SME Innovation in Regional Innovation Systems

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Contents

Chapter 1

Introduction

Innovation and economic growth

Innovation is the key driver of economic growth. From a theoretical perspective, in both the older Solow growth model as well as the literature on endogenous growth theory, the capacity and potential to innovate determines economic development (Solow, 1956; Grossman and Helpman 1991; Rodríguez-Pose and Crescenzi 2008; Kremer, 1993). In early growth models, neoclassical economic theory modeled technological progress as exogenously given (Solow, 1956; Aghion and Howitt, 1998). From the point of view of endogenous growth theory, "innovations do not fall like manna from heaven" (Aghion and Howitt, 1998:1). Technological progress is rather seen as an endogenous factor, which interacts with and alters the economic system in which it emerges (Aghion and Howitt, 1998; Grossman and Helpman 1991). In this view, innovation is characterized as a social process of knowledge generation and exploitation that is influenced by laws and other institutions (Aghion and Howitt, 1998), eventually promoting economic growth.

From a linear process of innovation to innovation systems

In the past, innovation was mainly understood as a linear process that starts with basic research, followed by applied research and invention, which eventually leads to innovation (Bush, 1945; Maclaurin, 1953). However, this view has been challenged in recent decades by the notion of innovation systems, a concept that is popular among scientists as well as policy-makers. The concept originates from evolutionary economic theory, which emphasizes processes of economic change (Nelson and Winter, 1982). Innovation system research assumes that complex, interactive and cumulative learning and knowledge exchange processes that are socially embedded and have to be viewed in their institutional and cultural contexts characterize innovation processes (Lundvall, 1992). Most of the early research on innovation systems focused on national innovation system (NIS), which mainly originated from emphasizing the importance of the development of the modern nation state for innovation processes and evaluating whether its role changes for innovation due to globalization (Lundvall, 1992; Cooke et al., 1997). However, subsequent research challenged the national perspective and introduced other views on innovation systems, defining them at different geographical (global, regional) as well as organizational (technological, sectoral, organizational) levels (Binz and Truffer, 2017; Lundvall, 1992; Edquist, 1997; Carlsson and Stankiewicz, 1991; Malerba, 2002; Van Lacker et al. 2016). These definitions must be seen as complementary perspectives to NIS that overlap to some extent and mainly differ in their respective level of analysis.

SME innovation in regional innovation systems

Among these perspectives, regional innovation systems (RIS) have emerged as the most widely used concept in recent years due to the importance of geographical proximity for innovation. Research on RIS argues that a subnational focus is more appropriate to analyze the complexity and diversity of innovation processes compared to the national perspective (Cooke et al., 1997). The emphasis of the regional dimension of innovation processes is also reflected by related concepts to RIS such as innovative milieus (Camagni, 1995; Crevoisier, 2004), industrial districts (Marshall, 1920; Pyke et al., 1990; Asheim, 2000), clusters (Porter, 1998; 2000), or learning regions (Asheim, 1996). RIS focus on the interaction between a multitude of actors such as private firms, universities, other research facilities, educational institutions, policy actors, financial institutions, regulatory authorities and intermediaries. All of these actors participate in the generation and diffusion of knowledge, which is also influenced by the regional environment, such as cultural and political contexts (Doloreux and Porto Gomez, 2017).

The linear model of innovation does not consider these contextual factors, which are especially relevant when looking at SME innovation. SMEs hold particular importance in Europe, accounting for 99% of all firms, two-thirds of total employment and 56% of total turnover (Papadopoulos et al., 2018). Compared to large firms, their innovation activities more strongly depend on external collaboration and regional specificities rather than internal R&D efforts due to missing internal capacities (Hervás-Oliver et al., 2021; Rammer et al., 2009). Their innovative efforts are much more market- than research-driven and often follow non-R&D-based innovation modes (Hervás-Oliver et al., 2021; Ortega-Argilés et al., 2009; Hervás-Oliver et al., 2011).

As a result, the RIS concept is a more suitable framework for analyzing SME innovation compared to the linear model of innovation, which does not account for the external environment and contextual factors driving innovation in SMEs. This dissertation hence uses the RIS framework to analyze three current topics of SME innovation. First, the literature on RIS emphasizes the importance of intangible characteristics of RIS for SME innovation (Parrilli and Radicic, 2021). However, only a limited number of quantitative studies have addressed this topic empirically. Chapters II and III of this dissertation hence quantitatively analyze the influence of a specific intangible or "soft" factor that affects SME innovation, namely generalized trust.

Second, the digital transformation is changing the nature of innovation as well as the way in which it emerges. On the one hand, the introduction of digital products or processes can constitute an innovation itself. On the other hand, they can be an input for other (non-) digital innovations. The introduction of digital technologies often requires significant changes to a company's internal processes (Agostini et al., 2020). As SMEs often have limited resources, they only consider the introduction of digital technologies if they are economically beneficial. Moreover, digitalization also has impacts on the RIS; for example, by changing the nature of knowledge flows and thus the appropriability of digital innovation outcomes (Teece, 2018; Miric et al., 2019; Butticè et al., 2020) or affecting the interplay of digital technologies and open innovation processes (Brunswicker and Schecter, 2019; Shaikh and Levina, 2019; Pershina et al., 2019). As innovation and digitalization activities in SMEs often depend on the firm's external environment (Fauzi and Sheng, 2020), analyzing the links between digitalization and innovation is particularly important for understanding SME innovation. Therefore, the fourth chapter analyzes the multifaceted relationship between digitalization and innovation in SMEs in an explorative manner based on qualitative data.

Third, SMEs often rely on external collaborations for innovation due to their missing in-house financial and personnel resources (Rammer et al., 2009; Hervás-Oliver et al., 2021). Therefore, owners of SMEs often play an important role in engaging in external collaborations with other actors from the RIS and for the inflow of new knowledge. The final chapter thus analyzes the effect of an SME owner's personality on the introduction of digital innovations at the company level.

The analyzes of all three topics share in common the fact that they account for either the heterogeneity of innovation processes in SMEs, the heterogeneity of RIS or both. On the one hand, the literature on innovation processes in SMEs suggests that firms differ in their modes of innovation. SMEs innovate based on an innovation mode located on a continuum between the *doing, using, interacting mode of innovation* (DUI) and the *science, technology and innovation mode* (STI) (Jensen et al., 2007; Thomä, 2017; Alhusen and Bennat, 2021). Based on the respective innovation mode, SMEs might depend more or less on their RIS. One could argue – for example – that innovation in SMEs using the DUI mode of innovation more strongly depend on the external resources available in the RIS compared to firms innovating in the STI mode, as smaller firms do not have sufficient internal resources for generating new knowledge and depend on external collaboration. On the other hand, RIS can also differ in their economic and innovative structure, resulting in differences in SME innovation patterns. Recent studies on RIS suggest that SME innovation in lagging regions indeed more strongly depends on external sources of knowledge and collaboration compared to innovation in leading regions (Hervás-Oliver et al., 2021; Filippopoulos and Fotopoulos, 2022). This dissertation takes these differences across SMEs and regions into account and contributes to the overall discussion on the heterogeneity of innovation across firms and regions, a topic that is not sufficiently accounted for in quantitative innovation research.

The following paragraphs summarize the chapters of this dissertation and elaborate on the theoretical and empirical contributions of the individual articles. The results are then used to discuss the limitations of this research and potential policy implications for SME innovation.

Chapter II: Firm innovation and generalized trust as a regional resource

This chapter analyzes the relationship between generalized trust at the regional level and firm innovation. Trust at the individual level is defined as "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" (Rousseau et al., 1998: 395). Through personal interactions, trust becomes part of societal structures at the regional level as generalized trust (Zucker, 1986). We argue that generalized trust at the regional level affects firm innovation through three channels. First, generalized trust in a region increases human capital. By reducing delinquency and crime rates, generalized trust promotes the accumulation of knowledge and increases human capital (Putnam, 1993; Coleman, 1988). Second, the RIS concept emphasizes the importance of interactions for innovation (Maskell and Malmberg, 1999). When people trust each other, it is more likely that they exchange information and cooperate, thus increasing the likelihood of firm innovation. Third, generalized trust reduces transaction costs. Trust reduces the likelihood of free riding in innovation projects as well as the necessity of costly legal arrangements to safeguard innovation projects (Aghion and Durlauf, 2005). Based on these arguments, we formulate two hypotheses for the relationship between generalized trust and innovation: (H1) The relationship between generalized trust within regions and the likelihood of firm innovation has an inverted U-shape. Although generalized trust in general should positively affect innovation, very high levels might lead to in-group cooperation, leading to lock-in effects, which hinder the inflow of new knowledge (McFadyen and Cannella, 2004; Uzzi and Spiro, 2005; Echebarria and Barrutia, 2013). (H2) Higher levels of trust particularly affect SME innovation, as opposed to larger firms. As SME innovation more strongly depends on collaboration and contextual factors (e.g. Doloreux and Porto Gomez, 2017), we assume that SMEs benefit more from increases in trust compared to large firms.

We empirically test these hypotheses by using the case of Germany, with its historically grown differences in generalized trust. We obtain firm-level data on innovation and other firm characteristics from the Mannheimer Innovationspanel (MIP) (ZEW, 2021), regional-level data on trust from aggregated responses to the German Socio-Economic Panel (GSOEP) (DIW, 2021) and data on other regional characteristics from the INKAR database (BBSR, 2021). The final dataset comprises 49,752 firm observations from 94 spatial planning regions observed between 2004 and 2018. As the RIS concept suggests that firm innovation is influenced by firm- as well as regional-level characteristics we use a multi-level regression approach to analyze our data. The panel data set allows us to build a three-level model with yearly observations of innovation as level 1, firms as level 2 and region as level 3. We use Markov-Chain-Monte-Carlo methods (MCMC) based on Bayesian statistics to estimate our models.

Our results provide evidence for both hypotheses, suggesting that the positive effects of trust vanish after regions reach a certain trust level and increases in trust are particularly beneficial for innovation in SMEs. Our contribution to the existing literature is twofold. First, previous empirical studies on the relationship between trust and innovation (Laursen et al., 2012; Hauser et al., 2007; Echebarria and Barrutia 2013; Doh and Acs, 2010; Akçomak and Ter Weel, 2009; Akçomak and Müller-Zick, 2018) mainly rely on cross-sectional data, which prevents them from including firm fixed effects to control for time-invariant firm characteristics. Furthermore, these studies use single-level models for their analysis. As firms in the same regional innovation system are affected by the same regional characteristics, the independence assumption of single-level models is violated (Snijders and Bsoker, 2012; Rabe-Hesketh and Skrondal, 2014). By accounting for this dependence between firms using multi-level models – which relax the independence assumption – we provide more reliable results. Second, while previous studies have already addressed the inverted U-shaped relationship between trust and innovation (Echebarria and Barrutia, 2013), we provide first empirical evidence that generalized trust is particularly important for SME innovation. However, the results also have their limitations that could be addressed by future research. First, we cannot rule out endogeneity concerns that might result from reverse causality between innovation and generalized trust. Although instrumental variable approaches might help to resolve this issue, we were not able to find appropriate instrumental variables for generalized trust. Second, our analysis is limited to a single country with relatively low regional differences in generalized trust. This issue has been addressed in the third chapter, in which we extend the analysis of the relationship between generalized trust and innovation at the European level.

Chapter III: Spatial heterogeneity in the effect of regional trust on innovation

Chapter III also analyzes the relationship between generalized trust and innovation but extends the analysis to European regions and uses NUTS2 regions as the level of analysis. We explore several reasons why the trust–innovation relationship is heterogeneous across geographical space. Therefore, we formulate four hypotheses: (H1) Generalized trust is more strongly related to innovation in regions with low levels of trust, the positive effect of which vanishes in regions with high levels of trust. Similar to H1 in chapter II, we assume that trust increases innovation when trust levels are relatively small. However, after a certain trust level is reached, increases in trust might foster in-group cooperation at the expense of cooperation with external partners and the inflow of new knowledge from outside the region. (H2) Generalized trust is especially beneficial for innovation in lagging regions and is less important for innovation in leading regions. Previous studies have shown that innovation in economically lagging regions more strongly depends on external collaboration than in leading regions (Hervás-Oliver et al., 2021; Filippopoulos and Fotopoulos, 2022). Therefore, we assume that the trust–innovation relationship is stronger in lagging regions. (H3) Generalized trust particularly affects innovation in regions with a high share of small firms and is less important in regions with high shares of large firms. Similar to H2 in chapter II, we assume that trust is more important for SMEs because their innovative activities more strongly depend on collaboration and the external environment to the firm (e.g. Doloreux and Porto Gomez, 2017). (H4) Generalized trust is particularly beneficial in regions with low levels of institutional trust. Formal institutions such as private property rights and contract enforcement are assumed to support innovation (North, 1993, 1990, 2010; Acemoglu et al., 2005; Easterly and Levine, 2016; Kaasa and Andriani, 2022). In the absence of these formal institutions, we assume that trust can serve as an alternative mean to safeguard cooperation for innovation.

