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Measuring drivers of innovation beyond R&D: The case of SMEs in lagging regions

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Abstract

This paper examines the role of learning by doing, using and interacting (DUI) in SME innovation, with a particular focus on lagging regions, thus combining two settings characterized by a comparatively limited role of formal R&D. To capture DUI beyond its common conceptualization as interaction with external actors, we operationalize and test a comprehensive set of indicators covering internal, user-driven, and external learning processes. Using original survey data and Lasso regression as a data-driven selection technique suited to a large set of potential predictors, we identify a broad range of DUI learning practices associated with SME innovation, extending well beyond external interaction. Firm-internal learning practices feature most prominently in our results. This pattern is even more pronounced in lagging regions, pointing to their potential role in enabling firms to cope with less favorable conditions in their regional innovation environment.

JEL classification codes: C50, C81, O3, O31, R11
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1 Introduction

A growing body of research suggests that a research and development (R&D)-oriented innovation policy does not reduce regional inequalities; in fact, it has the opposite effect (Boschma et al., 2025; Fitjar, 2025). Moreover, it is well established that innovation works differently in lagging regions than in leading ones, with the relevance of different innovation inputs and capabilities varying across regional contexts (Ganau and Grandinetti, 2021). Policies effective in advanced regions may therefore not translate well to less-developed contexts (Filippopoulos and Fotopoulos, 2022; Hädrich et al., 2024; Hervás-Oliver et al., 2021). However, little attention has been given to systematically identifying and measuring the factors associated with innovation in lagging region contexts although this is precisely what is needed in order to develop suitable policy measures aimed at reducing regional inequality that are 'place-sensitive' (Iammarino et al., 2019, p.274). In this paper, we therefore operationalize and empirically test a comprehensive set of indicators beyond formal R&D for the first time, capturing internal, user-driven, and external learning processes in a comprehensive way.

Lagging regions are typically characterized by low private investment in formal R&D, the absence of large companies, and low patent output. In addition to lacking cutting-edge firms, public research infrastructure, and other innovation-related resources, they often fail to benefit from agglomeration economies (Broekel et al., 2023). Despite these disadvantages, innovation does occur in such contexts (Fritsch and Wyrwich, 2021; Glückler et al., 2023; Kesidou et al., 2024). Given the relative scarcity of large firms (Bischoff et al., 2024; Hädrich et al., 2024), small and medium-sized enterprises (SMEs) are a key player in driving change through innovation in lagging regions (Hervás-Oliver et al., 2021).

The majority of SME innovation is defined by informal learning and innovation practices that do not rely on formal R&D, with previous research identifying distinct patterns of R&D- and non-R&D-based innovation (Spescha and Woerter, 2019; Trigo, 2013). More generally, firms' learning capabilities are widely recognized as a prerequisite for innovation and for increasing the novelty of innovation outcomes, particularly among SMEs (Amara et al., 2008). These practices are anchored in what Jensen et al. (2007) label the DUI ('Learning by Doing, Using and Interacting') innovation mode. This encompasses a wide range of learning and innovation practices, including interaction with customers and suppliers, access to new equipment (Hervás-Oliver et al., 2014; Rammer et al., 2009), collaboration (Bjerke and Johansson, 2015; Fitjar and Rodríguez-Pose, 2013; Grillitsch and Nilsson, 2015), and learning-by-doing (Gertler, 2003). As the DUI approach goes beyond a narrow focus on R&D-based learning to explain how SMEs learn and innovate, it enables a deeper understanding of innovation in lagging regions (Bischoff et al., 2024; Doloreux and Shearmur, 2023; Filippopoulos and Fotopoulos, 2022; Hädrich et al., 2024; Heidenreich, 2009; Hervás-Oliver et al., 2021; Lopez-Rodriguez and Martinez-Lopez, 2017; Reher et al., 2024).

While there is growing recognition that this conception of SME innovation is critical to understanding and explaining the heterogeneity found in regional innovation patterns (Isaksen and Trippl, 2017), R&D support — exemplified by programs such as Horizon Europe — still remains the "cornerstone of EU innovation policy" (Hervás-Oliver et al., 2021, p.3). This prevailing paradigm (Edler and Fagerberg, 2017) not only overlooks firms innovating through non-R&D activities (Hervás-Oliver et al., 2011; Hirsch-Kreinsen, 2008) but also risks reinforcing regional inequalities (Boschma et al., 2025), for instance by channeling public R&D funds to regions that are already well-endowed (Fitjar, 2025). To address this imbalance, a thorough understanding of the DUI mode of innovation is required, particularly in lagging region contexts. However, the current literature lacks a systematic measurement of DUI-related learning — a prerequisite for stronger acknowledgment of DUI in innovation policy practice.

The innovation mode framework by Jensen et al. (2007) constitutes a major step in distinguishing between the STI mode ('Learning by Science, Technology and Innovation'), which is based on R&D and corresponding knowledge inputs, and the DUI mode, which emphasizes experiential and interaction-based learning. Measuring DUI-related innovation activities, however, is more challenging than in the case of STI - not least due to the informal nature of less or non-R&D-based innovation activities. Previous studies in the literature often narrowly focus on external interactions because the corresponding indicators are more easily available. However, this approach misses key aspects of DUI such as internal and organizational aspects (e.g. Apanasovich et al., 2016; Fitjar and Rodríguez-Pose, 2013; Haus-Reve et al., 2019, 2023; Parrilli and Heras, 2016). This is particularly problematic because innovation depends not only on firms' access to external knowledge but also on their internal learning processes and capabilities to absorb, combine, and exploit knowledge (Roper and Love, 2018). To address this gap, recent work by Alhusen et al. (2021) attempts to overcome this selective

approach by conceptually defining all DUI dimensions and proposing a comprehensive set of indicators.

Building on this, our study aims to enhance the measurement of innovation activities among SMEs in lagging regions. We contribute to the literature by being the first to operationalize and test a comprehensive set of indicators beyond formal R&D, capturing internal, user-driven, and external learning processes in a systematic way. We have therefore incorporated the 47 innovation indicators conceptualized by Alhusen et al. (2021) into a dedicated innovation survey. Our next contribution is the use of an Ordinal Group Lasso approach, a novel method in innovation research that allows us to identify key predictors of innovation outcomes while retaining the ordinal structure of our indicators and reducing dimensionality in a theoretically informed way. Finally, given the particular importance of DUI in lagging regions (e.g. Bischoff et al., 2024; Hädrich et al., 2024; Hervás-Oliver et al., 2021; Reher et al., 2024), our analysis sheds light on hitherto overlooked DUI capabilities that are critical in these innovation contexts, thereby challenging the dominant external-collaboration focus in the existing literature.

