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Measuring non-R&D drivers of innovation: The case of SMEs in lagging regions*

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Abstract

In order to better capture non-R&D based processes related to Learning by Doing, Using and Interacting (DUI) as a basis for policy advice, this paper empirically identifies DUI mode drivers of SME innovation. For the first time, a large set of conceptually derived indicators is used in a self-conducted survey. Using lasso regression as a data-driven selection technique capable of handling such a large number of potential predictors, we find that DUI learning involves a wide range of elements beyond interaction with external actors. Moreover, our results suggest that the relevance of DUI learning for predicting SME innovation depends on both the region and the type of innovation output. SME innovation in lagging regions is strongly related to the DUI mode, which is particularly pronounced in the case of intra-firm learning processes. These results suggest that R&D capacity is not the only main driver of SME innovation, especially in lagging regions, and therefore provide an indication of how firms can compensate for unfavourable conditions in their regional innovation environment. This in turn implies going beyond innovation policy in the narrow sense to a more holistic approach that may include links with other policy areas.

JEL: C50, C81, O3, O31, R11

Keywords: innovation measurement; innovation indicator; modes of innovation; SME innovation; regional innovation; lagging regions; lasso regression; variable selection; group lasso; ordinal predictors

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1 Introduction

A sound innovation policy needs to take account of the different ways in which firms learn and innovate. Current policy practice, such as that set out in Horizon Europe, tends to focus on innovation processes in those firms that undertake targeted and intensive research and development (R&D) on their own. Against this background, Hervás-Oliver et al. (2021a) conclude that despite tentative efforts at the policy level to understand 'innovation' as something broader than just R&D, the public support of R&D remains the "cornerstone of EU innovation policy" (p. 3). In addition to the relative ease with which funds can be allocated to a few, often larger firms, this policy paradigm is based on the assumption that although in-house R&D can generate high growth at the firm level (Coad et al., 2016), there is under-investment in R&D activities by firms from an economy-wide perspective due to positive externalities in the wake of market failures in the generation of new knowledge (Schot and Steinmueller, 2018).

However, this continued focus on R&D and the associated "market failure approach to innovation policy" (Edler and Fagerberg, 2017) means that policymakers tend to pay little attention to non-R&D innovation activities and their relationship to policies and indicators. There are a number of studies dealing with innovation in firms and sectors with low or no R&D intensity (e.g. Barge-Gil et al., 2011; Heidenreich, 2009; Hervás-Oliver et al., 2012, 2011; Kirner et al., 2009; Lee and Walsh, 2016; Santamaría et al., 2009; Simms and Frishammar, 2024). It is shown that it is often small and medium-sized enterprises (SMEs) that compensate for a lack of in-house R&D with learning and management practices that foster creativity and interaction, thereby achieving considerable innovation success and in many cases being able to compete economically with their R&D-intensive counterparts (Hervás-Oliver et al., 2016, 2014; Moilanen et al., 2014; Rammer et al., 2009; Runst and Thomä, 2021, 2024; Thomä and Zimmermann, 2020). Recently, this picture of the phenomenon of non-R&D innovation has been further differentiated geographically: Non-R&D intensive SMEs are among the main drivers of innovation, especially in non-core, less developed regions, which means that an innovation policy targeting SMEs and going beyond a narrow R&D-oriented definition of innovation is likely to play an important role in initiating an economic catch-up process in lagging regions (e.g. Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021a; Hädrich et al., 2023; Lopez-Rodriguez and Martinez-Lopez, 2017; Reher et al., 2024).

Not least because it touches on the soft (difficult-to-capture) side of innovation, it is an ongoing measurement challenge to approach the elusive topic of non-R&D innovation empirically with appropriate indicators (Gault, 2013; Martin, 2013). However, a number of the studies just mentioned have been able to shed more light on the subject by drawing on the innovation mode approach of Jensen et al. (2007) (see e.g. Hervás-Oliver et al., 2021a; Runst and Thomä, 2021; Thomä and Zimmermann, 2020). According to this approach, there are two different modes of learning and innovation at the firm level. On the one hand, Jensen et al. (2007) describe the Science-Technology-Innovation mode (STI). This refers to a targeted search for novel solutions based on codified, global and explicit scientific knowledge. It is strongly embedded in formal R&D processes with an emphasis on mechanistic knowledge ('knowing-why'). In contrast, the Doing-Using-Interacting (DUI) mode of innovation is based on informal, non-R&D-based learning practices, where new ideas tend to emerge through casual or non-innovation-related interactions, for example with customers or suppliers. In this sense, innovation is often an unintended by-product of day-to-day business and problem solving activities. The knowledge base of the DUI mode tends to be highly localized and uncodified, i.e. it is context specific and often tacit due to an embodiment of knowledge in individuals and teams. It can also be characterized by a focus on practical knowledge ('knowing-who' and 'knowing-how'). The empirical classification carried out by Jensen et al. (2007) suggests that in practice R&D innovation depends on both DUI and STI processes, but is predominantly associated with the latter. Non-R&D innovation, on the other hand, is strongly linked to DUI-based learning processes.

The STI/DUI concept of Jensen et al. (2007) has attracted considerable research interest over the years (see the literature reviews by Apanasovich (2016); Santos et al. (2022)). Of particular relevance in the context of our paper is that existing evidence suggests that the DUI mode is well suited to understanding the informal, less R&D-intensive ways of learning and innovating that are typical of the majority of SMEs (Bischoff et al., 2023; Runst and Thomä, 2021; Simms and Frishammar, 2024; Thomä, 2017; Thomä and Zimmermann, 2020), and that these are particularly pronounced in the context of lagging regions (Bischoff et al., 2024; Doloreux and Shearmur, 2023; Hervás-Oliver et al., 2021a,b; Hädrich et al., 2023). In addition to these contributions to the literature, the empirical capture of innovation modes has also taken a decisive step forward recently: In the measurement approach developed by Alhusen et al. (2021), the core dimensions of the DUI mode in SMEs are described conceptually for the first time for the purpose of innovation measurement and a comprehensive set of indicators is proposed. This potentially allows, on the one hand, a complete coverage of the different dimensions of the DUI mode at the firm level and, within these dimensions, a more precise innovation measurement than was previously possible. Together, this provides a promising starting point for making the DUI mode, and thus the elusive phenomenon of non-R&D innovation, more tangible.

Building on these insights, our paper aims to better capture non-R&D innovation as a basis for policy advice by empirically identifying DUI mode drivers in SMEs. Our contribution is threefold. First, based on Alhusen et al. (2021), we use a comprehensive set of DUI mode indicators. So far, the measurement of the DUI mode is rather inconsistent in the empirical literature and often covers only specific and selectively chosen DUI activities, often with a strong focus on the external dimension, i.e. on interactions, for example with customers, suppliers or competitors (e.g. Apanasovich et al., 2016; Fitjar and Rodríguez-Pose, 2013; Haus-Reve et al., 2019; Parrilli and Heras, 2016). This has recently been criticized as an incomplete coverage of the DUI mode, because it means that important aspects of non-R&D innovation activity remain hidden (Haus-Reve et al., 2023). Therefore, we use the hitherto untested indicator set by Alhusen et al. (2021), which covers the full range of DUI dimensions in SMEs (i.e. learning-by-doing incl. learning-by-internal-interacting, learning-by-using, learning-by-external-interacting, and examine it empirically.

Second, as mentioned above, the advantage of Alhusen et al.'s (2021) measurement approach is not only that it fully covers the DUI mode in its various dimensions, but also that it provides a comprehensive set of 47 individual DUI indicators. This has the advantage over previous studies that have attempted to capture the DUI mode empirically, in that it can be measured more precisely in its various dimensions. However, although Alhusen et al.'s (2021) set of indicators in principle allows for a more complete and accurate measurement of DUI-related learning processes at the company level, it also poses challenges in practice. For example, the scope and length requirements of innovation surveys are certainly a major obstacle to the application of such a broad set of 47 DUI indicators in practice. Furthermore, the inclusion of such a large number of variables exceeds the tolerable limits of many empirical model specifications. We address this by applying the Alhusen et al. (2021) indicator set for the first time in the context of a self-conducted innovation survey focusing on the measurement of the DUI mode in SMEs. To analyze our data, we use the Ordinal Group Lasso as a novel method in innovation research capable of dealing with such a large number of variables. The reduction of high-dimensional data using a penalty parameter allows us to identify the most important DUI drivers of SME innovation in a data-driven way.

Finally, as mentioned above, recent research suggests that DUI is particularly important in lagging regions and their many less R&D-intensive SMEs. Indeed, a low level of private R&D and a widespread absence of large firms are typical features of lagging regions (e.g. Alecke et al., 2021; Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021a,b; Pelkonen and Nieminen, 2016). As a result, firm sizes are substantially smaller in lagging regions, which further increases their propensity to engage in innovation without R&D (Bischoff et al., 2023). Against this background, we expect that a more comprehensive coverage of the DUI mode and its improved measurement is particularly important for understanding the innovation processes of SMEs in lagging regions. Our empirical innovation survey therefore places particular emphasis on this regional factor. In doing so, we also contribute to recent studies that use the STI/DUI concept in a spatial context (e.g. Bischoff et al., 2024; Hervás-Oliver et al., 2021a; Hädrich et al., 2023; Reher et al., 2024).

Our results suggest that important components of DUI mode learning and innovation which are often neglected in previous studies (i.e. learning-by-doing incl. learning-by-internal-interaction or learning-by-using) are strong predictors of SME innovation regardless of the regional context. Using the lasso method, we can identify the key non-R&D drivers of different innovation outcomes in a data-driven way. Our results imply that a comprehensive empirical operationalization of the DUI mode requires a departure from the measurement approaches that have dominated the innovation mode literature to date, which are often incomplete and only very roughly measure the various DUI components. They also suggest that innovation by SMEs from lagging regions is strongly linked to internal DUI processes, which provides an indication of how firms can succeed in innovation even under the conditions of an unfavourable business environment. By focusing on external DUI processes, many previous studies on the regional dimensions of innovation modes have therefore most likely underestimated the relevance of non-R&D-innovation for economic development and growth.

The paper proceeds as follows: Section 2 elaborates on the conceptual background of our study. Section 3 describes the data and our methodology. The results are presented in Section 4. Finally, Section 5 provides a discussion and summary of our findings and formulates implications for policy, innovation measurement and further research.

2 Conceptual background

2.1 DUI Measurement

Due to the lack of a coherent measurement framework, the empirical operationalization of DUI mode learning varies considerably across previous papers, in terms of both the selection of DUI indicators and their methodological handling. Two broad approaches have been followed, sometimes in combination. First, the existing literature often focuses on a small number of specific and selectively chosen DUI activities. The focus is mostly on external DUI activities such as interactions with suppliers or competitors (e.g. Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016), which means that intra-firm DUI processes or activities related to learning-by-using tend to be neglected. In most cases, survey items that were originally asked on Likert scales are hereby transformed into binary variables (e.g. Doloreux and Shearmur, 2023; Parrilli and Radicic, 2021), thereby losing a substantial part of the variation in the underlying variables. On the one hand, the use of few indicators has the advantage that it is easily facilitated by surveys with strict length requirements and it can be applied to existing data sets with only a few questions on the innovation process. Moreover, there are fewer parameters to estimate in a regression analysis. On the other hand, its inability to comprehensively capture the multifaceted nature of DUI, in particular intra-firm processes, has been discussed as an important disadvantage (Alhusen et al., 2021; Haus-Reve et al., 2023).

