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The effects of knowledge management on innovative success – an empirical analysis of German firms†

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Abstract: The aim of this paper is to analyse the effects of knowledge management on the innovation success of firms in Germany. Using a matching procedure on data from the German Innovation Survey of 2003 ("Mannheim Innovation Panel"), we pair firms applying knowledge management with twin firms with similar characteristics not applying knowledge management. Our focus is on investigating the effects of knowledge management techniques on the economic success of firms with product and process innovations. The results of our matching analysis reveal that firms which apply knowledge management perform better in terms of higher-than-average shares of turnover with innovative products compared to their twins. We do not find a significant effect of knowledge management on the share of cost reductions with process innovation.

Keywords: knowledge management, innovation, matching estimator

JEL Codes: O32, L23, L25, M11

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The effects of knowledge management on innovative success – an empirical analysis of German firms

1 Introduction

"The modern corporation, as it accepts the challenges of the new knowledge economy, will need to evolve into a knowledge-generating, knowledge-integrating and knowledge-protecting organisation." (Teece, 2000, 42). An increasing amount of research on innovation and strategic management puts knowledge in the center of interest (Darroch, 2005, Davenport et al., 1997; Grant, 1996; Hall et al., 2002, Hargadon et al. 2002, Nonaka et al., 1995, Swan et al., 1999). In literature related to innovation, knowledge is discussed as the element of a recombination process to generate innovation (Galunic, 1998, Grant, 1996). It has an inherent value to be managed, applied, developed and exploited. Knowledge can be seen as an asset, raising traditional asset questions to management such as when, how much and what to invest in. Owing to the particular properties of knowledge, however, knowledge assets require special attention. Knowledge is (1) often embedded in employees; (2) has features of a public good (Jaffe, 1986: 984; Liebeskind, 1997); and (3) it can hardly be bought in the market (Hall et. al., 2006, 296). Therefore, innovating firms have a need for a sophisticated knowledge management (KM), which pays a lot of attention to the special requirements for and the interactive dimensions of knowledge (creation).

The importance of knowledge management (KM) and its relationship to innovation is widely acknowledged. Empirical work, however, is still in its infancy and characterized by heterogeneous measurement approaches (Hall et al., 2006, 296). Various studies on technological (ICT-based) (Adamides et al., 2006), human resource (Carter et al., 2001) or social aspects (Gupta et al., 2000) of KM exist, focusing on innovation performance in general (Darroch, 2005). An approach that tries to measure firms' quantifiable success with innovations achieved through KM is still missing. We make a first step towards filling this gap in the literature with this paper.

Our main focus is on assessing the impact of KM measures that try to foster knowledge flows and idea exchange across departments within a given firm, e.g. joint development of innovation strategies or temporary exchange of personnel. We assume these KM measures to be of special importance for innovation success. An additional question addressed in our empirical analysis is whether KM has different impacts on the success with different types of innovation, namely product and process innovations. Empirical findings and theoretical considerations (Darroch et al., 2002; Darroch, 2005) give reason to assume that differences do exist.

In the empirical part of our paper we apply a matching method, usually used for impact assessment in labour market economics. It allows us to assess the difference between a KM firm and a twin firm which represents the firm as if it had not at all applied KM. Furthermore, we are able to attribute the innovation success to the deployment of KM since we keep, owing to the matching procedure, other firm characteristics similar between the twins.

The paper is structured as follows. In the first section we identify theoretical arguments and empirical findings on the different impact which KM has with regard to innovation, namely product and process innovation. We derive our hypotheses on the basis of this. In section 3 we present the underlying data and measurement of variables. Afterwards, we discuss the matching method as our empirical approach to investigate the impact of KM on innovation success. The results of the matching procedure, interpretation of our findings and finally a conclusion will end our paper.

2 Literature Review and Hypotheses

Our literature review is guided by our main research question: “Does KM have an impact on a firm’s success with innovations?” We start our review of the literature with papers related to definitions and forms of knowledge management, before reviewing studies dealing with the link between KM and the success of innovation activities.