Our findings show that the previously underexplored components — such as learning-by-doing, internal interaction, and learning-by-using — are frequently selected as predictors of SME innovation in general, and in lagging regions in particular. The Lasso results imply that moving beyond partial DUI measurement approaches is important, as they often fail to adequately represent intra-firm learning processes. Overall, our results suggest that non-R&D learning activities are relevant correlates of innovation outcomes under structural constraints. Prior studies that focus primarily on external interaction may therefore have underestimated the developmental potential of non-R&D innovation in lagging regions. Finally, our results also provide guidance for the design of future surveys by highlighting the key facets of SME innovation that merit systematic inclusion.

2 Conceptual background

2.1 DUI Measurement

Innovation measurement has long been characterized by a broad variety of indicators and operationalizations, reflecting the multidimensional nature of innovation and the diversity of underlying innovation processes (Dziallas and Blind, 2019). These challenges are particularly evident in the measurement of DUI learning, where previous empirical studies vary considerably in both indicator selection and methodology. Two main approaches dominate. First, many studies focus on a few selectively chosen DUI activities — typically external DUI interactions such as with suppliers or competitors (e.g. Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016). This selective focus neglects internal learning processes and learning-by-using activities. Moreover, even within the external dimension, firms may access knowledge through different forms of interaction, ranging from informal information sourcing to formal collaboration (Freitas et al., 2011). Likert-scale survey items are frequently reduced to binary variables (e.g. Doloreux and Shearmur, 2023; Parrilli and Radicic, 2021), which simplifies analysis but discards valuable variation. While such a minimalistic approach is compatible with short or pre-existing surveys and avoids model complexity, it fails to capture the full scope of DUI, particularly intra-firm learning dynamics (Alhusen et al., 2021; Haus-Reve et al., 2023).

The second approach combines multiple DUI indicators into composite variables, either by aggregating binary items (e.g. Haus-Reve et al., 2023; Parrilli et al., 2020) or by applying dimensionality-reduction techniques such as factor or principal component analysis (e.g. Bischoff et al., 2023; Runst and Thomä, 2022; Thomä, 2017). While this strategy captures a broader range of DUI aspects, including internal learning, it remains constrained by the availability and consistency of available survey items. Moreover, collapsing items into latent factors prevents the assessment of how specific DUI activities are related to innovation outcomes.

As a result, existing measurements of the DUI mode have often been ad hoc and fragmented, resulting in inconsistent coverage of its key dimensions. To overcome this limitations, Alhusen et al. (2021) developed a comprehensive framework based on 81 interviews with SME stakeholders. They propose 47 indicators across 15 categories, mapped to three core DUI dimensions: (i) learning-by-doing (incl. 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, 2015; 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.[1]

In practice, none of these three dimensions has been fully captured in prior empirical studies (see the literature reviews of Apanasovich (2016); Santos et al. (2022)). This problem is particularly pronounced for internal DUI, which is often neglected. Many studies focus exclusively on external DUI interactions (Fitjar and Rodríguez-Pose, 2013; Haus-Reve et al., 2019; Matsiuk et al., 2024; Parrilli and Heras, 2016; Wassmann et al., 2016). 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. Due to measurement constraints, they do not capture the corresponding role of learning-by-doing and learning through internal interaction between employees, however. Conversely, some studies focus narrowly on internal DUI processes (e.g. Parrilli and Elola, 2012). While not explicitly using the label 'DUI-internal', this includes studies on the innovation impact of human resources within the firm through learning-by-doing and learning-by-internal-interaction (see Haus-Reve et al. (2023) for more details). A few recent studies have started to broaden the empirical coverage of DUI by considering both internal and external knowledge and learning processes (Doloreux and Shearmur, 2023; Haus-Reve et al., 2023; Marzucchi and Montresor, 2017; Parrilli and Radicic, 2021), yet measurement remains selective. Typically, these studies rely on a limited set of available survey items, often dichotomized or aggregated, which reduces variation and may obscure the contributions of specific DUI activities. Consequently, measurement approaches differ substantially across studies, and so do the estimated relationships between DUI dimensions and innovation, which appear to vary by outcome type and regional context (Alhusen et al., 2021; Doloreux and Shearmur, 2023). For example, Parrilli and Radicic (2021) stress the importance of internal DUI drivers for innovation in micro-, small- and medium-sized firms irrespective of innovation outcome, although their analysis yields the largest coefficients of internal DUI in the case of product innovation. According to their results, cooperation with customers is most beneficial for marketing innovations, while cooperation with other firms is most associated with organizational innovations. Haus-Reve et al. (2023) find that internal DUI and external DUI have a significant positive effect on product and a slightly smaller effect on process innovation, while external DUI contributes more to both types of innovation. Further, they provide evidence for a substitutional relationship between internal DUI and external DUI or internal STI, respectively. Doloreux and Shearmur (2023) find a positive association of internal DUI with all types of innovation and all geographical contexts, being more important for non-technological innovations and in non-metropolitan areas, while they do not find any significant positive association between external DUI and innovation. It is unclear to what extent these mixed findings are the result of differences in measurement approaches.

In summary, previous empirical studies show an incomplete and inconsistent measurement of the DUI mode. They fail to capture all three dimensions of DUI comprehensively: learning-by-doing (including internal interaction), learning-by-using and learning-by-external-interaction. Their measurement approaches often lack strong theoretical grounding and are fragmented and selective. They are also often overly simplified (e.g. indicators are dichotomized or aggregated), which obscures the relationships between specific DUI activities and innovation outcomes and limits comparability across studies.

2.2 Modes of Innovation: From the firm to the regional level

Originally developed with the firm level in mind, innovation mode theory has been widely applied to analyze corporate learning and business innovation behavior (for an overview, see Apanasovich, 2016; Santos et al., 2022). This literature yields two key findings that underscore the importance of adopting a comprehensive DUI measurement approach. First, the impact of the DUI mode varies by innovation type. While it contributes to product innovations — including those eligible for patenting (e.g. Haus-Reve et al., 2019, 2023; Jensen et al., 2007), it is especially effective for process, incremental, new-to-firm, and non-technological innovations (e.g. Fitjar and Rodríguez-Pose, 2013; Parrilli et al., 2020; Parrilli and Heras, 2016; Wassmann et al., 2016)). Secondly, although DUI is particularly relevant for SMEs, especially those with a lower R&D intensity, it is important for innovation in firms in general, regardless of their STI intensity. This reflects the

[1] 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.

fact that, in practice, DUI and STI should not be viewed as distinct modes, but rather as a continuum of various learning practices that can be combined in various ways (e.g. Alhusen and Bennat, 2021; Apanasovich et al., 2016; Parrilli and Radicic, 2021; Runst and Thomä, 2022; Thomä, 2017; Thomä and Zimmermann, 2020). For example, even within the realm of technological knowledge, the relative importance of scientific and other knowledge sources has been shown to vary across innovation regimes (Gilsing et al., 2011).