In a second measurement approach, researchers construct composite DUI measures, e.g. by combining indicators of internal and external DUI interactions, from a larger set of questions. This can be done by setting the composite measure equal to one if any one of the underlying items apply (e.g. Haus-Reve et al., 2023; Parrilli et al., 2020). Alternatively, by building upon the original method proposed by Jensen et al. (2007), a larger battery of items can also be reduced and compressed via Factor Analysis or Principal Component Analysis (PCA) (e.g. Bischoff et al., 2023; Runst and Thomä, 2021; Thomä, 2017).[1]. While this second approach often sheds light on a wider range of DUI learning processes (or DUI dimensions), including internal ones, researchers still have to make do with the whatever items are available in existing surveys, rendering such measurement approaches somewhat improvised and inconsistent. Furthermore, by reducing the items to a smaller number of dimensions, it is no longer possible to determine the impact of particular items on firm-level innovation outcomes.

Overall, therefore, it can be stated that DUI measurement in the existing empirical literature has been ad-hoc and non-uniform. With the aim of conceptualizing a more consistent and comprehensive measurement framework for DUI innovation activities, Alhusen et al. (2021) conduct 81 interviews with SME representatives and regional innovation consultants. Based on these data and a review of the literature, they identify and elaborate DUI innovation processes in SMEs and propose a set of 47 indicators grouped into 15 categories, which in turn can be mapped onto three dimensions of the DUI innovation mode: i.) learning-by-doing incl. learning-by-internal-interaction, ii.) learning-by-using, and iii.) learning-by-external-interaction. Knowledge from learning-by-doing and learning-by-internal-interacting is created within the firm, as a by-product of the repeated practice of a task related to the firm's core business model. It is disseminated through facilitated intra-firm interaction (Alhusen et al., 2021; Jensen et al., 2007; Nunes and Lopes, 2021; Parrilli and Heras, 2016; Thomä and Zimmermann, 2020). Learning-by-using takes place in interaction with customers, i.e. the users of the company's products or services. Learning-by-external-interacting then refers to learning through all other types of external interaction, such as with suppliers, competitors or networks. (Alhusen et al., 2021) [2] These three main dimensions of DUI, as conceptualized in the measurement approach of (Alhusen et al., 2021), are generally never fully captured in studies of the existing empirical literature (see the literature reviews of Apanasovich (2016); Santos et al. (2022)).

[1]While most papers using factor analysis or PCA in this context use the resulting dimensions in a subsequent latent class Jensen et al. (2007) or cluster Thomä (2017) analysis to identify *different types of innovating firms*, this is not strictly necessary if one wants to examine drivers of innovation at the variable level.

[2]Interaction with customers has often been subsumed under learning-by-external-interaction (see e.g. Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016) at the expense of the tripartite division of DUI mode learning processes which the acronym 'DUI' implies.

This problem is particularly pronounced in the case of internal DUI. Indeed, it appears that, as a result of selective measurement, many previous studies have focused exclusively on external DUI interaction. For example, Fitjar and Rodríguez-Pose (2013) and Parrilli and Heras (2016) study the impact of external DUI interactions - cooperation with customers, suppliers and competitors - on innovation output and find a positive effect of the former two on all types of innovation outcomes, which is strongest for process or non-technological innovations - but neglect the corresponding role of learning-by-doing and learning through internal interaction between employees. Likewise, Wassmann et al. (2016) emphasize a positive effect of external DUI interaction on non-technological innovation in the German region of Lower Bavaria. Haus-Reve et al. (2019) show that collaboration with external DUI partners within the supply chain increases the likelihood of firm-level product innovation. On the other hand, some studies focus exclusively on DUI indicators for internal interacting (e.g., Parrilli and Elola (2012)). While not explicitly using the label 'DUI-internal', this also includes studies that analyze the impact of individual contributions to innovation activities (i.e. related to human resources within the firm) that would fall under learning-by-doing and learning-by-internal-interaction (see Haus-Reve et al. (2023) for more details). Recent empirical studies have made some progress in taking into account a number of both external and internal DUI measures (Doloreux and Shearmur, 2023; Haus-Reve et al., 2023; Parrilli and Radicic, 2021). Importantly, they all point to the importance of the internal dimension.

To sum up, there are a number of specific issues that remain unaddressed in the literature on DUI mode measurement. First, despite the emerging awareness of inadequate dimensional coverage, internal and external DUI innovation activities continue to be measured in an inconsistent and ad-hoc manner, presumably due to a lack of suitable and agreed indicators. To date, binary measures, which only roughly measure either internal or external DUI, or even composite measures, which combine multiple items on internal and external DUI into single dimensional variables, have been common in prior studies; in both cases, potentially important information is lost or missing. Second, learning-by-using is not separated from external DUI as a distinct category in previous studies. Even more importantly, the intra-firm dimension of the DUI mode is often neglected in favour of a focus on indicators of external DUI interaction. We consequently fill the corresponding research gap by covering all three DUI dimensions conceptualized by Alhusen et al. (2021). We also measure them more precisely and comprehensively than has previously been possible, using for the first time the DUI indicators proposed by Alhusen et al. (2021) in an innovation survey. In doing so, we map the varying importance of a full set of DUI drivers in predicting different SME innovation outcomes – such as new or significantly improved products or processes – as is typically done in innovation mode research (Santos et al., 2022). As an empirical implementation of Alhusen et al.'s (2021) conceptual measurement framework, we use a lasso regression approach that avoids some of the weaknesses of the described methodological approaches common in the previous literature. Ordinal group lasso allows us to include a multitude of DUI-items (i.e the full set of indicators proposed by Alhusen et al. 2021) in our regressions to identify the most important individual DUI drivers for different innovation outcomes without having to omit certain individual variables a priori or simplify their scaling or create some kind of composite measure.[3] Nevertheless, we can still also examine the importance of the broader DUI dimensions composed of these items by aggregating their selection frequencies from lasso into the regression model.

2.2 Our application case: modes of innovation at the regional level

Introduced as a firm-level concept, innovation modes have been widely used to study the learning and innovation behaviour of companies (for an overview, see Apanasovich, 2016; Santos et al., 2022). When looking for a relevant use case for the measurement approach just described, two findings from this literature are of particular interest. First, the relevance of the DUI mode depends on the type of innovation outcome. For example, while DUI activities also play a role in such product innovation activities that potentially lead to patenting and new-to-market novelties (e.g. Haus-Reve et al., 2019, 2023; Jensen et al., 2007), it unfolds its strongest impact in the area of process innovation, incremental and new-to-firm product innovation below the patenting threshold and non-technological innovation (e.g. Fitjar and Rodríguez-Pose, 2013; Parrilli et al., 2020; Parrilli and Heras, 2016; Wassmann et al., 2016)). Second, the DUI mode is relatively more important for SMEs than for large firms, and in particular for the majority of smaller firms that are characterized by low R&D intensities (e.g. Alhusen and Bennat, 2021; Apanasovich et al., 2016; Parrilli and Radicic, 2021;

[3]We define importance in terms of the frequency of selection into the model, which is is supported by the median effect sizes of the coefficients (see Section 4.2).

Runst and Thomä, 2021; Thomä, 2017; Thomä and Zimmermann, 2020). For example, Thomä (2017) shows that the DUI innovation mode occurs more frequently in small-sized firms. To take another example, Parrilli and Radicic (2021) find that micro, small, and medium-sized firms benefit from both internal and external DUI, while larger ones, according to their results, benefit only from internal DUI. In sum, therefore, DUI activities are more likely to be present and more productive in less R&D-intensive SMEs.

Given these stylized facts, we argue that a regional contextualization of Jensen et al.'s (2007) innovation mode approach has considerable potential from a DUI measurement (and policy) perspective, because regions with low investment in private R&D and a low presence of large firms are more likely to rely on DUI innovation activities (Hädrich et al., 2023). As these features are two of the primary defining characteristics of lagging regions (e.g. Alecke et al., 2021; Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021a; Pelkonen and Nieminen, 2016; Reher et al., 2024), a better understanding and measurement of DUI can contribute to policy discussions on regional disparities and catch-up growth in less developed areas. Indeed, previous research has pointed to non-R&D intensive SMEs as a key driver of innovation in lagging regions. For example, Hervás-Oliver et al. (2021a) analyze aggregated data of European NUTS2 regions and find that innovation in lagging regions is strongly influenced by SMEs and their DUI-based learning and innovation processes. Doloreux et al. (2023) explore the role of knowledge-intensive business services (KIBS) for rural firms from an innovation mode perspective and find that external STI can be crucial for DUI-oriented SMEs in very remote rural areas. Consistent results are reported in studies using the well-established knowledge base approach, a related conceptual framework from the regional innovation system research, finding that in less developed regions a synthetic knowledge base often dominates, which is closely linked to DUI learning and innovation at the firm level (see e.g. Blažek and Kadlec, 2019; Hädrich et al., 2023).

In summary, recent studies have started to emphasize the regional context in the study of innovation modes (see e.g. Bischoff et al., 2024; Doloreux et al., 2023; Hervás-Oliver et al., 2021a; Isaksen and Trippl, 2017; Reher et al., 2024; Wassmann et al., 2016), with a particular focus on the potential role of the DUI mode for innovation-driven development in lagging regions (for a literature review see Hädrich et al. (2023)). However, despite these first important steps towards incorporating the geographical dimension into non-R&D and DUI mode research, the problems of DUI measurement described above persist (see Section 2.1). The RIS data used by Hervás-Oliver et al. (2021a), for example, contains a measure of SME collaboration as a DUI indicator, but does not differentiate external STI interaction from this, instead lumping the two together. Similarly, Doloreux et al. (2023) make a conceptual distinction between external and internal measures of DUI, but their data only allow them to construct a single composite DUI variable without distinguishing between the two different dimensions. Assuming that a large part of innovation activity in lagging regions is based on DUI processes, overcoming the inadequate coverage and measurement of the three DUI mode dimensions described in Section 2.1 is therefore a worthwhile endeavour, especially from a policy perspective. As reducing regional disparities is a key objective of regional development policy, a sound understanding and measurement of DUI innovation drivers in lagging regions is of paramount importance.

For example, the often neglected internal dimension of DUI (see Section 2.1) could be expected to serve as a compensatory mechanism for SMEs in lagging regions (Flåten et al., 2015). Given their lack of R&D capacities and regionally available knowledge, and the consequent lack of opportunities for collaboration, firms in lagging regions may turn inwards and build up less R&D-oriented innovation capacities by investing in DUI learning, e.g. by giving employees autonomy to experiment with new ideas or by cultivating internal collaboration and exchange. In line with this hypothesis, Doloreux and Shearmur (2023) find that internal DUI is more important for non-technological innovations and in non-metropolitan areas. On the other hand, for the same reasons, extra-regional DUI collaboration, which would fall under external DUI (see Section 2.1), can be an important driver of innovation in lagging regions if it serves to compensate for the lack of regionally endogenous resources and capacities (Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021a).[4]

[4]Unfortunately, we cannot distinguish between intra- and extra-regional knowledge sources in our data (see Section 3.1). Existing research stresses the importance of both spatial scales of collaboration for DUI innovation in lagging regions (e.g. Gyurkovics and Vas, 2018; Wassmann et al., 2016).