We test our hypotheses using regional patent data from the OECD (2022) RegPat database, data on generalized and institutional trust from the European Social Survey (ESS-ERIC, 2021), data on institutional quality from the Heritage Foundation (2022), data on control variables from Eurostat (2021) and the Office of National Statistics (UK) (2021) and data on total employment by firm size category from the ESPON (2022) database. The final sample comprises 1,942 region observations observed between 2005 and 2018. We first apply geographically weighted regressions to reveal spatial heterogeneity in the relationship between trust and innovation. The results show that trust is more strongly related to innovation in regions in the east and south of Europe. To analyze our hypotheses, we apply cluster analysis and fixed effects panel regressions. Our results provide robust evidence for hypotheses 1 and 3, showing that trust is more strongly related to innovation in regions with relatively low levels of trust and high shares of SMEs. Using the average distance between co-inventors, we further show that the positive effect of trust on innovation plays out within small geographical distances.

We contribute to the literature by revealing spatial heterogeneity in the trust–innovation relationship. Previous studies have mainly focused on the general relationship without taking spatial heterogeneity into account. Similar to chapter II, we also provide novel evidence that trust is more important in regions with a relatively high share of SMEs.

Chapter IV: From automation to databased business models: Digitalization and its links to innovation in small and medium-sized enterprises

Based on the ongoing digital transformation of many economic processes, chapter IV exploratively analyzes how digitalization changes innovation processes in SMEs. Therefore, we build on the input-process-output model developed by Agostini et al. (2020) and the conceptual framework of digital innovation of Kohli and Melville (2019) by defining three dimensions of the digitalization–innovation link. (1) Preconditions for digital-based innovation (input): On the one hand, these conditions include the internal organizational environment such as the organizational willingness to adapt to digitalization as well as sufficient resources and capabilities. On the other hand, several external factors are a precondition for digital-based innovation as SMEs in particular often interact with their external environment for digitalization and innovation activities. (2) The role of digital competences in shaping innovation processes (process), which includes digital competences and knowledge-based activities throughout the entire innovation process. (3) Digitalization as an outcome of innovation (output), whereby based on Agostini et al. (2020) one can distinguish between innovation outcomes characterized by “doing the same with less” and “doing something new”. The former describes improved processes through digitalization that reduce operating costs, while the latter implements digital technologies to introduce product or service innovations. Based on these theoretical foundations, this chapter explores the research questions of how digital technologies, competences and innovation are related in SMEs and which types of innovative SMEs can be identified in terms of digitalization.

As the analysis of the relationship between digitalization and innovation has only recently entered innovation research (e.g. Ciarli et al., 2021; De Paula et al. 2022), we adopt a qualitative research approach to analyze our research questions and obtain explorative findings about the specified dimensions of the digitalization–innovation link. We use interview data from 49 German SME owners and managers. The interviews covered various facets of innovation and digitalization in SMEs from several regions and sectors, making them a suitable information source for an explorative analysis of the digitalization–innovation link. We use the

2018 edition of the Oslo Manual (OECD/EUROSTAT, 2018) as our starting point to deductively derive a first set of categories because this version of the Oso Manual covered digitalization-relevant aspects for the first time. We then used these categories to code relevant text passages. During the coding process, we inductively identified further main and subcategories and repeated the coding process until we obtained a sufficiently detailed category system describing the digitalization–innovation link. The final category system comprises seven main categories: (1) internal drivers of digital-based innovation; (2) external drivers of digital-based innovation; (3) innovation-related data development activities; (4) digital competences for innovation; (5) innovation-related knowledge flows in digital networks; (6) the type of innovation and the role of digitized information; and (7) the general relevance of digitalization for innovation. All of these main categories are further divided into various subcategories, whose contents and interrelationships are described in detail in chapter IV. After this content-related description of results, we use a cluster analysis approach at the company level to conduct a basic validity test of the category system and identify different groups of innovative SMEs in terms of digitalization. The analysis identifies three clusters: (1) beginners in digital-based innovations; (2) digital-oriented process innovators; and (3) digital product/business model innovators.

Our contribution to the literature is twofold. First, the analysis of the relationship between digitalization and innovation has only recently entered innovation research. Rather than focusing on a single facet of this relationship, we provide a first overview of the various dimensions of the digitalization–innovation link and provide a typology of innovative SMEs in terms of digitalization to illustrate the use of our category system. Second, starting from the 2018 Oslo Manual, our results can be used to further improve the measurement of digital-based innovation in SMEs. Future research could transfer the results to quantitative methods, developing indicators for the different categories and testing several relationships of the digitalization–innovation link.

Chapter V: Beauty attracts the eye but personality captures the heart … of digital transformation in crafts SMEs

The previous chapters have already emphasized the importance of external collaborations for SMEs due to their missing in-house financial and personnel resources (Rammer et al., 2009; Hervás-Oliver et al., 2021). The owners of SMEs are therefore often important for engaging in cooperation for innovation and digitalization activities with other actors from their RIS. The final chapter of this dissertation thus analyzes the relationship between the personality of a crafts SME owner and the use of digital technologies at the company level. Personality is conceptualized using the Big Five personality model, which comprises the traits of extraversion, conscientiousness, openness, agreeableness, and neuroticism (Digman, 1990; Obschonka and Stuetzer, 2017). Extraversion is defined as being sociable and active. Conscientious people are self-controlled, organized, engage in long-term planning and are on time. Openness is characterized by being open to new experiences and agreeable people trust others, are helpful and cooperative. Finally, neuroticism is defined as experiencing negative emotions (Iqbal et al., 2021; Barrick and Mount, 1991; Mewes et al., 2022; Runst and Thomä, 2022). Previous research has already analyzed the role of personality for entrepreneurship and innovation (e.g. Marcati et al., 2008; McCrae and Costa, 2008; Obschonka and Stuetzer, 2017; Runst and Thomä, 2022). However, the link between personality and digitalization is missing in the literature thus far. Based on the results of previous empirical studies on the relationship between personality and entrepreneurship as well as innovation, we first formulate the following two hypotheses: (H1a) Extraversion positively affects the digitalization activity of a company; and (H1b) Openness positively affects the digitalization activity of a company. Extraverted and open individuals are more likely to engage in cooperation with other RIS actors for exchanging knowledge about digital technologies and should therefore be more likely to introduce digital innovations. Second, based on the observation that digitalization is an evolutionary path comprising different stages (e.g. Brodny and Tutak, 2021; Jones et al., 2021; Mittal et al., 2018; Rodrigues-Espindola et al., 2022), we further hypothesize that the effect of personality on digitalization differs based on the level of digital maturity within the company (H2). For example, one could argue that the use of social networks for communication and recruitment is more likely if the owner of the SME is more extraverted. Moreover, open SME owners might be more likely to experiment with rather unknown and advanced digital technologies. Finally, we hypothesize that the effect of an owner's extraversion on digitalization is mediated by the owner's local embeddedness (H3), as more extraverted owners are expected to more frequently engage in external and local networks, which in turn is assumed to promote digitalization.

We test our hypotheses using survey data of 554 German crafts SMEs. The survey covered several question on digitalization activities, other firm characteristics as well as the owner's personality. We apply principal component analysis to several digitalization items to identify different stages of digitalization. We then apply linear regression analysis with cluster-robust standard errors at the county level to analyze the relationship between personality and digitalization. Our results provide evidence that openness and extraversion are positively related to the overall digitalization level of the company. Using mediation analysis, we further show that the effect of extraversion on digitalization is partially mediated by the local embeddedness of the owner. Finally, we find that extraversion is particularly important in the early stages of the digitalization process, while openness is important when it comes to introducing advanced digital technologies in later stages of digitalization. These results provide evidence that extraversion is particularly important for taking the first steps of digitalization within the company, e.g. when using digital tools for communication or digitalizing further internal process. By contrast, openness is important at later stages of digitalization as it promotes experimenting with advanced digital innovations.

We contribute to the literature by adding another factor to the discussion that drives digitalization in crafts SMEs, namely personality. Although there is evidence of the relationship between personality and entrepreneurship as well as innovation, evidence of the role of personality in relation to digitalization has been missing thus far. We further shed light on the importance of different personality traits at different stages of the digitalization process. These results highlight the importance of the role of an SME owner for engaging in collaboration with other RIS actors and thus promoting digital innovations within the firm.

Policy implications for SME innovation

To sum up, chapters II-V have reveal the heterogeneity of innovation processes in SMEs and across different RIS. Chapters II and III showed that only particular firms and regions benefit from increases in generalized trust. Chapter IV opened up on the diverse interrelationships between digitalization and innovation and suggested different groups of innovative SMEs in terms of digitalization. Finally, chapter V provided evidence that different personality traits are important at different stages of the digitalization process within SMEs.

The beginning of this introduction argued that innovation is a key driver of economic growth and that the understanding of the innovation process has shifted from a linear to a systemic perspective. This has prompted policy-makers to start implementing further policy measures apart from R&D support. Although there remains a strong focus on R&D (e.g. the goal to invest 3% of GDP on R&D) – which rather represents a measure based on the linear perspective on innovation – policy-makers have started to introduce measures such as the SME instrument, smart specialization or digital innovation hubs (Hervás-Oliver et al., 2021).

Based on these policy measures and the overall result of this dissertation regarding the heterogeneity of innovation in SMEs and across regions, one can discuss two opposite views on policy implications for innovation. (1) on the one hand, the diversity of innovation patterns across firms and regions should be addressed by place-sensitive innovation policies that consider local specificities and the particular demands of SMEs; and (2) on the other hand, the heterogeneity of innovation processes across firms and regions would demand complex knowledge about local innovation patterns that is difficult and costly to obtain for policy-makers. From this perspective, one should question the suitability and effectiveness of place-sensitive innovation policies and focus on more general policy measures that address market failures.

Starting from the systemic understanding of innovation processes, the first view argues that there is no one-size-fits-all policy approach to innovation (Tödtling and Trippl, 2005; Asheim, 2019; Morisson and Doussineau, 2019). Innovation policy should rather address regional specificities and consider the supply and demand side of innovation (Barca et al., 2012; Asheim, 2019). One example of such a policy is the EU's smart specialization strategy. This measure aims at the diversification of regions into related and unrelated sectors based on existing strengths and capabilities (European Commission, 2014). The decision about the domains in which regions specialize should be achieved by "entrepreneurial discovery," which includes the participation of all relevant actors of the RIS (Asheim, 2019; Grillitsch and Sotarauta, 2018). Despite such policy efforts, many proponents of place-based policies still criticize the fact that EU innovation policy – with its strong focus on R&D – does not sufficiently account for the diversity of innovation processes in SMEs (Hervás-Oliver et al., 2021; Simonelli, 2016; De Marco et al., 2020; Mazzucato and Lazonick, 2010; Demirel and Mazzukato, 2012; Renda, 2015).

In contrast to this view, the observation of heterogeneous innovation patterns across firms and regions can also be used to criticize place-based innovation policies. According to the second view, such a policy approach demands many highly complex measures that take into account the particularities of each region. One could question whether policy-makers are able to obtain all relevant knowledge about local conditions. This knowledge is likely to be dispersed and practically difficult to be collected by anyone (Hayek, 1945). Additionally, policy-makers might even lack the incentive to gather this knowledge. From a public choice perspective (Buchanan & Tullock, 1964), self-interest in collective decision-making does not lead to efficient decisions due to the missing competitive pressure. It is more likely that interest groups influence policy-making and that decisions are based on the own survival of public administration.

Apart from this general critique of place-based innovation policy, one could question whether certain aspects of SMEs and RIS can even be influenced by policy measures. Not claiming to cover all facets of RIS, the following paragraphs discuss this issue for the particular drivers of innovation analyzed in this dissertation, namely trust, digital technologies and personality.

Chapter II shows that generalized trust is positively related to innovation in regions with relatively low trust levels and it positively affects SME innovation in contrast to innovation in large firms. The theoretical part of the chapter as well as the part on the evolution of trust in German regions shows how generalized trust is the result of historic processes; for example, resulting in differences in regional trust levels between West and East German regions. This observation limits the potential for policy measures to promote innovation via increases in generalized trust. As trust is largely the result of past experiences, it is difficult – if not impossible – to be influenced by policy measures. However, the moderate effect sizes of trust suggest that regions with low trust levels are not locked in their current innovation performance and innovation can still be promoted through other channels. However, the results provide explanations for regional disparities in innovation. Chapter III confirms these results and additionally shows that the effective range of trust is within small geographical distances. Generalized trust is thus important to utilize the innovation potential within regions.

Chapter IV provides a more general overview of the many links between innovation processes and digitalization in SMEs. The explorative nature of the analysis in this chapter thus limits the possibility to infer about the usefulness of innovation policies for digital innovation. However, the presented category system can be applied to develop more appropriate indicators for innovation and digitalization and enhance innovation measurement. Such an improved measurement of innovation and digitalization processes can in turn be used to discuss whether certain policy measures should be used for innovation and digitalization in SMEs.

Finally, chapter V shows how the personality of an SME owner relates to digitalization. Although we find positive and significant effects of certain personality traits on the overall digitalization level as well as different stages of the digitalization process, it is difficult to derive any policy implications from these results. On the one hand, as personality is largely biologically based and considered stable throughout the life (Obschonka and Stuetzer, 2017), it is difficult to influence personality by policy measures. Moreover, it is questionable whether policy should aim at an individual’s personality at all. On the other hand, entrepreneurship education may consider personality to offer more suitable contents for potential entrepreneurs. This does not imply that potential founders with certain personality traits should not be considered but rather that their strength and weaknesses are addressed (Runst and Thomä, 2022). Overall, the results again point to the diversity of innovation processes across regions, firms and even individuals within firms that innovation policy should consider when aiming to promote SME innovation.