These insights highlight the potential of applying the innovation mode framework of Jensen et al. (2007) in a regional context: Regions with low private R&D investment, a focus on process innovation, and a lack of large firms — typical characteristics of lagging regions (Alecke et al., 2021; Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021; Pelkonen and Nieminen, 2016; Reher et al., 2024) — are likely to be relatively more dependent on DUI innovation (Hädrich et al., 2024). The elevated importance of DUI for lagging regions is supported by the literature on the dominant knowledge-bases of regional innovation systems (Asheim and Coenen, 2005). Lagging regions are typically characterized by a synthetic knowledge base (see e.g. Blažek and Kadlec, 2019), which both drives and emerges from DUI-based learning and innovation at the firm level (Hädrich et al., 2024). The innovation mode approach thus links firm-level learning processes to the knowledge-based development of regional innovation systems, providing a "missing piece of the innovation puzzle in lagging regions" (Hädrich et al., 2024). Advancing the understanding and measurement of DUI in these regions is therefore particularly important for regional development policy, as it identifies the micro-foundations and policy levers for fostering effective, innovation-driven growth. This perspective might then imply, for example, that a narrow focus on external DUI risks overlooking other DUI policy channels that could also effectively support innovation in lagging regions, analogous to evidence that R&D policy may exacerbate spatial inequalities (Fitjar, 2025).

Recent studies increasingly incorporate the regional dimension into innovation mode research (e.g. Bischoff et al., 2024; Doloreux et al., 2023, 2024; Hervás-Oliver et al., 2021; 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. (2024)). Yet the measurement issues highlighted above remain unresolved. For example, Hervás-Oliver et al. (2021) draw on RIS data that does not clearly distinguish between external STI and DUI, while Doloreux et al. (2023) — despite conceptually differentiating internal and external DUI — rely on a single composite DUI measure due to data limitations. Improving both the coverage and the distinction of the three DUI dimensions therefore remains a key empirical challenge, particularly for research on innovation in lagging regions.

For example, better measurement of the often-overlooked internal DUI dimension (see Section 2.1) would be crucial to understanding innovation in lagging regions as it may serve as a compensatory mechanism for SMEs (Flåten et al., 2015; Weidner et al., 2023). Given their limited R&D capacity and scarce regional knowledge inputs, such firms may strengthen their absorptive capacities through employee autonomy and intra-firm collaboration. Supporting this, Doloreux and Shearmur (2023) find that internal DUI is particularly relevant for non-technological innovation and in non-metropolitan settings. At the same time, extra-regional DUI collaboration may help compensate for local resource gaps (Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021).[2] These findings underscore the need for a comprehensive measurement approach to capturing DUI-related innovation activities. This is particularly important given current policy ambitions to support the innovation-driven development of lagging regions. The latter tend to rely more heavily on DUI-based learning and are therefore disproportionately affected by the inherent difficulties of measuring DUI activities and the shortcomings of prevailing measurement practices.

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 ("NUTS3"). 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

[2]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).

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.[3] 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.[4] 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. In Sample 2, 62.75 per cent of the firms are located in non-lagging regions.[5]

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/States 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.[6] 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, 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 user-driven') 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 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); 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

[3]The project is entitled "XXXXX, funded by the Federal Ministry of Education and Research (BMBF)", XXXXX and XXXXX

[4]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).

[5]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.

[6]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

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 modified 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.[7] Lasso is a data-driven procedure for selecting a subset of relevant predictors among a large set of candidate regressors. However, as a predictive variable selection method, it does not provide a basis for causal inference. Lasso selects variables based on their contribution to predictive performance, capturing correlations with the outcome rather than causal effects.[8] 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:

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

with

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

[8]Variables may be chosen because they proxy for unobserved factors or are jointly correlated with other relevant variables. In the presence of multicollinearity, Lasso may also arbitrarily select one variable while excluding others, without reflecting the underlying causal structure.

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

However, in order to incorporate the ordinal scale of our DUI variables (and the two variables *Importance of R&D* and *Scientific knowledge*), 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 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.[9]

Second, since the group lasso method as such does not account for the ordinal scale of the majority of our 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 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 variables are

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

split-coded using the `coding()` function from the R-package `ordPens`[10]. 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 variables (all DUI variables, *Importance of R&D*, and *Scientific knowledge*), 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.[11] 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 estimations:

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

In other words, the frequency measure F_i captures the share of estimations in which an indicator is selected by the model. Furthermore, as we are 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 $d \in \{\text{internal, user-driven, external}\}$ 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

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

The resulting selection frequencies should be interpreted as an indication of how consistently an indicator contributes to innovation prediction when the model is estimated repeatedly. While a high frequency indicates stable predictive relevance, it does not automatically imply a large effect, economic importance or a causal role. As the internal dimension contains 16 indicators, the indicators in this case could be selected a total of 1,600 times in the course of 100 estimations. In contrast, there are only 9 indicators in the user-driven dimension, and they could therefore only be selected 900 times in 100 estimations. Our frequency measure F_d therefore normalizes the share of estimations in which an indicator i from dimension d is selected by the model by the total number of indicators i in each dimension. F_d has a minimum of zero (none of the variables

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

[11] 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.

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

Table 3 shows the frequency measures F_d at the level of three DUI dimensions, calculated from the Lasso regression results. As mentioned above, these findings reflect patterns of association rather than causal relationships, and the selection frequencies should be interpreted as indicators of predictive relevance rather than effect sizes or economic importance. Irrespective of whether the sample consists of companies randomly 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 related to 'DUI internal' and 'DUI user-driven' 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.

Table 3: Selection frequency of DUI dimensions

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

Notes: Only results for DUI are presented here based on Equation 8. In addition, Table A.5 displays individual variables selected by Lasso for each innovation outcome and sample, sorted by their item-selection frequency F_i.

