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DUI mode learning and barriers to innovation – the case of Germany

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Abstract

This paper aims to provide a better understanding of informal modes of learning based on Doing, Using and Interacting (DUI). Innovating firms from Germany are grouped according to the degree to which they combine DUI mode competencies with formal learning of science and technology (i.e. the Science, Technology and Innovation – STI – mode). To more deeply assess the practical relevance of this grouping for innovation policy, it is subsequently examined how a firm's learning mode relates to the relevance of different sets of innovation barriers. According to the empirical results, DUI mode learning is generally important in the field of innovation, since it occurs either in its pure form or in combination with formal processes of research and development (R&D). Moreover, the more dominant that the DUI mode of learning is at the company level, the more likely that the corresponding firm is small. In such a less R&D-oriented knowledge environment, innovating firms can exploit certain competitive advantages when they concentrate on their experience-based DUI mode competencies. On the other hand, firms trying to compensate for limited in-house R&D capabilities through collaboration with external partners have to overcome a number of knowledge and market barriers to innovation. The paper concludes with implications for policy and research.

Keywords

Modes of learning; Barriers to innovation; Innovation without R&D; Small firms; Non-technological innovation; Vocational education

JEL classifications

O31; O38

1. Introduction

An important feature of innovation is its heterogeneous nature across sectors and industries. Starting with the seminal work of Nelson and Winter (1982), several studies have pointed to the shaping role of specific knowledge bases on innovation activities in explaining the systematic differences arising from this variability (Malerba, 2002; Malerba and Orsenigo, 1997; for an overview, see Fagerberg, 2005). One implication of this evidence is that policy-makers should be aware that innovation can occur under various knowledge environments; otherwise, they might easily fail to meet the needs of certain firms and industries.

To take such differences into account when designing policies, information is needed on how ways of learning can differ in innovating firms. In a seminal paper, Jensen et al. (2007) contrasted two *ideal* modes of learning being integrated and combined at the company level to a greater or lesser degree by innovating firms. The first one – labelled the Science, Technology and Innovation (STI) mode – is dominated by scientific and technical knowledge, which is explicit and codified due to being embedded in formal processes of research and development (R&D). By contrast, the second one – labelled the Doing, Using and Interacting (DUI) mode – is described as being dominated by informal processes of learning and experience-based know-how. Here, the creation and use of tacit knowledge lies at the heart of the innovation process. In light of this, Jensen et al. (2007) argue for an ongoing bias towards an orientation on STI indicators such as R&D data or patent grants and citations. As a result, policy-makers tend to overly focus on formal R&D activities that lead to product innovation in high-technology industries, prompting the authors' plea for "a realignment of policy objectives and priorities" (p. 690).

However, the other side of the coin is that at the level of scholarly research, relatively little is known about the DUI mode of learning. For example, this holds with respect to innovation in low- and medium-tech companies (see Tunzelmann and Acha, 2005; Hirsch-Kreinsen and Jacobson, 2008; Santamaría et al., 2009), the role of DUI mode learning for non-technological innovation (i.e. organisational and marketing innovations, see Parrilli and Alcalde Heras, 2016) or the general importance of experience-based learning in the context of innovation (see Lundvall and Borrás, 2005).

The dichotomy between the emphasis on STI indicators and the little known about the DUI mode of learning should be especially pronounced in the case of Germany. On the one hand, a core competitive strength of the German production and innovation model is seen as resulting from a special mix of academic and vocational qualifications (EFI, 2014). Innovation activities of German firms are strongly rooted in the interaction between graduates from tertiary education institutions (notably university graduates of natural sciences and engineering) and graduates from the dual system of vocational education and training (VET). The latter – comprising technicians, craftspeople and other skilled workers – form a major part of the German workforce. Dual training includes workplace learning to acquire experience-based, practical knowledge as well as the provision of theoretical expertise through accompanying school-based vocational instruction. On this basis, VET trained workers have the ability to engage in complex problem-solving. They also share a common professional language, which enables them to communicate and closely interact with a firm's scientific and engineering staff. Both aspects are especially important for incremental innovation (Toner, 2010; 2011). Thus, due to the significant role that the dual system of VET plays in the skill formation regime of Germany, one would expect the DUI mode of learning to be strongly embedded in the German innovation system.

On the other hand, German innovation and technology policy-making strongly relies on a linear R&D-based model of innovation (Lay and Som, 2015). The focus lies on high-tech manufacturing, while non-R&D-intensive firms and industries – with their stronger dependence on DUI mode learning – tend to be overlooked in terms of national competitiveness and innovativeness. For example, low-tech industries account for the majority of the industrial workforce in Germany. Compared to the total manufacturing sector, a relatively large share of personnel employed there are VET graduates (Frietsch and Gehrke, 2006; Frietsch and Neuhäusler, 2015). Recent company-level evidence also suggests that experience-based, practical knowledge and distinct customer-related competences are a key source of innovation for non-R&D-performing and non-R&D-intensive firms across all sectors of the German economy (Kirner and Som, 2015). However, the patterns of knowledge creation that underlie innovation activities in these firms can still be regarded as a "black box", which is why policy-makers from Germany (as well as other countries) who aim to promote innovation in less-R&D-oriented knowledge environments require further insights into the functioning of the DUI mode of learning.

Previous research motivated by the paper of Jensen et al. (2007) has investigated different types of interaction typically associated with STI and DUI mode learning (see Fitjar and Rodríguez-Pose, 2013; González-Pernía et al. 2015; Parrilli and Alcalde Heras, 2016). The present analysis more directly draws upon Jensen et al. (2007). Based upon a broad survey of innovating firms from Germany, different modes of learning are identified. Accordingly, this paper aims to provide a better understanding of DUI-based innovation in less-R&D-oriented knowledge environments through a twofold contribution, as outlined below.

First, contrary to Jensen et al. (2007), who refer to the use of high-performance work practices, the organisational structure of firms and the extent of customer involvement as indicators to measure DUI mode learning, the present paper makes informal processes of learning and experience-based know-how more concrete by adopting a competence-based approach. For this purpose, answers to a question prompting respondents to assess the distinctiveness of several innovation competencies in their enterprise are evaluated, which are directly related to the build-up of tacit knowledge at the level of the firm (e.g. learning by trial-and-error, person-embodied creativity or the inclusion of external partners). Some additional profiling variables are also included in the present analysis to better illustrate some particularities of DUI mode learning in a less-R&D-oriented knowledge environment (e.g. the important role of the non-academic workforce and the relative neglect by policy-makers). Finally, the present paper provides a deeper understanding on DUI mode learning and its interrelationship to the STI mode by also considering non-technological innovation. Without directly referring to it, Jensen et al. (2007) already briefly touched upon this issue when stating that DUI mode learning can be either unintentionally triggered at the company level as a by-product of design, production and marketing activities or intentionally stimulated by changing organisational procedures that enhance and utilize learning by doing, using and interacting. Parrilli and Alcalde Heras (2016) provide recent evidence in this regard, with their results indicating that DUI mode learning is indeed closely related to marketing and organisational innovations, whereas technological innovations tend to primarily rely on the STI mode. This is supplemented by the finding of Hervas-Oliver et al. (2015) that non-R&D technological innovators heavily rely on organisational and marketing activities to compensate for the lack of in-house R&D capacities. Hence, a consideration of non-technological innovation should be crucially important to achieve a better understanding of DUI mode learning in less-R&D-oriented knowledge environments.

Second, after identifying and profiling the different modes of learning, it is examined how they relate to the company-specific relevance of different sets of innovation barriers (i.e. cost barriers, knowledge barriers, market barriers and regulation barriers). This further ensures the practical significance of the derived modes from policy-makers' perspective. Moreover, it provides them with information about the factors that can hinder innovation in a less-R&D-oriented knowledge environment dominated by DUI mode learning: an issue not directly addressed by Jensen et al. (2007) or prior studies on barriers to innovation (e.g. Baldwin and Lin, 2002; Galia and Legros, 2004; Tourigny and Le, 2004; D'Este et al., 2012). To approach this theoretically, the present paper refers to the case of small firm innovation. It is important to keep in mind that analysing the informal processes of learning and experience-based know-how in less-R&D-oriented knowledge environments primarily implies thinking about small and medium-sized enterprises (SMEs), given that non-R&D-performing and non-R&D-intensive firms are predominantly found in the "Mittelstand", the so-called backbone of the German economy (Kirner et al., 2009; Kirner and Som, 2015). In light of this, Hirsch-Kreinsen (2015) argues that the organisation and management of knowledge in non-R&D-intensive firms and industries is characterised by practices that are typically found in SMEs. According to him, this not only holds true for Germany, but also for Europe in general. In fact, the typical features associated with DUI mode learning (see Section 2) strongly resemble those discussed in the literature on the nature of small firm innovation (e.g. Baldwin and Gellatly, 2003; Mazzarol and Reboud, 2009; Thomä and Bizer, 2013). The relative importance of pure DUI mode learning in small innovating firms has already become evident in the empirical results of Jensen et al. (2007). In the case of Germany, a first indication in this direction is that vocational training in the dual system primarily takes place in companies with fewer than 249 employees (BIBB 2015). As such, the typical strengths and weaknesses that small innovating firms have under the conditions of their less R&D-oriented knowledge environment may help to explain the role of certain innovation barriers in the context of DUI mode learning.

