.0192)	(0.0212)
Market Dynamics[d]	0.0994**	0.0190
	(0.0377)	(0.0470)
Geographical Activities: Germany[d]	-0.0353	0.1182**
	(0.0382)	(0.0385)
Geographical Activities: Germany & EU[d]	-0.0228	0.1156**
	(0.0395)	(0.0392)
All three Geographical Areas[d]	0.0762*	0.0837*
	(0.0364)	(0.0388)
Distance to Technological Frontier	-0.1078*	-0.0089
	(0.0456)	(0.0619)
Labor Productivity	-0.0349**	-0.0051
	(0.0129)	(0.0308)
Share of Higher Educated Staff	0.0019*	-0.0016*
	(0.0007)	(0.0007)
Industry Indicator Variables	*Applied*	*Applied*

N = 2,524 observations; robust standard errors are given in parentheses; **/* denotes significance at the 1/5 percent level; indicator variables for the firm's location in East Germany and industry affiliation based on aggregated NACE 2-digits have been applied as well (not reported here; for details on the classification see Table A 1 in the Appendix);
[d] marginal effects of indicator variables are for discrete change from 0 to 1.
Source: Mannheim Innovation Panel (ZEW) 2009, calculations by the author.

The Shannon-Weaver entropy E is applied as a further diversity measure (see, e.g., Stirling 2007). For each information source, its importance share is multiplied by its logarithm and summed up over all information sources:

$$E = -\sum_{j=1}^{12} s_j \log s_j \qquad (4)$$

Estimations results with these different measures of search balance only yield minor changes the effects of control variables.[18] All three measures find a significantly positive connection between search balance and process innovativeness.[19] Further, two of the three measures show a significantly positive effect on the probability to introduce product innovations. In total, our results are robust to the choice of the measure for search balance.

We now interpret results on control variables. Firm size is negatively connected to product innovations, but positively to process innovations. The effect of improving production processes is especially valuable for large firms where the innovation has an effect on a larger scale (Aschhoff *et al.* 2007). In our sample of innovative firms, a small firm size is rather related to the introduction of product innovations. Our findings are partly in line with Roper *et al.* (2008) who find positive effects of the log number of employees on the introduction of process innovations. However, Roper et al. do not find any significant effects on product innovations.

Internal R&D intensity has no significant effect on innovativeness, whereas continuous R&D is significantly connected to product innovations, compared with the base group of not performing R&D at all. Temporary R&D activities have a smaller, but still significant effect. Continuous R&D activities indicate firm-internal innovation capabilities. Our results indicate R&D is rather connected to product innovations than to process innovations. The qualification of the employees as a second indicator of firm-internal capabilities is positively related to product innovations as well. The connection to process innovations, however, is negative.[20] On average, a formally higher qualified workforce is rather associated with product innovation: a rise in the share of higher educated staff by 10 percentage points is linked to a 1.9 percentage points increase in the probability to introduce product innovations. For process innovations, the respective probability is reduced by 1.6 percentage points.

Geographical activities in all three areas (Germany, Europe, and others) are significantly positive for the introduction of product as well as process innovations. For product innovations, broad geographical activities yield ideas for new products in different countries. In the other direction, a product innovator may find it necessary to be active in more geographical areas to increase the returns of the innovation. Broader geographical activities also offer a larger production scale affected by process innovations and related cost reductions. Note that differences in geographical activities are rather related to process than to product innovations.

[18] The results of coefficient estimation for all models are given in Table A 4 (Appendix).

[19] Results are given in Table A 3 (Appendix).