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 suggests that the external dimension plays a comparatively smaller role in the set of frequently selected predictors for product innovation in lagging regions. One possible interpretation is that external DUI activities are less strongly associated with product innovation in lagging regions because SMEs in these regions lack opportunities for external collaboration and consequently struggle to utilize external resources for this purpose. When we move beyond the selection-frequency of the three dimensions - by analyzing the selection of the 47 underlying individual items instead (see A.5) - another key insight emerges in this regard. The three external predictors for product innovation that are selected in the overall sample but not the lagging region sample are related to suppliers and consultants. In contrast, the predictor "importance of network relations" is only selected in the lagging region sample. Thus, while the external dimension appears to be less prominent among the frequently selected predictors in lagging compared to more advanced regions, the results also point to a qualitative difference in the types of external DUI variables associated with product innovation across contexts.

These patterns are consistent with the interpretation that the lack of regionally available innovation stimuli in lagging regions - due to fewer opportunities for exchange with suppliers and consultants and thus fewer regional knowledge spillovers - may be associated with strong constraints on product innovation in corresponding business environments. However, our data do not allow us to identify the underlying mechanisms or the spatial scope of these interactions directly. One possible interpretation is that product innovators in lagging regions either compensate for the lack of external stimuli by relying on customer interaction (local or otherwise), or develop 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. Alternatively, firms may draw on different types of external resources, such as networks that are unrelated to suppliers or consultants, or non-local networks, consistent with previous research showing that firms pursuing different innovation modes rely on different types of partners (Chen et al., 2011).

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 context. These innovators may either rely on less proximate external interaction or use (external) intra-regional interaction more productively. Unfortunately, we cannot distinguish between these two interpretations, nor can we consider 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 the Germany-wide sample. This pattern 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 strongly associated with innovation outcomes among SMEs in lagging regions, as "[...] companies innovating in a less-R&D-oriented knowledge environment heavily rely on organizational and marketing activities" (p. 1336 Thomä, 2017). Moreover, this finding should be interpreted in line with the empirical evidence that organizational learning is often a prerequisite for subsequent engagement in technological innovation (Camisón and Villar-López, 2014; Haned et al., 2014; Mothe et al., 2015).

5 Robustness

To complement the Lasso-based selection frequencies, which capture predictive relevance rather than effect sizes, we also estimate regressions based on DUI dimensions derived by Principal Component Analysis (PCA). This provides additional evidence regarding the direction and statistical significance of broader DUI constructs. Moreover, it could be argued that the theory-driven classification by Alhusen et al. (2021) is somewhat subjective, and therefore contestable. For example, 'DUI user-driven' could also be considered an aspect of 'DUI external', as it relates to interactive learning with the customer side, suggesting that the two could be grouped together. Therefore, as a robustness check, we additionally apply PCA as an exploratory approach to empirically derive the three DUI dimensions and to examine potential interactions between them. The loadings from the PCA are reported in Table A.6. While not all factor loadings fully align with Alhusen et al.'s (2021) theoretical classification, the resulting components broadly correspond to their three dimensions. 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 user-driven', and 'DUI external'. We then estimate regressions of the innovation outcomes on the three PCA-derived DUI components, their interactions and the set of controls (Table 4). To facilitate the interpretation of the interaction term coefficients, we report OLS estimates.[12]

[12]In addition, we have also estimated a probit model without interactions. The corresponding average marginal effects are shown in Table A.7.

Table 4: 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 user-driven	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 user-driven		-0.006		-0.004		-0.004
DUI internal × DUI external		-0.001		-0.004		-0.001
DUI user-driven × DUI external		0.010		0.009		0.005
DUI internal × DUI user-driven × 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 user-driven	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 user-driven		0.008**		0.003		0.006*
DUI internal × DUI external		-0.002		0.003		0.006
DUI user-driven × DUI external		-0.009		-0.001		-0.003
DUI internal × DUI user-driven × 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 results are in line with our previous findings (see Table 3 and Table 4). Among the DUI dimensions in the Germany-wide sample, 'DUI internal' is positively and significantly associated with product and organizational innovation, but not with process innovation. The 'DUI user-driven' dimension is positively and significantly associated with all outcomes, while 'DUI external' is mostly insignificant (but positive) across outcomes. In the sample of the 10 lagging regions, 'DUI internal' is positively and highly significant for process and organizational innovation, while it is only weakly significant in the case of product innovation. 'DUI external' shows the largest coefficient and highest significance for organizational innovation, whereas 'DUI user-driven' is insignificant. In Table 4 we further show that our results remain robust when including interaction terms between the three DUI dimensions. The triple interaction term is positive and significant in the lagging-regions sample, suggesting that the associations between DUI dimensions and innovation outcomes are not only additive in the estimated model but also interaction-based. In other words, the estimates are consistent with complementarities between the three main DUI dimensions.

6 Discussion & Conclusion

As SMEs with little or no R&D intensity are a main driver of economic development in lagging regions, it is crucial to better capture their learning and innovation activities. In this regard, the innovation mode concept of Jensen et al. (2007) has been an important step toward understanding how 'Learning by Doing, Using, and Interacting' (DUI) processes unfold in less developed areas. Alhusen et al. (2021) have provided a measurement framework for DUI, outlining its main dimensions and conceptualizing a detailed set of

indicators. Such instruments are needed to lay the groundwork for making DUI-driven innovation in SMEs from lagging regions more tangible, and to improve the basis of information for a place-sensitive innovation policy aimed at reducing regional inequalities (Iammarino et al., 2019).

This study's main contribution is its systematic approach to operationalizing and empirically testing a comprehensive set of DUI-related innovation indicators that go beyond formal R&D. For the first time, internal, user-driven, and external learning processes are fully captured within a single measurement framework. On this basis, Lasso regression is used to identify the specific DUI activities most frequently selected as predictors of innovation outcomes. A main finding is that hitherto neglected indicators, in particular those within the internal and user-driven dimensions constitute important predictors of SME innovation. Furthermore, we apply this framework to a dataset specifically covering lagging regions, thereby advancing the measurement of DUI processes in contexts where SMEs and low R&D intensities are defining characteristics of the innovation landscape. Altogether, this demonstrates how the comprehensive measurement framework of Alhusen et al. (2021) can be used quantitatively, and shows that doing so changes the substantive picture of which learning processes matter most in lagging regions.