The remainder of this paper is structured as follows. In Section 2, the theoretical background is described, before Section 3 presents the data set. The empirical analysis is conducted in Section 4. In the first part, factor analysis and cluster analysis are combined to group and classify innovating firms according to their mode of learning. In the second part, by employing multivariate probit regression, it is investigated how the identified learning modes relate to the importance of different sets of innovation barriers. Finally, concluding remarks and implications for policy and research are provided in Section 5.

2. Theoretical background

2.1 Concepts of knowledge creation in innovating firms

In the first part of the empirical analysis (Subsection 4.1), it is examined whether innovating firms form distinct groups with respect to their mode of learning. From a theoretical perspective, two closely-related concepts of the knowledge creation process at the company level hold relevance here: the distinction between STI and DUI mode learning provided by Jensen et al. (2007), as well as the differentiation of industrial knowledge bases in terms of being either "analytical" (science-based) or "synthetic" (experienced-based), which was first proposed by Laestadius (1998) and subsequently developed in detail by Asheim and Gertler (2005). Both concepts contrast two opposing (ideal) types of knowledge environments under which innovation occurs, while their authors fully acknowledge that in practice innovating firms need to mix – at least to some degree – different forms of knowledge to be successful. While the concept of Jensen et al. (2007) more narrowly focuses on the different forms of knowledge and corresponding management systems, the distinction proposed by Asheim and Gertler (2005) places a greater emphasis on the resulting differences in a firm's innovation activity (e.g. in terms of required qualifications and skills, the institutional embedding of innovation processes and the character of innovation output). Hence, despite being motivated by the seminal contribution of Jensen et al. (2007), I perceive the concept of Asheim and Gertler (2005) as useful in providing additional information about the typical characteristics of STI and DUI mode learning. To provide a concise overview, both concepts are discussed together in the following.

The STI mode of learning refers to the formation and use of explicit and codified knowledge within formal processes of own in-house R&D. This is often complemented by scientific and technical knowledge generated by universities or other research establishments. The underlying science-based understanding of innovation is typical for the activities of R&D departments in large industrial firms. The objective novelty of new products and processes is thus often quite high, which is why STI-based innovation tends to be more radical compared to non-R&D-intense firms and industries with a greater dependence on DUI mode learning. Nonetheless, this does not imply that locally-embedded tacit knowledge is not important in STI-mode learning, given that it still requires the person-embodied know-how of scientists and engineers to successfully conduct R&D projects at the frontier of technological development. However, formal learning of science and technology is pivotal for knowledge creation in this environment, since a strong emphasis throughout the entire process of STI-based innovation lies in making knowledge explicit and transferring innovative results into a codified form for documentation and communication purposes. Accordingly, employees in corresponding firms and industries must own specific competencies, e.g. in terms of the understanding of previous (codified) scientific research, the application of common scientific principles and methods used in the conduct of own R&D or their ability to describe the characteristics of an invention in reports or patent descriptions by adopting a techno-scientific language. Hence, even if it starts as a local problem, the STI mode of learning often results in codified knowledge – which is easy to transfer and widely accessible – unless it is protected by strong IPRs (notably patents).

At its core, DUI mode learning relates to the overall importance of tacit knowledge learned by employees on the job through trial-and-error when confronted with new problems. Finding solutions to them enhances their professional skills and know-how, thus leading to the continuous improvement of a company's person-embodied competencies. Such experience-based learning by doing and using also strongly involves interaction; for example, between innovators and users or between employees and departments within firms. This is because the transfer of tacit knowledge at different organisational levels of innovating firms is largely based upon personal interaction (for intra-firm, firm-customer or firm-institution dimensions of tacit knowledge flows, see Howells, 1996).

In a knowledge environment dominated by DUI mode learning, there is little formal learning of science and technology. Own in-house R&D activities are thus a less important source of innovation in corresponding firms and industries; instead, the impetus for innovation often comes from a strong link to suppliers or customers. "Innovativeness" is less associated with fundamental novelties; rather, it is determined by the incremental improvement of existing products and processes (for example, when individual problem solutions need to be found from the perspective of the customer, such as in terms of reliability, practical utility or user-friendliness). Tacit knowledge is relatively important here, because innovating firms must possess experience-based know-how (e.g. in terms of craft and engineering skills acquired through VET, concrete product know-how or a sound understanding of customer requirements) and successfully integrate pragmatic and practical ways of learning by doing, using and interacting to meet such specific market needs. Overall, this suggests that DUI-based innovation is especially likely to occur in non-R&D-intensive firms and industries, which are traditionally dominated by SMEs (see Section 1).

2.2 DUI mode learning: innovation barriers in a less-R&D-oriented knowledge environment?

The discussion concerning the DUI mode of learning implies that innovation without formal R&D is largely based upon two main preconditions: the possession of an application-oriented practical knowledge base and the typical need to compensate for limited in-house R&D capabilities by using and integrating externally generated knowledge inputs, notably through collaboration with partners (on this issue, see e.g. Hirsch-Kreinsen and Jacobson, 2008; Rammer et al., 2009; Santamaría et al., 2009; Hirsch-Kreinsen, 2015). In this context, a firm's organisational conditions and managements skills play a key role. This issue is intimately connected with the typical strengths and weaknesses of smaller firms in innovation, given that non-R&D-performing and non-R&D-intensive firms are mostly SMEs.

The resource constraints that smaller firms face in terms of R&D are widely acknowledged in the literature (see, e.g. Cohen, 1995; Acs and Audretsch, 2005). Nevertheless, many SMEs succeed in innovation, whereby they compensate for their lack of formal R&D by either relying instead on the know-how of their employees or performing in-house R&D in a more informal and occasional manner than large firms (Kleinknecht, 1987, 1991; Thomä and Bizer, 2013). Under such conditions, innovation often results from collaborative activities with customers; for example, when SMEs offer them a superior differentiation of existing products through a focus on personalised service or by providing a fast, flexible and incremental adjustment of product quality to individual customer needs (Baldwin and Gellatly, 2003; Mazzarol and Reboud, 2009). The mode of learning underlying such potential strengths has been tackled theoretically by Nooteboom (1994), who suggests that problem-solving and learning in smaller firms is largely based upon tacit knowledge. Typical advantages of innovating SMEs – such as their capacity for specialisation, customisation and product flexibility – can thus be explained by possessing scarce and unique competencies acquired through learning by doing and using. Such an application-oriented practical knowledge base also leads to distinct advantages for smaller firms in terms of appropriability, given that its strong tacit knowledge elements are difficult to imitate due to limited communicability and transferability.

However, several weaknesses of SMEs in innovation are also related to the fact that much of their operating knowledge is tacit. The typical dependence of smaller firms on a few key employees is one such example, with the resulting vulnerability when their experienced-based know-how leaves the company (Thomä and Zimmermann, 2013). Another example is the often-limited capacity of non-R&D-performing and non-R&D-intensive SMEs to absorb external sources of scientific and technical knowledge. Moreover, a smaller firm's informal processes of learning and experience-based know-how tend to go along with an unstructured and unsystematic approach of managing and organising internal innovation processes. Despite often being associated with behavioural advantages in terms of flexibility and internal communication, this can actually hinder the development of a strong innovation culture in SMEs (Rothwell and Zegveld, 1982; Rothwell, 1989, Nooteboom, 1994). The low transferability of tacit knowledge also leads to disadvantages in cases where the replication and sharing of knowledge within firms or between partners generates interactive learning as a basis for further innovation (Hurmelinna et al., 2007). Hence, their emphasis on experience-based, tacit know-how can make it more difficult for innovating SMEs to profit from collaboration with external partners, which is problematic because external partnerships are considered to occupy major importance for smaller firms to overcome an internal lack of capabilities (Hewitt-Dundas, 2006).

As a result, non-R&D-performing and non-R&D-intensive SMEs must often overcome a number of knowledge barriers, particularly in case of collaboration with high-tech partners (Mattes et al., 2015). This includes the necessity of organising and managing the internal processes of innovation in a systematic and structured way without the advantage of having an own R&D department. It also refers to the development of internal capacities to successfully absorb external knowledge and adapt to new technologies. To summarise, the emphasis on DUI mode learning in the knowledge environment of non-R&D-intensive firms and industries is likely to involve certain barriers to innovation. The following analysis includes an empirical investigation of this hypothesis.