[20] Note that both the share of higher educated employees and its squared term are included in the model. The average marginal effect of increasing the share of higher educated employees is therefore calculated for each firm, taking into account the squared term. However, linear and squared term in combination give the total effect of marginally increasing the share of higher educated employees on the probability to introduce product resp. process innovations. (The total effect is *one* number)

The connection between distance to the technological frontier and the introduction of product innovations is significantly negative. A lower distance to the technological frontier is therefore significantly positive for product innovativeness. A firm close to the technological frontier is using the most productive technology available in its industry (Amable *et al.* 2010). The firm can then focus solely on the introduction of product innovations.[21] Contrary, labor productivity shows a significantly negative connection to product innovations suggesting the negative connection between the distance to the technological frontier and product innovativeness is driven by firms with lower levels of labor productivity.

4.2 Absolute and Relative Effect of Search Balance

We now analyze the effects of search balance for two subsamples. Firms are distinguished by the number of information sources they use. The reasoning behind is to disentangle the direct and the absolute effect of search balance to some degree. Firms in sample 1 use 0 to 8 information sources, firms in sample 2 use 9 to 12 information sources. As we argued in section 2.5, when firms already use a high number of information sources, searching in one further information sources has a lower additional effect than in a case where only few sources are used.

Table 8: Average Marginal Effect of Search Balance

Sample	Product Innovations	Process Innovations
Sample 1: 0-8 information sources	0.2254*	0.2554*
(659 observations)	(0.0921)	(0.1023)
Control Variables	*Applied*	*Applied*
Sample 2:		
9-12 Information sources	-0.1735	2.2255*
(1,865 observations)	(0.7625)	(0.8966)
Control Variables	Applied	Applied

Probit estimation results; standard errors are given in parentheses; **/* denotes significance at the 1/5 percent level;
Source: Mannheim Innovation Panel (ZEW), calculations by the author.

For process innovations, search balance is significantly positive when firms use a lower or a higher number of information sources, indicating both absolute and relative effect are contributing to the positive relation between search balance and process innovativeness. The results therefore support hypothesis 2b. Contrary, regarding product innovations, search balance is not significant when a lower number of information sources is used. Here, search balance is driven by the absolute effect of increasing the number of information sources. As this effect is lower when many information sources are used (sample 2), search balance is getting insignificant, indicating the relative effect is of minor importance for product innovations, rejecting hypothesis 2a.

[21] This mechanism is found to be present at one point in time as we use cross-sectional data. In a dynamic setting, one would expect firms near the technological frontier to perform process innovation as well to keep their frontier position.

Table 9: Coefficient Estimation Results of Interaction Model

Explanatory Variables	Product Innovations	Process Innovations	Product Innovations	Process Innovations
Search Balance (1- info HHI)	0.5646*	0.8918**	0.6183*	0.6304*
	(0.2510)	(0.2534)	(0.2815)	(0.2753)
(9-12 info sources) *x* (1-HHI)			-0.0342	0.1576*
			(0.0771)	(0.0719)
Control Variables (see Table 7)	*Applied*	*Applied*	*Applied*	*Applied*

Probit estimation results; standard errors are given in parentheses; **/* denotes significance at the 1/5 percent level; for the coefficients of control variables, N = 2,524 observations; probit models; robust standard errors are given in parentheses; **/* denotes significance at the 1/5 percent level; Coefficient estimation results for all variables are given in Table A 5 (Appendix).
Source: Mannheim Innovation Panel (ZEW) 2009, calculations by the author.

Here, a difference between product and process innovations is found. Whereas product innovations rather profit from the absolute effect from increasing the number of information sources (search breadth), process innovations are both positively connected to the use of many information sources and the relative balance between these sources. A model with interaction effects confirms that the differences in coefficients of search balance in the two samples are significantly different from each other as the interaction term in Table 9 is significantly different from zero.

4.3 Search Balance and Search Directions

We now include variables for the four search directions *Within Firm or Firm Group*, *Market-Based, Supplier-Based*, and *Science-Based knowledge*.[22] A similar distinction is made by authors studying search strategies (e.g., Sofka and Grimpe 2010). The measure is applied as normalized sum of importance ratings in each search direction. For example, for the importance of market-based knowledge, we sum up the importance ratings of the three information sources "clients", "competitors and other firms of the same industry", and "professional associations and chambers". The sum is subsequently divided by 3, being the number of information sources included in this search direction.