Our findings suggest that DUI learning goes far beyond interaction with external actors, challenging the prevailing focus in much of the innovation mode literature. Importantly, DUI's relevance for innovation outcomes varies by both region and innovation type, confirming Parrilli et al. (2020). The DUI mode — and in particular its often neglected internal component — is especially strongly associated with innovation in lagging regions, notably when it comes to organizational innovation. This supports the findings of Flåten et al. (2015) on the crucial role of workplace learning for a firms' absorptive capacity in organizationally thin regions and empirical studies showing that organizational innovation can be an important enabler of technological innovation (Bartoloni and Baussola, 2018; Camisón and Villar-López, 2014; Haned et al., 2014; Mothe et al., 2015). Taken together, our findings are consistent with the interpretation that firms in lagging regions may compensate for unfavorable business environments through DUI-related learning processes. By concentrating mainly on external DUI, many previous studies on the regional dimensions of innovation modes may have underestimated the importance of DUI-related innovation activities for economic development. Our findings indicate that both internal and external DUI dimensions matter for innovation outcomes, consistent with recent research emphasizing that firms' ability to combine internal learning capabilities with external knowledge interactions depends on absorptive capacity (Weidner et al., 2023). This also aligns with evidence that the innovation benefits of external collaboration are contingent on firm-internal organizational practices and the knowledge context in which such interactions take place (Bodas Freitas and Fontana, 2018).

These insights also carry policy implications. Firstly, given the likely innovation productivity of DUI in lagging regions, our results suggest that DUI-oriented innovation policies is a promising lever for reducing regional disparities. However, the present analysis does not allow us to draw any conclusions about the actual effectiveness of such policies. Secondly, in order to promote innovation capacity in lagging regions, policymakers should consider the full range of DUI dimensions ('DUI internal', 'DUI user-driven', 'DUI external'). This would involve going beyond narrowly defined innovation policy and extending to related areas such as vocational education and training, which can constitute an important component of regional learning and innovation systems (Lund and Karlsen, 2020), as well as labor market policies, in order to strengthen firms' DUI innovation capacities beyond R&D. This could also involve explicitly addressing user-driven learning by SMEs in lagging regions by strengthening their capacity to systematically collect, process, and integrate customer feedback (e.g. through pilot-user schemes or support for prototype testing and adaptation). Thirdly, although our findings suggest that external DUI is generally less prevalent in lagging regions, certain types of network development appear to be crucial for offsetting local disadvantages in these areas. This suggests that policies encouraging inter- and supra-regional collaboration and knowledge transfer should remain part of the innovation policy mix for lagging regions (but not as the only focus), especially where local knowledge resources are scarce, for example, in terms of support for network building, inter-regional collaboration or knowledge brokerage. At the same time, our data does not provide information on the most relevant network types in lagging regions, therefore our policy recommendations at this point must remain tentative.

Fourthly, the policy implications of our findings are most direct with respect to internal firm capabilities. We find that an open communication culture, employee freedom, and room for trial-and-error learning are as relevant as the development of required skills through training. This aligns with evidence that organizational practices related to problem-solving, decentralization, and employee incentives form an integral part of firms'

learning environments (Bodas Freitas, 2011), and with research highlighting the role of CEO characteristics in firm-internal DUI learning and employees' innovation activities (Bennat and Sternberg, 2022). More broadly, the importance of such internal capabilities resonates with evidence that developing intangible assets through internal resources and competences can be particularly important for firms' innovativeness (Montresor and Vezzani, 2016). Importantly, our results suggest that these internal learning capabilities are particularly relevant in lagging regions, where firm-internal ecosystems of learning and exchange may help firms navigate some of the disadvantages associated with their regional environment. Against this background, our findings suggest that innovation support in lagging-region contexts should not be confined to formal R&D subsidies, but may also seek to strengthen the organizational conditions for learning, for instance through firm-level training, workplace-based learning, employee participation schemes, structured experimentation formats, and advisory programs that support internal communication and problem-solving in SMEs.

Our study is not without limitations, however. While our results are robust to the choice of two distinct methods (Lasso and PCA) we cannot claim causality. Our analysis is based on cross-sectional survey data and therefore identifies patterns of association rather than causal effects. In particular, reverse causality cannot be ruled out, as more innovative firms may also be more likely to report DUI-related learning activities. In addition, omitted firm-level or regional characteristics may simultaneously influence both DUI activities and innovation outcomes. Another disadvantage pertains to Lasso regression as a data-driven method for variable selection. While this approach is well suited to identify variables with high predictive relevance, it does not provide a basis for causal inference. Moreover, in the presence of correlated predictors, Lasso may select variables in a way that does not necessarily reflect the underlying data-generating process. Future studies should apply our rich set of indicators in the context of panel data and by using methods suitable for causal inference.

Moreover, our measurement strategy relies on self-reported Likert-scale survey data, which may be subject to common method bias given that DUI activities and innovation outcomes are assessed using the same survey instrument. Consequently, the observed associations between reported DUI practices and reported innovation outcomes may be inflated. Future research could address this limitation by combining survey-based measures with more objective indicators of innovation performance, such as linked administrative data or externally validated innovation metrics, for example based on patent or trademark data.

In addition, our study uses firm data from Germany only. Therefore, it could be argued that, due to Germany's specific geographic and economic structure, our results may be limited in terms of external validity, for example regarding countries with thinner institutional support systems, weaker vocational training structures or a less equal distribution of capable SME innovators. However, contexts in which SMEs dominate the business landscape, formal R&D investment is limited and innovation depends heavily on experiential and interaction-based learning are a typical feature of less developed regions in general. Therefore, the importance of all three DUI dimensions, and in particular the association between internal DUI capabilities and SME innovation output, might be expected to hold across a variety of lagging or peripheral regional contexts beyond Germany. While economic strength remains unevenly distributed and lagging regions possess fewer knowledge resources than one or more economic core regions, it is plausible to hypothesize that fostering an internal learning environment conducive to innovation is one of the few remaining sources of innovation capacity available to firms in lagging region contexts. However, this should be further explored by future studies that broaden the geographic scope conditions.

Finally, our study distinguishes between innovation resources that are either internal or external to the firm. We also find that network relations are important predictor of production in lagging regions. However, our data does not allow us to distinguish whether the relevant external interactions are intra-regional or extra-regional. It is conceivable that firms in developed core regions may simply need to tap into the rich set of locally available resources inside the region in a way that firms in lagging regions are not able to. To what extent can firms in lagging regions compensate for this disadvantage by accessing geographically distant knowledge sources, and what kinds of networks are required specifically for this? And is internal DUI a prerequisite for developing the required absorptive capacities? This remains another avenue for future research.

References

Alecke, B., Mitze, T., and Niebuhr, A. (2021). Building a bridge over the valley of death? New pathways for innovation policy in structurally weak regions. *Review of Regional Research*, 41(2):185–210. https://doi.org/10.1007/s10037-021-00156-9.

Alhusen, H. and Bennat, T. (2021). Combinatorial innovation modes in SMEs: Mechanisms integrating STI processes into DUI mode learning and the role of regional innovation policy. *European Planning Studies*, 29(4):779–805. https://doi.org/10.1080/09654313.2020.1786009.