Knowledge management

Several definitions and conceptions of KM exist (Alavi et al., 2001; Coombs et al., 1998; Davenport, 1998; Nonaka et al., 1995; Probst et al., 1999).[1] These different approaches to KM concentrate on the creation, diffusion, storage and application of either existing or new knowledge (see e.g. Coombs et al., 1998). Wiig (1997) puts his emphasis on the management of existing knowledge and states that the purpose of KM is "to maximize the enterprise's knowledge-related effectiveness and returns from its knowledge assets and to renew them constantly." (Wiig, 1997, 2). Davenport et al. (1998) stress that KM consists of making knowledge visible and developing a knowledge-intensive culture. Several studies identify acquisition, identification, development, diffusion, usage and repository of knowledge as core KM processes (see e.g. Probst et al. ,1999; Alavi et al., 2001). Swan et al. (1999) argue that knowledge exploration and exploitation are the core objectives of KM.

KM implementation can be divided into IT-based KM and human-resource-related KM, as well as process-based approaches (Tidd et al., 2001). IT-based or supply-driven KM emphasizes the need for (easy) access to existing knowledge stored in databases or elsewhere (Swan et al., 1999). In contrast to that, the demand-driven approach is more concerned with facilitating interactive knowledge sharing and creation (Swan et al., 1999). Our study focuses on the latter type of KM implementation.

Knowledge Management and innovative success

That knowledge management and innovation activities are closely linked is obvious. According to Schumpeter, innovation is the result of a recombination of conceptual and physical materials that were previously in existence (Schumpeter, 1935). In other words, innovation is the combination of a firm's existing knowledge assets to create new knowledge. The primary task of the innovating firm is therefore to reconfigure existing knowledge assets and resources and to explore new knowledge (Galunic et al., 1998; Grant, 1996; Nonaka et al., 1995). Both exploration and exploitation of knowledge have been shown to contribute to the innovativeness of firms and to its

[1] See Dick et al. (2002); Earl (2001); Gold et al. (2001) for additional KM conceptions.

competitive advantage (Swan et al., 1999; Hall et al., 2002; Levinthal et al., 1993; March, 1991).

Various studies focus on the role of KM in the innovation process. The results found by Liao and Chuang (2006) confirm the vital role which KM has for the knowledge processing capability and in turn, on speed and activity of innovation. Huergo (2006) provides evidence for the positive role technology management plays for the likelihood and success of firm innovations. A slightly different approach is applied by Yang (2006). He hypothesises that knowledge integration and knowledge innovation improve new product performance, via the moderating effects of marketing and manufacturing competencies, knowledge acquisition, and knowledge dissemination. This finding is supported by Brockman et al. (2003). They argue that the KM tools "use of innovative information", "efficient information gathering" and "shared interpretation" improve the performance and innovativeness of new products.

With regard to our special focus on "demand-driven" or "collaborative" KM methods, theoretical considerations provide ambiguous arguments. Alavi et al. (2001) argue that excessively close ties in a knowledge-sharing community may limit knowledge creation because of redundant information. Brown et al. (1998) and Nonaka et al. (2002), on the other hand, make the case that a shared knowledge base increases knowledge creation within the community. Empirical case study evidence shows mixed results as well. The findings of two studies by Darroch and co-authors are a good example: whereas Darroch et al. (2005) confirm the positive role of knowledge dissemination on innovation success, Darroch (2002) does not find any significant effects.

Another aspect of the link between KM and innovation is how different types of innovation are affected by KM. According to Darroch et al. (2002) different types of innovation require different resources and hence a differentiated KM strategy. They investigate the effects KM has on three types of innovation: incremental innovations, innovations that change consumers' behaviour and innovations destroying existing firm competencies. According to their findings different KM activities are important for different types of innovative success.