3 Data and Method

3.1 Data

We use primary data from a quantitative online survey of SMEs conducted in two waves between February and July 2023, with regions defined at the county level ("Landkreise"). This provides two samples that can be compared in the empirical analysis. Company addresses were obtained from the Creditreform database, a pool of business information provided by the largest credit reference agency in Germany. CEOs of private sector companies with up to 249 employees were contacted by postal mail with a link to an online survey. The first survey (Sample 1) targeted all SMEs in a number of selected regions - 10 of which are lagging regions analyzed using a case study approach as part of a larger research project.[5] After data cleaning - and because we need responses to the full battery of Alhusen et al.'s (2021) DUI indicators - there are 530 observations from the 10 lagging regions that can be used in our main specification. The second survey (Sample 2) collected responses from a Germany-wide random sample.[6] Of these responses, 400 full observations can be used in our main specification. Unfortunately, this sample size does not allow for a subdivision into leading and lagging regions, so we have to rely on Sample 1 to analyze DUI mode processes in lagging regions. Furthermore, in the course of the empirical analysis, we use Sample 2 as a benchmark to compare and interpret the results for our sample of the 10 lagging regions, since the Germany-wide sample is clearly dominated by firms from non-lagging regions (the corresponding sample share is 62.75 per cent).[7]

The 10 lagging case regions were selected on the basis of the following criteria (see Table 1): As a basic requirement, the regions must be eligible for funding in the 2014-2021 period under the Joint Federal/Länder Task for the Improvement of Regional Economic Structures (GRW), the most important instrument of German regional policy to promote balanced regional development. Under this program, lagging regions are identified by means of an index score, which is generated using income, labour market and infrastructure indicators.[8]. As a next criterion to validate the backwardness of our 10 case regions, we cross-checked their lagging status by consulting the *Prognos Zukunftsatlas* (Prognos AG, 2019) to identify regions that are labelled with 'at high risk' or 'at risk', and by selecting regions with declining population size. Moreover, in order to ensure that the diversity of lagging regions is covered in terms of different spatial characteristics, both rural (7) and urban (3) regions (according of the classification by the *Federal Office for Building and Regional Planning*, BBSR) as well as western (6) and eastern (4) regions were included. Different degrees of rurality were considered using the Landatlas 2016 (Thünen-Institut, 2016). The BBSR's INKAR database was used to identify lagging regions with different shares of manufacturing and knowledge-intensive service industries, as well as lagging regions suffering from demographic decline. Our 10 lagging case regions are located in different German federal states with varying levels of accessibility to urban centers. Of course, this 'most-different-design' selection procedure does not result in a representative sample of SMEs from all lagging regions in Germany, but it does improve the comparability with the nationwide results of Sample 2 because it takes into account the underlying heterogeneity of lagging regions.

With regard to the main research interest of this study, our questionnaire includes all the DUI indicators proposed by Alhusen et al. (2021) (see Table A.1 for a mapping of our survey questions to Alhusen et al. (2021) indicators). Following their measurement approach, we assign indicators to three main DUI dimensions, i.e., learning-by-doing-and-internal-interacting ('DUI internal'), learning-by-using ('DUI using') and learning-by-external-interacting ('DUI external'). We also include two questions related to the STI mode, i.e. the importance of R&D and the role of technical-scientific knowledge in the innovation process of a firm. All DUI and STI variables have been asked on a 5-point ordinal Likert scale. Information on the introduction of innovations (product/service, process, organization) in the years 2020-2022 serves as our binary dependent

[5] The project is entitled "DUI.REG - Measurement of the Doing-Using-Interacting mode of SMEs in lagging regions, funded by the Federal Ministry of Education and Research (BMBF)", 03ISWIR04A and 03ISWIR04C

[6] We excluded the firms which had been contacted in the first survey to comply with data protection laws, and then ex-post randomly added a representative share of each of these regions to our Germany-wide sample. However, we show that our results are also robust to the exclusion of these case region observations from the nationwide sample (Table A.3).

[7] Here, we define a region as non-lagging if it is not eligible for funding under the Joint Federal/Länder Task for the Improvement of Regional Economic Structures (GRW) in 2022-2027.

[8] The individual indicators and their respective weights can be found in Maretzke et al. (2019): the average gross annual wage per employee in 2010 (40%) and the unemployment rate in 2009-2012 (45%) both from the Federal Employment Agency, the employment forecast for 2011-2018 (7.5%) from Bade (2011), and the infrastructure indicator for 2012 (7.5%) from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).

Table 1: Characteristics of the case regions according to selection criteria

County	GRW region[a]	Urban/ Rural[b]	West/ East	Ageing/ shrinkage	Future viability[c]	Rurality[d]	#obs.
Donnersbergkreis	Yes	R	W	Yes	-	+	29
Goslar	Yes	R	W	Yes	-	-	63
Saalekreis	Yes	R	E	Yes	–	-	62
Eichsfeld	Yes	R	E	Yes	—	+	58
Werra-Meißner-Kreis	Yes	R	E	Yes	-	++	49
Birkenfeld	Yes	R	W	Yes	–	++	21
Holzminden	Yes	R	W	Yes	-	+	23
Saarbrücken	Yes	U	W	Yes	–		81
Dortmund	Yes	U	W	No	-		85
Rostock	Yes	U	E	No	-		59

Notes: [a]all study regions are "funding areas" according to the current GRW framework plan 2014-2021
[b]4 types of "settlement structure district types" according to the BBSR classification (two rural and two urban)
[c]8 classes from "best future opportunities" (++++) to "very high risks" (—-), according to Prognos Zukunftsatlas 2019
[d]5 classes from "extremely rural" (++) to "hardly rural" (–) according to Thünen-Landatlas 2016

variables - the corresponding definitions given in the survey are in line with common standards for innovation measurement as outlined in the Oslo Manual. Controls are included at the level of the firm (number of employees), sector (15 industry dummies in the Germany-wide sample and 10 industry dummies for the 10 lagging regions), and the region (population density (NUTS3); GDP (NUTS3); dummies for NUTS2 region in the case of the Germany-wide sample and dummies for NUTS3 region in the case of the 10 selected lagging regions). Table A.1 in the Appendix provides summary statistics for all variables used in the empirical analysis and shows the corresponding questions asked in our survey. On average, the 10 lagging case regions have a lower share of innovating SMEs for all three innovation outcomes and, on average, attach less importance to the STI and DUI items except for *Use of experience*. As expected, population density and the average number of employees are also lower (see Table A.1). Table A.2 shows the industry composition of the two samples. The largest share in both samples is accounted for by companies from industry G (trade; repair and maintenance of motor vehicles) with 20 and 21.13% respectively. The three next most frequently represented industries in both samples are industries M (provision of freelance, scientific and technical services services), F (construction) and C (manufacturing), although in a different order in the two samples.

3.2 Method

We perform a modification of logistic lasso regression on our binary innovation outcome variables to select the most important predictors from the large number of Alhusen et al.'s (2021) DUI indicators included in our analysis.[9] Lasso is a data-driven procedure for selecting a subset of relevant predictors among a large set of candidate regressors. In the present case, we have a large number of variables (which becomes even larger if we take into account the ordinal nature of the main variables of interest). Thus, due to the limited size of our two samples, the number of observations is not much larger than the number of variables, which would lead to a large variance of least squares estimates. Lasso reduces this problem by shrinking the estimated coefficients of the unimportant predictors towards zero, or even setting them to exactly zero, so that they are dropped from the regression equation (James et al., 2013). For coefficient shrinking and predictor selection, lasso imposes an L_1 penalty on the sum of the absolute values of the slope coefficients when maximizing the following penalized log-likelihood:

$$l_p(\boldsymbol{\beta}) = l(\boldsymbol{\beta}) - \lambda J(\boldsymbol{\beta}) \tag{1}$$

[9]In other firm-level studies, logistic lasso has, for example, been applied to predict high growth firms (see Coad and Srhoj, 2020).

with

$$J(\boldsymbol{\beta}) = \sum_{j=1}^{p} |\boldsymbol{\beta}_j| = ||\boldsymbol{\beta}_j||_1 \tag{2}$$

However, in order to incorporate the ordinal scale of our DUI (and STI) variables, two things have to be taken into account: first, since we want to select entire ordinal variables and not just some single-level parameters, i.e. certain levels $k_j \in \{1, ..., K_j\}$ of each variable $j = 1, ..., p$, we use the group lasso method (Meier et al., 2008; Yuan and Lin, 2006), which is a modification of the standard lasso regression approach that allows for group-wise selection by using the following L_2 penalty:

$$J(\boldsymbol{\beta}) = \sum_{j=1}^{p} \sqrt{\mathrm{df}_j} ||\boldsymbol{\beta}_j||_2 \tag{3}$$

with $\mathrm{df}_j = k_j - 1$ and $||\boldsymbol{\beta}_j||_2 = \sqrt{(\beta_{j1}^2 + ... + \beta_{jK_j}^2)}$ representing the L_2-norm on the coefficients within the jth group (see Meier et al. (2008) and Tutz and Gertheiss (2016) for more details), whereby only the ordinal scaled DUI and STI variables are truly grouped ($K_j = 5$) and all other variables form groups of one ($K_j = 1$). As in ridge regression where the penalty is $\lambda \sum_{j=1}^{p} \beta_j^2$, there is no selection of variables within the groups. However, group-wise selection is encouraged by the lasso penalty imposed by the square root (Gertheiss et al., 2011). In this way, the group lasso applies a ridge penalty to coefficients within the same group and a lasso penalty to coefficients in different groups. In other words, if each variable were a separate group of size one, then the group lasso would be reduced to the standard lasso. At the other extreme, if all the variables were a single large group, the group lasso would be equivalent to ridge regression.

Thus, the L_2 penalty can be rewritten as

$$J(\boldsymbol{\beta}) = \sum_{j=1}^{p} \sqrt{(\boldsymbol{\beta}_j{}^T \boldsymbol{\Omega}_j \boldsymbol{\beta}_j)} \tag{4}$$

with the penalty matrix $\boldsymbol{\Omega}_j = \mathrm{df}_j \boldsymbol{I}_j$ being the scaled identity matrix.[10]

Second, since the group lasso method as such does not account for the ordinal scale of our DUI and STI variables, we penalize differences between coefficients of adjacent levels, as suggested by Gertheiss and Tutz (2009), by using the ordinal penalty

$$J(\boldsymbol{\beta}) = \sum_{j=1}^{p} \sqrt{\mathrm{df}_j \sum_{k=2}^{K_j} (\beta_{jk} - \beta_{j,k-1})^2} \tag{5}$$

which can be rewritten as

$$J(\boldsymbol{\beta}) = \sum_{j=1}^{p} \sqrt{(\boldsymbol{\beta}_j{}^T \boldsymbol{D}_j{}^T \boldsymbol{D}_j \boldsymbol{\beta}_j)} \tag{6}$$

, so that the penalty matrix becomes $\boldsymbol{\Omega}_j = \mathrm{df}_j(\boldsymbol{D}_j{}^T \boldsymbol{D}_j)$ where $\boldsymbol{D}_j$ is the first-order differences matrix:

$$\boldsymbol{D}_j = \begin{pmatrix} -1 & 1 & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & -1 & 1 \end{pmatrix}$$

In practice, our ordinal DUI/STI variables are defined in groups of four dummies (the first variable level serves as the reference category) for group-wise selection, i.e. they are either selected as a whole group with estimates for all four levels or not selected at all. Categorical variables are dummy coded and form groups of one, i.e. they can be selected individually. Continuous variables simply form groups of one. The ordinal

[10]See Meier et al. (2008) for more detail.