Our results show that knowledge from within the firm or firm group and market-based knowledge is significantly positive for product innovations, whereas supplier-based knowledge is significantly positive for process innovations. Regarding search balance, we again find a stronger connection to process than to product innovations. Whereas the link between balanced search and product innovations is insignificant when the variables on importance of search directions are included, the

[22] Knowledge from within a firm or firm group contains knowledge from sources inside the firm or within the firm group (1; the number refers to the number of the information source as given in Table 1). Market-based knowledge contains knowledge from customers and clients (2), competitors and other firms of the same industry (4), and professional associations and chambers (10). Supplier-based knowledge contains knowledge from suppliers (3), consultancy firms and private research service firms (5), trade fairs, conferences, and exhibitions (8), and standardization panels and documents (12). Science-based knowledge contains knowledge from universities and other higher education institutions (6), public research institutions (7), patent specifications (11), and scientific and specialist journals and literature (9).

connection between balanced search and process innovations remains stable and significant, being only reduced from 3.2 to 3.1 percentage points (see Model 2 in Table 10).

The results reject hypothesis 3a. Searching for market-based and internal knowledge are preferred strategies for product innovation, offering an alternative to balanced search. Contrary, search balance is still significant for process innovations, supporting hypothesis 3b. The search direction of supplier-based knowledge is found to be of outstanding importance here, but search in this direction has to be accompanied by balanced search in other search directions. Otherwise it would be difficult to include the knowledge from this channel into the innovation process.

Table 10: Average Marginal Effects of Search Balance and Search Directions

	Model 1: Base Model		**Model 2: Search Directions**	
Variable	**Product Innovations**	**Process Innovations**	**Product Innovations**	**Process Innovations**
(1-info-HHI)	0.1689*	0.3237**	0.1377	0.3087**
	(0.0749)	(0.0913)	(0.0772)	(0.0935)
High importance of Search Direction:				
Within Firm or Firm Group			0.0584**	0.0360
			(0.0180)	(0.0200)
Market-Based Knowledge			0.1146**	-0.0566
			(0.0379)	(0.0419)
Supplier-Based Knowledge			-0.0223	0.1429*
			(0.0586)	(0.0659)
Science-Based Knowledge			-0.0126	-0.0043
			(0.0603)	(0.0636)
Control Variables	*Applied*	*Applied*	*Applied*	*Applied*

Coefficient estimation results for probit models; standard errors are given in parentheses; **/* denotes significance at the 1/5 percent level; coefficient estimation results for all variables are given in Table A 6 (Appendix);
Source: Mannheim Innovation Panel (ZEW), calculations by the author.

5 Conclusion

5.1 Discussion of Results

Our study adds to the empirical literature on search and the use of information sources and its connection to innovation. The main contribution is threefold. First, we integrate search breadth and depth, taking into account not only how many information sources firms use, but also the importance relation between these sources. Whereas Laursen and Salter (2006) and similar studies analyze general openness and search effort of firms, we introduce the new concept of search balance, consisting of an absolute effect and a relative effect. Whereas the absolute effect is obtained by increasing the number of information sources being used, the relative effect is derived from balancing the knowledge coming from information sources already in use. We have found a significantly positive connection between balanced search and the introduction of product and process innovations. Heterogeneity in the knowledge base of firms – indicated by search balance – is therefore positively connected to firms' innovativeness. Results are robust to different measures of search balance. Our analysis shows that this dimension of search is a relevant determinant of the innovativeness of firms. Search balance should therefore be considered as an important determinant of innovation in subsequent empirical studies.