3. Data set

This paper is based upon data from the 2011 survey wave of the Mannheim Innovation Panel (MIP), which refers to the 2008-2010 period. The MIP represents the German contribution to the Community Innovation Surveys (CIS). It is conducted annually by the Centre for European Economic Research (ZEW) on behalf of the German Federal Ministry of Education and Research (BMBF). While fully meeting the methodological standards of the harmonised CIS questionnaires (see OECD/Eurostat, 2005), it includes a number of additional questions beyond the CIS. For example, in the present case, information is available on the distinctiveness of innovation competencies, which is intimately connected with the DUI mode of learning.

The core population of the MIP 2011 was drawn as a stratified random sample that covers firms with five or more employees from a broad range of German manufacturing and service industries. The variables used for stratification were sector (55 divisions and one group of NACE Rev 2.), firm size (eight size classes) and region (Western and Eastern Germany, the latter including Berlin). The total population of the MIP 2011 was estimated by the ZEW as 269,459 firms. The gross sample corrected for neutral losses (e.g. owing to closures or double entries) comprised 26,992 firms, 1,928 of which were sampled outside the survey coverage having responded to previous survey waves (including firms having fewer than five employees or those in sectors not considered in the core sample). This number further includes 1,283 firms that were not part of the random sample but have received public funding for R&D or innovation provided by the BMBF. Overall, 6,851 firms returned a completed questionnaire, representing a response rate of 25.4 %. Finally, a telephone survey with non-responding firms was conducted to check for potential non-response bias (for more details, see Aschhoff et al., 2013).

The Scientific Use File of the MIP 2011 used for the following empirical analysis includes anonymised information about 5,751 firms.[1] I restricted this data to the sub-sample of innova-

[1] Some information is not provided in the MIP Scientific Use File for external use. The anonymisation process conducted by the ZEW, for example, included removing all firms from the data set that responded on behalf of their entire group of companies and not just their own firm.

tors for conceptual and methodological reasons. First and foremost, as noted in Section 1, the main interest of the present paper lies on the different modes of learning integrated and combined by innovating firms. Thus, to assess the variability of firm-level innovation from a knowledge-based perspective, it is straightforward to confine the data set to the sub-sample of innovating companies. Second, and closely related to this, the correlations between the eight innovation competencies used in the present paper to measure DUI mode learning (see Subsection 4.1) are much more pronounced in case of innovating firms. Thus, it is also necessary to focus on the sub-sample of innovators in methodological terms.

For this purpose, a broad concept of innovation is applied, as laid down in the Oslo Manual (OECD/Eurostat, 2005). As mentioned in Section 1, the present paper not only focuses on firms that have introduced new or significantly improved products, services or processes during the reference period[2], but also those firms reporting the introduction of non-technological types of innovation (i.e. marketing and organisational innovation).[3] Accordingly, a company is classified as innovating if it has introduced at least one of these types of innovation during the reference period (i.e. product innovations and/or process innovations and/or non-technological types of innovation). Accordingly, observations from 1,719 companies that have neither introduced technological nor non-technological innovations were removed from the data set. The sample size at the starting point of the empirical analysis thus amounts to n = 4,032. Given that not all firms provided full information on all survey variables, this number of observations reduces in the course of the empirical analysis. In the first part (Section 4.1), the derived cluster solution is based on the observations of 2,695 firms that provided full information on the four clustering variables. The multivariate probit regression in the second part of the empirical analysis (Section 4.2) combines these cluster results with information on a number of control variables. Consequently, the number of observations with full information reduces to n = 1.658 at that stage.

4. Empirical analysis

4.1 Identifying modes of learning

The starting point of the empirical analysis involves searching for indicators to measure different modes of learning and innovation. To capture the creation and use of codified scientific and technical knowledge, two variables indicating whether an innovating firm conducted own in-house R&D activities and/or applied for patents to protect its intellectual property are used,

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[2] Exact questions asked in the MIP: *Product innovation*: "During the years 2008 to 2010, did your enterprise introduce new or significantly improved products / services?*; Process innovation*: "During 2008 to 2010, did your enterprise introduce new or significantly improved internal processes (incl. processes for service performance and product delivery?"

[3] Exact questions asked in the MIP: *Marketing innovation*: "Did your enterprise introduce the following marketing innovations during 2008 to 2010?"; *Organisational Innovation*: "Did your enterprise introduce the following organisational innovations during 2008 to 2010?"

both of which are standard measures for formal learning of science and technology. Empirical research has shown that they are related to a more intensive use of explicit and codified knowledge (see Brusoni et al., 2005; González-Álvarez and Nieto-Antolín, 2007; Nieto and Pérez-Cano, 2004).

Another set of variables is used as an indicator for informal ways of learning and innovation characterised by experience-based know-how with strong tacit elements. It is based upon a question that asked respondents to assess on a five-point Likert scale how distinct the following eight innovation competencies are within their enterprise: (1) development of new technical solutions; (2) scope for development via 'trial-and-error'; (3) strong individual responsibility of employees; (4) creativity of employees; (5) incentive schemes for employees to innovate; (6) stimulation of internal competition between projects; (7) internal co-operation between departments/firm units; and (8) inclusion of external partners.[4]

As argued above, developing new problem solutions typically involves trial-and-error processes of learning by doing and using. Items 1 and 2 thus point to a critical element of tacit knowledge formation in innovating firms. To a certain degree, items 3 to 8 all refer to management practices used by firms to increase incentives for employees to innovate and increase their involvement in problem-solving and decision-making by different means of interaction. Illustrative examples are high-performance work practices (e.g. the implementation of interdisciplinary workgroups, quality circles, systems for collecting proposals or autonomous teams). They are seen as a trigger for the systematic implementation of informal learning processes at the company level. Therefore, Jensen et al. (2007) use whether or not a firm makes use of them as an indicator of DUI mode learning. On the other hand, especially items 3 and 4 reflect the notion that tacit knowledge "is something very much to do with direct experience and is person-embodied" (Howells, 1996, p. 95). Hence, especially these two items also represent the personal trait of tacit knowledge residing in the employees of innovating firms.

Descriptive statistics of the original variables used to cluster innovating firms into different modes of learning are provided in Table A1 in the Appendix. Before undertaking the clustering procedure, factor analysis is employed to compress the eight original variables on the distinctiveness of innovation competencies into factor scores. Subsequently, these composite measures are used as clustering variables, given that the grouping of highly correlated variables into factors avoids the overweighting of single variable sets. Moreover, factor scores can represent more robust clustering variables than the original ones, since they are a linear combination of weighted individual variables (Hair et al., 1998). Two standard measures are used

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[4] Another competence named "detecting new customer needs" is not considered in the following factor analysis, since a consideration of the corresponding variable would result in equally low loadings on the two factors derived. Therefore, it is dropped from the analysis; otherwise, the quality of the cluster solution searched for based upon the factor analysis results would deteriorate. However, this variable among others is used to profile the cluster solution on relevant dimensions (see Table 3).

to ensure that the eight competence variables are sufficiently correlated with each other to justify the application of factor analysis, with Bartlett's test of sphericity (Chi-square = 5868.98, $p < 0.000$) and the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO = 0.778) both showing satisfactory results.

I apply the latent root criterion (i.e. the eigenvalue > 1 rule) and the Scree test criterion to decide upon the number of factors to extract. On this basis, by using principal component factoring with varimax rotation, a two-factor solution is found (Table 1). It accounts for 51.3% of the total variance, which is relatively low but still can be considered satisfactory in light of the difficulties facing surveys like the MIP or the CIS in terms of capturing the "soft" side of innovation; for example, regarding the role of experience-based know-how in complex problem-solving (Smith, 2005).

Table 1

Factor analysis of the distinctiveness of innovation competencies (principal component factoring, varimax rotated factor loadings, higher loadings are marked in bold)

	Factor 1	Factor 2
Development of new technical solutions	0.266	**0.627**
Scope for development via 'trial-and-error'	0.372	**0.495**
Strong individual responsibility of employees	**0.805**	0.051
Creativity of employees	**0.828**	0.120
Incentive schemes for employees to innovate	**0.739**	0.150
Stimulation of internal competition between projects	**0.490**	0.317
Internal co-operation between departments / firm units	0.363	**0.512**
Inclusion of external partners in projects	-0.039	**0.777**
Interpretation:	Personal knowledge and human resource management	Technical problem-solving through trial-and-error and interaction
Proportion of variance accounted for:	30.78%	20.55%

Note: The factor analysis is based on observations of 3,307 companies who provided full information on the eight competency variables. The sample size of the later cluster analysis only amounts to n = 2,695 (see Table 2). The reason is that cluster analysis also requires full information, i.e. not only on the two factor scores, but also on the other two clustering variables.