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Chapter 2

Firm innovation and generalized trust as a regional resource

Firm innovation and generalized trust as a regional resource

Thore Sören Bischoff, Ann Hipp & Petrik Runst

Abstract

Generalized trust represents an important regional firm resource. It increases human capital, fosters frequent interaction and information sharing, and lowers transaction costs. We provide empirical evidence on the impact of generalized trust among people in regions on firm innovation. Our observation period ranges from 2004 to 2018. A trust measure is generated by survey data from the German Socio-Economic Panel (GSOEP), firm-level data is obtained from the Mannheim Innovation Panel (MIP) and regional data is retrieved from the INKAR database. We apply a 3-level multilevel model, with yearly observations nested in firms, which are nested in regions. Our results show that the relationship between trust and firm innovation has an inverted U-shape. An increase in trust is particularly beneficial for firms inside regions with very low levels of trust. In addition, the impact of trust on innovation is stronger for innovation in small and medium-sized enterprises (SMEs). The robustness of our findings is supported by a broad range of tests.

JEL: D02, D83, O12, O18, O31
Keywords: Trust, firm innovation, regional innovation systems, SMEs

1. Introduction

It has been stated that generalized trust within regions represents an important firm resource (see Cooke et al., 1997; Yoon et al., 2015; Doloreux and Porto Gomez, 2017). It fosters interaction and increases the exchange of information and cooperation (Becattini, 1990; Putnam, 1995; 2000; Westlund and Adam, 2010; Brockman et al., 2018). This exchange culture is of particular importance in small and medium-sized firms (SMEs) that frequently engage in interactions, informal information sharing, and innovation based on doing-using-interacting (DUI) (Thomä, 2017). Based on a number of case studies, the literature on regional systems of innovation (RIS) outlines how trust emerges within regions and affects innovation (Yoon et al., 2015; Aragón Amonarriz et al., 2017; Cooke, 2001; Cooke et al., 2005). These contributions suggest that the high degree of theoretic significance assigned to this topic is warranted, especially with regard to the role of SMEs therein (e.g. Cooke et al., 1997). However, at present it is not sufficiently matched by quantitative research and little robust evidence is available.

To our knowledge, there only exist few quantitative studies on the relationship between generalized trust and innovation (Laursen et al., 2012; Hauser et al., 2007; Echebarria and Barrutia 2013; Doh and Acs, 2010; Akçomak and Ter Weel, 2009; Akçomak and Müller-Zick, 2018), only some of which relate trust to firm-level innovation. Laursen et al. (2012) build on survey data from Italy within 21 regions, showing that being located in a high trust area increases a firm's research and development (R&D) investments. However, the cross-sectional nature of the data prevents the use of firm fixed effects and restricts the analysis to a snapshot in time. Moreover, the focus on a small number of regions limits the external validity of the results. Similarly, Landry et al. (2002) use firm-level survey data from a single region, which does not allow the application of panel data techniques. Doh and Acs (2010) use country level data on trust and the number of patents. The authors are aware that relying on patents as a proxy for codified knowledge within a science and technology mode of innovation (STI) neglects the implicit component of lower-tech knowledge, thereby ignoring innovation based on the DUI mode (see Jensen et al., 2007; Thomä, 2017, Runst and Thomä, 2022). Similarly, Hauser et al. (2007), Akçomak and Ter Weel (2009), Echebarria and Barrutia (2013) and Akçomak and Müller-Zick (2018) exclusively focus on patents in (European) regions and their data sets are purely cross-sectional. Roth (2009) practically demonstrates that the absence of a time component leads to erroneous conclusions when analyzing the effect of trust on economic outcomes such as economic growth.

We seek to overcome these limitations by selecting a more encompassing measure of innovation, by utilizing firm-level panel data and a large number of geographic regions. We contribute to this novel empirical literature by using a multilevel model (MLM). As the RIS concept suggests, a multilevel structure is inherent to innovation processes (Srholec, 2010; Cooke, 2001; Fernandes et al., 2020). In addition, only few empirical studies exist on innovation in general that use a multilevel model and longitudinal data (Srholec, 2010; Srholec, 2011; Schmutzler and Lorenz, 2018; Aiello et al., 2020).

Our main data set contains 94 planning regions within Germany between 2004 and 2018. We combine three different databases that relate a region's characteristics to firm innovation output. The Mannheim Innovation Panel (MIP) provides annual data on firms' innovation activities, the German Socio-Economic Panel (GSOEP) yields data on regional levels of trust, and the INKAR database offers several region-specific controls. By relying on firm survey data, we capture both innovation modes based on an STI and DUI type. As we expect trust to exert a more profound influence on innovation in SMEs, which are more likely to operate in a DUI fashion (Thomä, 2017), the broader measurement of innovation – including its multilevel and longitudinal structure – seems to hold particular importance.

While we know much about the role of relational trust and collaboration in the innovation process (e.g., Landry et al., 2002; Doh and Acs, 2010; Hipp, 2021), this approach is important to better understand the mechanisms that connect generalized trust and firm innovation. In addition to our empirical contribution, we provide theoretical insights on the channels through which trust affects firm innovation, i.e. increased human capital, information sharing, and lower transaction costs. These channels are particularly relevant for innovation in SMEs, which lack the respective capacities and STI-related knowledge (e.g., Rammer et al., 2009; Doh and Kim, 2014; Jensen et al., 2007). However, very high levels of generalized trust can have diminishing returns, too, resulting in an inverted U-shaped relation to firm innovation.

Apart from the innovation literature, a large body of empirical research exists on the macroeconomic implications of trust (Lichter et al., 2021; Algan and Cahuc, 2014; Algan and Cahuc, 2010; Zak and Knack, 2001; Knack and Keefer, 1997; Rodríguez-Pose, 2013), presenting robust evidence on the relationship between trust and economic growth at the aggregate (i.e. mostly country) level. However, only a few authors empirically address innovation, which likely has an influence in this relation. For example, Knack and Keefer (1997) establish a link between trust and investment as a fraction of GDP but do not consider R&D investment, nor do they investigate output measures of innovation. Akcomak and Ter Weel (2009) present evidence of a causal impact of trust on growth via innovation but exclusively rely on patents as a proxy for innovation. Thus, by building a bridge between generalized trust and economic growth via the channel of firm-level innovation (in particular SMEs), we also contribute to the literature on economic growth and regional development.

The remainder of this paper is structured as follows: Section 2 reviews the literature on social capital, trust and innovation. Section 3 describes the empirical case and Section 4 shows the data used and our empirical strategy. Section 5 presents the empirical results, after which section 6 discusses the implications and section 7 concludes.

2. Theoretical background

2.1 Social capital and generalized trust

Social capital was firstly conceptualized as networks of social connections that generate resources for individuals or firms that are either positioned within a dense network of strong ties (i.e. bonding communities) (Coleman, 1988) or whose social ties are weaker but more far reaching, thereby bridging resource gaps (Granovetter, 1973). Both types of linkages create opportunities for knowledge transfer and affect economic performance in regions as described by Becattini (1990).

Strong ties, or bonding social capital, can be conceptualized as a dense cluster of interconnected individuals, most of whom have a dyadic relationship with each other, thereby forming a close-tie social network. Individuals in this network frequently interact with each other, and information possessed by one person quickly spreads to the whole network. Because of this, any violation of social norms, such as not keeping an agreement, will likely be spotted and subsequently communicated to all members of the network, potentially triggering sanctioning mechanisms, such as a loss of reputation. Most importantly, monitoring and sanctioning in dense social networks give rise to high levels of trust as individuals strive to conform to the social standards of their group. In other words, trust can be understood as an indicator for a dense social network, fostering interaction, information sharing and cooperation. By focusing on the local geography, Putnam (1993, 2000) explained this phenomenon by citizen’s engagement in community groups, which influenced the performance of Italian regions. His work prompted a large body of studies focusing on the relation between bonding social capital/generalized trust and the economic performance of cities, regions and countries (e.g., Nahapiet and Ghoshal, 1998; Knack and Keefer, 1997; Laursen et al. 2012; Schneider et al., 2000; Aghion and Durlauf, 2005).

In contrast, a weak tie (or what Putnam (2000) introduced as bridging social capital) represents a far-reaching connection from one person to another, each of which is located in a different network (Granovetter, 1973). Thus, a weak tie bridges the gap between two clusters of densely connected individuals. An individual who possesses weak ties will be able to access novel knowledge, unknown to the other member of one’s own social network, and is therefore able to (commercially) exploit that knowledge before anyone else. While bonding social capital encompasses groups of densely connected individuals, and is therefore an aggregate phenomenon already, bridging social capital is an individual level phenomenon only (see Putnam, 2000).

At this individual level, trust is understood as “a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another” (Rousseau et al., 1998: 395). Through personal interaction of specific individuals, trust becomes relational, and, being tied to societal structures on the regional level, of a generalized type (Zucker, 1986). Generalized trust can be persistent over long time periods as regions inherit a history and traditions of fostering trust and facilitating future cooperation (Becker et al., 2016; Putnam, 1993; 2000). Generalized trust questions in surveys – such as `How much can people be trusted in general?’ – measure the expectation of fair play and cooperation by others (Sapienza et al., 2013), which is key to its purported positive impact on firm innovation and economic growth. There is evidence that generalized and relational trust are causally connected (Sapienza et al., 2013; Robbins, 2016; Selten and Ockenfels, 1998, Henrich et al., 2010). For example, individuals in high trust countries/regions are more likely to cooperate with others in public goods games (e.g. Selten and Ockenfels, 1998; Henrich et al., 2010) or in regions with entrepreneurial communities (Mickiewicz et al., 2019).

If individuals can be trusted, transaction costs are reduced and cooperation becomes more frequent, an idea already expressed by Adam Smith (see Carl and Billari, 2014; Smith, 1776). Social relations are usually based on mutual respect and reliance, supporting cooperative attitudes and leading to a positive sum game for the local economy (Parrilli, 2009; Trigilia, 2001). Studies have repeatedly found a robust causal relationship between trust and economic growth (Algan and Cahuc, 2014; Algan and Cahuc, 2010; Zak and Knack, 2001; Knack and Keefer, 1997; Rodríguez-Pose, 2013; Aghion and Durlauf, 2005) and better public institutions (Putnam, 1993; Tabellini, 2008). Thus, generalized trust represents a geographically-constrained resource that can be accessed by individuals and firms, and which has been found to positively affect economic development. However, whether trust is linked to firm innovation remains an underexplored issue.

2.2 Regional trust as a firm resource

Firm learning and innovation is, amongst other things, dependent on the structure of the RIS. Systems of innovation can be defined at many different levels (e.g. global, national, regional, technological, sectoral) (Lundvall, 1992; Edquist, 1997; Malerba, 2002, for an overview see Rakas and Hain, 2019). Due to the importance of geographical proximity, most research on innovation systems focuses on the regional level, assuming that innovation processes are embedded within a geographically-constrained system (Cooke et al., 1997; Cooke et al., 2005; Maskell and Malmberg, 1999; for an overview see Doloreux and Porto Gomez, 2017; Fernandes et al., 2020 and Ruhrmann et al., 2021). A RIS comprises firms, organizations, a supporting infrastructure, a minimum governance capacity, and the quality of institutions. The competitive advantage that it confers cannot be easily reproduced in other regions (Storper, 1997; Maskell and Malmberg, 1999). Recent studies point to the high spatial-temporal stability of economic processes (Runst and Wyrwich, 2022; Fritsch and Wyrwich, 2014). Innovative regions are thus likely to remain innovative in the future (Asheim et al., 2011; Martin and Moodysson, 2013; Hipp and Binz, 2020; Moretti, 2012). As a result, we can observe increasing regional disparities driven by the differing innovation capacities (Feldman et al., 2021).

In line with former studies (e.g., Cooke et al., 1997; Yoon et al., 2015; Doloreux and Porto Gomez, 2017), we argue that generalized trust is an important component of a RIS. Firms inside a RIS high in generalized trust benefit from this regional resource. We identify three main channels through which trust can positively affect firms inside a RIS and its innovation enhancing capacity, i.e. increased human capital, information sharing, and lower transaction costs, which will be explained as follows.

First, reputation and trust can more easily be built up in tight-knit communities of individuals that monitor and sanction each other’s behavior. Putnam (1993) argues that schools which parents are involved in, representing an indicator for dense community networks, produce better outcomes for individuals (Coleman, 1988) and their surrounding communities, reducing rates of delinquency and crime. At risk individuals can be more easily identified in denser networks with frequent information sharing, increasing the likelihood of intervention. Overall, high trust regions will therefore exhibit increased human capital through the accumulation of knowledge and skills and lower crime. As Jacobs (1961) pointed out, the close-knit urban communities of the United States in the 1930s were safer and more productive because they had "eyes on the street" throughout the day. Generally speaking, non-conformance to social standards will be more frequently monitored, communicated and socially sanctioned in higher trust, dense networks. Firm innovation can benefit from higher regional human capital, especially if labor is less than perfectly mobile.

Second, firms rarely innovate in isolation. Instead, they interact with other organizations to share knowledge for supporting the development of new products and technologies. Maskell and Malmberg (1999: 179) state that "learning processes are inherently interactive in nature". Empirical findings underline the importance of knowledge exchanges in the creation of innovation (Audretsch and Feldman, 1996; Chesbrough, 2003; De Faria et al., 2010; Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016). More specifically, the combination of different kinds of knowledge often carried by diverse actors is critical in generating innovation. A number of findings suggest that the combination of analytic, synthetic and symbolic knowledge supports innovation (Asheim et al., 2011; Grillitsch and Trippl, 2014; Strambach and Klement, 2012), presupposing information sharing and interaction. In this regard, the effect of high-density networks fostering trust become apparent. "Higher trust levels might produce increases in information sharing that would allow faster dissemination of new research and ideas regarding how to make production processes more efficient" (Dearmon and Grier, 2009: 213). In addition, regions that exhibit faster knowledge dissemination will find themselves in an advantageous position compared to other regions as they are able to exploit that knowledge before others. Firms inside high-density-network regions benefit from earlier access to knowledge, thereby increasing their likelihood to use that knowledge for innovative purposes.