Second, we analyze both product and process innovations, yielding a more comprehensive understanding of innovative activities than studies focusing on product innovations only. Our approach proves valuable as we find major differences between these two innovation types. We especially find that the absolute effect of search balance is driving product innovativeness, whereas both absolute and relative effects are connected to process innovativeness. Product innovations merely profit from increasing the number of information sources in use. Contrary, process innovations are connected to both using many information sources and sufficiently balancing the relation of these sources.

Third, regarding search balance and different search directions, further differences are found between the two innovation types. Information sources within the firm or firm group as well as market-based information sources are highly important for product innovations. Focusing on these sources offers an alternative to balanced search. Such an alternative does not exist for process innovations. Although supplier-based knowledge is of high importance, search balance is found to be significant as well suggesting search in this direction has to be accompanied by balanced search. Otherwise, the supplier-based knowledge cannot successfully be integrated into the innovation process.

Some policy and management advice can be given. Management should be aware of the balance dimension of search and the differences between product and process innovations. Product innovativeness is connected to specific search directions a firm should focus on. Contrary, the ability to introduce process innovations is especially connected to supplier-based knowledge. However, focusing on this search direction would be misleading as knowledge from this direction should be balanced with knowledge from other information sources. When a firm so far only introduced product-innovations, more balanced search activities than before may prove necessary when the firm also wants to introduce process innovations as well in the future.

Innovation policy should try to support innovation processes as they occur within firms (OECD 2010). It should therefore be recognized that balanced search for knowledge is positively related to firms' innovativeness. As innovation policy cannot facilitate the introduction of innovation directly, it should focus on the search aspects. It could therefore promote and facilitate firms' balanced search in reducing search costs and providing better access to information sources. This is difficult in cases where knowledge is bound to specific actors. However, policy could try to bring together relevant actors, e.g. from universities, public research institutions, firms and customers and improve the access to knowledge which is not bound to certain actors.

5.2 Limitations and Directions for Further Research

There are some limitations of our analysis. Causal effects cannot be identified as the results are based on cross-sectional data and we do not have suitable instrumental variables for search. Nevertheless, we find valuable evidence for the relation of search balance and innovativeness. Further, the balance of search based on only 12 information sources is only a rough measure of the knowledge base of firms. Finer-grained measures of heterogeneous knowledge would be desirable to obtain.

Analyzing a firm-based sample offers valuable insights about the connection of balanced search and innovativeness within each firm. However, the value of search balance is likely to be project-specific and differs between different innovation projects. Some projects need balanced search while others profit from focused or strategic search. An analysis at the firm level cannot capture these considerations and can only identify firm-average effects. An analysis at the project level may provide further insights on a more detailed unit of observation. In the firm-based sample we can only distinguish between product and process innovations. With project-based data, one could, for example, find out which characteristics of innovation projects make balanced search more promising than focusing on specific search directions. It would also be possible to construct more refined, project-based measures on the heterogeneity of firm internal knowledge bases.

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Appendix

Table A 1: Aggregated NACE 2 Industries

Industry	Label	NACE 2/3 Digits (rev. 1.1)
1	Mining and quarrying	10-14
2	Manufacture of food products, tobacco	15. 16
3	Textiles, clothing and leather products	17-19
4	Wood, paper, printing	20-22
5	Refining petroleum, coke manufacture, chemical industry	23, 24
6	Manufacture of rubber and plastic products	25
7	Glass, ceramics, other non-metallic mineral products	26
8	Manufacture of basic metals and fabricated metal products; steel, metal structures	27, 28
9	Manufacturing of machinery, weapons and ammunition, domestic appliances n.e.c.	29
10	Manufacturing of office machinery and computers, electrical machinery and apparatus; radio, television and communication equipment and apparatus	30-32
11	Manufacture of medical, precision and optical instruments	33
12	Manufacturing of motor vehicles and parts, other transport equipment, aircraft and spacecraft	34, 35
13	manufacturing of furniture, jewelry, musical instruments, sports equipment, games and toys; Recycling	36, 37
14	Electricity, gas and water supply	40, 41
15	Construction	45
16	Wholesale trade and commission trade, except of motor vehicles and motorcycles	51
17	Sale, maintenance and repair of motor vehicles and motorcycles, retail sale of automotive fuel; retail trade, repair of personal and household goods	50, 52
18	Land transport, transport via pipelines; water transport; air transport;	60-62
19	Financial intermediation (Banking and Insurance)	65-67
20	Computer and related activities, telecommunications	72, 642, 643
21	Research & development; architectural and engineering activities; technical, physical and chemical testing and analysis	73, 742, 743
22	Legal, accounting, book-keeping and auditing activities, tax consultancy, market research and public opinion polling, holdings; advertising	741, 744
23	Labour recruitment and provision of personnel; information and security services; industrial cleaning; miscellaneous firm-related business activities.;sewage and refuse disposal, sanitation and similar activities	745, 746, 747
24	Real estate activities; renting of machinery and equipment and of personal and household goods	70, 71
25	Motion picture and video activities, radio and television activities	921, 922