DUI/STI variables are split-coded using the `coding()` function from the R-package `ordPens`[11]. The split coding scheme (see e.g. Gertheiss et al., 2011; Hoshiyar et al., 2023) is shown in Table 2 for observation i, $i = 1, ..., n$, and variable j, $j = 1, ..., p$, with Likert values $k \in \{1, ..., 5\}$.

Table 2: Split-coding scheme for ordinal variables

Likert value	Dummy variable			
	z_{ij1}	z_{ij2}	z_{ij3}	z_{ij4}
1	0	0	0	0
2	1	0	0	0
3	1	1	0	0
4	1	1	1	0
5	1	1	1	1

Notes: Source (Hoshiyar et al., 2023, p. 14).

In the end, our predictor matrix consists of the grouped transformed ordinal DUI/STI variables, the individual dummies for industries and regions, and the continuous variables for the number of employees and population density.

The optimal penalization parameter, λ, is chosen by 5-fold cross-validation.[12] Our training set consists of 80% of the total number of observations included in the samples. As our sample sizes for both samples are quite small, and both the training/test sample split and the cross-validation rely on randomization, we run a total of 2,500 iterations with 50 random seeds for each of the two processes subject to randomization. We then construct a measure based on the frequency of a predictor being selected into the model where s is the number of specifications with non-zero coefficients for the indicator i and n is the total number of specifications:

$$F_i = \frac{s}{n} \tag{7}$$

Furthermore, as we are also interested in the three main DUI dimensions, as outlined in the measurement approach of Alhusen et al. (2021), we sum up F_i by DUI dimension $d \in \{\text{internal, using, external}\}$ and divide this by the total number of variables defined for this dimension, D:

$$F_d = \sum_{i=1}^{D} \frac{F_{id}}{D} \qquad \in [0, 1] \tag{8}$$

with

$$D = \begin{cases} 16 & \text{if } d = \text{internal} \\ 9 & \text{if } d = \text{using} \\ 15 & \text{if } d = \text{external} \end{cases}$$

Our frequency measure thus has a minimum of zero (none of the variables are chosen in any specification) and a maximum of one (all of the variables are chosen in all specifications). We repeat this procedure for all innovation outcomes and separately for the two samples.

4 Results

4.1 Predictor selection by DUI dimension

Table 3 shows the frequency measures F_d at the level of Alhusen et al.'s (2021) three DUI dimensions, calculated from the Lasso regression results. Irrespective of whether the sample consists of companies randomly

[11]Unfortunately, we cannot use `ordPens` as it does not impose a penalty on categorical or metric variables.

[12]We use the R-package `gglasso` (Yang and Zou, 2015) to run the group lasso regressions, as it has an implementation of this cross-validation.

drawn from all over Germany or from the 10 lagging case regions, the results indicate that the dominant focus on 'DUI external' prevalent in the previous literature overlooks relevant learning processes in the context of DUI mode innovation. Variables within both, 'DUI internal' and 'DUI using' are frequently selected as predictors of innovation in both samples. In fact, 'DUI internal' has the highest value of F_d across the two samples and the different outcome measures, making it the most frequently selected DUI dimension for predicting innovation outcomes, regardless of the region type. In contrast, and with the exception of organizational innovation, 'DUI external' displays the lowest frequency measure.

Comparing the results across samples, we observe that DUI mode variables are selected more frequently to predict all innovation outcomes in the 10 lagging case regions (Panel B) than in the Germany-wide sample (Panel A). In particular, the selection share is higher in the case regions compared to the overall benchmark in eight out of nine cases, with the sole exception of 'DUI external' for predicting product innovation. This exception is noteworthy, however. It could indicate that SMEs in lagging regions lack opportunities for external exchange and therefore find it difficult to use external resources for product innovation. This suggests a hypothesis for future research, namely that the lack of regionally available innovation stimuli in lagging regions - due to fewer opportunities for exchange and thus fewer regional knowledge spillovers - represents a hard constraint on product innovation in corresponding business environments, which firms may try to overcome by developing far-reaching network connections. Moreover, product innovators in lagging regions may compensate for the lack of external stimuli, for example, by relying on customer interaction (local or otherwise) or by developing strong internal learning capabilities, as variables related to the corresponding DUI dimensions are selected more frequently in our sample of 10 lagging regions than in the comparison case.

In contrast, when we look at process and organizational innovation, external DUI stimuli are more frequently selected in lagging regions compared to the Germany-wide sample. These innovators may either rely on less proximate external interaction or use (external) intra-regional interaction more productively. Unfortunately, we cannot distinguish between intra- and extra-regional interaction in this study. In addition, variables from all three DUI dimensions are selected more frequently as predictors of process and organizational innovation in the case of our 10 lagging regions than in Germany-wide sample. This effect is most pronounced in the case of organizational innovation, reflecting the strong relationship between DUI and non-technological innovation described in the literature (see e.g. Parrilli and Heras, 2016; Thomä, 2017) and suggesting that DUI mode processes, especially intra-firms ones, are particularly important for SMEs in lagging regions, as "[...] companies innovating in a less-R&D-oriented knowledge environment heavily rely on organisational and marketing activities" (p. 1336 Thomä, 2017).

Table 3: Selection frequency of DUI dimensions

DUI dimension	Innovation outcome Product	Process	Orga
PANEL A:	*Germany-wide sample*		
internal	0.314	0.216	0.129
using	0.260	0.205	0.038
external	0.205	0.086	0.064
N	400	390	383
PANEL B:	*10 lagging case regions*		
internal	0.356	0.264	0.383
using	0.338	0.209	0.218
external	0.123	0.174	0.267
N	530	521	515

Notes: Based on Equation 8.

4.2 Predictor selection by item

While the three DUI dimensions proposed by Alhusen et al. (2021) represent a plausible classification of a firm's DUI-related learning activities, it could be argued that the resulting partitioning is somewhat strict.

Moreover, it may potentially obscure the interaction of various DUI processes (and corresponding indicators) across dimensional boundaries. Table 4 therefore displays the variables selected by Lasso for each innovation outcome and sample, sorted by their item-selection frequency F_i.[13] For the sake of conciseness, only variables selected in at least 50% of the specifications are shown.

Overall (i.e. regardless of the region type), it is interesting to note that while the perceived importance of R&D capabilities for generating innovation is selected by Lasso as a predictor for product innovation as expected, the corresponding selection share is lower than for many DUI items, and R&D does not play a predictive role in the case of process and organizational innovation. This finding is consistent with the literature on sources of innovation beyond R&D (e.g. Hervás-Oliver et al., 2012, 2011; Santamaría et al., 2009) and suggests that a focus on DUI capabilities is therefore justified in these cases and especially when it comes to lagging regions. Moreover, it is noteworthy that the DUI indicator *New technology introduction* is selected by Lasso in all six resulting sets of specifications, i.e. irrespective of the sample and the innovation outcome - which is why we check the dependence of our results on this specific indicator in a robustness test (see Table A.4). A likely explanation could be that the identification and introduction of new technologies is an obvious feature of innovation activities in general.[14]

Product innovation

In a first step, we describe and compare the single-item predictors of product innovation across the two samples. On the one hand, we find certain predictors on both sides of Table 4. Whether a firm is a product innovator or not in both samples is predicted by *Open communication culture*, *Knowledge exchange among employees with different tasks*, and *Importance of R&D*, suggesting that these processes are not affected by the regional context. On the other hand, we also observe considerable differences in the predictor profiles. While firms in the Germany-wide sample benefit from *Competent customers* and *Customized products*, the former is absent in the lagging regions sample. Instead, we find that *Active request for feedback* in combination with *Customized products* are predictors for SME innovators from lagging regions. This finding may reflect the lack of potential innovation partners in such business environments. Nevertheless, product innovation in both samples is stimulated by the customization of products, and firms in lagging regions seem to have to be more active in approaching their customers in order to obtain relevant feedback. Taken together, these findings could suggest that it is in the context of lagging regions that innovating SMEs need to succeed in efficiently exploiting the available potential of scarce customer resources.

The selection of *Training regarding general qualification* in the Germany-wide sample and, in contrast, that of *Training regarding firm-specific qualifications* in the case of lagging regions may indicate a higher degree of specialization of innovating firms in lagging contexts and, perhaps, a greater need for those in non-lagging contexts to be alert to a wide range of new technological developments. In addition, the selection of *Maintaining informal contacts within the firm* in the national and *Scope for trial-and-error learning* in the lagging region sample may indicate a higher internal complexity of innovation processes in firms in the former sample (due to this they need to ensure efficient intra-firm communication, for example) and a more individualized tinkering approach in the case of lagging regions, where innovation activities may perhaps be more in the hands and responsibility of individuals.

Interaction with suppliers, and cooperation with consultants/service providers in terms of innovation are more important for innovation in the national sample - a result that now reveals at the level of individual items why 'DUI external' is a less dominant driver of innovation in lagging regions in terms of selection frequency (see Section 4.1). An obvious explanation is that the lack of exchange opportunities with suppliers, consultants and service providers in a lagging region is due to the lower development of the respective regional innovation system, which is why the corresponding knowledge spillovers can have less effect. At the same time, the *Importance of network relation* only appears in the lagging region sample. Given that we can assume

[13] To provide further detail on the item-based Lasso results, Figures A.1 to A.3 in the appendix show the median estimate for each level of items being selected in at least 1250 out of 2500 group ordinal lasso specifications. In support of our frequency measure, variables with the highest median coefficients also have the highest selection frequency F_i in Table 4. Most of the effect sizes exhibit a concave trend across the ordinal levels, with a fairly steep increase from a DUI indicator being of no importance to some importance in the innovation process (level 1), and flatter slopes after level 2; often even negative slopes after level 3 or 4. We interpret this as diminishing returns in the company's DUI learning processes.

[14] *Customized Products* shows a similar importance in predicting innovation for all outcomes and both samples (except organizational innovation in the Germany-wide sample). *Relation with consultancies and service providers* predicts all innovation outcomes except product innovation in both samples.

a certain lack of endogenous resources and capabilities for innovation in the context of a lagging region, it is a plausible conjecture that maintaining good relations and regular interactions with network partners from within or outside one's own region is a common way for firms to compensate for the unfavorable features of their regional innovation environment. It would be interesting for future research to find out whether these networks developed naturally in a self-organized way or whether they were imposed on actors in these regions.