The first factor is marked by high loadings on the two competencies that directly relate to the experience-based know-how of employees (strong individual responsibility of employees; creativity of employees), which is complemented by higher loadings of the variables on incentive schemes and the internal competition between different projects. In line with the discussion above, I interpret this as an indication that – in the context of innovation – the personal nature of tacit knowledge is strongly intertwined with human resource management tools aiming to increase incentives for employees to accumulate person-embodied skills and know-how. Factor 1 is thus labelled as 'personal knowledge and human resource management'. Technical problem-solving activities, trial-and-error learning and the interaction with internal and external contacts all have higher loadings on Factor 2. Hence, the second factor relates to direct on-site learning and experience in interaction with others, whereby it is named as 'technical problem-solving by trial-and-error and interaction'.

While factor analysis helps to create composite measures of certain innovation competencies for each individual company (i.e. factor scores standardised to zero mean and a standard deviation of one), the following cluster analysis aims to group innovating firms based upon the following four variables: distinctiveness of personal knowledge and human resource management (Factor 1), distinctiveness of technical problem-solving through trial-and-error and interaction' (Factor 2), in-house R&D activity and use of patent protection. Hierarchical and non-hierarchical cluster analyses are combined to gain the benefits of each (Hair et al., 1998). Hierarchical techniques were used to identify outliers and determine the number of clusters. Ward's algorithm with squared Euclidean distance as the measure of similarity led to a five-cluster solution.[5] Prior to this, the single linkage method is employed to identify outliers, given that this procedure is particularly prone to chaining. The corresponding dendrogram prompted me to delete 85 observations as outliers. In a next step, to adjust the hierarchical results, the cluster centroids from the Ward method served as initial seed points for a k-means (non-hierarchical) cluster procedure. Table 2 shows the final cluster solution in terms of the clustering variables. Additional information is given in case of the eight innovation competencies, since the mean values of the original variables are also provided. The robustness of the cluster solution is corroborated by the fact that the average values of the clustering variables significantly differ across the five clusters. Robustness is further corroborated by a second non-hierarchical cluster analysis in which the initial seed points for the clustering procedure are randomly selected. The main results remain consistent between specified seed points and random selection, which lends further empirical support to the cluster solution presented in Table 2.[6]

[5] To determine the number of clusters, I visually inspected the dendrogram and used two stopping rules implemented in my statistical software (Calinski-Harabasz pseudo-F index and the Duda-Hart Je(2)/Je(1) index).

[6] The results from the non-hierarchical cluster analysis with random seed points are available on request.

Table 2

Cluster solution: mean values of the clustering variables and statistical significance of cluster differences (N = 2695, above-average values are marked in bold)

	Total	Cluster[b] (1)	(2)	(3)	(4)	(5)	Chi-square
Innovation competencies (factor scores)							
Factor 1: Personal knowledge and human resource management	0.00	-0.05	**1.07**	-0.95	**0.60**	-1.01	1991.8*
Factor 2: Technical problem-solving through trial-and-error and interaction	0.03	**0.55**	**0.62**	**0.58**	-0.93	-1.22	1743.6*
Innovation competencies (original variables)[a]							
Development of new technical solutions	3.49	**3.99**	**4.09**	3.49	3.03	2.36	872.3 *
Scope for development via 'trial-and-error'	2.77	**3.03**	**3.48**	2.63	2.48	1.82	671.1*
Strong individual responsibility of employees	3.74	3.74	**4.45**	3.12	**4.09**	3.03	1162.9*
Creativity of employees	3.60	3.69	**4.39**	2.97	**3.95**	2.68	1330.7*
Incentive schemes for employees to innovate	2.88	2.84	**3.80**	2.31	**3.18**	1.95	1051.1*
Stimulation of internal competition between projects	2.06	2.09	**2.86**	1.79	2.00	1.27	641.4*
Internal co-operation between departments / firm units	3.46	**3.66**	**4.17**	3.44	3.24	2.36	642.2*
Inclusion of external partners in projects	2.76	**3.13**	**3.22**	**3.34**	1.93	1.75	993.2*
In-house R&D activity	0.50	**1.00**	**0.58**	0.29	0.28	0.18	995.3*
Use of patent protection	0.22	**0.65**	0.19	0.05	0.06	0.03	960.1*
Share of sample in %	100	23.27	20.78	21.74	21.37	12.84	

[a] In case of the original variables, the values are means of Likert scale responses (0 = not existing, 1 = weakly distinct, 2 = medium, 3 = distinct, 4 = strongly distinct).

[b] Cluster 1 (science and technology-oriented group), Cluster 2 (mixed learning group), Cluster 3 (external partnership group), Cluster 4 (employee-focused group), Cluster 5 (low learning group)

* report a significance level of 1% (Innovation competencies: Kruskal-Wallis test with ties; In-house R&D activity and use of patent protection: Pearson's chi-square test)

A specific feature of the 'science and technology-oriented group' (Cluster 1) - comprising 627 innovating firms (23.27% of the total sample) - is the general prevalence of own in-house R&D activities and a strong preference for patent protection. Moreover, the distinctiveness of innovation competencies related to technical problem-solving through trial-and-error and interaction is above-average compared to the total sample, whereas competencies rooted in the personal knowledge of employees and the use of human resource management tools only occupy medium importance. The 'mixed learning group' (Cluster 2) - with 560 members (20.78% of the total sample) - is characterised by a marked combination of formal and informal learning processes. Members of this group assign the highest relevance to factors 1 ('personal knowledge and human resource management') and 2 ('technical problem-solving through trial-and-error and interaction') on average, while they also rely on own in-house R&D and the use of patent protection to a certain degree, albeit much less than firms in Cluster 1, implying that formal learning of science and technology plays a less dominant role in the innovation activities of firms in the second cluster.

By contrast, Clusters 3 and 4 refer to an even more informal mode of learning. Both groups have similar low scores on the two indicators used to measure formal learning of science and technology, although they differentiate in terms of the innovation competencies considered most distinctive in their field. Like in the first and second clusters, competencies in technical problem-solving through trial-and-error and interaction are also important in the 'external partnership group' (Cluster 3), with 586 members, representing 21.74% of the total sample. In this regard, a closer inspection of the original variables shows that firms in the third cluster place the strongest emphasis on the inclusion of external partners. At the same time, competencies relating to the personal knowledge base of innovating firms are much less distinctive in this group. Exactly the opposite is true in case of the 'employee-focused group' (Cluster 4, 21.37% of the total sample), i.e. for this group, innovation seems strongly based upon personal knowledge and much less on technical problem-solving through trial-and-error and interaction. Hence, the marked difference between the third and fourth clusters could point to the fact that the non-R&D performing and non-R&D-intensive firms in Cluster 3 lack critical in-house capabilities needed for innovation and thus they must compensate for this deficit by employing external knowledge sources through collaboration with partners.

Finally, the fifth cluster – referred to as the 'low learning group' – comprises 346 members (12.84% of the total sample). Firms belonging to this group neither use in-house R&D or patents to create or protect codified scientific and technical knowledge nor do they seem to have developed distinct innovation competencies related to DUI mode learning. However, one has to bear in mind that Cluster 5 also comprises firms reporting innovation activities with respect to the reference period. This fact renders the low learning group an interesting case at the validation and profiling stage of the cluster analysis.

To assess the predictive validity of a cluster solution, one needs to consider variables that should theoretically relate to it but are not used for clustering (Hair et al., 1998). In the present case, the focus lies on firm size classes and the industry composition by knowledge intensity, since – as the discussion above suggests – there should be significant variation in these two variables across different modes of learning and innovation. In fact, the within-cluster results given in Table 3 support this assumption. The science and technology-oriented group (Cluster 1) comprises above-average shares of large and medium-sized firms. As a result, the first cluster is characterised by the lowest share of small firms compared to the other groups (32.4 %). By contrast, small firm innovators are dominating in the employee-focused group (Cluster 4, 70.8 %) and the low learning group (Cluster 5, 62.6 %). In case of the mixed learning group (Cluster 2) and the external partnership group (Cluster 3) the percentage shares of small-sized firms are slightly above the mean of the total sample.

In a similar manner, the results of Table 3 imply that the industry composition of the individual clusters tends to be concentrated in a knowledge-related way. The large majority of firms in the science and technology-oriented group operates in R&D-intensive manufacturing industries (44.0 %). The mixed learning group (Cluster 2) shows a marked above-average share of innovating firms belonging to knowledge-intensive services (32.7 %). Compared to the total sample, R&D-intensive manufacturing firms are also relatively often members of the second cluster (23.9 %). In case of the external partnership group (Cluster 3), a large above-average share amounts to manufacturing firms that are not located in research-intensive industries (46.9 %). In comparison to the sample average, service innovators are also often found in this group (25.1 and 14.0 %). Distinctive features of the employee-focused group (Cluster 4) are above-average shares of knowledge-intensive and other service firms. In the low learning group (Cluster 5), firms from manufacturing and service industries – characterised by a lower degree of knowledge intensity – dominate (51.5 and 21.4 %).