Third, any joint (innovation) project involves uncertainty and suffers from asymmetric information problems. Thus, firm innovation projects that require investments over time and involve external partners, such as universities or other firms, face the risk of failure if any of the involved parties behaves opportunistically. For instance, if monitoring is imperfect, one of the participating firms may free ride, spending fewer resources but reaping the full rewards upon project completion. The more information about firms' contributions is asymmetrically distributed, the larger the likelihood of free riding becomes. Similarly, a firm may commercially exploit some of the knowledge gained through the joint project if it can access the information ahead of time and before its cooperation partners can act. While legal agreements mitigate problems of non-cooperative behavior, they represent considerable transaction costs themselves. Closer networks and high trust environments increase monitoring, lower transaction costs and thereby decrease the likelihood of defection (Aghion and Durlauf, 2005). Trust serves as a mental heuristic based on which people expect fair play and enter into cooperative action. The relationship between trust as a regional resource and actual cooperative behavior is supported by previous empirical research in the innovation literature (e.g., Audretsch and Feldman, 1996; Chesbrough, 2003; De Faria et al., 2010) and in experimental settings, in which cooperation at the individual level correlates with the generalized trust of a region (e.g., Henrich et al., 2010; Selten and Ockenfels, 1998). Moreover, firms in high-trust regions with dense social connections can monitor other's behavior. Firms can subsequently select cooperation partners which have proven to be trustworthy. As Tullock (1999) shows, once individuals are free to select cooperation partners in sequential public goods games, a high degree of cooperation can be sustained.

Overall, we expect to observe a positive effect of generalized trust of a region on firm innovation inside that region. On the other hand, very high levels of trust and social cohesion may produce diminishing returns or even adverse effects, too (McFadyen and Cannella, 2004; Uzzi and Spiro, 2005; Echebarria and Barrutia, 2013). High density/high trust social networks may foster in-group social interaction to the point of exclusivity, and to the detriment of external relationships. Lock-in effects can result if too few weak-tie connections exist through which external knowledge enters the regional system. In fact, it has been empirically shown that the relationship between trust and patents follows an inverted U-shape (Echebarria and Barrutia, 2013). In addition, McFadyen and Cannella (2004) observe a peak in knowledge creation for researchers of biomedicine at 1.56 collaborations, after which the collaboration brings negative returns. Leenders et al. (2003) found an inverted U-shaped relation between tie strength and creativity in new product development teams. Thus, the trust-innovation-relationship will be relatively large and positive when regional trust levels are low. The trust-innovation relationship will become weaker, or even negative, as trust levels rise. We therefore hypothesize that there are diminishing returns of generalized trust after a certain threshold is reached:

H1: Generalized trust within regions and the likelihood of firm innovation have an inverted U-shaped relationship.

However, the opportunities and risks associated with innovation are not distributed equally across firms. SMEs must rely on cooperative innovation more frequently than larger firms because they lack essential technological and business-related in-house capacities (Cooke et al., 1997) due to higher fixed costs, minimum investment requirements as well as financial restrictions (Rammer et al., 2009). They have a lower capacity to engage in R&D (which lowers absorptive capacity) and require interactions with other firms or institutions to leverage their own strengths and compensate for their shortcomings (Cooke et al., 2005). As transaction costs and the probability of defection in cooperation increase with the number of cooperation partners, and SMEs are likely to engage in such cooperative ventures more frequently (Hervás-Oliver et al., 2021; Aragón Amonarriz et al., 2017), SMEs should particularly benefit from higher regional levels of trust. In contrast, larger firms with well-developed internal R&D departments are less dependent on external cooperation and therefore less susceptible to opportunistic behavior.

Moreover, SMEs are likely to be disproportionately burdened because they lack the specialized legal departments to set up comprehensive contractual arrangements to safeguard against non-cooperative behavior (Doh and Kim, 2014). Consequently, SME cooperation often occurs in an informal way (Apa et al., 2020). High levels of generalized trust can compensate for the lack of formal contractual arrangements. When firms negotiate and act based on the assumption of fair play, implicitly drawing on the regional resource of trust that is embedded within dense social networks, the likelihood of defection decreases. Firms in high-trust regions, characterized by close-knit social networks, are better able to monitor the past and present behavior of others and can select trustworthy partners based on that information. Thus, while larger firms can hedge against non-cooperation by using contractual legal arrangements, SMEs are less able to do so. They are therefore more likely to benefit from generalized trust in order to sustain cooperation.

In addition, SMEs rely more frequently on their DUI capacities (Jensen et al., 2007; Thomä, 2017; Hervás-Oliver et al., 2021; Runst and Thomä, 2022) whereas larger firms more often rely on the Science and Technology mode of Innovation (STI). According to Alhusen et. al (2022: 2) "DUI is defined as a by-product of other activities and it often results in tacit knowledge with a focus on 'know-how' and 'know-who', which tends to have a rather local reach in terms of its connections to customers, suppliers and competitors." The doing component speaks to practical problem-solving, reverse engineering and experimentation, where knowledge emerges in the process of product or service creation. The using component refers to the frequent incorporation of feedback from users, who directly affect the re-design of the product or service through their requests. External knowledge enters the firms via interactions with other professionals, e.g. at trade fairs or via meetings with former colleagues. DUI innovation is incremental, likely focusing on processes in lower-tech settings (Rammer et al., 2009). If the firm is embedded within a close community characterized by dense network connections and a high degree of trust, one can argue that it will be more able to access knowledge from customers or suppliers. While far reaching ties are useful because they reach into other networks, and therefore tap into completely novel information, the repeat-interactions on which DUI processes are based are more likely to benefit from close-knit groups. For example, if an existing product or service is being redesigned in response to customer feedback, it involves an element of trust since the customer is free not to purchase the new product or design upon completion of the innovation project. If the firm finds itself in a repeat-relationship with the customer, and if its embeddedness within close network ties enable it to obtain knowledge about the customer's commercial behavior in the past, it is more likely that such a risk will be accepted. In addition, the nature of incremental innovation requires a frequent back and forth between the innovating firms and its partners, in order to receive feedback during the many small steps taken along the way. Denser social networks are more likely to facilitate frequent communications, be it via planned or chance meetings of individuals involved in these projects, even outside of a narrowly defined work context. In contrast, the STI mode relies on the existence of internal R&D departments in large firms. Research personnel with academic backgrounds generate innovations based on codified knowledge. It is therefore less dependent on external partners or frequent interactions. The need for external interaction is further reduced because its innovation output is less incremental and less user-driven. Thus, in contrast to SMEs, dense social connections inside a region and its accompanying higher trust level are less important factors in the innovation process of the large firm.

H2: Higher levels of trust particularly affect SME innovation, as opposed to larger firms.

3. Trust and innovation in German regions

In order to test the hypotheses, we focus on the case of Germany, which allows us to utilize historically grown differences in generalized trust levels between regions. After World War II, Germany was divided into several planning regions, with those in the Western part belonging to the parliamentary democracy of the Federal Republic of Germany (FRG) and the regions in the East becoming part of the socialist republic of the German Democratic Republic (GDR) (Fulbrook, 2011). The superordinate political bodies of the Western Allies and the Soviet Union led to the formation of different institutions and opportunities for innovation (Hipp et al., 2021). Even after Germany’s reunification in 1990, this divide-and-rule strategy has shaped the regions’ institutions and economic growth until today (Cooke et al., 1997; Broekel et al., 2018; Obschonka et al., 2019; Ockenfels, 1998).

While East Germany’s formal institutions became part of the FRG’s economic system, the informal institutions and the level of generalized trust were affected by the autocratic regime and the transformation into the new system (Sztompka, 1995). This history and the conditions of the former regime have left an imprint on how people trust each other (Traunmuller, 2011; Lichter et al., 2021). Especially the experience of communism and surveillance in the GDR caused continuous insecurity in personal relationships (Fulbrook, 2011). A wide variety of norms and values, such as solidarity (Brosig-Koch et al., 2011), locus of control (Runst, 2013), openness to new experiences as well as extraversion differ between eastern and western Germany (Obschonka et al., 2019).

The delimitation of German regions further caused substantial differences in the structures of the respective innovation systems. The innovation systems are characterized by strong disparities in GDP, entrepreneurship and innovation outcomes across regions (Cantner et al., 2019). The number of patent applications varies between regions in East Germany (Hornych and Schwartz, 2009) and West Germany (Fritsch and Slavtchev, 2007), while the regional innovation efficiency is higher in West than East German regions and particularly high in the southern part of Germany (Broekel et al., 2018). These regional patterns seem to persist over time (Fritsch and Wyrwich, 2014). East German regions are characterized by weak industry structures with more SMEs (Cantner et al., 2018) and they receive more subsidies on average (Broekel et al., 2017). However, the national synergy of these policy programs depends on the region's level of analysis (Ruhrmann et al., 2021).

Despite the structural weaknesses of East Germany's innovation system, its cooperation intensity is higher than in West German regions, which show large disparities among themselves (Cantner et al., 2018). However, East German firms mostly tend to cooperate with public research institutes, which are per se trustful partners (Bstieler et al., 2015), but less with other firms like suppliers or competitors (Günther, 2004). Moreover, their cooperation behavior is driven by formal contracts (Welter et al., 2004), funding programs (Eickelpasch and Fritsch, 2005) and West German firms (Günther et al., 2008). The past exposure to authoritarian regimes reduces the likelihood of future cooperation (Wyrwich et al., 2022).

4. Data and methods

4.1 Data

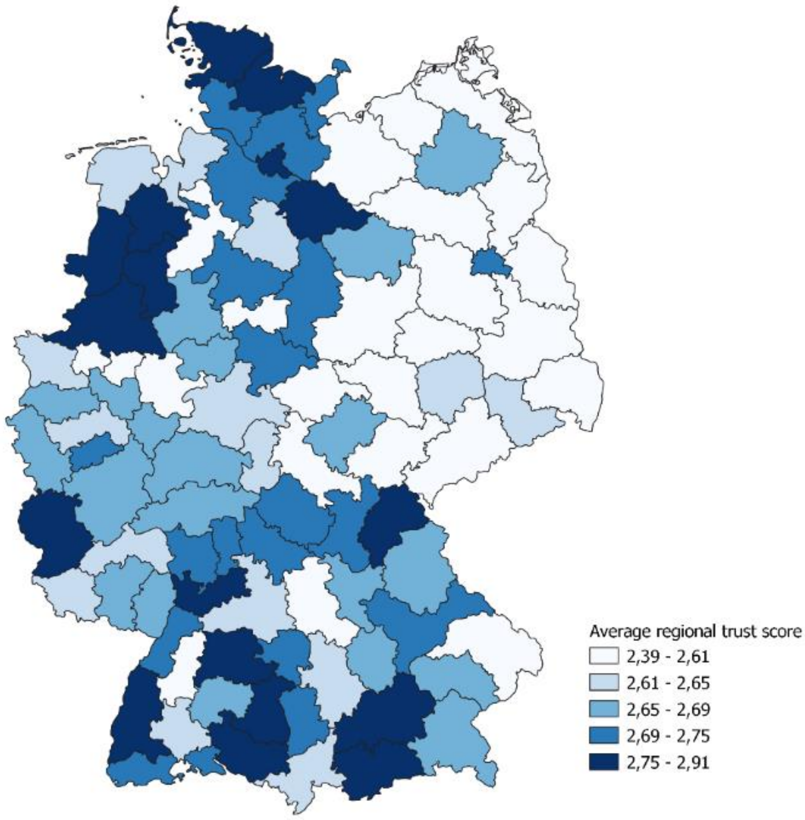
Our data set combines three different data sources. First, the MIP (ZEW, 2022) contains yearly information on innovation activities and the characteristics of German firms since 1993. It is representative for the German economy, and seeks to account for closures, M&A, and compensates for panel attrition every two years. The MIP is the source of the German contribution to the Community Innovation Survey (CIS) of the European Union every two years. However, it is not identical to the German component of the CIS. Second, we use the GSOEP (DIW, 2022), which is one of the largest and longest-running multidisciplinary household surveys worldwide by interviewing more than 30,000 people in Germany every year since 1984, providing a broad set of data on social and economic behavior such as trust between people. We use this dataset to include a measure for regional levels of trust. Third, we use the INKAR database of the German Federal Office for Building and Regional Planning (BBSR, 2022) to include further regional control variables. The INKAR database contains more than 700 regional indicators from Europe and Germany. All databases provide data on a yearly basis. Our observation period is from 2004 to 2018, as the GSOEP does not provide information on trust before that period.

The dependent variable is derived from a combination of two questions of the MIP questionnaire, which asks whether the firm has introduced new or significantly improved goods or services during the last three years or whether it has introduced new or significantly improved processes. INNO is equal to 1 if the firm has introduced a new or significantly improved product or process in the past three years, and 0 otherwise. This variable represents a broad measure of innovation, including patent protected STI innovation as well as DUI type innovations. It is available in the MIP every year.