Process innovation

In the case of process innovation there are again some items that are selected as predictors in both samples, namely *New technology introduction*, *Additional or complementary products and services*, *Customized products*, and *Relation with consultancies/service providers*. It is interesting to note that consultants and service providers, which are not predictive of product innovation in lagging regions, turn out to be important for process innovation, suggesting that this channel may be less sensitive to the lack of local resources. Indeed, there are two items related to consultancies/service providers in the lagging regions sample, and both are selected more frequently than the one item related to consultancies/service providers in the Germany-wide sample, suggesting that consultancies and service providers play a role in overcoming the lack of local knowledge spillover in the case of process innovation (but not in the case of product innovation). Furthermore, we find a pattern that has already been identified above. While the selection of *Maintaining good relations within the firm* again suggests the need for efficient intra-firm communication in the national sample (see above), the (considerably smaller-sized) firms in the lagging sample seem to rely on the freedom of individual employees to learn by trial and error, complemented by an open communication culture, also in the case of process innovation. Clearly, the success of innovations and improvements resulting from trial-and-error tinkering would be enhanced if employees are able to openly share their thoughts and ideas with each other.

Organizational innovation

Finally, there are three predictors of organizational innovation which are selected in both samples: *Regular team meetings*, *Relation with consultancies*, and, again, *New technology introduction*. These can be said to be predictors that are independent of the regional context. As before, the selection of *Knowledge exchange among employees with different tasks* only in the Germany-wide sample speaks to the need for cross-departmental exchange in these relatively larger firms. However, DUI processes in general seem to play a considerable role for organizational innovation in the lagging sample, as the total number of frequently selected predictors is higher than in the Germany-wide sample, reflecting the fact that DUI innovation and organizational learning are closely intertwined (Thomä, 2017). As with process innovation, external input from consultancies/service providers also predicts organizational innovation in lagging regions which the selection of the item *Innovation cooperation with consultancies* in 99.3% of the specifications suggests. This confirms the intuition that, in contrast to product innovation, external consultants/service providers can help to overcome a lack of locally available knowledge for other forms of innovation output (process and organizational). The simultaneous selection of firm-specific and general training in the case of lagging regions shows that a heavy weight of the high frequency measure of 'DUI internal' (0.383) in 4.1 falls on a qualification component. Further, an important finding is that *Trial-and-error learning* and an *Open communication culture* are always selected together in lagging regions, but not in the Germany-wide sample, and thus seem to be a key feature of innovation in lagging contexts. Finally, the selection of *Innovation cooperation within the own sector* may either indicate either a co-location of firms within sectors in their own region, or their ability to communicate across larger distances with similar firms. However, we cannot explore these possibilities further with the given data.

Table 4: Selection frequency of DUI variables

Sample:	Germany-wide		10 lagging case regions	
Outcome	Variable	F_i	Variable	F_i
Product	(U) Competent customers	0.942	(U) Active request for feedback	0.999
	(E) Suppliers' competences	0.874	(I) New technology introduction	0.992
	(I) Open communication culture	0.867	(U) Customized products	0.934
	(I) Knowledge exchange among employees with different tasks	0.836	(I) Knowledge exchange among employees with different tasks	0.931
	(U) Customized products	0.772	(I) Open communication culture	0.892
	(I) New technology introduction	0.731	(I) Training regarding firm-specific qualifications	0.731
	(E) Innovation cooperation with suppliers	0.680	(I) Scope for trial-and-error learning	0.720
	(I) Training regarding general qualification	0.588	(E) Importance of network relations	0.613
	(E) Innovation cooperation with consultancies/service prov.	0.556	(STI) Importance R&D	0.632
	(I) Maintaining informal contacts within the firm	0.535		
	(STI) Importance R&D	0.596		
Process	(I) New technology introduction	0.999	(I) New technology introduction	0.997
	(U) Customized products	0.836	(U) Additional or complementary products and services	0.948
	(U) Additional or complementary products and services	0.708	(E) Innovation cooperation with consultancies/service prov.	0.835
	(I) Maintaining good relations within the firm	0.675	(I) Current technology improvement	0.802
	(E) Relation with consultancies/service prov.	0.585	(E) Relation with consultancies/service prov.	0.788
			(I) Open communication culture	0.785
			(U) Customized products	0.581
			(I) Scope for trial-and-error learning	0.534
Orga	(I) Regular team meetings	0.751	(I) New technology introduction	1.000
	(E) Relation with consultancies/service prov.	0.722	(E) Innovation cooperation with consultancies/service prov.	0.993
	(I) New technology introduction	0.558	(U) Customized products	0.966
	(I) Knowledge exchange among employees with different tasks	0.506	(E) Relation with consultancies/service prov.	0.936
			(I) Regular team meetings	0.931
			(I) Scope for trial-and-error learning	0.880
			(I) Training regarding firm-specific qualifications	0.860
			(I) Training regarding general qualification	0.798
			(I) Open communication culture	0.753
			(E) Innovation cooperation within the sector	0.600

Notes: Based on Equation 7. Only variables with a frequency measure higher than 0.5 are shown with the exception of the number of employees and the population density which were chosen in 83-100% of the specifications in all Panels.

4.3 Robustness

The assignment of DUI items to three main DUI dimensions, as it is done in Section 4.1, is based on the measurement framework developed by Alhusen et al. (2021). It could be argued that this theory-driven classification is somewhat subjective and contestable. For example, 'DUI using' could also be seen as an aspect of 'DUI external' as it relates to interactive learning with the customer side, so the two could be intuitively grouped together. Therefore, as a robustness check, we additionally use Principal Component Analysis (PCA) to conduct an exploratory data analysis to empirically generate the three DUI dimensions and allow for interactions between them. The loadings from the PCA can be found in Table A.5.While not all factor loadings are fully consistent with Alhusen et al.'s (2021) theoretical classification, we can still obtain their three dimensions in the form of principal components. As linear combinations of Alhusen et al.'s (2021) set of individual DUI indicators, these components fit well with the tripartite division between 'DUI internal', 'DUI external', and 'DUI using'. We then regress our dependent variables on the innovation outcome against the three DUI components, their interactions and the set of controls (Table 5). To facilitate the interpretation of the coefficients on the interactions, we run OLS regressions. [15]

Table 5: Results from OLS regressions with preceding PCA

Innovation outcome:	Product		Process		Orga	
PANEL A:			*Germany-wide*			
DUI_internal	0.032***	0.031**	0.010	0.014	0.030**	0.038**
DUI_using	0.034**	0.044***	0.044**	0.060***	0.027*	0.038**
DUI_external	0.021	0.020	0.006	0.010	0.025	0.029
DUI_internal × DUI_using		-0.006		-0.004		-0.004
DUI_internal × DUI_external		-0.001		-0.004		-0.001
DUI_using × DUI_external		0.010		0.009		0.005
DUI_internal × DUI_using × DUI_external		-0.002		-0.003		-0.003*
Importance R&D	0.037*	0.036	0.040	0.036	0.027	0.023
Scientific knowledge	-0.039**	-0.039*	-0.014	-0.011	-0.046	-0.042
Number of employees	0.001	0.001	0.001	0.001	0.002	0.002
Population density	-0.000	-0.000	-0.000*	-0.000	-0.000	-0.000
Constant	0.673***	0.648***	0.653***	0.624***	0.337**	0.315**
N	400	400	390	390	383	383
R^2	0.289	0.294	0.246	0.255	0.267	0.274
PANEL B:			*10 lagging case regions*			
DUI_internal	0.030*	0.024	0.029***	0.022***	0.036***	0.036***
DUI_using	0.027**	0.021*	0.016**	0.010	0.014	0.013
DUI_external	0.016	0.019	0.026**	0.014	0.042***	0.032**
DUI_internal × DUI_using		0.008**		0.003		0.006*
DUI_internal × DUI_external		-0.002		0.003		0.006
DUI_using × DUI_external		-0.009		-0.001		-0.003
DUI_internal × DUI_using × DUI_external		0.003*		0.004***		0.003**
Importance R&D	0.031**	0.033**	0.024	0.026	0.023	0.024
Scientific knowledge	-0.004	-0.008	-0.019	-0.025	-0.025	-0.030
Number of employees	0.001	0.001	0.003***	0.003***	0.002*	0.002*
Population density	-0.008***	-0.008***	0.033***	0.034***	-0.000	0.002
Constant	1.230***	1.215***	-2.997***	-3.084***	0.34	0.047
N	530	530	521	521	515	515
R^2	0.188	0.197	0.178	0.195	0.218	0.238

Notes: The three DUI variables are generated from PCA enforcing a three component solution. Importance R&D and Scientific knowledge are treated as metric. Region and industry dummies are included. Standard errors are clustered at the level of NUTS2 regions or case study regions respectively.

Overall, the robustness test's results are in line with our previous findings (see Table 3 and Table 5). Among the DUI dimensions in the Germany-wide sample, 'DUI internal' is positive and significant for product and organizational innovation, but not for process innovation. The 'DUI using' dimension exerts a significant

[15] In addition, we have also estimated a probit model without interactions. The resulting average marginal effects are shown in Table A.6.

positive effect for all outcomes, while the effect of 'DUI external' is mostly insignificant (but positive) across outcomes. In the sample of the 10 lagging regions, 'DUI internal' is positive and highly significant for process and organizational innovation while it is only slightly significant in the case of product innovation. 'DUI external' has the largest effect size and highest significance for organizational innovation where 'DUI using' is insignificant. In Table 5 we further show that our results remain robust when allowing for interactions between the DUI dimensions. Moreover, the triple interaction of all dimensions yields significant and positive effects in the lagging regions sample, suggesting that the positive effects of DUI learning on innovation in lagging regions are not just additive but multiplicative. In other words, there are synergies (or complementarities) between the three main DUI dimensions.

5 Conclusion

Not least because it touches on the soft, elusive side of innovation, it is an ongoing challenge to make the learning and innovation activities of the many SMEs with little or no R&D intensity more concrete from an innovation policy perspective. In this regard, the innovation mode concept of Jensen et al. (2007) and its subsequent wide reception in the literature has been an important step to better understand theoretically how the Learning by Doing, Using, and Interacting (DUI) processes that underlie much of the non-R&D innovation phenomenon take place. However, in addition to understanding why one policy approach or another makes sense, policy makers need appropriate indicators to identify the relevant areas of innovation activity, to monitor them on an ongoing basis and, where necessary, to assess the potential impact of related policies. The measurement conception of Alhusen et al. (2021) was the first to provide the necessary basis for this with regard to the DUI mode. They conceptually describe its different main dimensions for the purpose of measuring DUI learning processes in innovating SMEs and propose a comprehensive set of indicators. From the perspective of innovation measurement, this offers a promising starting point for making the DUI mode, and thus the phenomenon of non-R&D innovation in SMEs, more tangible, creating a possible basis for an innovation policy oriented towards it.

Our paper takes this as its starting point and for the first time empirically applies Alhusen et al.'s (2021) set of indicators to identify the key DUI drivers of innovation in SMEs using lasso regression (which is useful in a multi-variable setting because it reduces the variance of the estimates and can perform variable selection by shrinking unimportant regression coefficients to exactly zero.). In this way, we contribute to the growing literature on the DUI mode of innovation, where new ideas often emerge as an unintended by-product of daily business and problem-solving activities, for example through interactions with customers or suppliers. We also contribute to the literature on innovation in lagging regions by focusing on this particular type of region with a separate data set. Recently, research interest in this regard has increased, with the relatively high importance of SMEs and non-R&D innovation in these spatial contexts being repeatedly emphasized. For this reason, it can be expected that a more comprehensive coverage of the DUI mode and its improved measurement will be particularly important for understanding innovation in lagging regions.