In her work, Darroch (2005) criticises the lack of literature explaining what effective KM means and how to measure its degree of success (Darroch, 2005). Particularly, many studies in which KM is a forerunner of innovative success fail to explicitly examine the relationship between the two constructs (Darroch et al., 2002). Our study is an attempt to provide research on that area. The literature which we have reviewed is limited in terms of the extent to which it allows hypotheses to be constructed on the different ways in which KM has an impact on innovative success. We expect, however, that KM acts differently on radical and incremental product innovation[2] success, as well as process innovation success. This expectation is based on Grupp's distinction (1997, 1998). In the case of radical innovation, the main thrust of KM is to recombine knowledge assets and generate new ideas. These tasks are undertaken by KM, which is concerned with the exploration of new knowledge (Nonaka & Takeuchi, 1995; Swan et al., 1999; Hall et al., 2002) and hence uses existing knowledge only to a limited degree. Incremental product and process innovations are based more intensely on existing knowledge. Process innovations occur continuously (Demarest, 1997; Tidd, 2001) and are characterized by investment in new production techniques or re-organization of firm structures (Grupp, 1997, 1998). Therefore, KM approaches that address the exploitation of existing knowledge assets (Alavi et al., 2001; Gold, .2001) are supposed to be more relevant for incremental innovation.

Hypotheses

Summing up our literature review, theoretical considerations and empirical findings support the importance of KM for innovation in general. We presented a differentiated perspective on the innovation success and on types of KM tools in order to prepare our hypotheses[3]. KM in general is expected to have a positive impact on the innovative performance of firms. Therefore our hypotheses are as follows:

H1: Firms applying KM are more successful with incremental innovations than firms without KM.

[2] For a discussion about how to differentiate innovations with respect to novelty see Dosi (1988), Booz Allen Hamilton (1982), Landry and Amara (2002) or Monjon and Waelbroeck (2003). An overview of different measures of innovative success can be found in Janz (2003) and Caloghirou et al. (2003)

[3] Since we are not able to construct a measure of the overall innovative success with the data available to us, we formulate separate hypothesis for each type of innovation.

H2: Firms applying KM are more successful with radical innovations than firms without KM.

H3: Firms applying KM are more successful with process innovations than firms without KM.

3 Data set and main variables

For our empirical analysis on the impact of KM on innovative success the data used for constructing the variables are taken from the Mannheim Innovation Survey (MIP). This annual survey is conducted by the Center for European Economic Research (ZEW) on behalf of the German Federal Ministry of Education and Research. The methodology, concepts and most of the questions of the survey are the same as those implemented in the Community Innovation Surveys (CIS) of Eurostat. This reliance on well tested questions leads to high quality data and comparability with data in other countries (Laursen and Salter, 2006). A non-response analysis is conducted to ensure that the stratified random sample drawn from the population of German firms with five or more employees in manufacturing and services is representative of the population.

For our analysis we use the 2003 wave of the survey, in which data were collected on the innovative behaviour of enterprises during the three-year period 2000-2002.[4] The information contained in the data set goes beyond that of traditional measures of innovation such as patents (Kaiser, 2002; Laursen and Salter, 2006) and allows us to construct a measure of knowledge management and various direct indicators of the economic success of firms' innovative activities.

Besides the core variables described below we make use of a number of control variables in various stages of the analysis.[5] All the information used to construct these control variables is taken from the Mannheim Innovation Panel of 2003.

[4] For a more detailed description of the 2003 MIP survey and expanded figures for a variety of topics related to the innovative behaviour of German firms see Rammer et al. (2005). A more general description of the MIP Surveys in English has been published by Janz et al. (2001).
[5] For a list of these variables and details on their construction see Table 4 in the appendix.

Measuring knowledge management activities

Our indicator for knowledge management activities is constructed using a question from the 2003 Mannheim Innovation Panel about internal modes of collaboration on innovative activities between different departments. The focus is on "collaborative" KM techniques that potentially lead to the exchange of ideas and knowledge. We restrict our analysis to modes that require active management activities and exclude more casual modes such as informal contacts in order to stress the management effect of knowledge management. Our measure is based on the following six modes of collaboration: (1) joint development of innovation strategies, (2) open communication of ideas and concepts among departments, (3) mutual support with innovation-related problems, (4) regular meetings of department heads, (5) temporary exchange of personnel, (6) seminars and workshops involving several departments. We expect that most firms perform at least some type of KM activities. Hence, the resulting variance would be too small to identify effects of KM on the success of firms. In order to avoid this problem, we take a conservative approach. We label as KM firms only those firms which indicated that the scope of collaboration between departments was high (compared to medium, low and KM tool not used) for more than three KM tools.