Source: table by the author, based on Eurostat information.

Table A 2: Descriptive Statistics of Search Balance Measures

Variables	Mean	Standard Dev.	Min.	Max.
(1 – info-CR1)	0.7889	0.1066	0.0000	1.0000
Shannon Weaver Entropy	1.9972	0.4245	0.0000	2.4849

N = 2,524 observations.
Source: Mannheim Innovation Panel (ZEW) 2009; author's calculations.

Table A 3: Average Marginal Effects for Different Diversity Measures

Explanatory Variable	Dependent Variable: Introduction of	
	Product Innovations	**Process Innovations**
Search Balance by Herfindahl Index *(1- HHI)*	0.1689*	0.3237**
	(0.0749)	(0.0913)
Search Balance by Concentration Ratio *(1-CR1)*	0.2240**	0.2597**
	(0.0771)	(0.0948)
Search Balance by Shannon-Weaver Entropy *(E)*	0.0391	0.1135**
	(0.0208)	(0.0239)
Control Variables (see Table 7)	*Applied*	*Applied*

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

Table A 4: Coefficient Estimation Results for Different Measures of Search Balance

Variable	Dependent Variable: Introduction of …					
	Product Innovations	Process Innovations	Product Innovations	Process Innovations	Product Innovations	Process Innovations
Search Balance by Herfindahl Index *(1- HHI)*	0.5646*	0.8918**				
	(0.2510)	(0.2534)				
Search Balance by Concentration Ratio *(1-CR1)*			0.7494**	0.7140**		
			(0.2593)	(0.2618)		
Search Balance *(E)* by Shannon-Weaver Entropy					0.1306	0.3137**
					(0.0695)	(0.0669)
Ln(Firm Size)	-0.0400*	0.1514**	-0.0426*	0.1518**	-0.0407*	0.1448**
	(0.0194)	(0.0194)	(0.0195)	(0.0194)	(0.0196)	(0.0195)
Internal R&D Intensity	-0.0007	-0.0008	-0.0007	-0.0007	-0.0007	-0.0008
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Continuous R&D Activities[d]	0.7549**	0.0949	0.7539**	0.1045	0.7535**	0.0786
	(0.0763)	(0.0711)	(0.0762)	(0.0710)	(0.0765)	(0.0714)
Temporary R&D Activities[d]	0.3246**	0.0260	0.3261**	0.0356	0.3249**	0.0168
	(0.0778)	(0.0749)	(0.0776)	(0.0748)	(0.0778)	(0.0751)
Location in East Germany	-0.0426	-0.0200	-0.0429	-0.0175	-0.0418	-0.0252
	(0.0651)	(0.0602)	(0.0651)	(0.0601)	(0.0651)	(0.0602)
Market Uncertainty[d]	-0.0949	-0.0181	-0.0911	-0.0140	-0.0926	-0.0142
	(0.0672)	(0.0626)	(0.0673)	(0.0625)	(0.0672)	(0.0627)
Market Competitiveness[d]	-0.0500	-0.0087	-0.0497	-0.0070	-0.0473	-0.0053
	(0.0635)	(0.0584)	(0.0635)	(0.0584)	(0.0635)	(0.0585)
Market Dynamics[d]	0.3643*	0.0528	0.3565*	0.0463	0.3640*	0.0471
	(0.1543)	(0.1314)	(0.1547)	(0.1313)	(0.1541)	(0.1314)
Geogr. Activities: Germany[d]	-0.1163	0.3353**	-0.1229	0.3285**	-0.1181	0.3327**
	(0.1240)	(0.1141)	(0.1244)	(0.1142)	(0.1241)	(0.1146)
Geogr. Act.: Germany & EU[d]	-0.0752	0.3318**	-0.0766	0.3321**	-0.0759	0.3288**