Our findings suggest that DUI learning involves a wide range of elements that go beyond interaction with external actors. This extends previous literature that has focused heavily on the firm-external dimension to measure the DUI mode. Furthermore, our results suggest that the relevance of DUI learning for predicting SME innovation depends on both the region and the type of innovation output, confirming Parrilli et al. (2020). For example, the DUI mode seems to be generally more productive in lagging regions than in a Germany-wide random sample of SMEs. Moreover, the internal dimension of the DUI mode in particular, which is often overlooked in the literature, seems to play a greater role in lagging regions. The analysis of the individual DUI items instead of the aggregated dimensions then shows that the (intra-firm) freedom for *Trial-and-error learning* combined with an *Open communication culture* is an important predictor of innovation success in SMEs from lagging regions, but not in the nationwide sample. The relatively greater importance of the DUI mode in lagging regions is also particularly pronounced when it comes to organizational innovation outcomes. All in all, our results thus suggest that innovation by SMEs from lagging regions is strongly linked to DUI processes, which provides an indication of how firms can compensate for the unfavorable conditions of such a business environment. By focusing on external DUI processes, many previous studies on the regional dimensions of innovation modes have therefore most likely underestimated the importance of non-R&D innovation for economic development and (regional) growth.

Our findings have policy implications. First, in line with previous studies, the results of this paper suggest that R&D capacity is not the only main driver of SME innovation, especially in lagging regions. Therefore, in order to promote innovation capacity building, policy makers should also consider each of the different DUI dimensions ('DUI internal', 'DUI using', 'DUI external'). This in turn implies going beyond innovation policy in the narrow sense to a more holistic approach that includes links with other policy areas such as education or labour market policy and possibly also management practices. Furthermore, our results suggest that although external DUI learning processes of firms are generally less relevant in lagging regions, networks seem to be particularly important to compensate for the conditions of an unfavorable regional innovation environment. This confirms and supports policy approaches that aim to promote the networking of intra- and supra-regional actors, resources and competences in order to strengthen the innovative capacity of lagging regions. As our results also indicate a higher productivity of DUI learning in lagging regions, our paper also contributes to the understanding of how a DUI-oriented innovation policy can potentially contribute to reducing regional disparities.

From the perspective of innovation measurement practice, our results imply that a comprehensive empirical operationalization of the DUI mode requires a departure from the measurement approaches that have dominated the literature on innovation modes to date, which are often incomplete and measure the various DUI components only very roughly. Rather, future innovation surveys in this area should aim to take greater account of the 'DUI internal' and 'DUI using' dimensions. Moreover, as the Alhusen et al.'s (2021) item battery used and tested in this paper is too extensive to be used in most survey contexts, it remains a task for future research to develop a short, practical scale that is able to capture the DUI mode via quantitative innovation surveys. Such a more manageable short scale would help to better classify and monitor the innovation-driven development of lagging regions.

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Appendix

Table A.1: Descriptive statistics

Sample:			Germany-wide			Case regions		
Variable	Type	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
OUTCOME VARIABLES:								
Product innovation	Binary	Introduction of product or service innovations 2020-2022	400	0.623	0.485	530	0.536	0.499
Process innovation	Binary	Introduction of process innovation 2020-2022 (production processes, service provision processes, logistical processes; information processing procedures, supporting procedures for administration/management)	387	0.512	0.501	521	0.357	0.480
Organizational innovation	Binary	Introduction of organizational and marketing innovation 2020-2022 (methods for organizing business processes, work organization, marketing methods)	380	0.450	0.498	515	0.332	0.471
STI:								
Importance R&D	Ordinal	Importance of in-house R&D for innovation	400	2.342	1.535	530	2.177	1.478
Scientific knowledge	Ordinal	Importance of scientific and technical knowledge from own R&D or third-party R&D (incl. universities/universities of applied sciences/other research institutions) for innovation	400	2.507	1.404	530	2.449	1.411
DUI INTERNAL:								
I. Employed technology		Technological developments influence the learning processes in our company ...						
1. New technology introduction	Ordinal	- by introducing new technologies from outside (from other industries, companies, etc.) into our company.	400	3.188	1.374	530	2.804	1.391
2. Current technology improvement	Ordinal	- by technically improving existing machines and systems in the company.	400	2.728	1.456	530	2.525	1.451
II. Training		Regularly organized training courses strengthen our employees' knowledge and skills required for innovation activities ...						

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Table A.1 – *Continued from previous page*

Sample:			Germany-wide			Case regions		
Variable	Type	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
3. Training regarding general qualification	Ordinal	- by imparting generally important qualifications that are also useful outside the company.	400	3.248	1.351	530	3.217	1.386
4. Training regarding firm-specific qualifications	Ordinal	- by imparting company-specific qualifications that can only be used for the company's tasks.	400	3.373	1.358	530	3.221	1.447
III. Trial-and-error learning		In order to explore new opportunities for innovation and improvement in our company ...						
5. Scope for trial-and-error learning	Ordinal	- we give our employees the freedom to learn by trial and error.	400	3.570	1.216	530	3.406	1.333
6. Use of experience	Ordinal	- we rely on our experience.	400	3.812	1.020	530	3.898	1.018
7. Creativity in the workplace	Ordinal	- we rely on the creativity of our employees.	400	3.752	1.147	530	3.623	1.244
IV. Informal contacts and firm-internal relations		To enable our employees to exchange knowledge and learn new things ...						
8. Maintaining informal contacts within the firm	Ordinal	- we support the cultivation of informal contacts within the company.	400	3.945	1.164	530	3.730	1.375
10. Maintaining good relations within the firm	Ordinal	- we support the establishment of exchange relationships within the company that promote innovation.	400	3.465	1.293	530	3.191	1.454
11. Learning by observing	Ordinal	- we support learning from experienced employees through observation and imitation.	400	3.910	1.196	530	3.762	1.336
V. Mechanisms of knowledge exchange		In order to support the exchange of experience among our employees ...						
12. Regular team meetings	Ordinal	- regular team meetings are held.	400	3.495	1.453	530	3.185	1.564
13. Knowledge exchange among employees with different tasks	Ordinal	- regular meetings are held between employees from different areas of responsibility on innovation-related issues.	400	3.355	1.409	530	3.111	1.521
14. Open communication culture	Ordinal	- we promote a generally open communication and error culture.	400	4.165	1.138	530	3.909	1.366
VI. Human resource management tools		In order to strengthen the involvement of our company's employees in innovation projects ...						
15. Delegation and degree of autonomy	Ordinal	- employees are given their own decision-making powers and areas of responsibility.	400	3.928	1.173	530	3.685	1.374
17. Monetary incentives for idea disclosure	Ordinal	- we rely on tangible and intangible incentives for employees to contribute ideas and develop innovations.	400	3.022	1.383	530	2.842	1.417

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Table A.1 – *Continued from previous page*

Sample:			Germany-wide			Case regions		
Variable	Type	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
18.+19. Knowledge & idea management	Ordinal	- we rely on organizational measures for the efficient use of existing know-how (knowledge management, suggestion scheme, etc.).	400	3.243	1.252	530	3.008	1.379
DUI USING:								
VII. Cooperation with customers		Our cooperative relationships with customers ...						
20.+22.+23. Competent customers	Ordinal	- focus on innovation-oriented customers who are particularly competent in our field of business.	400	2.815	1.386	530	2.751	1.349
21.+24. Intensity & duration of customer contact	Ordinal	- are intensive, based on trust and as long-term as possible.	400	4.277	1.069	530	4.123	1.203
VIII. Customer contact		In order to give our customers the opportunity to influence innovations and improvements to the company as part of customer contact ...						
25. Organizational area of cooperation with customers	Ordinal	- we ensure internally that customer knowledge reaches the relevant places in the company.	400	3.775	1.224	530	3.579	1.376
26. Active request for feedback	Ordinal	- we actively ask them for feedback on their experiences of using new products/services.	400	3.223	1.443	530	3.094	1.487
27. Use of customer support	Ordinal	- we use the personal exchange during customer support.	400	3.925	1.238	530	3.785	1.304
28. Use of social media	Ordinal	- we make use of social media.	400	2.422	1.463	530	2.374	1.428
IX. Product specification		In order to satisfy our customers in terms of product specification ...						
29. Customized products	Ordinal	- we develop products or services that are specifically adapted to the wishes and needs of individual customers.	400	3.655	1.423	530	3.56	1.463
30.+31. Additional or complementary products and services	Ordinal	- we offer additional or complementary products/services.	400	3.522	1.369	530	3.311	1.448
32. Customer involvement	Ordinal	- we involve the customer in the development and adaptation of products/services.	400	3.255	1.472	530	2.921	1.490
DUI EXTERNAL:								
X. Interaction with suppliers		When we work with our suppliers or subcontractors, we focus on ...						

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Table A.1 – *Continued from previous page*

Sample:			Germany-wide			Case regions		
Variable	Type	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
33. Innovation cooperation with suppliers	Ordinal	- cooperation in the area of innovation.	400	2.885	1.327	530	2.730	1.357
34. Suppliers' competences	Ordinal	- learning from their expertise in order to obtain innovation-relevant information on new materials, processes, etc.	400	3.340	1.356	530	3.142	1.390
35. Supplier relationship	Ordinal	- a close relationship based on trust.	400	4.207	1.064	530	3.983	1.305
XI. Interaction with competitors		As part of our innovation activities, we benefit from our competitors ...						
36. Competitor relationship	Ordinal	- by learning from their successes and failures.	400	3.462	1.286	530	3.453	1.334
37. Competitive pressure	Ordinal	- in that we have an incentive to innovate due to the mutual competitive relationship.	400	2.975	1.367	530	3.017	1.362
XII. Interaction with intra-sectoral firms		As part of our innovation activities, we benefit from other companies in our industry ...						
38. Innovation cooperation within the sector	Ordinal	- by maintaining an innovation cooperation with them.	400	2.195	1.321	530	2.130	1.297
39. Intra-sectoral relationship	Ordinal	- by maintaining a close and trusting relationship.	400	2.938	1.374	530	2.774	1.429
XIII. Interaction with extra-sectoral firms		As part of our innovation activities, we benefit from companies from other sectors ...						
40. Innovation cooperation across sectors	Ordinal	- by maintaining an innovation cooperation with them.	400	2.183	1.301	530	2.125	1.284
41. Extra-industry relationship	Ordinal	- by maintaining a close and trusting relationship.	400	2.775	1.423	530	2.609	1.455
XIV. Interaction with consultancies and service providers		As part of our innovation activities, we benefit from consulting firms and other public and non-public service providers ...						
42. Innovation cooperation with consultancies/service providers	Ordinal	- by maintaining an innovation cooperation with them.	400	1.923	1.231	530	1.706	1.119
43. Relation with consultancies/service providers	Ordinal	- by maintaining a close and trusting relationship.	400	2.310	1.435	530	2.079	1.345
44. Collaboration financing	Ordinal	- by gaining better access to external funding.	400	1.815	1.204	530	1.594	1.036
45. Importance of innovation awards	Ordinal	- by achieving greater visibility by participating in innovation award ceremonies.	400	1.520	0.978	530	1.440	0.923

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Table A.1 – *Continued from previous page*