Measuring innovative success[6]

The data from the Mannheim Innovation Panel contains several different measures of the economic success of innovations. The survey distinguishes between the success with product and process innovations and further differentiates between market novelties and innovations at least new to the firm. Market novelties are the subgroup of product innovations that not only fulfil the minimum novelty criterion of being considered as an innovation ("new to the firm"- incremental innovations) but also the stricter criterion of being new to the market of the firm ("market novelties" - radical innovations). Accordingly, there are two different measures for the economic success of product innovations. The first is the share of total turnover in 2002 that can be attributed to product innovations introduced between 2000 and 2002 (used to test hypothesis 1) and the second one is the share of turnover in 2002 that is due to market

[6] Similar measures of innovative success have been used by Belderbos et al. (2004), Lööf and Broström (2004), Love and Roper (2004), Gemünden and Ritter (1997) or Aschhoff and Schmidt (2008).

novelties between 2000 and 2002 (employed to test hypothesis 2). By definition the latter share is zero for innovative firms that did not introduce any market novelties.

Similar to the success measures for product innovations, the questionnaire of the Mannheim Innovation Panel also includes a direct question on the success with process innovations. Firms are asked whether they introduced any process innovations during the previous three years that led to cost reductions in the year prior to the survey. Conditional on having any cost reducing process innovation the survey asks them to provide the share of cost reductions realized in the year prior to the survey. In our case this means that we have a measure of the economic success of process innovations introduced between 2000 and 2002, i.e. the share of cost reductions in total costs in 2002.

Obviously, information on the success variables is not available for firms that did not introduce innovations between 2000 and 2002 or that had ongoing or abandoned innovative activities during that period. We therefore restrict our sample to innovation active firms instead of replacing the missing values with zeros. If the latter procedure had been employed, our estimated effects would have contained two effects of KM at the same time, the effect on the likelihood to introduce innovations and the effect on the share of cost reduction or turnover. Using the matching procedure on the restricted sample (innovative firms) allows us to identify the pure effect of KM on the share of turnover for innovation active firms.

4 Empirical analysis - the matching procedure

In order to test the impact of knowledge management on the success with innovations we make use of a technique that is usually used to evaluate the impact of public programs, “matching”. Its roots are in labour market research (Heckman et al., 1998; Heckman et al., 1999; Lechner, 1998), but the technique has also been used in other areas, such as the evaluation of public R&D funding (Almus and Czarnitzki, 2003; Lööf and Heshmati, 2005; Aerts and Czarnitzki, 2004). Sofka and Teichert (2006) just recently applied the matching method to compare the outcome of firms that

are active in global sensing to those that are not. They argue that the matching procedure is suited to the analysis of the resource based view and the capability based view, because it allows comparing “firms with similar contexts and dynamics in their environment” and “preserves the heterogeneity of firms” (Sofka and Teichert, 2006: 5).

The basic idea of the non-parametric matching method, which does not require the specification of a particular functional form of equations, is to compare means of outcome variables for a firm that exhibits a special characteristic (“treatment”) with those of a firm (“twin”) that is similar in terms of a predefined set of variables but does not exhibit that particular characteristic. The matching procedure allows its user to answer the question as to how a firm would have performed if it had not received the treatment (“counterfactual”), by re-establishing the conditions of an experiment with treatment and control groups. By comparing the performance of the treated firm in the hypothetical state (counterfactual) with its actual performance, the impact of the treatment on performance (“average treatment effect on the treated (ATT)”) can be isolated from other influences while keeping the heterogeneity of the firms intact instead of evaluating the mean impact, as would be done in a regression analysis.

For determining the performance of firms in their counterfactual state one cannot use the average performance of the non-treated firms. This would lead to biased results. Therefore one attempts to match each treated firm with a non-treated firm which shows the same characteristics except the treatment variable.