Alhusen, H., Bennat, T., Bizer, K., Cantner, U., Horstmann, E., Kalthaus, M., Proeger, T., Sternberg, R., and Töpfer, S. (2021). A new measurement conception for the 'doing-using-interacting' mode of innovation. *Research Policy*, 50(4):104214. https://doi.org/10.1016/j.respol.2021.104214.

Amara, N., Landry, R., Becheikh, N., and Ouimet, M. (2008). Learning and novelty of innovation in established manufacturing SMEs. *Technovation*, 28(7):450–463.

Apanasovich, N. (2016). Modes of innovation: A grounded meta-analysis. *Journal of the Knowledge Economy*, 7:720–737. https://doi.org/10.1007/s13132-014-0237-0.

Apanasovich, N., Heras, H. A., and Parrilli, M. D. (2016). The impact of business innovation modes on SME innovation performance in post-Soviet transition economies: The case of Belarus. *Technovation*, 57:30–40. https://doi.org/10.1016/j.technovation.2016.05.001.

Asheim, B. T. and Coenen, L. (2005). Knowledge bases and regional innovation systems: Comparing Nordic clusters. *Research Policy*, 34(8):1173–1190. https://doi.org/10.1016/j.respol.2005.03.013.

Bartoloni, E. and Baussola, M. (2018). Driving business performance: innovation complementarities and persistence patterns. *Industry and Innovation*, 25(5):505–525.

Bennat, T. and Sternberg, R. (2022). CEO characteristics and the Doing-Using-Interacting mode of innovation: a new upper echelons perspective. *Industry and Innovation*, 29(10):1202–1230.

Bischoff, T. S., Hipp, A., and Runst, P. (2023). Firm innovation and generalized trust as a regional resource. *Research Policy*, 52(8):104813. https://doi.org/10.1016/j.respol.2023.104813.

Bischoff, T. S., Runst, P., and Bizer, K. (2024). Spatial heterogeneity in the effect of regional trust on innovation. *Economic Geography*, 100(1):80–101. https://doi.org/10.1080/00130095.2023.2252552.

Bjerke, L. and Johansson, S. (2015). Patterns of innovation and collaboration in small and large firms. *The Annals of Regional Science*, 55:221–247. https://doi.org/10.1007/s00168-015-0712-y.

Blažek, J. and Kadlec, V. (2019). Knowledge bases, R&D structure and socio-economic and innovation performance of European regions. *Innovation: The European Journal of Social Science Research*, 32(1):26–47. https://doi.org/10.1080/13511610.2018.1491000.

Bodas Freitas, I. M. (2011). Technological learning environments and organizational practices—cross-sectoral evidence from Britain. *Industrial and Corporate Change*, 20(5):1439–1474.

Bodas Freitas, I. M. and Fontana, R. (2018). Formalized problem-solving practices and the effects of collaboration with suppliers on a firm's product innovation performance. *Journal of Product Innovation Management*, 35(4):565–587.

Boschma, R., Fitjar, R. D., Giuliani, E., and Iammarino, S. (2025). Unseen costs: the inequities of the geography of innovation. *Regional Studies*, 59(1):2445594. https://doi.org/10.1080/00343404.2024.2445594.

Broekel, T., Knuepling, L., and Mewes, L. (2023). Boosting, sorting and complexity—urban scaling of innovation around the world. *Journal of Economic Geography*, 23(5):979–1016. https://doi.org/10.1093/jeg/lbad006.

Camisón, C. and Villar-López, A. (2014). Organizational innovation as an enabler of technological innovation capabilities and firm performance. *Journal of Business Research*, 67(1):2891–2902.

Chen, J., Chen, Y., and Vanhaverbeke, W. (2011). The influence of scope, depth, and orientation of external technology sources on the innovative performance of Chinese firms. *Technovation*, 31(8):362–373.

Coad, A. and Srhoj, S. (2020). Catching gazelles with a lasso: Big data techniques for the prediction of high-growth firms. *Small Business Economics*, 55(3):541–565. https://doi.org/10.1007/s11187-019-00203-3.

Doloreux, D. and Shearmur, R. (2023). Does location matter? STI and DUI innovation modes in different geographic settings. *Technovation*, 119:102609. https://doi.org/10.1016/j.technovation.2022.102609.

Doloreux, D., Shearmur, R., and Kristensen, I. (2023). KIBS as knowledge sources for innovation in rural regions. *Journal of Rural Studies*, 99:53–61. https://doi.org/10.1016/j.jrurstud.2023.02.011.

Doloreux, D., Shearmur, R., and St-Pierre, L.-A. (2024). Innovation modes and knowledge interactions: A micro-geographic approach. *Technovation*, 137:103096.

Dziallas, M. and Blind, K. (2019). Innovation indicators throughout the innovation process: An extensive literature analysis. *Technovation*, 80:3–29.

Edler, J. and Fagerberg, J. (2017). Innovation policy: What, why, and how. *Oxford Review of Economic Policy*, 33(1):2–23. https://doi.org/10.1093/oxrep/grx001.

Filippopoulos, N. and Fotopoulos, G. (2022). Innovation in economically developed and lagging European regions: A configurational analysis. *Research Policy*, 51(2):104424. https://doi.org/10.1016/j.respol.2021.104424.

Fitjar, R. D. (2025). Does public R&D funding reinforce regional disparities? Exploring the changing geography of public and business R&D expenditure in Europe. *Research Policy*, 54(9):105312. https://doi.org/10.1016/j.respol.2025.105312.

Fitjar, R. D. and Rodríguez-Pose, A. (2013). Firm collaboration and modes of innovation in Norway. *Research Policy*, 42(1):128–138. https://doi.org/10.1016/j.respol.2012.05.009.

Flåten, B.-T., Isaksen, A., and Karlsen, J. (2015). Competitive firms in thin regions in Norway: The importance of workplace learning. *Norsk Geografisk Tidsskrift-Norwegian Journal of Geography*, 69(2):102–111. https://doi.org/10.1080/00291951.2015.1016875.

Freitas, I. M. B., Clausen, T. H., Fontana, R., and Verspagen, B. (2011). Formal and informal external linkages and firms' innovative strategies. A cross-country comparison. *Journal of Evolutionary Economics*, 21(1):91–119.

Fritsch, M. and Wyrwich, M. (2021). Is innovation (increasingly) concentrated in large cities? An international comparison. *Research Policy*, 50(6):104237. https://doi.org/10.1016/j.respol.2021.104237.