Sample:			Germany-wide			Case regions		
Variable	Type	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
XV. Trade associations and networks		As part of our innovation activities, we benefit from trade associations, chambers and networks ...						
46. Participation in network events	Ordinal	- by participating in networking events to gain access to new external knowledge.	400	2.712	1.456	530	2.468	1.464
47. Importance of network relations	Ordinal	- by maintaining good relationships and regular interactions with our network partners.	400	2.768	1.431	530	2.498	1.437
CONTROLS:								
Population density	Metric	Inhabitants per km^2 in 2020 (from INKAR database)	400	868.196	1133.434	530	652.894	728.442
Number of employees	Metric	Number of employees	400	17.824	32.074	530	11.709	25.917

Table A.2: Industry composition of the two samples

	Germany-wide		Case regions	
Industry	#firms	Share(%)	#firms	Share(%)
C - manufacturing	60	15.00	61	11.51
D - energy supply	3	0.75		
E - water supply; sewage and waste disposal and removal of environmental pollution	3	0.75		
F - construction	80	20.00	62	11.70
G - trade; repair and maintenance of motor vehicles	80	20.00	112	21.13
H - transportation and warehousing	20	5.00	18	3.40
I - hospitality industry	4	1.00		
J - information and communication	33	8.25	31	5.85
K - provision of financial and insurance services	12	3.00	39	7.36
L - real estate and housing	20	5.00	31	5.85
M - provision of freelance, scientific and technical services services	60	15.00	110	20.75
N - provision of other business services	13	3.25	37	6.98
Q - health and social services	1	0.25		
R - art, entertainment and recreation	2	0.50		
S - provision of other services	9	2.25	29	5.47

Notes: Classification of main product group according to Statistisches Bundesamt (2008).

Table A.3: Selection frequency of DUI dimensions excluding the case regions

	Innovation outcome		
DUI dimension	Product	Process	Orga
internal	0.326	0.254	0.191
using	0.298	0.239	0.094
external	0.177	0.102	0.128
N	380	370	363

Notes: Based on Equation 8 computed for the Germany-wide random sample excluding the case regions.

Table A.4: Selection frequency of DUI dimensions excluding *New technology introduction*

	Innovation outcome		
DUI dimension	Product	Process	Orga
PANEL A:	*Germany-wide sample*		
internal	0.286	0.164	0.101
using	0.260	0.205	0.038
external	0.205	0.086	0.064
N	400	390	383
PANEL B:	*10 lagging case regions*		
internal	0.314	0.215	0.342
using	0.338	0.209	0.218
external	0.123	0.174	0.267
N	530	521	515

Notes: Based on Equation 8 without the variable *New technology introduction*.

Figure A.1: Group lasso estimates - Product innovation

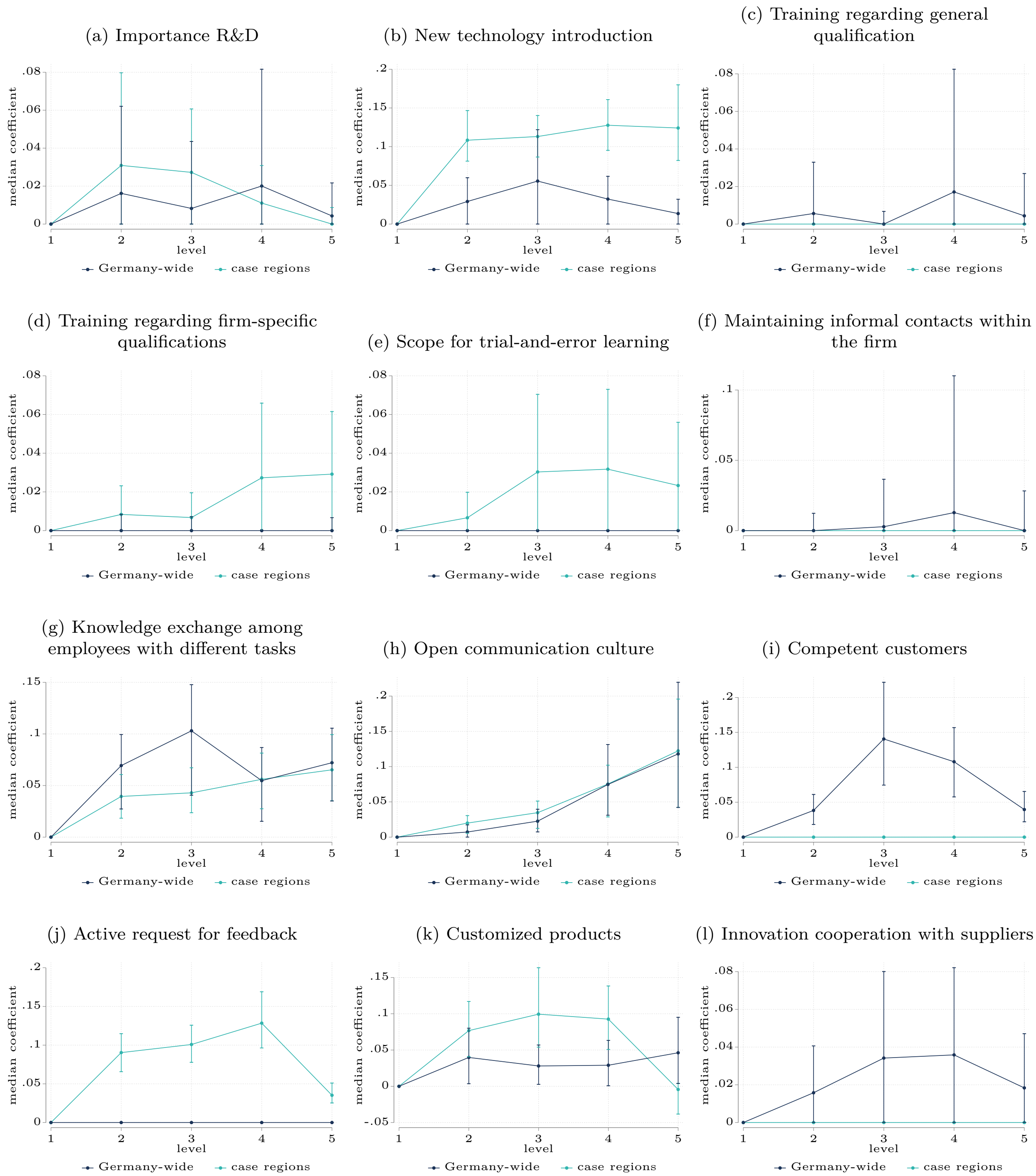
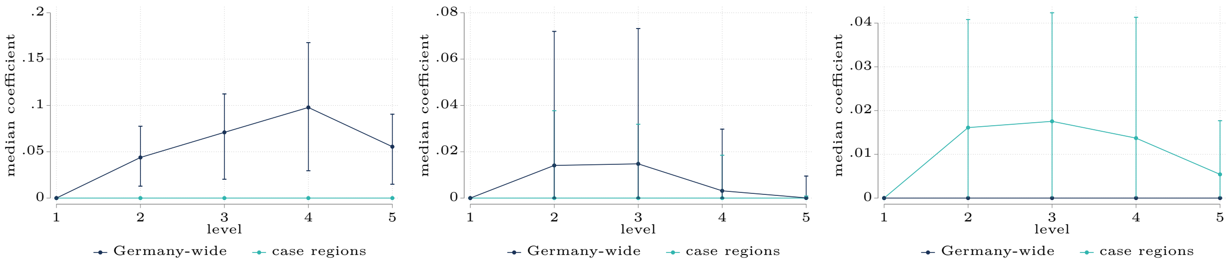


Figure A.1: (continued) Group lasso estimates - Product innovation

(m) Suppliers' competences

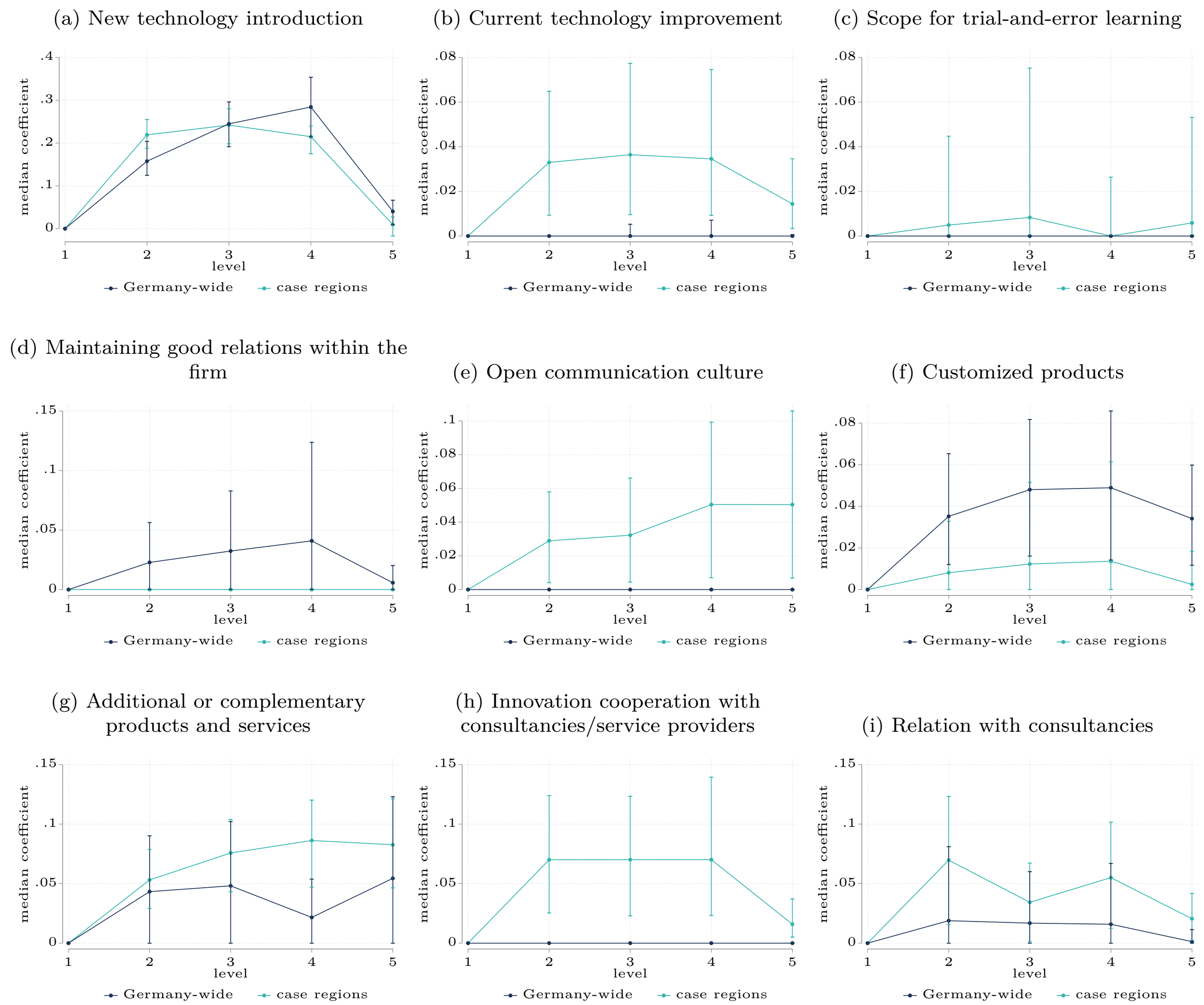
(n) Innovation cooperation with consultancies/service providers