Our main explanatory variable TRUST is a measure of the generalized levels of trust within regions, which we derive from the GSOEP. We build this variable from a survey question on a four-point scale, asking whether one can trust people. We then use the official planning region codes (Raumordnungsregionen) to derive a region's level of trust by calculating the average of all individual responses to this question within each region (see Laursen et al., 2012; Akçomak and Ter Weel, 2009; Akçomak and Müller-Zick, 2018 for a similar approach). The question is part of the survey every five years (2003, 2008, 2013, and 2018). The number of observations per region and year ranges from 47 to more than 1,000 depending on the size of the region, with a mean of 258. We approximate missing years by calculating linear trends of the regional levels of trust between the available years, as there is strong persistence of this variable of interest. Figure A1 in the appendix shows that the levels of trust deviate by only 0.2 on average between 2003 and 2018, which we assess, with regard to an average trust score of 2.662, as relatively low, indicating a strong persistence of trust over time. Intrapolating the aggregated trust variable allows us to generate a larger time series, as all other variables are available for the years between 2004 and 2018. Depending on the data availability, we chose the most fine-grained spatial level available, which are planning regions (i.e. the level between NUTS2 and NUTS3) to ensure a high explanatory power (Ruhrmann et al., 2021). The GSOEP does not contain sufficient observations to generate an aggregated trust measure at the county level (NUTS3). By contrast, the state level (NUTS1) only contains 16 and the NUTS2 level only 38 observations. In our main specifications, we use the lagged trust value from one year earlier as our main explanatory variable because innovation processes usually take some time (Cantner et al., 2019). However, as a robustness check, we also use trust values from current years and included a time lag of two and three years.

Figure 1 depicts the regional scores of trust for the German planning regions as average values across 2003, 2008, 2013, and 2018. Darker colors represent higher levels of trust averaged over time. We observe considerable differences in the trust levels across the German regions. For example, levels of trust are consistently higher in West Germany than in East Germany, which is in line with former research (e.g. Lichter et al., 2021). Moreover, northern and northwestern regions, in addition to certain regions in Bavaria and Baden-Wuerttemberg, show higher levels of trust.

Figure 1. Regional levels of trust in German spatial planning regions



Source: GSOEP, aggregated to regional levels (German planning regions). The depicted values are averages over the years 2003, 2008, 2013 and 2018, which is also why minimum and maximum values on the map differ from the descriptive statistics in table 2. The minimum and maximum values in table 2 refer to individual year observations.

Based on previous works, we include several firm-level controls from the MIP. We include EXP as an indicator for export activity because firms with experience in international markets are more likely to successfully exploit novel knowledge (Srholec, 2009). R&D indicates whether a firm invested in R&D activities in order to absorb external knowledge, which affects firm innovation output (Freeman, 1994; Cohen and Levinthal, 1989). Furthermore, we control for firm size, using the natural log of the number of employees (SIZE). The literature shows that firm size can have ambiguous effects on firm innovation (Veugelers, 1997; Christensen and Bower, 1996, Laursen et al., 2012; Tödtling and Kaufmann, 2001; Cooke et al., 2005; Schmutzler and Lorenz, 2018). On the one hand, large firms are able to spread innovation risks, might have easier access to finance and benefit from economies of scale (Veugelers, 1997). On the other hand, SMEs benefit from their smaller size by making more flexible and faster decisions, which is crucial for innovation (Christensen and Bower, 1996; Schmutzler and Lorenz, 2018). SECTOR indicates the sector affiliation according to 21 branches (Wirtschaftszweige), which is based on the NACE classification of the European Union. We control for the sector affiliation as sectors differ in their innovative activities and outcomes (Pavitt, 1984; Malerba, 2002). We control for the remaining structural differences between Eastern and Western parts of Germany using a binary indicator for the regions located in East Germany (EAST). Finally, we include the respective year in the analysis (YEAR) to account for time effects.

The RIS literature provides ample evidence on the impact of contextual factors within regions (Cooke et al., 1997; Doloreux and Porto Gomez, 2017; Fernandes et al., 2020). Thus, we include several control variables at the regional level in our analysis. POP_DEN measures the natural log of population density of the spatial planning regions, GDP is the natural log of region's per capita income, and UNEMP means the regional unemployment rate to control for the economic structure of the region and potential agglomeration effects (Schmutzler and Lorenz, 2018). STUDENTS accounts for the number of students as percent of the total population between 18 and 25 years as an indicator of regional human capital (Pfister et al., 2021). Table 1 provides the descriptive statistics of the firm-level variables and table 2 includes the regional-level variables. Our final sample comprises 49,752 firms in the observation period from 2004 to 2018.

Table 1. Descriptive statistics (firm level)

Variable	Description	Mean	SD	Min	Max
INNO	1 if firm introduced an innovation, 0 if not	0.454	0.498	0	1
EXP	1 if firm exports, 0 if not	0.496	0.500	0	1
R&D	1 if firm performs R&D, 0 if not	0.348	0.476	0	1
SIZE	Natural log of number of employees	3.719	1.681	0	13.071
SECTOR	Indicator for 21 different sectors				
EAST	1 if firm is located in the former eastern part of Germany, 0 if not	0.341	0.474	0	1

Sources: MIP. N= 49,752. The sample is an unbalanced panel of 18,443 unique firms that are observed over the period 2004-2018. The number of firms per year varies between 2,178 and 4,175.

Table 2. Descriptive statistics (regional level)

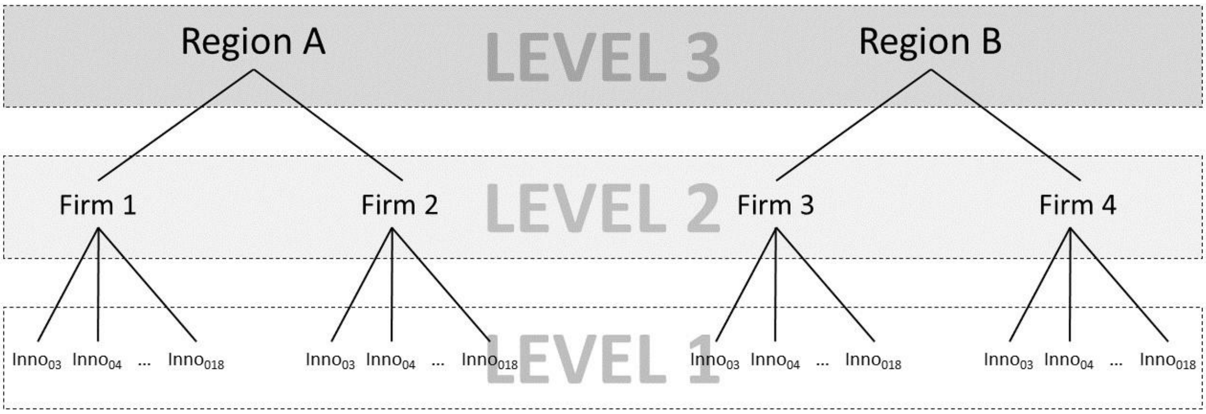
Variable	Description	Mean	SD	Min	Max
TRUST	average trust score in t-1	2.664	0.114	2.275	3.048
POP_DEN	Natural log of inhabitants per square kilometer	5.348	0.819	3.732	8.312
GDP	Natural log GDP per capita	3.391	0.260	2.688	4.227
UNEMP	Unemployment rate	7.749	3.922	2.1	24.0
STUDENTS	Percent of Students on the total population between 18 and 25 years	31.145	20.347	0	124.5

Sources: GSOEP (trust only), INKAR. N=1,440. Regional variables are collected yearly on the level of German planning regions. 94 regions are included in the analysis.

4.2 Methods

Firms' innovative activities are embedded within regions, which are hierarchically organized (Srholec, 2011; Cooke, 2001; Fernandes et al., 2020). The assumption of independent observations is violated and would lead to biased results (Snijders and Bsoker, 2012; Rabe-Hesketh and Skrondal, 2014). An MLM (Hox, 2002; Goldstein, 2003; Luke, 2004) is an appropriate approach to analyze data with a nested structure. MLMs relax the independence assumption and allow us to analyze the effects of regional characteristics on firm-level outcomes (Srholec, 2010) by decomposing the hierarchical heterogeneity in the dependent variable. Having a panel data set further allows us to model the time dimension as an additional level in the MLM. Similar to firms nested in regions, it can be argued that yearly firm observations are not independent from each other and thus constitute multiple observations of innovation over time which are nested within firms. Therefore, we apply a 3-level MLM, with yearly measurements of innovation (level 1) nested in firms (level 2) which are again nested in regions (level 3). Figure 2 illustrates the hierarchical structure of our data.

Figure 2. Multilevel structure of the data



In analytical terms, the model looks as follows. At level 1 innovation depends on the observation year. The effect of year on innovation ($\delta_{.ij}$) is assumed to be the same across all firms. The term γ_{0ij} represents the random intercept that varies between firms and e_{tij} is the random residual at the year level with a normal distribution. At level 2, γ_{00j} is the random intercept at the firm level that varies across regions and u_{0ij} is the level 2 random residual that is normally distributed. X_{tij} is a vector of firm level predictors and β_1 is assumed to be the same across regions. At level 3, γ_{000} denotes the overall intercept and u_{00j} is the regional level residual with a normal distribution. $C_{t.j}$ represents a vector of regional level predictors.

Level 1:

$$INNO_{tij} = \gamma_{0ij} + \delta_{.ij}Year + e_{tij}$$

Introducing level 2:

$$\gamma_{0ij} = \gamma_{00j} + \beta_1 X_{tij} + u_{0ij}$$

Introducing level 3:

$$\gamma_{00j} = \gamma_{000} + \beta_2 C_{t.j} + u_{00j}$$

Substituting all equations yields the full main model that can be divided into a fixed part $\gamma_{000} + \beta_1 X_{tij} + \beta_2 C_{t.j} + \delta_{.ij}Year$ and a random part $u_{0ij} + u_{00j} + e_{tij}$. We also included a cross-level interaction (Trust and R&D) as well as a random slope for R&D in one of our specifications (see table 3). However, as making these changes does not alter the overall results and, because we do not find a significant effect of the cross-level interaction, we decided to continue the analysis with the simpler random intercept model.

$$INNO_{tij} = \gamma_{000} + \beta_1 X_{tij} + \beta_2 C_{t.j} + \delta_{.ij}Year + u_{0ij} + u_{00j} + e_{tij}$$

For estimating binary response MLMs there exist two possibilities: quasi-likelihood estimation, and Markov-Chain-Monte-Carlo methods (MCMC) that are based on Bayesian statistics. As studies have shown that quasi-likelihood estimation is biased for these kinds of models (Leckie and Charlton, 2012; Stegmueller, 2013; Browne and Draper, 2006) we decided to estimate our models by MCMC. MCMC is a simulation approach that uses starting values and prior distributions of all model parameters. We obtain starting values from first-order quasi-likelihood estimation and use non-informative prior distributions. Then a Markov chain is initialized that "sequentially samples subsets of parameters from their conditional posterior distributions given current values of the other parameters" (Leckie and Charlton, 2012: 17). After the chain converges to its stationary distribution it is monitored for further periods. Final parameter estimates are obtained from means and standard deviations of the sampled parameters during the monitoring period. MCMC convergence diagnostics confirm that a burn-in period of 1,000 iterations and a monitoring period of 10,000 iterations is sufficient for our analysis. We perform our analysis by using the runmlwin command in Stata that automatically calls the MLwiN software that is specialized in multilevel modeling.

5. Results

5.1 Trust and firm innovation

Table 3 shows the multilevel regression results for the full sample (1-4), the analysis of large companies (5) and SMEs (6) as well as firms with low R&D-intensities (7) and high R&D-intensities (8). We include the last two specifications as a possible explanation for the differences between large firms and SMEs that is different modes of innovation. Specification 1 reports the empty MLM results, which enables estimating the variability of firm innovation between regions and between firms, as indicated by the interclass correlation coefficients (ICC level 2, ICC level 3). The size of the level 2 ICC (0.678) and the level 3 ICC (0.017) indicate that 67.8 % of the variability in innovation exists between firms, while 1.7% of the variability occurs across regions. These numbers confirm that although the regional environment matters for innovation processes, differences in firm innovation are mainly driven by firm characteristics.

Specification 2 reports the coefficients of the MLM, regressing innovation on regional trust and all covariates but without the squared trust term. Trust has a positive and significant (10 percent level) impact on the probability of being an innovator, supporting the results of previous studies (Laursen et al., 2012; Doh and Acs, 2010; Akçomak and Müller-Zick, 2018; Akçomak and Weel, 2009). Translating the coefficient of trust into odds ratios reveals that the odds of being an innovator increase by 1.581 if trust increases by one unit. The coefficients of all firm-level covariates are significant and have the expected signs. Except for STUDENTS (positive impact on innovation), all regional-level covariates are insignificant.

Specification 3 adds a quadratic trust term in order to analyze whether there is an inverted U-shape relationship. The coefficient of the quadratic term is negative and significant, indicating an inverted U-shape relationship. A simple back-of-the-envelope calculation[1] suggests that the maximum of the inverted U-shape relationship between trust and innovation is reached when trust is close to its mean (maximum = 2.749, mean = 2.662). It follows that the positive relationship between regional trust and innovation is valid in regions within the lower half of the trust distribution and that the positive effect of trust on innovation decreases with higher trust levels, a result that is corroborated by previous research (Echebarria and Barrutia, 2013). Overall, the results support Hypothesis 1.