The basic method in our case works as follows (see, for example, Czarnitzki et al., 2007): The first step is to split up the sample into two groups, the firms that use knowledge management and those that do not. In the second step we find for each innovative firm from the pool of knowledge management firms one similar “twin” firm from the pool of innovative firms without knowledge management practices. In order to find the twin firm the user of the matching procedure has to define a list of characteristics common to both the firm with KM and the twin firm without KM. It is tempting to define as many characteristics as possible in order to achieve the highest degree of similarity possible. However, the more characteristics are defined the harder

it is to find a twin firm in the control group of firms not using KM. This phenomenon is called the "curse of dimensionality" (Czarnitzki et al., 2007).

Rosenbaum and Rubin (1983, 1985) propose using the propensity score (or probability) for a firm to have KM as a criterion for finding a comparable firm in the control group. To obtain the propensity score we estimate a probit model on the full sample with a dummy variable for KM as the dependent variable and the determinants of KM described above as the independent variables.[7]

Lechner (1998) combined the two approaches to what is called "hybrid-matching", which we use in our study. This method allows specifying a set of characteristics that have to be similar between KM firms and matched non-KM firms in addition to the propensity score. In our study we will only match KM firms with non-KM firms of a similar size (number of employees) and from the same industry and region (eastern Germany or western Germany). The similarity between two firms with respect to these characteristics and the propensity score is evaluated using the Mahalanobis distance between the variables for the two firms. To improve the quality of the matches we reduce the sample to firms with "common support", i.e. we eliminate firms that have a propensity score higher than the maximum or smaller than the minimum in the potential control group (Czarnitzki et al., 2007)[8].

In order to be able to use the matching procedure two assumptions have to hold. The first is the conditional independence assumption (CIA) as described by Rubin (1977). It states that the independent variables that affect both the success and the status of a KM firm, the success variable and the KM variable are statistically independent. This CIA helps to overcome the problem that the KM firm cannot be observed without KM activities, i.e. the counterfactual outcome is unobservable. If the CIA is fulfilled, we can obtain the average outcome of KM firms in the absence of KM from the sample of twin firms. It implies that all variables that influence the success and the status of a KM firm are known and available in the data set (see Aerts and Schmidt, 2008). Unfortunately the CIA cannot be validated empirically (Almus et al., 1999). We

[7] The set-up of the model is similar to the one in Cantner et al. (2009). The results of our probit estimation are reported in the appendix (Table 5).
[8] Only six firms that had KM activities had to be deleted from the sample because they lacked "common support".

therefore have to assume that the CIA is fulfilled following previous studies using the Mannheim Innovation Data for matching/evaluation exercises which made the same assumptions (Czarnitzki et al., 2007, Arnold and Hussinger, 2004, Sofka and Teichert, 2006). What is more, we are quite confident that the survey which covers a wide range of innovative activities contains all factors relevant for explaining KM and the success in the form we use it. Hence, we assume that the CIA is fulfilled. In Table 3 in the appendix the steps undertaken in the "nearest neighbour matching using the propensity score" are summarized.

The second assumption we follow is the *stable unit treatment value assumption* (SUTVA) stating that the usage of KM does not impact on any other firms (Rubin, 1990, 1991). In our context, this implies that KM usage does not impact on non-KM firms by market effects or knowledge spillovers. Thus, SUTVA rules out general equilibrium effects of KM implementation. However, interaction effects can both over- and underestimate the ATT. On the one hand, the ATT is overestimated when the innovative success of KM firms is realized at the expense of non-KM firms. On the other hand, non-KM firms might profit from knowledge spillovers generated in KM firms, which leads to an underestimation of the KM's impact. Since these mechanisms of action are difficult to identify empirically, we follow the SUTVA and ignore general equilibrium effects.

5 Empirical Results

The probit estimation for the first step of the matching procedure, i.e. the estimation of the likelihood that a firm uses KM, yields the expected results (see Table 5 in the appendix). We find that the size of a firm, the importance of employment fluctuations, the structure of firms' innovative activities (continuous R&D activities and consumer orientation) and belonging to a high-tech or knowledge-intensive industry significantly increase the likelihood that a firm uses KM techniques.[9] The results of the probit

[9] As expected, these results are fully in line with Cantner et al. (2009), who focus in their analysis on the determinants of KM using the same data as we do for this paper.

estimation are used to calculate the propensity score, which is necessary to minimize the distance between two firms, as described above.