After confirming the predictive validity of the cluster solution, additional variables are used to profile the cluster solution on relevant dimensions, whereby the results of the validation stage are completed in a certain manner. Across-cluster results are shown here (see Table 3) to better describe the specific determinants of the identified clusters. The across-cluster percentages are presented in relation to the expected frequency distribution to assess the impact of the profiling variables on cluster membership.

In relative terms, the science and technology-oriented group (Cluster 1) is by far most likely to comprise firms that have received public financial support for innovation projects during the reference period. The introduction of new or significantly improved products or processes that incorporate a high degree of innovation (e.g. in terms of market novelty or improvements in quality of goods and services) is another specific characteristic of this group. Consistent with the above discussion on the importance of formal processes of learning in the first cluster (see Table 2), I interpret these findings as an indication of the strong focus in German policy lying on STI-based innovation in high-tech manufacturing that is often more radical in nature than the innovation output in non-R&D-intensive firms and industries (on this issue, see Section 1).

Firms receiving public financial support for their innovation projects and those having introduced significant product and process innovations are also likely to be members of the mixed learning group (Cluster 2), albeit with a much lower probability compared to Cluster 1. Apart from this, distinct competencies in detecting new customer needs are – relatively speaking – frequently found in the second cluster. Demand-side innovation based upon an experienced understanding of customer needs and requirements apparently plays an important role in the less-R&D-oriented knowledge environment of these firms. Hence, the high relevance of person-embodied know-how and informal processes of learning in the second cluster (together with a lower emphasis placed on formal learning of science and technology, see Table 2) can be explained by the fact that interacting with customers is an integral part of DUI-based innovation (Jensen et al. 2007).

Innovating firms having no employees with a university degree are very likely to be found in the employee-focused group (Cluster 4) and the low learning group (Cluster 5). Moreover, the firms in the fourth and fifth clusters have the lowest propensity to introduce any kind of significant product and process innovation. This matches the finding of the validating stage, namely that these two groups are characterised by low shares of innovators belonging to R&D-intensive manufacturing. It is also in line with the argument discussed in Section 1 that in Germany the VET trained workforce plays a key role for incremental innovation in non-R&D-intensive firms and industries.

Table 3

Predictive validity and profiling of the cluster solution

		Cluster					Chi-square
	Total	(1)	(2)	(3)	(4)	(5)	
Predictive validity of the cluster solution[a]							
Firm size							
Small enterprise	54.4	32.4	57.0	55.0	70.8	62.6	
Medium-sized enterprise	29.8	38.5	27.0	31.1	20.7	31.3	
Large enterprise	15.8	29.1	16.1	14.4	8.5	6.1	233.2*
Knowledge intensity of industries							
R&D-intensive manufacturing	22.9	44.0	23.9	14.0	16.0	9.8	
Other manufacturing	40.3	37.0	31.8	46.9	38.5	51.5	
Knowledge-intensive services	23.9	15.6	32.7	25.1	27.1	17.3	
Other services	12.9	3.4	11.6	14.0	18.4	21.4	333.0*
Profiling of the cluster solution[b]							
No employees with university degree		-18.1	-5.7	-1.2	+12.8	+12.3	127.8*
Public financial support		+23.2	+4.7	-7.3	-9.5	-11.2	467.1*
Distinct competencies in detecting new customer needs		+2.6	+5.6	-1.7	-1.3	-5.2	221.2*
Degree of product innovation							
Introduction of new-to-market innovations		+17.4	+5.2	-6.4	-8.5	-7.7	276.1*
Introduction of new-to-firm innovations		+13.7	+2.8	-3.5	-6.8	-6.1	196.7*
Degree of process innovation							
Introduction of quality innovations		+12.6	+4.5	-4.1	-5.1	-7.9	210.8*
Introduction of efficiency innovations		+16.3	+3.3	-4.5	-7.3	-7.7	205.9*
Only non-technological innovation		-18.7	-4.4	-4.5	+8.5	+10.1	305.8*

Note: Descriptions of the variables used for validating and profiling the cluster solution are shown in Table A2 in the Appendix.

* report a significance level of 1% (Pearson's chi-squared test)

[a] Within-cluster results are provided, i.e. the percentage share per cluster is shown. For example, 32.4% of firms in Cluster 1 are of small size.

[b] Across-cluster results are provided, i.e. the observed frequency distribution of firms across clusters minus the expected frequency in percentage points is shown. For example, in case of the two-way association of employee qualification and cluster affiliation, around 75 of firms with only non-academic employees (i.e. 5.4 %) are members of Cluster 1, although 599 firms with only non-academic employees should be members of this group by chance (i.e. 23.4 %). Hence, innovating firms employing no employees with university degree are much less likely to be members of the science and technology-oriented group (-18.1 %).

Apart from that, it is interesting to note that only-non-technological innovators – namely firms introducing only organisational and/or marketing innovations – are more inclined to be in the employee-focused group or the low learning group. This emphasis on non-technological innovation helps to explain why the distinctiveness of competencies in technical problem-solving through trial-and-error and interaction is low in corresponding firms, at least compared to the other groups (see Table 2). However, it has to be kept in mind that non-technological innovation is often an initial basis for incremental improvements of products and processes (Mothe and Thi, 2012; Schubert, 2010). From a knowledge-based view, this can be explained by the fact that DUI mode learning is more or less intentionally triggered at the company level when organisational procedures and marketing strategies are changed in the course of a firm's day-to-day activities (Jensen et al. 2007; Parrilli and Alcalde Heras 2016). Hence, together with the finding that VET trained workers are important for incremental innovation there, the employee-focused and the low learning groups may be an interesting case study for policy-makers who aim to promote informal processes of learning and experience-based know-how in less-R&D-oriented knowledge environments.

Something similar is true with respect to the external partnership group (Cluster 3). In a sense, it seems that the corresponding firms operate at the intersection between the employee-focused group (Cluster 4) and the mixed learning group (Cluster 2), since the values of almost all the profiling variables in the third cluster are between these two groups; e.g. those relating to the role of non-academic workers and the degree of product and process innovations. In light of the discussion on Table 2 (see above), one may interpret this as a sign that the members of the third cluster seek to be more successful in technological innovation by putting a stronger focus on STI-mode learning. This probably presents a major challenge to them because they still lack internal (R&D-based) capabilities needed to achieve this goal, which explains why they strongly rely on collaboration with external partners. Thus, firms in the external partnership group may have to overcome a number of significant barriers to innovation. This leads to the next part of the empirical analysis.

4.2 Barriers to innovation

To investigate how the modes of learning identified in the previous section relate to the firm-level perception of a number of innovation barriers, a multivariate probit model is used. The data set includes information on fifteen variables that reflect the binary information of whether innovation projects in a responding firm were abandoned, discontinued or already stopped at the planning stage due to a certain innovation barrier during the reference period of 2008 to 2010 (1 if this has occurred and 0 otherwise).[7] The reason for employing a multivariate probit framework is that different innovation barriers are often complementary to each other. As a result, separate single-equation probit models would lead to inefficient estimates. Prior studies

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[7] Information on barriers in postponed projects was not considered as the results of Galia and Legros (2004) show that the firm-level perception of innovation barriers differs between projects with extended duration and those being abandoned. Moreover, effects of innovation barriers on the decision to abandon or even not start a project may lead to higher welfare losses than obstacles resulting only in a postponement in finishing innovation projects. This should make them more important in the eyes of policy-makers.

on impediments associated with innovation have resolved this problem by using a multivariate probit model since this method allows for the joint estimation of more than two equations with correlated binary outcomes (see Galia and Legros, 2004; D'Este et al., 2012).

To provide a coherent overview, the present paper follows D'Este et al. (2012) in reclassifying the fifteen variables into four distinct sets of innovations barriers and thereafter using this information as dependent variables in the multivariate probit analysis (see Table 4). In accordance with their classification scheme[8], financial constraints, high costs and high economic risks are summarised as 'cost barriers'. The second type of innovation barriers ('knowledge barriers') refers to internal resistance, organisational problems, a lack of skilled personnel and a lack of information relating to technologies or markets. A lack of demand for innovation, a lack of access to IPRs and barriers caused by the dominant market position of established firms are classified as 'market barriers'. Finally, obstacles resulting from legislation, regulations, standards, norms and the length of administrative procedures are grouped together under the heading 'regulation barriers'. Principal component factoring reveals that the dominant patterns of correlation among the fifteen innovation barriers are empirically consistent with this classification scheme (see Table A3 in the Appendix). Furthermore, the descriptive statistics presented in Table 4 show that – as expected – cost barriers are most frequently reported to have hindered innovation activities (52.7%). A relatively large number of innovating firms also see knowledge barriers and market barriers as the causes for their problems. On average, less importance is attributed to regulation barriers.