	(0.1289)	(0.1190)	(0.1293)	(0.1191)	(0.1291)	(0.1194)
All three Geographical Areas[d]	0.2543*	0.2329*	0.2500*	0.2326*	0.2507*	0.2229*
	(0.1220)	(0.1098)	(0.1225)	(0.1099)	(0.1222)	(0.1104)
Distance to Techn. Frontier	-0.3601*	-0.0245	-0.3645*	-0.0331	-0.3587*	-0.0088
	(0.1527)	(0.1707)	(0.1528)	(0.1705)	(0.1525)	(0.1436)
Labor Productivity	-0.1179**	-0.0148	-0.1171**	-0.0158	-0.1169**	-0.0063
	(0.0436)	(0.0885)	(0.0435)	(0.0883)	(0.0435)	(0.0487)
(Labor Productivity)^2	0.0014**	0.0009	0.0014**	0.0010	0.0014**	0.0004
	(0.0005)	(0.0046)	(0.0005)	(0.0046)	(0.0005)	(0.0014)
Share of Higher Educated Staff	0.0103*	-0.0071+	0.0102*	-0.0071+	0.0103*	-0.0075*
	(0.0040)	(0.0037)	(0.0040)	(0.0037)	(0.0040)	(0.0037)
(Share of Higher Ed. Staff)^2	-0.0001*	0.0001	-0.0001*	0.0001	-0.0001*	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industry Indicator Variables	*Applied*	*Applied*	*Applied*	*Applied*	*Applied*	*Applied*
Constant	0.1656	-1.2756**	0.0704	-1.0889**	0.3861	-1.1099**
	(0.3035)	(0.3043)	(0.2957)	(0.2967)	(0.2598)	(0.2438)

N = 2,524 observations; probit models; robust standard errors are given in parentheses; **/* denotes significance at the 1/5 percent level;

Source: Mannheim Innovation Panel (ZEW) 2009, calculations by the author.

Table A 5: Coefficient Estimation Results for Interaction Models

	Dependent variable: Introduction of…	
Variable	**Product Innovations**	**Process Innovations**
Search Balance (1- info HHI)	0.6183*	0.6304*
	(0.2815)	(0.2753)
(9-12 info sources) *x* (1-HHI)	-0.0342	0.1576*
	(0.0771)	(0.0719)
Ln(Firm Size)	-0.0387*	0.1453**
	(0.0197)	(0.0195)
Internal R&D Intensity	-0.0007	-0.0008
	(0.0010)	(0.0010)
Continuous R&D Activities[d]	0.7586**	0.0798
	(0.0766)	(0.0715)
Temporary R&D Activities[d]	0.3269**	0.0167
	(0.0778)	(0.0751)
Location in East Germany	-0.0414	-0.0264
	(0.0651)	(0.0602)
Market Uncertainty[d]	-0.0955	-0.0158
	(0.0672)	(0.0627)
Market Competitiveness[d]	-0.0509	-0.0047
	(0.0636)	(0.0585)
Market Dynamics[d]	0.3653*	0.0475
	(0.1543)	(0.1312)
Geographical Activities: Germany[d]	-0.1154	0.3327**
	(0.1240)	(0.1142)
Geographical Activities: Germany & EU[d]	-0.0737	0.3263**
	(0.1290)	(0.1191)
All three Geographical Areas[d]	0.2575*	0.2197*
	(0.1223)	(0.1101)
Distance to Technological Frontier	-0.3620*	-0.0094
	(0.1529)	(0.1461)
Labor Productivity	-0.1182**	-0.0081
	(0.0438)	(0.0530)
(Labor Productivity)^2	0.0014**	0.0004
	(0.0005)	(0.0019)
Share of Higher Educated Staff	0.0104**	-0.0074*
	(0.0040)	(0.0037)
(Share of Higher Educated Staff)^2	-0.0001*	0.0001
	(0.0000)	(0.0000)
Industry Indicator Variables	*Applied*	*Applied*
Constant	0.1266	-1.0862**
	(0.3179)	(0.3043)