Table 1 Results before and after matching

	Unmatched		Matched	
	(1)	(2)	(3)	(4)
Variable	KM firms	Non-KM firms (potential control)	KM firms	Non-KM firms
Number of employees (log)	4.533	4.431	4.533	4.526
Number of employees (sqr, log)	23.57	22.84	23.57	23.40
Employee fluctuations	0.228	0.174**	0.228	0.202
Consumer orientation	0.538	0.458	0.538	0.521
Continuous R&D activities	0.751	0.573***	0.751	0.746
Multinational group	0.267	0.258	0.267	0.228
Average product life cycle	8.988	9.558	8.988	8.9724
Eastern Germany	0.308	0.331	0.308	0.308
Medium-tech manufacturing	0.333	0.363	0.333	0.333
High-tech manufacturing	0.156	0.12**	0.156	0.156
Knowledge intensive services	0.356	0.98**	0.356	0.356
Propensity score	0.327	0.78***	0.327	0.325
Number of observations	390	944	390	390

Notes: Mean difference between (1) and (2) is statistically significant at the ** 95 % significance level; *** 99% significance level.

Table 1 shows that after applying the matching procedure we really compare similar firms. For this compare columns (1) and (2) for the unmatched case with columns (3) and (4) in the matched case. For the 11 independent variables also used in the probit analysis (upper part of table 1) we find in the unmatched case that, statistically, the means of *employee fluctuation*, *continuous R&D*, *high-tech manufacturing*, and *knowledge- intensive services* differ significantly between the KM and the non-KM

firms (columns (1) and (2)). After the matching procedure these differences vanished (columns (3) and (4)). Moreover, of the characteristics which we specified before the matching procedure and which in addition to the propensity score have to be similar between KM and non-KM firms, the means of the dummy variables referring to industry and location are identical. For the number of employees and the propensity score the differences are not significant after matching. In the end, we compare 390 KM firms with 390 twin observations which show a rather similar if not identical structure as expressed by the 11 independent variables.

What remains different after the matching, however, is the mean for two of the three measures of innovative success. As table 2 shows, KM affects the *turnover with product innovations* and the *turnover with market novelties* positively and significantly. These results are in favour of our hypotheses 1 and 2. The effect of KM on the *turnover with market novelties* (i.e. the more radical innovations) is not only more significant than the effect on the *turnover with product innovations,* but also larger. The respective differences together with their bootstrapped stand errors are displayed in the third column. The share of turnover which firms with KM achieve with market novelties is, on average, 5.23 percentage points higher than the corresponding figure for non-KM firms. For the turnover with product innovations the average treatment effect on the treated is 3.37 percentage points.

Surprisingly, KM has no significant effect on cost reductions with process innovations. Hypothesis 3 is therefore rejected. We expected to find a positive effect since KM is usually linked directly to processes and should help to streamline and improve productive processes, a fact which eventually leads to lower production costs. Our results indicate that this is not the case. One has to keep in mind, however, that we are not looking at the effects of all the processes of a firm but only at the effects of innovative processes introduced over a three-year period. It would therefore be premature to conclude that KM does not lead to cost reductions at all. Furthermore, it could be argued that our selection of KM techniques (imposed upon us by the data available) is more related to product development activities rather than process innovation activities.

Table 2 Treatment effects - results after matching

	Mean KM firms	Mean non-KM firms	Difference ("Treatment Effect")
Share of turnover with product innovations	28.811	25.444	3.367 ** (1.969)
Share of turnover with market novelties	12.032	6.800	5.232 *** (1.710)
Cost reductions due to process innovations	3.317	3.241	0.076 (0.710)

Notes: ** 95 % significance level; *** 99% significance level; bootstrapped Standard Errors in parenthesis (100 repetitions).