As trust might also affect firm innovation indirectly through the included firm-level covariates (e.g. R&D activity), we add the cross-level interaction between trust and R&D and a random slope for R&D in specification 4. Heisig and Schaeffer (2019) argue that a random slope for the lower level variable should always be included when using a cross-level interaction. The overall results do not change and we still find evidence for an inverted U-shape relationship between trust and innovation. However, the coefficient on the cross-level interaction is insignificant and does not provide evidence for a mediating role of R&D activity

[1] The maximum of the inverted U-shape relationship between trust and innovation is reached when $x = -a/2b$, where a denotes the regression coefficient of trust and b denotes the coefficient for trust squared.

in the relationship between trust and innovation. We thus continue our analysis with the random intercept model of specification 3.

Next, we analyze the effect of trust for large firms and SMEs, respectively. Therefore, we divide the sample into firms with 500 and more employees (large firms) and firms with fewer than 500 employees (SMEs). Specification 5 reports the results including all firm- and regional-level covariates for the sample of large firms. The coefficient of trust becomes negative and insignificant. The coefficients of the firm-level control variables remain the same, but the coefficients for the regional characteristics change, i.e. POP_DEN becomes positive and significant, GDP and UNEMP become negative and significant, and STUDENTS becomes insignificant. By contrast, when running the same regression model for the sample of SMEs (Specification 6), the coefficient of trust is of a similar size compared to the full sample and statistically significant, indicating that trust is especially important for SMEs.

Finally, specifications 7 and 8 run the main model separately for firms with below- and above-average R&D-intensities. We assume that the innovation activities of firms with below-average R&D-intensities mainly rely on the DUI mode of innovation while firms with above-average R&D-intensities operate in the STI innovation mode. For the sample of firms with below-average R&D-intensities we again find an inverted U-shape relation between trust and innovation that reaches its maximum at a trust value of 2.717, which is similar to the baseline model, indicating a positive impact at lower levels of trust. For the sample of firms with above-average R&D-intensities we find a U-shape relation between trust and innovation. However, we identify the minimum of this U-function at a relatively low trust value of 2.569, after which the relation turns positive. As the relevant range of our trust variable lies between 2.275 (minimum) and 3.048 (maximum), the relationship between trust and innovation is mostly zero (at low trust values) or positive (for trust values around the mean and above). Overall, there is very limited evidence for a differential impact of trust on low vis-à-vis high-R&D companies, as hypothesized above.

This either means that higher-tech STI innovation benefits from regional trust in a similar manner as lower-tech DUI innovation. Alternatively, trust might exclusively affect DUI-processes - but R&D-innovation is often a result of a combination of the STI and DUI-modes of innovation (Alhusen and Bennat, 2021), and therefore firms with R&D departments benefit from trust indirectly. Our results cannot differentiate between these two explanations and the issue must therefore remain open for further inquiry. Moreover, the R&D variable provides only a limited picture of all the innovation processes in firms, and we are unable to clearly distinguish between STI-based innovation and DUI-based innovation based on this single variable.

Table 3. Multilevel regressions (3-MLM, binary dep. var.: INNO)

	(1) Empty	(2) Baseline linear	(3) Baseline quadratic	(4) Random slope	(5) Large	(6) SME	(7) Low R&D	(8) High R&D
TRUST		**0.427***	**12.863****	**13.991****	**-7.626**	**13.326****	**17.164*****	**-40.179****
TRUST^2			**-2.340****	**-2.546****	**1.260**	**-2.409****	**-3.158*****	**7.820****
TRUST*R&D				-0.240				
EXP		0.436***	0.438***	0.435***	0.505**	0.459***	0.394***	0.759***
R&D		3.651***	3.654***	4.281***	3.868***	3.657***	3.568***	5.603***
SIZE		0.274***	0.274***	0.276***	0.529***	0.242***	0.271***	0.384***
EAST		0.050	0.041	-0.002	-0.124	0.074	0.008	0.256
SECTOR		YES	YES	YES	YES	YES	YES	YES
YEAR		YES	YES	YES	YES	YES	YES	YES
POP_DEN		0.026	0.019	-0.013	0.501***	0.003	0.021	0.104
GDP		-0.124	-0.094	-0.020	-1.058*	-0.076	-0.065	-0.855*
UNEMP		-0.013	-0.009	-0.004	-0.119**	-0.007	-0.005	-0.063*
STUDENTS		0.003**	0.003**	0.003**	0.002	0.003**	0.002*	0.012**
Constant	-0.299***	-4.681***	-20.517***	-22.165***	8.136	-21.174***	-26.870***	47.034*
Var(constant level 2)	7.328	2.208	2.214	2.214	3.627	2.162	2.194	4.992
Var(constant level 3)	0.183	0.013	0.012	0.007	0.017	0.008	0.007	0.064
Cov(constant, R&D)				0.013				
Var(R&D)				0.044				
Observations	49752	49752	49752	49752	3980	45772	42606	7146
ICC (level 2)	0.678							
ICC (level 3)	0.017							

*Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01 respectively. The results are robust when using current trust instead of lagged trust (see table 5). SMEs are defined as firms with fewer than 500 employees. Large firms are defined as firms with 500 or more employees. The results are robust when using a SME definition of firms with fewer than 250 employees (see robustness section).*

5.2 Robustness checks

To test the robustness of our firm-level results, we first use current values of trust (specification 1 in table 4) and the second and third lag of trust (specifications 2 and 3) instead of the first lag used in the baseline model. The coefficients of trust and trust squared have the same sign as in our baseline model and remain significant when we use current trust values or its second lag. Only the coefficient on the third lag of trust becomes insignificant This suggests that current levels of regional trust support firm innovation in the present, but its positive effects dissipate over time, as past levels of trust become less relevant for current innovation processes.

In specification 4, we again use our baseline model but also include a dummy variable for border and coastal regions to control for regional spillover effects. Especially the different institutional systems in neighboring regions might affect the relationship between trust and innovation. The inclusion of the dummy variable does not change the results and the coefficients on trust and trust squared remain significant and of similar size.

Specifications 5 and 6 rerun the SME analysis but with a different classification of SMEs. We now only consider firms with fewer than 250 employees as SMEs and firms with 250 or more employees as large firms. Our results remain robust when using this alternative definition of SMEs as the effect of trust and trust squared on innovation is only significant for the SME sample.

Next, specification 7 addresses endogeneity issues that might arise from correlations between firm characteristics and unobserved regional variables (Hanchane and Mostafa, 2012). Therefore, we introduce the region as a fixed-effects dummy variable instead of including the regional level as random effects. The resulting 2-level model confirms the previous results of an inverted U-shape relationship between trust and firm innovation.

Finally, we perform panel regressions on the regional level in which PATENTS[2] (i.e. the number of patents per 10,000 inhabitants) represents the dependent variable (see table A2). Patents can be seen as a measure of invention and innovation (Griliches, 1990; Artz et al., 2010). If seen as an indicator for innovation it shifts the analysis closer to STI, rather than DUI. With this caveat in mind, the results provide some support for Hypothesis 1 and 2.

To sum up, in our baseline model (specification 1), the coefficient of trust is positive and significant. An increase in the regional level of trust by one unit is associated with an increase of 1.115 patents per 10,000 inhabitants. Put differently, a one standard deviation increase in trust leads to an additional 0.14 patents per 10,000 inhabitants. For a typical region of 1 million inhabitants this amounts to an addition twelve patents per year. As the average number of patents is equal to 5.46, the effect size should be regarded as small to moderate. Once we

[2] Patent information can be obtained from the German Patent and Trademark Office (DPMA). We used SQL queries to download quarter annual lists of all patent applications from its archive DEPATIS. We then use text recognition algorithms to extract postal codes of all participating inventors, applying fractional counting of patents and assigning each inventor 1/x share of a patent, where x is the number of inventors per patent. We aggregate these numbers by planning regions.

restrict the sample to all regions with a below average trust level (specification 2), the effect size considerably increases. Analogous to the findings above, trust seems to affect innovation more strongly when trust levels are relatively low (Hypothesis 1). Finally, we drop all regions with an above-average share of large firms (specification 3). The trust coefficient is larger than in the baseline result, which is in line with Hypothesis 2.

Table 4. Multilevel regressions (3/2-MLM, binary dep. var.: INNO)

	(1) Trust (t)	(2) Trust (t-2)	(3) Trust (t-3)	(4) Border	(5) SME	(6) Large	(7) Endogeneity
TRUST	**13.648****	**10.383***	**7.386**	**12.752****	**11.995****	**14.611**	**21.638*****
TRUST^2	**-2.501****	**-1.886***	**-1.347**	**-2.324****	**-2.167****	**-2.709**	**-3.995*****
EXP	0.436***	0.424***	0.458***	0.436***	0.455***	0.395**	0.435***
R&D	3.650***	3.706***	3.763***	3.648***	3.676***	3.744***	3.673***
SIZE	0.274***	0.275***	0.268***	0.274***	0.234***	0.469***	0.280***
EAST	0.028	0.065	0.093	0.044	0.026	0.235	-0.101
SECTOR	YES	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES	YES
BORDER	NO	NO	NO	YES	NO	NO	NO
REGION	NO	NO	NO	NO	NO	NO	YES
POP_DEN	0.023	0.038	0.045	0.024	-0.001	0.240**	1.018
GDP	-0.108	-0.129	-0.125	-0.078	-0.045	-0.773*	-0.195
UNEMP	-0.010	-0.013	-0.021*	-0.009	0.001	-0.102***	0.022
STUDENTS	0.003**	0.003**	0.004***	0.003**	0.003**	0.001	0.012***
Constant	-21.441	-17.892**	-13.785**	-20.443***	-19.508**	-21.664	-37.623
Var(constant level 2)	2.208	2.254	2.293	2.199	2.144	3.284	2.267
Var(constant level 3)	0.012	0.008	0.008	0.012	0.012	0.041	
Observations	49572	47574	44893	49752	42462	7290	49752

*Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01 respectively. SMEs are defined as firms with fewer than 250 employees. Large firms are defined as firms with 250 or more employees.*

6. Discussion

Our findings have important implications for the innovation literature, including studies on RIS, SMEs and economic growth. First, we show an inverted U-shaped relation between generalized trust between people in regions and firm innovation (Hypothesis 1), which remains robust across all our specifications. We contribute to the case studies literature that underlines the relevance of trust for firm innovation (e.g., Doloreux and Porto Gomez, 2017), and cross-sectional studies that use R&D expenditures or patents as proxies for innovation (e.g., Laursen et al., 2012). Trust has a positive impact on firm innovation for trust values up to 2.7 (trust is distributed between 2.28 and 3.05), after which it turns negative. These innovation-diminishing effects of trust have been previously observed by Echebarria and Barrutia (2013) for European regions as well as McFadyen and Cannella (2004) and Leenders et al. (2003) at the individual and team level. The trust-innovation relation turns negative as firms become locked into a situation in which the benefits from increased human capital, information sharing and lower transaction costs are only marginal. After restricting the sample to low-trust regions, we find that regions with below-average trust values benefit more from an increase in trust than those with higher trust values.

Second, we find that the trust-innovation relationship is stronger for SMEs (Hypothesis 2). Based on these results, one could argue that firm size (with its increasing firm capabilities) and trust represent substitutes, or alternative means for achieving the same end, i.e. to reduce transaction costs. We extend previous findings that underline the need for SMEs to exchange knowledge and compensate for their lacking resources (Aragón Amonarriz et al., 2017; Apa et al., 2020; Thomä, 2017). However, our results do not support the notion that DUI-processes benefit more strongly from trust than STI-processes, as we theorized in hypothesis 2. Nevertheless, our results cannot fully resolve this question because we sorted companies into DUI vis-à-vis based on a single variable (R&D intensity). Overall, we therefore tentatively state the fact that SMEs benefit more from trust than large firms cannot be explained by their reliance on DUI (as trust seems to support both DUI and STI processes) but because small companies are more reliant on interaction, and exchange and they lack the specialized legal departments to facilitate these interactions via formalized contract.

One might furthermore object that the interclass correlation coefficient of the regional level (see e.g. table 3) seems to be somewhat low, indicating that the regional level plays a minor role in firm innovation. However, there are three reasons why this should not cause alarm. First, firm innovation should predominantly be driven by firm-level characteristics. For example, a non-innovative firm, say a small food vendor, will not become innovative because the trust level within its region is higher, or because the population density increases. Innovation is fundamentally a firm level phenomenon. The surprising fact is that we find an impact of a regional characteristic, i.e. trust, at all. Second, we use a binary independent variable that distinguishes between innovators and non-innovators – our observable innovation characteristic. This variable records innovativeness in a limited way. For example, once a firm has moved from being a non-innovator to being an innovator, and even if the firm continues to become considerably more innovative after that point, the binary variable does not capture this development. Thus, in essence there is a latent variable (innovativeness) which we do not observe, and a binary variable INNO, which we do observe. It is only when a change in the regional characteristic pushes the latent variable beyond the threshold, that our INNO variable changes from zero to one, and we may therefore underestimate the impact of regional characteristics. Third, even before firms decide to either undertake or not undertake innovative endeavors, there is a locational decision to be made. Firms that benefit from regional trust will locate more frequently in higher-trust regions, and less frequently in low-trust regions. To some degree, we are therefore missing the relevant counterfactual firms, i.e. firms that would have benefitted from high trust values but located in a low-trust region nevertheless. As we are not observing some of these firms (whose innovation value would have suffered in a low-trust region) the impact of regional variables (like trust) is being underestimated.