Table 4

Descriptive statistics of the dependent variables used in multivariate probit regression (N = 1.658)

	Variable description Innovation projects have been abandoned, discontinued or have not begun due to *at least one* of the following barriers...	Min/Max	in %
Cost barriers	Too high economic risk; Too high costs; Lack of internal funding; Lack of external funding	0/1	52.7
Knowledge barriers	Internal resistance; Organisational problems; Lack of qualified personnel; Lack of technological information; Lack of market information	0/1	35.7
Market barriers	Lack of demand for innovation; Lack of access to IPRs; Market dominance by established firms	0/1	33.8
Regulation barriers	Legislation and regulations; Long administrative procedures; Standards and norms	0/1	23.0

Descriptions of the independent variables are shown in Table A4 (see Appendix). Apart from the mode of learning-variable, several control variables are added to the multivariate probit regression. First of all, given that firms with no or low R&R-intensity are likely to conduct less innovation projects per employee (Rammer et al., 2010), it is critical to account for the

[8] The same scheme is proposed by the Oslo Manual (see OECD/Eurostat, 2005).

number of innovation projects conducted during the reference period. This is due to the fact that there is a positive association between the absolute level of a firm's involvement in innovation activity and its perceived importance of innovation barriers (i.e. the more intensively a firm is engaged in innovation, the more it is likely to encounter certain obstacles; for an overview of this issue, see D'Este et al., 2012). Next, the number of employees (linear and quadratic) is included to account for the notion that smaller firms may perceive innovation barriers simply due to suffering from size-related disadvantages compared to their larger counterparts (e.g. see Tourigny and Le, 2004; Hewitt-Dundas, 2006; D'Este et al., 2012). To control for further variability, a set of 21 industry dummies in accordance with two-digit WZ 2008 classes ("Klassifikation der Wirtschaftszweige", the German version of NACE Rev.2) is used and a binary variable is added, indicating whether a respondent's company is located in East Germany.

Simulated maximum likelihood estimation is employed for multivariate probit regression, using Stata's mvprobit-command. This uses the Geweke-Hajivassiliou-Keane (GHK) smooth recursive conditioning simulator and has been discussed in depth by Cappellari and Jenkins (2003). To obtain an accurate estimate of the multivariate normal probabilities using the GHK simulator, a certain number of random draws from upper-truncated standard normal distributions is required. Simulation bias decreases if the number of random draws increases with the sample size. Thus, Cappellari and Jenkins (2003) argue that mvprobit provides good estimates in surveys as long as the number of random draws is at least equal to the square root of the sample size. Hence, as 1,658 innovating firms are included in the present analysis, the number of draws is set to 45 to be safe in this regard.

The estimation results are shown in Table 5, which enables assessing the effect of the mode of learning on the relevance of different sets of innovation barriers. The model as a whole is statistically significant (Wald's Chi-squared test for full model, significance level 1%), which demonstrates the overall explanatory power of the chosen specification. Moreover, Table 5 provides the pair-wise correlations between the equations' disturbances. In this context, a likelihood-ratio test compares the unrestricted model to a multivariate probit in which all correlations between the equation error terms are restricted to zero. Its significant result implies that separate (univariate) probit estimations for the different sets of innovation barriers would lead to inefficient results due to correlated disturbances. Hence, the decision to use a multivariate probit model was appropriate. Moreover, to assess the robustness of the aggregate results provided by the multivariate probit regression, fifteen separate regressions were run using the initial information on the single barriers to innovation (see Table 4). The corresponding results – which are available on request – are consistent with the empirical picture drawn by Table 5.

The effect of the learning mode is shown by providing pair-wise comparisons of estimates across all five levels of the cluster solution identified above (see Table 5), obtaining several findings. First, an innovating firms' mode of learning does not play a role in case of cost barriers. This shows that economies of scale and scope are the primary driver behind this set of innovation barriers, as the results on the number of innovation projects and the number of employees imply. Second, innovating firms in the science and technology-oriented group (Cluster 1) are more likely than those in the mixed learning and the employee-focused groups (Cluster 2 and 4) to face knowledge barriers. In Subsection 4.1, it is shown that the first cluster includes firms with a strong focus on formal processes of R&D, whereas members of the second and the fourth clusters have distinct competencies in informal (experience-based) learning. Hence, the empirical evidence on innovation barriers points to the potential strengths of those firms that successfully innovate under the conditions of a less-R&D-oriented knowledge environment, with its stronger dependence on DUI mode learning.

Third, firms in the external partnership group (Cluster 3) are characterised above as seeking to be more successful in technological innovation by putting a stronger focus on STI-mode learning, since they are operating at the transition from the employee-focused group (Cluster 4) to the mixed learning group (Cluster 2). In Subsection 4.1, it is assumed that the members of the third cluster have developed distinct competencies in external partner involvement to overcome a critical lack of internal (R&D-based) capabilities towards achieving this goal. In this regard, a hypothesis was proposed that firms in the external partnership group may have to overcome a number of significant barriers to innovation. Indeed, the results of Table 5 provide support in this direction. The firms in the external partnership group are most likely to perceive knowledge barriers as a major burden. In addition, compared to the other groups, innovators in the third cluster are more hampered by market barriers (e.g. a lack of demand for innovative goods or services and the market dominance of established firms). This is a hint that firms in the third cluster intensify their innovation efforts through collaboration with external partners to increase their market share or successfully enter new markets. During this process, they are apparently confronted with a number of internal, knowledge-related barriers, which explains their focus on external partner involvement. Hence, despite the fact that – in practice – the probability of public support is low in case of the third cluster (see Table 3), the external partnership group should hold particular relevance to innovation policy.

Fourth, the evidence on the low learning group (Cluster 5) – with its strong emphasis on non-technological innovation – shows that being a member of the fifth cluster reduces the probability of assessing the legal framework (i.e. legislation, regulations, administrative procedures, standards and norms) as a significant barrier to innovation. This reflects the fact that many technological areas are highly regulated (Blind, 2010), suggesting that difficulties with regulatory compliance have lower overall relevance in the context of non-technological innovation.

The results on the control variables hold interest in two respects. As expected, there is a positive and statistically significant relationship between the number of innovations projects conducted during the reference period and the probability of facing obstacles to innovation. This is most notably true for cost, knowledge and market barriers, while to a lesser degree it also holds for regulation barriers. With respect to the effects of firm size, a non-linear and statistically significant relationship is found in case of cost, knowledge and market barriers. This may be a clear indication that smaller firms are more hampered in their innovation activities than larger ones. However, the non-linearity of the relationship implies here that after a certain turning point is reached, the relevance of these innovation barriers tends to increase with firm size to some degree. An explanation for this could be that the potential disadvantages of larger firm size (Rothwell and Zegveld, 1982; Rothwell, 1989, Nooteboom, 1994) are finally coming into effect. However, a closer examination would be necessary to validate this assumption.

Table 5

Importance of different sets of innovation barriers - results from multivariate probit regression

	Cost barriers	Knowledge barriers	Market barriers	Regulation barriers
Intercept	0.476 (0.239) **	-0.189 (0.250)	-0.287 (0.247)	-0.581 (0.266) **
Number of innovation projects				
Less than 5	Left out	Left out	Left out	Left out
Between 5 and less than 10	0.371 (0.091) ***	0.328 (0.091) ***	0.338 (0.092) ***	0.145 (0.098)
Between 10 and less than 20	0.485 (0.117) ***	0.369 (0.119) ***	0.599 (0.117) ***	0.263 (0.125) **
20 or more	0.625 (0.142) ***	0.382 (0.140) ***	0.475 (0.139) ***	0.311 (0.147) **
ln(employees)	-0.261 (0.073) ***	-0.228 (0.072) ***	-0.208 (0.071) ***	0.034 (0.081)
$\ln(\text{employees})^2$	0.020 (0.009) **	0.024 (0.009) ***	0.022 (0.009) **	-0.010 (0.010)
Mode of learning[a]				
Cluster 2 vs. Cluster 1	0.096 (0.099)	-0.230 (0.100) **	0.007 (0.100)	0.100 (0.107)
Cluster 3 vs. Cluster 1	0.099 (0.102)	0.071 (0.102)	0.223 (0.104) **	0.078 (0.111)
Cluster 4 vs. Cluster 1	-0.002 (0.101)	-0.233 (0.104) **	-0.125 (0.105)	-0.085 (0.113)
Cluster 5 vs. Cluster 1	-0.099 (0.125)	-0.163 (0.126)	-0.016 (0.128)	-0.298 (0.140) **
Cluster 3 vs. Cluster 2	0.003 (0.099)	0.301 (0.102) ***	0.216 (0.102) **	-0.022 (0.106)
Cluster 4 vs. Cluster 2	-0.097 (0.098)	-0.003 (0.102)	-0.131 (0.102)	-0.185 (0.107) *
Cluster 5 vs. Cluster 2	-0.194 (0.120)	0.066 (0.124)	-0.023 (0.124)	-0.398 (0.134) ***
Cluster 4 vs. Cluster 3	-0.101 (0.097)	-0.304 (0.099) ***	-0.348 (0.100) ***	-0.163 (0.107)
Cluster 5 vs. Cluster 3	-0.197 (0.117) *	-0.234 (0.120) **	-0.239 (0.121) **	-0.376 (0.131) ***
Cluster 5 vs. Cluster 4	-0.097 (0.116)	0.069 (0.120)	0.108 (0.121)	-0.213 (0.132)
East Germany	-0.060 (0.069)	-0.179 (0.071) **	-0.170 (0.072) **	-0.068 (0.075)
21 industry dummies	yes	yes	yes	yes

[a] Pair-wise comparisons across the levels of the cluster variable.