Comparing the matching results with the results of the unmatched samples, we find the following: If we had looked at the means without matching KM firms and non-KM firms, we would have compared innovation active firms with significantly different levels of employee fluctuations, differences with respect to their R&D orientation and from different industries (columns (1) and (2) of table 1). Despite these differences in the independent variables, we would have found that KM firms are more successful with product innovations and market novelties than non-KM firms but not more successful when it comes to cost reductions with process innovations. In qualitative terms this result is similar to the one obtained with the matching procedure. The size of the estimated effect of KM would have been overestimated without matching, however. For the turnover with product innovations the average effect of KM ("treatment effect on the treated") is 3.37 percentage points; without matching we would have estimated an effect almost twice as high with 6.48 percentage points (difference between column (1) and (2)). For market novelties the difference is smaller. After matching, the share of turnover which firms with KM achieve with market novelties is, on average, 5.23 percentage points higher than the corresponding figure for non-KM firms. Without matching KM and non-KM firms the corresponding figure is only slightly higher with 5.32 percentage points (again difference between column (1) and (2)).

6 Interpretation of results and conclusion

Our findings for German firms contribute to empirical research on the impact of knowledge management on the (direct) economic success with product and process innovations. Based on a large-scale data set and using a matching procedure to crystallize the pure KM effects on innovation success, this empirical analysis provides strong evidence for the positive effect of KM. In concentrating on KM for interactive knowledge creation we pick out an element of KM which is very important for innovation. Our two main conclusions are, first, KM significantly increases the success with product innovations and market novelties and, second, KM has a differentiated effect on different types of innovation. With regard to the first finding, that means that firms which apply KM have on average a higher success with product innovations and a much higher success with market novelties compared to non-KM firms.

Regarding our second conclusion, namely that KM impacts differently on different types of innovation success, we find that, all other things remaining equal, product innovation success and success with market novelties are significantly positive but affected differently by KM. This is indicated by the finding that both success measures are significantly higher in the treated (KM) group compared with the untreated (non-KM) group of twin firms. Success with market novelties differs even more between KM and non-KM firms than success with product innovations. Our findings are distinct from those of Darroch (2005), who finds that KM firms are less likely to increase the development of new to the world innovations (not fully comparable to our market novelties concept) and more likely to develop incremental innovations (comparable to our product innovations concept) than non-KM firms. However, in our study we look at the success with innovations and not at the likelihood that they get successfully developed. In contrast to product innovation success, process innovation is not impacted by KM. There is only a very small difference between the treated and untreated group, and furthermore, this difference is insignificant.

The differences between product and process innovation success can be explained by the selected KM tool focus. Since we only focus on “collaborative” KM, we leave out KM efforts such as knowledge storage and retrieval, or provision of ICT infrastructure

for access to and transfer of knowledge. These KM activities are more inclined to enhance exploitation of existing knowledge rather than the exploration of new knowledge, most relevant for product innovation development. They are more relevant for process innovation than for product innovation development. Since we leave out knowledge exploitation activities and their respective KM methods, the presented finding makes sense. However, it would be premature to conclude that other KM activities are more likely to increase success with process innovations. Based on our findings we just argue that "collaborative" KM is less likely to enhance the success with process innovations.

Obvious links to other strands of literature exist that could be explored in subsequent studies. KM of the type we have analysed is part of the absorptive capacity of a firm, i.e. firms' "ability to identify, assimilate, and exploit knowledge from the environment" (Cohen and Levinthal 1989: 569). It would be interesting to analyse how KM, which can be assigned to the assimilation part of absorptive capacity, interacts with the other layers of absorptive capacity to lead to increased performance. What is more, the KM could be interpreted as the absorptive capacity for internal knowledge as well, as it clearly helps to identify, assimilate or distribute and eventually exploit knowledge which the firm has within its boundaries. The literature on "open innovation" (Chesbrough, 2003) is also linked to KM. It would be interesting to see whether firms that have a more open strategy towards sharing knowledge with other firms are also more willing to adopt KM or more efficient in using KM than firms with a less open strategy.