N = 2,524 observations; probit models; robust standard errors are given in parentheses; **/* denotes significance at the 1/5 percent level; [d] marginal effects of indicator variables are for discrete change from 0 to 1.
Source: Mannheim Innovation Panel (ZEW) 2009, calculations by the author.

Table A 6: Coefficient Estimation Results for Models with Search Direction

Variable	Dependent variable: Introduction of… Product Innovations	Process Innovations
Search Balance (1- info-HHI)	0.4641	0.8531**
	(0.2605)	(0.2603)
High importance of Search Direction:		
Within Firm or Firm Group	0.1935**	0.0991
	(0.0589)	(0.0551)
Market-based Information Sources	0.3863**	-0.1566
	(0.1288)	(0.1159)
Supplier-Based Information Sources	-0.0753	0.3950*
	(0.1976)	(0.1827)
Science-Based Information Sources	-0.0426	-0.0119
	(0.2032)	(0.1758)
Ln(Firm Size)	-0.0424*	0.1512**
	(0.0194)	(0.0194)
Internal R&D Intensity	-0.0007	-0.0008
	(0.0010)	(0.0011)
Continuous R&D Activities[d]	0.7069**	0.0810
	(0.0779)	(0.0725)
Temporary R&D Activities[d]	0.2988**	0.0236
	(0.0783)	(0.0754)
Location in East Germany	-0.0278	-0.0109
	(0.0656)	(0.0605)
Market Uncertainty[d]	-0.1071	-0.0218
	(0.0675)	(0.0628)
Market Competitiveness[d]	-0.0576	-0.0026
	(0.0638)	(0.0585)
Market Dynamics[d]	0.3375*	0.0403
	(0.1553)	(0.1317)
Geographical Activities: Germany[d]	-0.0997	0.3361**
	(0.1237)	(0.1139)
Geographical Activities: Germany & EU[d]	-0.0707	0.3309**
	(0.1283)	(0.1188)
All three Geographical Areas[d]	0.2383*	0.2333*
	(0.1212)	(0.1097)
Distance to Technological Frontier	-0.3716*	-0.0248
	(0.1533)	(0.1707)
Labor Productivity	-0.1214**	-0.0174
	(0.0428)	(0.0878)
(Labor Productivity)^2	0.0015**	0.0011
	(0.0005)	(0.0046)
Share of Higher Educated Staff	0.0089*	-0.0073
	(0.0040)	(0.0037)
(Share of Higher Educated Staff)^2	-0.0001	0.0001
	(0.0000)	(0.0000)
Industry Indicator Variables	*Applied*	*Applied*
Constant	0.1081	-1.2858**
	(0.3087)	(0.3063)

N = 2,524 observations; probit models; robust standard errors are given in parentheses; **/* denotes significance at the 1/5 percent level; [d] marginal effects of indicator variables are for discrete change from 0 to 1.
Source: Mannheim Innovation Panel (ZEW) 2009, calculations by the author.