*** report a significance level of 1%, ** of 5% and * of 10%; Robust standard errors in parentheses

Note: Cluster 1 (science and technology-oriented group), Cluster 2 (mixed learning group), Cluster 3 (external partnership group), Cluster 4 (employee-focused group), Cluster 5 (low learning group)

Table 5 continued

Correlations between the equation error terms				
	Cost barriers (ρ_1)	Knowledge barriers (ρ_2)	Market barriers (ρ_3)	Regulation barriers (ρ_4)
Cost barriers (ρ_1)	1.000			
Knowledge barriers (ρ_2)	0.548 (0.032)***	1.000		
Market barriers (ρ_3)	0.597 (0.030)***	0.578 (0.030)***	1.000	
Regulation barriers (ρ_4)	0.560 (0.034)***	0.539 (0.033)***	0.630 (0.030)***	1.000
Number of observations	1658			
Number of random draws	45			
Log pseudo-likelihood	-3546.69			
Wald Test $\chi^2(120)$	322.47***			
Likelihood-ratio Test $\chi^2(6)$	910.84***			

*** report a significance level of 1%

5. Conclusion

Motivated by Jensen et al. (2007), this paper identifies different modes of learning based upon a sample of innovating German firms, covering all size classes and a broad variety of industries. To more deeply assess the practical relevance of these modes for innovation policy, it is subsequently examined how a firm's learning mode relates to the relevance of different sets of innovation barriers. Accordingly, the present paper aims to provide a better understanding of innovation under the conditions of less-R&D-oriented knowledge environments dominated by the Doing, Using and Interacting (DUI) mode of learning.

The results obtained show that innovating firms can be grouped according to the degree to which they are combining competencies based upon learning by doing, using and interacting with strategies placing an emphasis on formal learning of science and technology. This is in line with the findings of Jensen et al. (2007). Evidence is also found that firms capable of combining the Science, Technology and Innovation (STI) mode with DUI mode learning (i.e. the science and technology-oriented group and the mixed learning group) are reaching a higher degree of innovativeness than those that mainly rely on informal processes of learning and experience-based know-how (i.e. the external partnership group and the employee-focused group). These results imply that DUI mode learning is generally important in the field of innovation. Put differently: DUI mode learning occurs either in its pure form or in combination with STI-mode learning. On the other hand, the latter is unlikely to be integrated alone.

The results further indicate that companies innovating in a less-R&D-oriented knowledge environment heavily rely on organisational and marketing activities. Thus, Parrilli and Alcalde Heras' (2016) suggestion that there is a close relationship between DUI mode learning and non-technological innovation is supported by the present analysis. Apart from this, as expected, the DUI mode of learning seems to play a major role in the German innovation system, prominently because vocational education and training (VET) in Germany occurs in a broad range of firms and industries (especially those with a lower emphasis on formal processes of R&D). At the same time, the results reflect the focus of German policy-making lying on R&D-based innovation in high-tech industries, implying that the innovation potential of non-R&D-performing and non-R&D-intensive firms tends to be overlooked. This especially holds for smaller companies. The more dominant that the DUI mode of learning is at the company level, the more likely that the corresponding firm is small. This finding explains why the organisation and management of knowledge in non-R&D-intensive firms and industries can be assumed to be characterised by practices typically to be found in SMEs (see Section 1).

On this basis, the examination of the relationship between the identified modes of learning and different sets of innovation barriers leads to two striking results. First, innovating firms with a stronger emphasis on DUI mode learning (i.e. the mixed learning and the employee-focused groups) are less likely to be hampered by knowledge barriers compared to those in the science and technology-oriented group. This is a hint that firms in less R&D-oriented knowledge environments can exploit certain competitive advantages when they concentrate on their experience-based DUI mode competencies. A second finding shows that firms trying to compensate for their limited in-house R&D capabilities by using and integrating externally generated knowledge inputs (i.e. the external partnership group) have to overcome a number of knowledge and market barriers to innovation. This fact points to the great importance of collaboration with external partners for innovation success in less-R&D-oriented knowledge environments.

With respect to the policy implications, two of the key arguments of Jensen et al. (2007) are confirmed by the empirical analysis: the prevalent bias in innovation policy towards the promotion of formal R&D activities, which neglects the general role that informal processes of DUI learning play in the context of innovation; and the ongoing need to strengthen linkages to sources of explicit and codified knowledge in more traditional industries. In light of these results, there are two general lessons for policy-makers, may they be from Germany or any other country with similar characteristics. *First*, they should recognise that innovation at the firm-level can occur with or without R&D activities, but rarely without DUI mode competencies acquired through informal processes of learning and experience-based know-how. An overly-strong focus on promoting only formal processes of in-house R&D thus ignores the fact that DUI mode competencies are a general prerequisite for successful innovation. This holds not only for firms in low-tech industries but also for those in the high-tech sector. Thus, there is an overall relevance of policy initiatives that aim to trigger DUI mode learning; for example, by fostering the use of human resource management tools and in-house team work practices. *Second*, at the same time, policy-makers should consider the notion that firms capable of combining their DUI mode competencies with STI-mode learning are likely to reach a higher degree of innovativeness. The results of the present analysis indicate that a number of significant barriers to innovation are likely to emerge precisely at the point when firms are starting to integrate the STI mode through the exclusion of external partners. Hence, there is also an ongoing need for support measures to strengthen the capacity at the company level to interact with external contacts, especially in case of firms that aim to participate in STI-mode types of interaction (e.g. collaborations with science-based partners like universities, research centres or other scientific laboratories) and that hitherto have little experience in R&D and lack the absorptive capacity to employ external sources of explicit and codified knowledge.

There are three implications that are specifically important for policy-makers in Germany. *First*, a recent cross-country comparison has shown that German SMEs are strong in non-R&D-based (DUI mode) innovation but weak with respect to R&D expenditure (EFI, 2016; Rammer et al., 2016). Hence, given the prominent role of the SME sector, one could argue that stimulating firms to reach a higher level of innovativeness by fostering STI-mode learning is a challenge, particularly in the German context. An instrument for German policy-makers to address this might be the introduction of R&D tax credits that meet the specific needs of SMEs. *Second*, another issue currently gaining increasing attention in the German policy debate is that in the long run the innovation activities in the SME sector have somewhat weakened. Primarily, the number of innovating SMEs with no or low R&D intensity tends to decline – i.e. the part of the German SME sector that is relatively strong in international comparison (EFI, 2015, 2016; Zimmermann, 2016; Rammer et al., 2016). This underscores the need for adequate support measures that also address non-R&D-intensive firms and industries. Third, given the significant role that the dual system of VET plays within the German innovation system, it is crucial especially for German policy-makers do not solely rely on a linear, R&D-focused view of innovation but rather also consider the DUI mode of learning. This is even more relevant because skilled labour shortages are expected to arise in the near future especially at the skill level of VET trained workers causing potential threats to the German production and innovation model (Maier et al., 2014; EFI, 2014).

Future research efforts could extend our understanding of DUI mode learning; for example, by examining the role and contribution of VET systems in innovation more deeply. Moreover, more advanced indicators to measure DUI-based innovation might be developed that complement typical STI indicators such as those relating to R&D, patents or the share of personnel with university degrees. Based upon this study, one might also more closely investigate the link between non-technological innovation and the DUI mode of learning. The results of this study indicate that, first of all, organizational and marketing activities are required to integrate DUI mode learning at the level of the firm. This might explain the finding of prior studies (e.g. Mothe and Thi, 2012; Schubert, 2010) that non-technological innovation is often the initial basis for the later introduction of new or significantly improved products/processes. Nonetheless, examining whether this is actually the case warrants a more detailed study.