Appendix

Table 3 Matching protocol (nearest neighbour matching)

Step 1	Specify and estimate a probit model to obtain the propensity scores $\hat{P}(X)$.
Step 2	Restrict the sample to common support: delete all observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group.
Step 3	Choose one observation from the subsample of KM firms and delete it from that pool.
Step 4	Calculate the Mahalanobis distance between this firm and all non-KM firms in order to find the most similar control observation. $MD_{ij} = (Z_j - Z_i)'\Omega^{-1}(Z_j - Z_i)$ Z contains the estimated propensity score, the firm size (number of employees), a dummy that indicates location in eastern Germany and the industry group to which the firm belongs. Ω is the empirical covariance matrix of these arguments based on the sample of potential controls.
Step 5	Select the observation with the minimum distance from the remaining sample. (Do not remove the selected controls from the pool of potential controls, so that it can be used again.)
Step 6	Repeat steps 3 to 5 for all observations on KM firms.
Step 7	Using the matched comparison group, the average treatment effect on the treated can therefore be calculated as the mean difference of the matched samples: $\hat{\alpha}_{TT}^{M} = \frac{1}{n^T}\left(\sum_i Y_i^T - \sum_i \hat{Y}_i^C\right)$ with $\hat{Y}_i^C$ being the counterfactual for firm i and n^T is the sample size (of treated firms). Note that the same observation may appear more than once in that group.
Step 8	As we perform sampling with replacement to estimate the counterfactual situation, an ordinary t-statistic on mean differences is biased, because it does not take the appearance of repeated observations into account. We bootstrap the standard errors to correct for that bias.

Source: Adapted from Aerts and Schmidt, 2008.

Table 4 Construction of the control variables

Variable name	Type	Description
Average product life cycle	Index	Average length of the product life cycle in years
Consumer orientation	Dummy	One, if the firm's strategy between 2000 and 2002 is to provide individual solutions for customers.
Continuous R&D activities	Dummy	One, if the firm is engaged in R&D activities on a continuous basis
Eastern Germany	Dummy	One, if the firm is located in eastern Germany
Employee fluctuation	Dummy	One, if the growth of employees between 2000 and 2002 was higher than the 90% percentile (+38 %) of all firms or lower than the 10% percentile of all firms (-17%).
Multinational group	Dummy	One, if the firm belongs to a multinational group.
Number of employees, log	Log	Number of employees in 2002
Number of employees, sqr., log	Log, squared	Number of employees in 2002, squared
Industries:		
Low-tech manufacturing	Dummy	One, if the firm belongs to NACE 15-23, 25-28, 36
Medium-tech manufacturing	Dummy	One, if the firm belongs to NACE 24 (excl. 24.4), 29, 31, 34-35 (excl. 35.3)
High-tech manufacturing	Dummy	One, if the firm belongs to NACE 24.4, 30, 32, 33, 35.3
Other services	Dummy	One, if the firm belongs to NACE 50-52, 55, 60-64, 70-74 (excl. 74.1, 74.4), 92.1, 92.2
Knowledge-intensive services	Dummy	One, if the firm belongs to NACE 65-67, 74.1, 74.4

Table 5 Results of the first step probit estimation

	Firm used KM practices between 2000 and 2002 (dummy)
Number of employees, log	0.257***
	(0.096)
Number of employees, sqr., log	-0.020**
	0.009
Employee fluctuation	0.249**
	0.097
Consumer orientation	0.179**
	(0.076)
Continuous R&D activities	0.474***
	(0.084)
Multinational group	-0.101
	(0.096)
Average product life cycle	-0.002
	(0.006)
Eastern Germany	-0.073
	(0.082)
Medium-tech manufacturing	0.011
	(0.112)
High-tech manufacturing	0.238*
	(0.139)
Knowledge-intensive services	0.299***
	(0.113)
Constant	-1.756***
	(0.276)
Number of observations	1,334
Log likelihood	-771.483
Chi^2	69.16***
F-test for significance of all industry dummies together	11.82 ***

Notes: ** 95 % significance level; *** 99% significance level; standard errors in parenthesis.

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