Future research should build on our findings and examine other countries or regions. Similar to other empirical studies (e.g., Laursen et al., 2012), we use a single country to investigate the trust-innovation link. Further research could focus on European regions, for which it is sometimes difficult to obtain data on firm innovation. Furthermore, the complementarities to relational trust could be disentangled, e.g. within the different phases of the innovation process. Future research could also revisit the question of a differential impact of trust on DUI or STI processes, for which we find no support.

7. Conclusion

This paper has attempted to provide novel empirical evidence on the link between generalized trust between people in regions and firm-level innovation. We combined knowledge from the social capital, innovation and economic growth literature and developed new hypotheses on the impact of generalized trust on the likelihood of being an innovator. We further tested the relationships empirically for firms nested within the 94 German planning regions during the observation period from 2004 to 2018.

Our findings show that generalized trust between people in regions increases the innovativeness of firms and SMEs in particular. Trust seems to be an important firm resource, which increases the likelihood of present and future innovation; however, very high levels can have detrimental effects, too. Especially SMEs profit from higher levels of trust within a region to engage in cooperative activities, compensate for lacking resources and exchange via close, personal and repeated interactions. Moreover, the effect of trust on innovation is stronger in regions with relatively low levels of trust.

Policy-makers aim to support regional innovation via different strategies such as smart specialization or cooperation subsidies (e.g., Ruhrmann et al., 2021; Doh and Kim, 2014; Eickelpasch and Fritsch, 2005), although this approach has limits when it comes to fostering generalized trust. Trust among people in regions is based upon common experiences and knowledge. These historical processes lead to different processes of economic development and distinct regional settings that cannot be easily reproduced nor influenced by policy makers. Especially for regions with distinct histories such as in the case of East Germany, current differences in the levels of trust can be still attributed to the former autocratic regime (Lichter et al., 2021). We thus recommend that policy makers take note of very low as a disadvantage. The moderate effect size of the trust-innovation relationship, however, means that low trust regions are not locked-in on their current developmental trajectory. Our study provides an explanation behind the disparities among the regions and the role of generalized trust therein.

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Appendix

Figure A1. Histogram of differences in regional trust levels over time

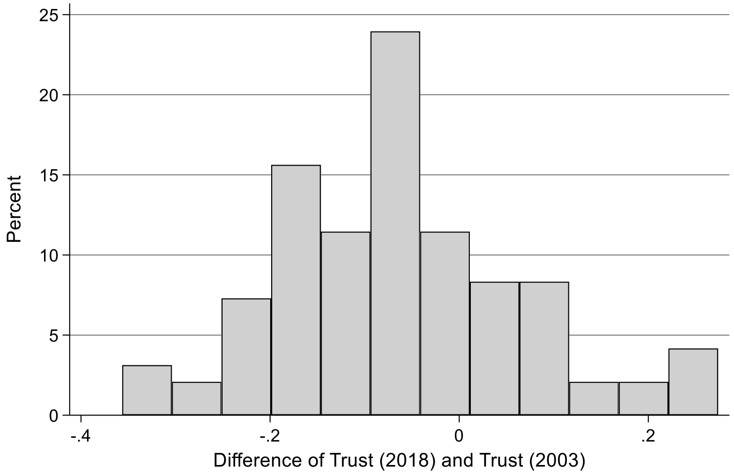


Table A1. Correlation matrix

	INNO	EXP	R&D	SIZE	EAST	TRUST	POP_DEN	GDP	UNEMP	STUDENTS
INNO	1									
EXP	0.319*	1								
R&D	0.631*	0.410*	1							
SIZE	0.280*	0.282*	0.310*	1						
EAST	-0.043*	-0.135*	-0.030*	-0.165*	1					
TRUST	0.023*	0.046*	-0.001	0.039*	-0.461*	1				
POP_DEN	0.045*	0.021*	0.039*	0.039*	-0.216*	0.331*	1			
GDP	0.029*	0.052*	0.008*	0.073*	-0.583*	0.626*	0.523*	1		
UNEMP	-0.012*	-0.108*	0.006	-0.054*	-0.598*	-0.525*	0.074*	-0.628*	1	
STUDENTS	0.015*	-0.021*	0.006	-0.023*	0.024*	0.327*	0.432*	0.327*	-0.027*	1

** p < 0.1*

Table A2. Panel regression results (data set 2, dep. var.: PATENTS, regional level)

	(1) Baseline	(2) Low Trust	(3) SME
TRUST	1.115**	2.412***	1.764**
GDP	0.324***	0.057*	0.485***
UNEMP	-0.056**	-0.094***	0.014
POP_DENSITY	-0.008***	0.006	-0.043***
STUDENTS	-0.011*	-0.009	-0.006
constant	-2.278	-3.147	-3.092
N	1344	533	700
R^2	0.448	0.397	0.523

** / ** / *** denote p-values of 0.1. / 0.05 / 0.01 respectively. All specifications contain region- and year fixed effects. The number of units is 94 planning regions. There is no trust information for two additional regions. 02*

Chapter 3

Spatial heterogeneity in the effect of regional trust on innovation

Spatial heterogeneity in the effect of regional trust on innovation

Thore Sören Bischoff, Petrik Runst & Kilian Bizer

Abstract

Previous studies have found that generalized trust positively affects innovation at the country and regional level. We extend this literature by arguing that there are four reasons to believe that the trust-innovation relationship is heterogeneous across geographic space. First, there is a saturation effect where regions in the lower half of the trust distribution are more likely to benefit from an increase in trust than regions in the upper half. Second, trust is more important in regions with less developed innovation capacities as it fosters cooperation and knowledge transfer, which is known to be especially relevant in lagging regions. Third, generalized trust and institutional trust can serve as substitutes: when institutional trust is low, generalized trust can be used as an alternative facilitator of cooperation. Finally, as smaller firms lack the legal capacities for sophisticated contractual arrangements and therefore resort to informal cooperation, the trust-innovation relationship is stronger in regions with a large share of small firms. Our results mostly support the small-firm and lower-trust region hypothesis. These findings underline the fact that regional innovation systems work differently and different mechanisms of cooperation can be leveraged to achieve innovation success depending on the regional characteristics.

JEL: D02, D83, O12, O18, O31
Keywords: Innovation, trust, regional innovation systems

> "Society [..] cannot subsist among those who are at all times ready to hurt and injure one another" (Smith, 1759: 189)

1. Introduction

The concept of generalized trust is ultimately derived from Coleman (1988), who he defines it as a dense network of strong ties between individuals who have strong dyadic relationships with each other. Trust facilitates frequent interaction, information sharing, and the enforcement of social norms. While this original conception is tied to the local level, it can also be applied to the regional level. In his seminal work, Putnam (1993, 2000) argues that regional trust confers a benefit on economic as well as democratic political processes in Italian and American regions. In economic terms, trust reduces the transaction costs of mutually beneficial exchanges, as neither party needs to incur the costs of safeguarding against defection, and cooperation increases, reflecting an idea that can already be found in Adam Smith (see Carl and Billari, 2014; Smith, 1776).

Generalized trust has been shown to be a driver of economic growth (Lichter et al., 2021; Algan and Cahuc, 2014; Algan and Cahuc, 2010; Zak and Knack, 2001; Knack and Keefer, 1997; Rodríguez-Pose, 2013, Muringani et al., 2021). More recent studies emphasize innovation as a primary mediating channel through which generalized trust increases growth (Laursen et al., 2012; Landry et al., 2002; Doh and Acs, 2010; Akçomak and Ter Weel, 2009; Akçomak and Müller-Zick, 2018, Bischoff et al., 2022). According to these studies, trust increases interaction, knowledge exchange and cooperation in innovation processes. Based on instrumental variable designs, the empirical evidence suggests a positive and causal effect of generalized trust on innovation (Akçomak and Ter Weel, 2009; Akçomak and Müller-Zick, 2018).

In this paper, we argue that there are four reasons why the trust-innovation relationship is not homogeneous across geographic space, and some regions are more likely to benefit from higher trust than others. First, very high levels of trust can increase in-group interaction at the expense of interacting with actors outside the region, and thereby hamper the inflow of new knowledge, i.e. individuals are locked into their strong-tie social network.

Second, the literature on regional innovation systems (RIS) emphasizes that regions substantially differ in their innovation patterns (Cooke et al. 1997; Camagni and Capello, 2013; Isaksen and Trippl, 2017). Most importantly, firms in less innovative regions rely on external sources of knowledge while innovation in more innovative regions is based on a combination of in-house R&D, external collaboration and non-R&D activities (Hervás-Oliver et al., 2021). Similarly, Filippopoulos and Fotopoulos (2022) suggest that economically lagging regions are more likely to benefit from collaboration than advanced regions. If innovation in lagging regions is more dependent on external sources of knowledge and collaboration than in leading regions, higher levels of trust should also hold stronger importance as it is a crucial driver of cooperation and knowledge exchange.

Third, smaller companies possess fewer in-house capacities than larger companies. This is particularly relevant when small firms cooperate with external partners. As they lack specialized legal departments to formalize contractual relationships, small firms are more likely to cooperate informally. Regional trust may support informal cooperation and can therefore serve as a substitute for lacking in-house resources.

Finally, in the presence of well-established institutions – defined as the political rules of the game (North, 1991) – governments enforce the law and protect property rights. In this way, transaction costs decline, and investments and cooperation become less risky, which fosters innovation and economic growth (North, 2010; Acemoglu et al., 2005; Knack and Keefer, 1997; Kaasa and Andriani, 2022), whether at the national or sub-national level (Rodríguez-Pose, 2013; Rodríguez-Pose and Ketterer, 2020). We argue that trust may serve as a facilitator of cooperation in the absence of high-quality formal institutions because trust replaces the need for legal protection to some degree. If contractual arrangements are less likely to be upheld in court, formal agreements may be substituted with informal ones, contingent on the fact that partners can be trusted. As the institutional quality varies across regions, the impact of trust on innovation should be similarly heterogeneous.

We contribute to the literature by introducing the spatially heterogeneous nature of the trust-innovation relationship at the regional level. While Akçomak and Müller-Zick (2018) test for spatial autocorrelation to analyze whether characteristics of neighboring regions affect innovation, they do not address whether the relationship between generalized trust and innovation differs across their sample of European regions. In addition, their analysis is limited to a cross-section of regions, with the associated risks from not controlling for time-invariant regional characteristics. Moreover, Peiró-Palomino (2019) uses non-parametric kernel regressions to explore spatial heterogeneity in the relationship between associational activity and innovation. The analysis focuses on the network dimension of social capital and does not analyze the effect of generalized trust on innovation. Again, the use of cross-section data prevents the author from using panel techniques.

We seek to extend the previous literature by analyzing a large sample of 216 European NUTS2 regions between 2005 and 2018. First, we apply geographically weighted regression (GWR) to reveal a considerable heterogeneity in the trust-innovation relationship, where eastern and southern European regions benefit more strongly from higher levels of trust than northern and western regions. Second, we apply fixed effects panel regressions to re-examine the results of previous studies that mainly rely on cross-sectional data and evaluate our own hypotheses. The use of cross-sectional data can lead to erroneous conclusions due to the missing time component (Roth, 2009), reversing the true sign of the coefficients in severe cases.

2. Generalized trust and regional innovation

Generalized trust was initially described as a form of social capital that emerges within dense clusters of interconnected individuals, many of whom have a dyadic relationship with each other, thereby forming a strong-tie social network (Coleman, 1988). Strong ties between individuals give rise to frequent interactions and information sharing, ensuring the rapid dissemination of information throughout the network. This feature of dense networks also aides in the enforcement of social norms, as norm violators are not only discovered more quickly but their transgressions are also quickly communicated throughout the network, ensuring a loss of reputation or other forms of social sanctions. Monitoring and sanctioning in dense social networks give rise to high levels of trust as individuals strive to conform to the social standards of their group. Empirically, the presence of high levels of trust can be understood as an indicator of a dense social network. Putnam (1993, 2000) illustrates how regional trust (or the lack thereof) can lead to more (or less) civic engagement in community groups, which influences the performance of Italian and American regions. His work prompted a large body of studies focusing on the relation between bonding social capital/generalized trust and the economic performance of cities, regions and countries (e.g. Nahapiet and Ghoshal, 1998; Knack and Keefer, 1997; Laursen et al., 2012; Schneider et al., 2000; Aghion and Durlauf, 2005).

There are multiple channels through which trust can increase innovation processes (see Bischoff et al., 2022). Close-knit communities are safer because individuals more actively observe and sanction the behavior of others (Jacobs, 1961, Putnam, 1993). Delinquency rates are lower and the investment in human capital is higher when parents are more involved in schools, and when at-risk individuals can be more easily identified. Both lower crime rates and higher investment in human capital should positively affect innovation processes, especially if labor is not completely mobile. Trust also increases firm interaction and knowledge exchange, which has been shown to support innovation processes (Audretsch and Feldman, 1996; Chesbrough, 2003; De Faria et al., 2010; Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016). Finally, higher levels of trust reduce transaction costs. Given that the social norm enforcement and information-sharing properties of dense social networks make it more costly for a firm to renege on cooperative agreements, trust therefore fosters firm cooperation and innovation (Audretsch and Feldman, 1996; Chesbrough, 2003; De Faria et al., 2010). A small body of literature has established a link between generalized trust and innovation at the firm (Bischoff et al., 2022; Laursen et al., 2012; Landry et al., 2002) and regional level (Doh and Acs, 2010; Akçomak and Ter Weel, 2009; Akçomak and Müller-Zick, 2018), with some studies applying instrumental variable techniques to argue for a robust causal impact of trust on innovation.