(o) Importance of network relations



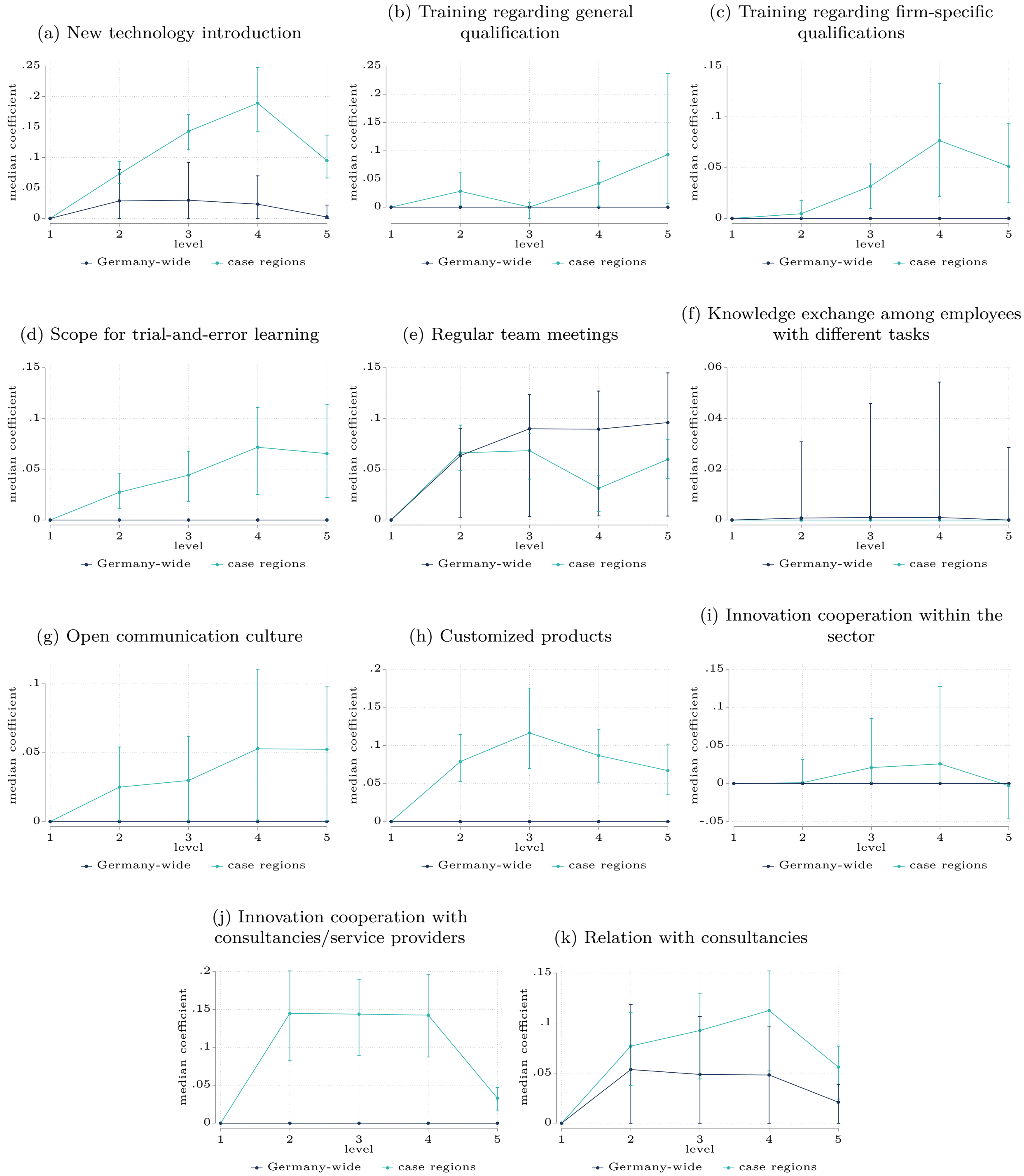
Notes: Median regression coefficients (y-axis) and 25th and 75th percentiles for each of the five levels (x-axis) of the covariates from Table 4, with product innovation as the outcome variable and level 1 as the reference category. The sub-figures are ordered according to Table A.1.

Figure A.2: Group lasso estimates - Process innovation



Notes: Median regression coefficients (y-axis) and 25th and 75th percentiles for each of the five levels (x-axis) of the covariates from Table 4, with process innovation as the outcome variable and level 1 as the reference category. The sub-figures are ordered according to Table A.1.

Figure A.3: Group lasso estimates - Organizational innovation



Notes: Median regression coefficients (y-axis) and 25th and 75th percentiles for each of the five levels (x-axis) of the covariates from Table 4 with organizational innovation as the outcome variable and level 1 as the reference category. The sub-figures are ordered as in Table A.1.

Table A.5: Loadings from PCA with varimax rotation

Sample:	Germany-wide				Case regions			
Variable	DUI internal	DUI using	DUI external	unexpl.	DUI using	DUI internal	DUI external	unexpl.
New technology introduction	0.075	0.115	0.070	0.724	0.129	0.089	0.015	0.726
Current technology improvement	0.093	0.108	0.048	0.734	0.108	0.086	0.004	0.794
Training regarding general qualification	0.199	0.020	0.059	0.618	0.008	0.166	0.109	0.676
Training regarding firm-specific qualifications	0.165	0.066	-0.001	0.711	-0.002	**0.225**	0.039	0.629
Use of experience	0.070	0.079	-0.087	0.922	0.031	0.068	-0.116	0.940
Scope for trial-and-error learning	**0.308**	-0.037	-0.010	0.472	0.100	**0.223**	-0.065	0.509
Creativity in the workplace	**0.264**	-0.008	-0.008	0.568	0.150	0.174	-0.093	0.547
Maintaining informal contacts within the firm	**0.311**	-0.018	-0.020	0.437	-0.034	**0.319**	0.029	0.376
Maintaining good relations within the firm	**0.312**	-0.023	0.022	0.379	0.010	**0.294**	0.029	0.372
Learning by observing	**0.279**	0.000	-0.050	0.548	0.020	**0.298**	-0.057	0.432
Regular team meetings	**0.265**	0.004	-0.009	0.541	-0.087	**0.315**	0.085	0.412
Knowledge exchange among employees with different tasks	**0.273**	-0.013	0.034	0.486	-0.052	**0.317**	0.063	0.372
Open communication culture	**0.292**	0.017	-0.055	0.472	-0.023	**0.336**	-0.036	0.362
Delegation and degree of autonomy	**0.287**	-0.021	-0.005	0.512	0.036	**0.295**	-0.074	0.422
Monetary incentives for idea disclosure	**0.215**	0.007	0.043	0.625	0.061	**0.224**	-0.012	0.553
Knowledge & idea management	**0.248**	0.018	0.024	0.522	0.053	**0.232**	0.022	0.504
Competent customers	0.048	0.146	0.072	0.708	**0.243**	-0.035	-0.008	0.658
Intensity & duration of customer contact	-0.025	**0.321**	-0.094	0.598	**0.209**	0.046	-0.100	0.695
Active request for feedback	0.049	**0.267**	-0.029	0.533	**0.244**	0.015	-0.008	0.568
Use of customer support	-0.020	**0.379**	-0.089	0.400	**0.274**	0.044	-0.074	0.470
Organizational area of cooperation with customers	0.022	**0.333**	-0.044	0.401	**0.247**	0.057	-0.032	0.493
Use of social media	0.038	0.026	0.169	0.773	0.091	0.002	0.156	0.754
Customized products	-0.024	**0.283**	0.018	0.578	**0.291**	-0.014	-0.099	0.552
Additional or complementary products and services	-0.027	**0.307**	0.004	0.534	**0.261**	-0.005	-0.011	0.552
Customer involvement	-0.031	**0.280**	0.076	0.491	**0.286**	-0.028	-0.013	0.508
Innovation cooperation with suppliers	0.116	0.095	0.095	0.618	**0.272**	-0.062	0.061	0.504
Suppliers' competences	0.078	0.192	0.002	0.634	**0.272**	-0.028	0.023	0.508
Supplier relationship	0.037	**0.220**	-0.050	0.717	**0.245**	-0.030	-0.034	0.672
Competitor relationship	0.004	0.174	0.069	0.732	0.188	-0.012	0.060	0.698
Competitive pressure	0.063	0.092	0.108	0.730	0.140	0.001	0.121	0.706
Innovation cooperation within the sector	-0.051	0.103	**0.280**	0.474	0.129	-0.050	**0.234**	0.560
Intra-sectoral relationship	-0.072	0.188	0.188	0.568	0.176	-0.041	0.166	0.578

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Table A.5 – *Continued from previous page*

Sample:	Germany-wide				Case regions			
Variable	DUI internal	DUI using	DUI external	unexpl.	DUI using	DUI internal	DUI external	unexpl.
Innovation cooperation across sectors	-0.060	0.136	**0.269**	0.447	0.155	-0.052	**0.246**	0.457
Extra-industry relationship	-0.040	0.172	0.197	0.533	0.182	-0.042	0.186	0.513
Innovation cooperation with consultancies/service prov.	0.007	-0.038	**0.359**	0.391	-0.020	0.014	**0.370**	0.411
Relation with consultancies/service prov.	-0.021	0.005	**0.334**	0.451	-0.015	0.027	**0.338**	0.483
Collaboration financing	-0.034	-0.066	**0.359**	0.484	-0.029	-0.021	**0.348**	0.538
Importance of innovation awards	0.013	-0.081	**0.351**	0.470	-0.019	-0.032	**0.370**	0.472
Participation in network events	0.072	-0.116	**0.294**	0.591	-0.071	0.087	**0.284**	0.615
Importance of network relations	0.058	-0.068	**0.284**	0.588	-0.052	0.078	**0.309**	0.538

Table A.6: Average marginal effects from probit regressions with preceding PCA

Innovation outcome:	Product	Process	Orga
PANEL A:		*Germany-wide*	
DUI_internal	0.032***	0.013	0.039***
DUI_using	0.030**	0.047***	0.031*
DUI_external	0.018	0.004	0.023
Importance R&D	0.034*	0.036	0.020
Scientific knowledge	-0.033*	-0.010	-0.045
Number of employees	0.001	0.001	0.002
Population density	-0.000	-0.000*	-0.000
N	385	386	357
PANEL B:		*10 lagging case regions*	
DUI_internal	0.029**	0.031***	0.041***
DUI_using	0.027***	0.017**	0.015
DUI_external	0.015	0.023**	0.035***
Importance R&D	0.029***	0.021	0.019
Scientific knowledge	-0.002	-0.020	-0.025
Number of employees	0.001	0.003***	0.002**
Population density	-0.008***	0.033***	0.005*
N	530	521	515

Notes: The importance R&D and scientific knowledge are treated as metric. The three DUI variables are generated by PCA enforcing a three-component solution. Region and industry dummies are included. Standard errors are clustered at the level of NUTS2 regions and case regions respectively.