Ganau, R. and Grandinetti, R. (2021). Disentangling regional innovation capability: what really matters? *Industry and Innovation*, 28(6):749–772.

Gertheiss, J., Hogger, S., Oberhauser, C., and Tutz, G. (2011). Selection of ordinally scaled independent variables with applications to international classification of functioning core sets. *Journal of the Royal Statistical Society Series C: Applied Statistics*, 60(3):377–395. https://doi.org/10.1111/j.1467-9876.2010.00753.x.

Gertheiss, J. and Tutz, G. (2009). Penalized regression with ordinal predictors. *International Statistical Review*, 77(3):345–365. https://doi.org/10.1111/j.1751-5823.2009.00088.

Gertler, M. S. (2003). Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). *Journal of Economic Geography*, 3(1):75–99. https://doi.org/10.1093/jeg/3.1.75.

Gilsing, V., Bekkers, R., Freitas, I. M. B., and Van der Steen, M. (2011). Differences in technology transfer between science-based and development-based industries: Transfer mechanisms and barriers. *Technovation*, 31(12):638–647.

Glückler, J., Shearmur, R., and Martinus, K. (2023). Liability or opportunity? Reconceptualizing the periphery and its role in innovation. *Journal of Economic Geography*, 23(1):231–249. https://doi.org/10.1093/jeg/lbac028.

Grillitsch, M. and Nilsson, M. (2015). Innovation in peripheral regions: Do collaborations compensate for a lack of local knowledge spillovers? *The Annals of Regional Science*, 54:299–321. https://doi.org/10.1007/s00168-014-0655-8.

Gyurkovics, J. and Vas, Z. (2018). Knowledge sourcing in a traditional industry: Prospects of peripheral regions. *International Journal of Innovation and Learning*, 24(2):220–237. https://doi.org/10.1504/IJIL.2018.094067.

Hädrich, T., Reher, L., and Thomä, J. (2024). Solving the puzzle? An innovation mode perspective on lagging regions. *International Regional Science Review*, page 01600176241283898. https://doi.org/10.1177/01600176241283898.

Haned, N., Mothe, C., and Nguyen-Thi, T. U. (2014). Firm persistence in technological innovation: the relevance of organizational innovation. *Economics of Innovation and New Technology*, 23(5-6):490–516.

Haus-Reve, S., Fitjar, R. D., and Rodríguez-Pose, A. (2019). Does combining different types of collaboration always benefit firms? Collaboration, complementarity and product innovation in Norway. *Research Policy*, 48(6):1476–1486. https://doi.org/10.1016/j.respol.2019.02.008.

Haus-Reve, S., Fitjar, R. D., and Rodríguez-Pose, A. (2023). DUI it yourself: Innovation and activities to promote learning by doing, using, and interacting within the firm. *Industry and Innovation*, 30(8):1008–1028. https://doi.org/10.1080/13662716.2022.2131509.

Heidenreich, M. (2009). Innovation patterns and location of European low-and medium-technology industries. *Research Policy*, 38(3):483–494. https://doi.org/10.1016/j.respol.2008.10.005.

Hervás-Oliver, J.-L., Garrigos, J. A., and Gil-Pechuan, I. (2011). Making sense of innovation by R&D and non-R&D innovators in low technology contexts: A forgotten lesson for policymakers. *Technovation*, 31(9):427–446. https://doi.org/10.1016/j.technovation.2011.06.006.

Hervás-Oliver, J.-L., Parrilli, M. D., Rodríguez-Pose, A., and Sempere-Ripoll, F. (2021). The drivers of SME innovation in the regions of the EU. *Research Policy*, 50(9):104316. https://doi.org/10.1016/j.respol.2021.104316.

Hervás-Oliver, J.-L., Sempere-Ripoll, F., and Boronat-Moll, C. (2014). Process innovation strategy in SMEs, organizational innovation and performance: A misleading debate? *Small Business Economics*, 43:873–886. https://doi.org/10.1007/s11187-014-9567-3.

Hirsch-Kreinsen, H. (2008). "Low-tech" innovations. *Industry and Innovation*, 15(1):19–43.

Hoshiyar, A., Gertheiss, L. H., and Gertheiss, J. (2023). Regularization and model selection for item-on-items regression with applications to food products' survey data. https://doi.org/10.48550/arXiv.2309.16373.

Iammarino, S., Rodriguez-Pose, A., and Storper, M. (2019). Regional inequality in Europe: evidence, theory and policy implications. *Journal of Economic Geography*, 19(2):273–298. https://doi.org/10.1093/jeg/lby021.

Isaksen, A. and Trippl, M. (2017). Innovation in space: The mosaic of regional innovation patterns. *Oxford Review of Economic Policy*, 33(1):122–140. https://doi.org/10.1093/oxrep/grw035.

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). *An introduction to statistical learning with applications in R*. Springer.

Jensen, M. B., Johnson, B., Lorenz, E., and Lundvall, B.-Å. (2007). Forms of knowledge and modes of innovation. In Lundvall, B.-Å., editor, *The learning economy and the economics of hope*, pages 155–180. Anthem Press London, New York.

Kesidou, E., Plakoyiannaki, E., and Tardios, J. A. (2024). Symbolic knowledge innovation through bricolage in the periphery: the Bauhaus movement. *Journal of Economic Geography*, 24(4):567–594. https://doi.org/10.1093/jeg/lbae010.

Lopez-Rodriguez, J. and Martinez-Lopez, D. (2017). Looking beyond the R&D effects on innovation: The contribution of non-R&D activities to total factor productivity growth in the EU. *Structural Change and Economic Dynamics*, 40:37–45. https://doi.org/10.1016/j.strueco.2016.11.002.

Lund, H. B. and Karlsen, A. (2020). The importance of vocational education institutions in manufacturing regions: adding content to a broad definition of regional innovation systems. *Industry and Innovation*, 27(6):660–679.

Maretzke, S., Ragnitz, J., and Untiedt, G. (2019). Betrachtung und Analyse von Regionalindikatoren zur Vorbereitung des GRW-Fördergebietes ab 2021 (Raumbeobachtung). *ifo Dresden Studien*, 83.

Marzucchi, A. and Montresor, S. (2017). Forms of knowledge and eco-innovation modes: Evidence from Spanish manufacturing firms. *Ecological Economics*, 131:208–221.

Matsiuk, N., Doloreux, D., and Shearmur, R. (2024). Beyond "buzz": knowledge interactions, innovation, and neighborhood characteristics. *Journal of Economic Geography*, 24(6):821–842. https://doi.org/10.1093/jeg/lbae026.