Appendix

Table A1

Descriptive statistics of the original variables used in the factor and cluster analysis

	Mean	S.D.	Min	Max
In-house R&D-activity[a]	0.50	0.50	0	1
Use of patent protection[b]	0.22	0.41	0	1

	Share of sample in %				
Innovation competencies within the enterprise[c]	Not existing	Weakly distinct	Medium	Distinct	Strongly distinct
Development of new technical solutions	4.8	10.0	30.9	40.3	14.0
Scope for development via 'trial-and-error'	13.3	22.0	42.7	18.9	3.2
Strong individual responsibility of employees	0.9	5.7	28.1	49.5	15.8
Creativity of employees	1.5	7.2	34.1	44.0	13.3
Incentive schemes for employees to innovate	9.4	23.6	40.9	21.9	4.3
Stimulation of internal competition between projects	34.0	34.0	25.0	6.0	1.0
Internal co-operation between departments / firm units	7.2	7.3	31.0	41.2	13.4
Inclusion of external partners in projects	15.4	22.2	36.8	21.8	3.8

Note: The total number of observations amounts to 2,695 companies in each case, since the sample of the final cluster solution presented in Table 2 was taken as a basis for calculating the descriptive statistics.

[a] Survey question: "Did your enterprise conduct in-house R&D in the years 2008 to 2010?"

[b] Survey question: "Which of the following measures did your enterprise use to protect its intellectual property during 2008 to 2010" (one answer option: "Applying for patents")

[c] Survey question: "How distinct are the following innovation competencies in your enterprise?"

Table A2

Description of variables used for validating and profiling the cluster solution; reference period: 2008-2010

Variable	N	Description
Firm size		
Small enterprise	1464	1 if firm has less than 50 employees, 0 otherwise
Medium-sized enterprise	801	1 if firm has between 50 and 249 employees, 0 otherwise
Large enterprise	426	1 if firm has 250 or more employees, 0 otherwise
Knowledge intensity of industries		
R&D-intensive manufacturing	618	1 for manufacture of chemical and pharmaceutical products, electronics and electrical equipment, machinery and transport equipment (NACE Rev 2. divisions 20-21, 26-30), 0 otherwise
Other manufacturing	1085	1 for all manufacturing sectors apart from the R&D-intensive manufacturing sectors as well as mining, energy and water supply and waste management (NACE Rev 2. divisions 5-19, 22-25, 31-39), 0 otherwise
Knowledge-intensive services	644	1 for publishing, audio-visual and broadcasting activities, telecommunications, IT and other information services, banking and insurance, engineering offices, technical laboratories, consultancy and advertising and scientific R&D (NACE Rev 2. divisions 58-66, 69-73), 0 otherwise
Other services	348	1 for wholesale trade, transportation incl. travel agencies, postal services, graphic design and photography, cleaning, security, provision of staff, office services and other support services (divisions 46, 49-53, 74, 78-82), 0 otherwise
No employees with university degree	2556	1 if firm has no employees holding a university degree (incl. universities of applied sciences and "Berufsakademien"), 0 otherwise
Public financial support	1164	1 if firm received public financial support for innovation projects from German federal states, the German government or the European Union, 0 otherwise
Distinct competencies in detecting new customer needs	2682	1 if firm assesses its competencies in detecting new customer needs to be "distinct" or "strongly distinct", 0 otherwise
Degree of product innovation		
Introduction of new-to-market innovations	2038	1 if firm introduced product innovations that had not yet been supplied to the respective market segment, 0 otherwise
Introduction of new-to-firm innovations	2042	1 if firm introduced product innovations that had no predecessors in the firm's range of products and services, 0 otherwise
Degree of process innovation		
Introduction of quality innovations	1585	1 if firm introduced process innovations that led to an increase in the quality of goods or services, 0 otherwise
Introduction of efficiency innovations	1577	1 if firm introduced process innovations that led to a decrease in unit costs of production, 0 otherwise
Only non-technological innovation[a]	2695	1 if firm only introduced marketing or organisational innovations (i.e. no product or process innovations), 0 otherwise

[a] In the questionnaire of the MIP 2011, *marketing innovation* is described to respondents as "the implementation of a new marketing concept or strategy that differs significantly from your enterprise's existing marketing methods and which has not been used before. It requires significant changes in product design or packaging, product placement, product promotion or pricing." *Organisational innovation* is defined in the following way: "A new organisational method in your enterprise's business practices (including knowledge management), workplace organisation or external relations that has not been previously used by your enterprise. It must be the result of strategic decisions taken by management."

Table A3

Factor analysis of innovation barriers analysed in Subsection 4.2 (principal component factoring, varimax rotated factor loadings, the sample of the multivariate probit regression was taken as the basis for calculation)

	Factor 1	Factor 2	Factor 3	Factor 4
Too high economic risk	0.659	0.053	0.076	0.383
Too high costs	0.740	0.072	0.087	0.324
Lack of internal funding	0.840	0.139	0.116	-0.030
Lack of external funding	0.810	0.143	0.068	-0.057
Internal resistance	0.216	0.075	0.552	0.148
Organisational problems	0.144	0.072	0.771	-0.009
Lack of qualified personnel	0.127	0.128	0.690	0.085
Lack of technological Information	0.020	0.268	0.553	0.319
Lack of market information	-0.028	0.090	0.468	0.536
Lack of demand for innovation	0.190	0.102	0.112	0.613
Legislation and regulations	0.144	0.788	0.097	0.086
Long administrative procedures	0.157	0.804	0.060	0.034
Standards and norms	0.086	0.710	0.147	0.233
Lack of access to IPRs	0.010	0.386	0.120	0.558
Market dominance by established firms	0.245	0.156	0.016	0.643
Interpretation:	Cost barriers	Regulation barriers	Knowledge barriers	Market barriers
Eigenvalue	4.38	1.74	1.35	1.05

Table A4

Descriptive statistics of independent variables used in the multivariate probit regression (Reference period: 2008-2010)

Continuous Variables	Description	Mean	S.D.
Employees	Number of full-time employees in 2010[a]	197.7	1258.6

Binary Variables	Description	Percentage
Number of innovation projects		
Less than 5	1 if firm's total number of innovation projects (incl. R&D projects) conducted during 2008 to 2010 is $x < 5$, 0 otherwise	67.3
Between 5 and less than 10	1 if firm's total number of innovation projects (incl. R&D projects) conducted during 2008 to 2010 is $5 \leq x < 10$, 0 otherwise	16.4
Between 10 and less than 20	1 if firm's total number of innovation projects (incl. R&D projects) conducted during 2008 to 2010 is $10 \leq x < 20$, 0 otherwise	9.2
20 or more	1 if firm's total number of innovation projects (incl. R&D projects) conducted during 2008 to 2010 is $x \geq 20$, 0 otherwise	7.1
Mode of learning		
Cluster1	1 if firm belongs to Cluster 1 (science and technology-oriented group), 0 otherwise	23.9
Cluster 2	1 if firm belongs to Cluster 2 (mixed learning group), 0 otherwise	20.9
Cluster 3	1 if firm belongs to Cluster 3 (external partnership group), 0 other-wise	21.4
Cluster 4	1 if firm belongs to Cluster 4 (employee-focused group), 0 otherwise	22.0
Cluster 5	1 if firm belongs to Cluster 5 (low learning group), 0 otherwise	11.8
East Germany	1 if firm is located in East Germany, 0 otherwise	32.8
Industry dummies		
Mining	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 5-9, 19, 35, 0 otherwise	3.3
Food/Tobacco	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 10-12, 0 otherwise	4.1
Textiles	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 13-15, 0 otherwise	4.5
Wood/Paper	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 16-17, 0 otherwise	2.8
Chemicals	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 20-21, 0 otherwise	4.2
Plastics	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 22, 0 otherwise	3.4
Glass/Ceramics	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 23, 0 otherwise	2.7
Metals	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 24-25, 0 otherwise	7.4
Electrical equipment	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 26-27, 0 otherwise	8.8
Machinery	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 28, 0 otherwise	7.2

Table A4

(Continued)

Retail/Automobile	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 29-30, 0 otherwise	2.8
Furniture /Toys/Medical technology/Maintenance	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 31-33, 0 otherwise	6.1
Energy / Water	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 36-39, 0 otherwise	4.0
Wholesale	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 46, 0 otherwise	3.4
Transport equipment/Postal Service	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 49-53, 79, 0 otherwise	6.2
Medical services	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 18, 58-60, 0 otherwise	5.0
IT/Telecommunications	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 61-63, 0 otherwise	4.5
Banking, insurance	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 64-66, 0 otherwise	3.6
Technical services/R&D services	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 71-72, 0 otherwise	7.1
Consulting/Advertisement	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 69, 70.2, 73, 0 otherwise	4.8
Firm-related services	1 if firms' classification in accordance with WZ2008 (NACE Rev 2.) is 74, 78, 80-82, 0 otherwise	4.2

[a] To support anonymity in the Scientific Use File employed for this empirical analysis, the ZEW multiplied the number of employees reported by the companies with a random number evenly distributed over the range 0.5 to 1.5. Hence, while this procedure guarantees anonymity for individual companies, the effect of this randomisation should be removed at the average level of the overall sample.

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