Meier, L., Van De Geer, S., and Bühlmann, P. (2008). The group lasso for logistic regression. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 70(1):53–71. https://doi.org/10.1111/j.1467-9868.2007.00627.x.

Montresor, S. and Vezzani, A. (2016). Intangible investments and innovation propensity: Evidence from the Innobarometer 2013. *Industry and Innovation*, 23(4):331–352.

Mothe, C., Nguyen-Thi, U. T., and Nguyen-Van, P. (2015). Assessing complementarity in organizational innovations for technological innovation: the role of knowledge management practices. *Applied Economics*, 47(29):3040–3058.

Nunes, S. and Lopes, R. (2015). Firm performance, innovation modes and territorial embeddedness. *European Planning Studies*, 23(9):1796–1826. https://doi.org/10.1080/09654313.2015.1021666.

Parrilli, M. D., Balavac, M., and Radicic, D. (2020). Business innovation modes and their impact on innovation outputs: Regional variations and the nature of innovation across EU regions. *Research Policy*, 49(8):104047. https://doi.org/10.1016/j.respol.2020.104047.

Parrilli, M. D. and Elola, A. (2012). The strength of science and technology drivers for SME innovation. *Small Business Economics*, 39:897–907. https://doi.org/10.1007/s11187-011-9319-6.

Parrilli, M. D. and Heras, H. A. (2016). STI and DUI innovation modes: Scientific-technological and context-specific nuances. *Research Policy*, 45(4):747–756. https://doi.org/10.1016/j.respol.2016.01.001.

Parrilli, M. D. and Radicic, D. (2021). STI and DUI innovation modes in micro-, small-, medium-and large-sized firms: Distinctive patterns across Europe and the US. *European Planning Studies*, 29(2):346–368. https://doi.org/10.1080/09654313.2020.1754343.

Pelkonen, A. and Nieminen, M. (2016). How beneficial is a knowledge-based development strategy for peripheral regions? A case study. *European Planning Studies*, 24(2):364–386. https://doi.org/10.1080/09654313.2015.1047740.

Prognos, A. (2019). Prognos zukunftsatlas 2019. *Das Ranking für Deutschlands Regionen. Berlin*.

Rammer, C., Czarnitzki, D., and Spielkamp, A. (2009). Innovation success of non-R&D-performers: Substituting technology by management in SMEs. *Small Business Economics*, 33:35–58. https://doi.org/10.1007/s11187-009-9185-7.

Reher, L., Runst, P., and Thomä, J. (2024). Personality and regional innovativeness: An empirical analysis of German patent data. *Research Policy*, 53(6):105006. https://doi.org/10.1016/j.respol.2024.105006.

Roper, S. and Love, J. H. (2018). Knowledge context, learning and innovation: an integrating framework. *Industry and Innovation*, 25(4):339–364.

Runst, P. and Thomä, J. (2022). Does personality matter? small business owners and modes of innovation. *Small Business Economics*, 58(4):2235–2260. https://doi.org/10.1007/s11187-021-00509-1.

Santos, D. M., Gonçalves, S. M., and Laranja, M. (2022). Drivers, processes, and outcomes of the STI and DUI Modes of Innovation: A systematic review. *International Journal of Innovation and Technology Management*, 19(03):2140015. https://doi.org/10.1142/S0219877021400150.

Spescha, A. and Woerter, M. (2019). Innovation and firm growth over the business cycle. *Industry and Innovation*, 26(3):321–347.

Statistisches Bundesamt (2008). Klassifikation der Wirtschaftszweige, Ausgabe 2008 (WZ 2008).

Thomä, J. (2017). DUI mode learning and barriers to innovation — A case from Germany. *Research Policy*, 46(7):1327–1339. https://doi.org/10.1016/j.respol.2017.06.004.

Thomä, J. and Zimmermann, V. (2020). Interactive learning – The key to innovation in non-R&D-intensive SMEs? A cluster analysis approach. *Journal of Small Business Management*, 58(4):747–776. https://doi.org/10.1080/00472778.2019.1671702.

Thünen-Institut (2016). Landatlas (2016). Monitoring ländlicher Räume. https://literatur.thuenen.de/digbib_extern/dn058101.pdf.

Trigo, A. (2013). The nature of innovation in r&d-and non-r&d-intensive service firms: Evidence from firm-level latent class analysis. *Industry and Innovation*, 20(1):48–68.

Tutz, G. and Gertheiss, J. (2016). Regularized regression for categorical data. *Statistical Modelling*, 16(3):161–200. https://doi.org/10.1177/1471082X16642560.

Wassmann, P., Schiller, D., and Thomsen, S. L. (2016). Spatial cooperation patterns and their impact on innovation outcomes: Lessons from firms in a low-technology region. *European Planning Studies*, 24(5):833–864. https://doi.org/10.1080/09654313.2016.1140721.

Weidner, N., Som, O., and Horvat, D. (2023). An integrated conceptual framework for analysing heterogeneous configurations of absorptive capacity in manufacturing firms with the DUI innovation mode. *Technovation*, 121:102635.

Yang, Y. and Zou, H. (2015). A fast unified algorithm for solving group-lasso penalize learning problems. *Statistics and Computing*, 25:1129–1141. https://doi.org/10.1007/s11222-014-9498-5.

Yuan, M. and Lin, Y. (2006). Model selection and estimation in regression with grouped variables. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 68(1):49–67. https://doi.org/10.1111/j.1467-9868.2005.00532.x.

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
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 ...						
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 ...						

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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.
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
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 USER-DRIVEN:								
VII. Cooperation with customers		Our cooperative relationships with customers ...						

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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.
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 ...						
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

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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.
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
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

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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.
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:								
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
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		
	Product	Process	Orga
DUI internal	0.326	0.254	0.191
DUI user-driven	0.298	0.239	0.094
DUI 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		
	Product	Process	Orga
Panel A:	*Germany-wide sample*		
DUI internal	0.286	0.164	0.101
DUI user-driven	0.260	0.205	0.038
DUI external	0.205	0.086	0.064
N	400	390	383
Panel B:	*10 lagging case regions*		
DUI internal	0.314	0.215	0.342
DUI user-driven	0.338	0.209	0.218
DUI external	0.123	0.174	0.267
N	530	521	515

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

Table A.5: 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	Importance R&D	0.632
	(I) Maintaining informal contacts within the firm	0.535		
	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. Letters in brackets refer to the DUI dimension (I–internal; U–user-driven; E–external)

Table A.6: Loadings from PCA with varimax rotation

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

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Table A.6 – *Continued from previous page*

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

Table A.7: 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 user-driven	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 user-driven	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.