In this paper, we aim to extend this literature by developing the argument that the trust-innovation relationship is spatially non-homogenous, and that regions with certain characteristics are more likely to benefit from higher trust levels than others.

First, we propose that there are diminishing returns to trust in the context of innovation. We argue that while the beneficial aspects of an increase in trust prevail in low-trust environments, there are countervailing forces as the level of trust rises, such as the risks of non-cooperative behavior and an excessive reliance on in-group cooperation.

When trust levels are low, an increase in trust leads to some information sharing and collaboration, the benefits of which are widely accepted. By contrast, when levels of trust are higher, and more agents are willing to share potentially valuable information in anticipation of reciprocal behavior, the expected value of non-cooperative behavior rises. Generally speaking, the likelihood of non-cooperative strategies to succeed is higher in high-trust environments, counteracting the positive effects of higher trust. Without some level of monitoring, too much trust can consequently lead to the failure of (joint) innovation projects.

A distinct but related scenario pertains to the dangers of excessive in-group cooperation in higher-trust environments. We can illustrate this argument by contrasting the *strong ties* between the members of a dense network cluster with so-called *weak ties* described by Granovetter (1973). A firm located at the edge of a network cluster of well-connected firms may sporadically interact with previously unknown firms (outside its own cluster), and it thereby possesses weak ties. Weak tie creation and maintenance may occur unintentionally – for example, by meeting future business partners at trade fairs – or intentionally, by actively seeking out and contacting potential cooperation partners. A firm in possession of weak ties has first access to novel information that is potentially unavailable to other firms within its dense network cluster, thereby gaining an innovative and commercial advantage. Consequently, higher density social networks (with their higher levels of trust) can foster in-group cooperation and knowledge exchanges at the expense of creating and maintaining loose external relationships. We can think of this as a lock-in effect, where higher levels of social cohesion – which could be the result of remaining within the boundaries of tried-and-tested business relationships – can lead to an excessive level of in-group interaction, whose exclusivity may hinder the absorption of new external knowledge. There is some empirical evidence in favor of diminishing returns to trust at the firm (Molina-Morales et al., 2011), regional (Echebarria and Barrutia, 2013), and country level (Roth, 2009).

H1: Generalized trust is more strongly related to innovation in regions with low levels of trust, the positive effect of which vanishes in regions with high levels of trust.

Second, RIS in lagging regions are more likely to benefit from higher levels of trust. Each RIS is characterized by a unique combination of firms, organizations, supporting infrastructure, governance capacity and institutions (Edquist, 1997). Two recent studies sort European regions into different innovation groups. Hervás-Oliver et al. (2021) analyze SME innovation and suggest that firms in lagging regions are more likely to benefit from collaboration with other firms and networks than firms in frontier regions, which benefit from a broader combination of firm-internal R&D and various kinds of collaboration (not only firm collaboration). Using fuzzy-set qualitative comparative analysis, Filippopoulos and Fotopoulos (2022) also find that networks of collaboration are more important for innovation in lagging regions than leading regions, in which R&D, human capital and tolerance values play a stronger role. If – based on these results – we accept that collaboration is generally more important in lagging than leading regions, the former should particularly benefit from higher levels of trust, as transaction costs will be lower, and non-cooperative behavior less frequent.

H2: Generalized trust is especially beneficial for innovation in lagging regions and is less important for innovation in leading regions.

Third, trust mostly increases innovation in regions with a higher share of small firms, but is less efficacious in the presence of many large firms. Small firms lack the specialized legal departments to set up comprehensive contractual arrangements, and are thereby less capable of safeguarding against non-cooperative behavior (Doh and Kim, 2014). Small firms consequently rely on informal arrangements instead, which are more susceptible to defection. As small firms are more vulnerable to non-cooperative behavior, the presence of dense social networks and high levels of trust should support small firm cooperation in particular. In addition, smaller firms also lack other internal resources besides the ability to set up legal contracts, i.e. they are generally more dependent on cooperating with external partners (Cooke et al., 1997; Rammer et al., 2009). They therefore engage in cooperative agreements more frequently (Hervás-Oliver et al., 2021; Aragón Amonarriz et al., 2017). Again, higher levels of trust should prove to be particularly beneficial for small firms.

H3: Generalized trust particularly affects innovation in regions with a high share of small firms and is less important in regions with high shares of large firms.

Finally, trust and formal institutions can be regarded as partial substitutes, and trust is more likely to increase innovation when formal institutions are weaker. The existence of formal institutions that support market economic processes (sometimes called inclusive institutions) – especially private property rights and contract enforcement – supports innovation and economic growth (North, 1993, 1990, 2010; Acemoglu et al., 2005; Easterly and Levine, 2016; Kaasa and Andriani, 2022), whether at the national or sub-national level (Rodríguez-Pose, 2013; Rodríguez-Pose and Ketterer, 2020). If the quality of formal institutions is high, firms can cooperate via written contractual arrangements, and if agreements are violated they may resort to the judicial system. As firms are partially protected against non-cooperative behavior in the presence of sound institutions, they are also more likely to cooperate in the first place, invest in longer-term projects, etc., all of which increases the probability of innovation. Conversely, in lower-quality institutional contexts, legal protection becomes less reliable and innovation capacity declines. It can be plausibly argued that high-density social networks or trust are especially relevant in these circumstances. If a firm can rely on informal mechanisms to obtain information on the trustworthiness of potential partners, or if non-cooperators can be informally sanctioned within a dense network cluster, confidence in the successful completion of cooperative ventures increases.

H4: Generalized trust is particularly beneficial in regions with low levels of institutional trust.

3. Data and methods

We combine several data sources. First, we obtain patent data from the OECD (2022) database RegPat. Second, we use the European Social Survey to derive regional levels of generalized and institutional trust (ESS-ERIC, 2021). Third, we obtain data for control variables from Eurostat (2021) and GDP data for the UK from the Office for National Statistics (Office of National Statistics (UK), 2021). Fourth, we use data provided by the Heritage Foundation (2022) on institutional quality in the robustness section. Fifth, we obtain data on total employment by firm size category from the ESPON (2022) project 'Small and Medium-Sized Enterprises in European Regions and Cities'. Our observation period ranges from 2005 to 2018 and we use European NUTS2 regions as our primary level of analysis, testing the robustness of our results with NUTS1-level data.

Our dependent variable *PATENTS* is the natural logarithm of (fractionally counted[3]) regional patents per one million inhabitants. The geographical distribution of this variable is depicted in figure 1 (left panel). The regions with the highest patent intensities are mainly located in northern and central Europe, while regions in eastern and southern regions tend to have lower patent intensities.

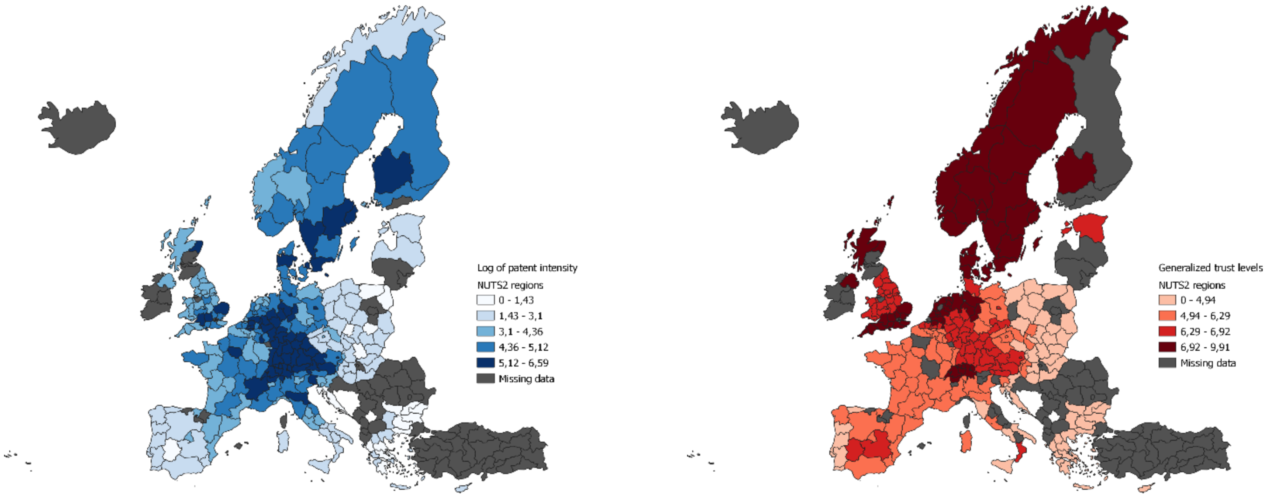
Our main independent variable GEN_*TRUST* is derived from three survey questions in the ESS that measure trust on a scale from 0 to 10.[4] These questions are part of the survey every other year. We aggregate individual responses to the survey questions at the regional level. By applying a principal component analysis (PCA) to the three trust items, we obtain a single indicator for generalized trust. Tables A1 and A2 in the appendix display the Eigenvalues and Eigenvectors from the PCA. We use the predicted scores of the first component as our final measure of generalized trust, on which all three items load strongly and positively, thereby generating average scores for each region. For missing years (odd years), we use lagged values. We also drop a region's value if the number of individual responses is lower than 50. We use the third lag of this variable in our regression analysis as it takes some time until the facilitating effects of trust can measured in terms of patent output. The geographical distribution of the average trust score is depicted in figure 1 (right panel). Regions in northern and central Europe have the highest scores of generalized trust, while trust levels are lowest in eastern and southern European regions. This pattern corresponds to expectations as the former socialist countries in particular display lower trust values and there is evidence with respect to an east-west split in trust at the micro level. Individuals from formerly socialist regions display markedly lower solidarity in experimental trust games (Ockenfels & Weimann, 1999; Brosig-Koch et al, 2011). Similarly, Putnam et al. (1992) have pointed to the persistently lower social capital and trust in southern Italian regions such as Sicily, a result that is mirrored by our data. The variable *LOW_TRUST* is equal to one if a region has trust values below the median of this variable.

We similarly derive regional levels of institutional trust (INST_TRUST), which is based on a question on how much people trust the legal system. Here, we use a single-item measure and therefore do not require a PCA. We again use the third lag of this variable in our regression analysis. The variable *LOW_INST_TRUST* is equal to one if a region has institutional trust values below the median of this variable. Table 1 presents the descriptive statistics for all variables.

[3] Each inventor is assigned a patent share that is equal to the inverse of the number of inventors of a patent.

[4] The following questions are included: 1. "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? 2. "Do you think that most people would try to take advantage of you if they got the chance, or would they try to be fair?" 3. "Would you say that most of the time people try to be helpful or that they are mostly looking out for themselves?"

Figure 1. Regional levels of patent intensity and generalized trust



Source: EPO for patent data and ESS for trust data, aggregated at the regional level (European NUTS2 regions). The depicted values are averages over the years 2005 to 2018.

We use the natural logarithm of R&D intensity (*R&D*), the share of people with tertiary education (*EDUCATION*), GDP per capita in thousands (*GDP*) and the natural logarithm of the population density (*POP_DENS*) as control variables, following a knowledge production function approach (Lee, 2017). To test the hypotheses concerning the spatial heterogeneity in the trust-innovation relationship, we create additional binary variables. *MICRO* is equal to one if a region has an above-median share of micro-sized firm employees among the total population. Similarly, SME and LARGE are equal to one if the share of SME or large-firm employees is above the median, where micro firms have up to nine employees, SMEs up to 249 and large firms more than 249 employees. The data is available for 2008 and 2014, and – depending on the country – at either the NUTS2 or NUTS3 level. As the variable values do not seem to fluctuate between years, we linearly intrapolate and extrapolate to fill the missing years of the panel structure.

Table 1. Descriptive statistics

Variable	Description	Mean	Std. Dev.	Min	Max
PATENTS	Natural log of patent intensity	4.185	1.458	0.114	6.875
GEN_TRUST	Regional level of generalized trust	6.169	1.576	0.649	10.668
R&D	Natural log of R&D intensity	2.595	0.939	-0.828	4.621
EDUCATION	Share of people with tertiary education	27.683	8.316	7.3	58.4
GDP	GDP per capita in thousands	26.366	9.379	7.5	66.3
POP_DENS	Natural log of population density	5.022	1.174	1.123	8.916
INST_TRUST	Regional level of institutional trust	5.062	1.047	1.243	8.013
INST_QUALITY	Heritage index of economic freedom	68.218	4.488	54.1	79.9
SME_SHARE	Employment share in SMEs (<250)	0.165	0.053	0.029	0.478
MICRO_SHARE	Employment share in micro-sized firms (<10)	0.072	0.027	0.037	0.276
LARGE_SHARE	Employment share in large firms (>249)	0.084	0.055	0.005	0.404
MICRO	Dummy variable equal to 1 if region has above-average employment share in micro-sized firms	0.5	0.5	0	1
LAGGING	Dummy variable equal to 1 if region was assigned to lagging cluster in cluster analysis	0.349	0.477	0	1
LOW_INST_TRUST	Dummy variable equal to 1 if region has below-average level of institutional trust	0.497	0.5	0	1
LOW_TRUST	Dummy variable equal to 1 if region has below-average level of generalized trust	0.497	0.5	0	1

Sources: OECD; Eurostat, ESS, Office for National Statistics (UK), Heritage Foundation, European Spatial Planning Observation Network. N=1942, except for the variables INST_QUALITY where N=1701, SME_SHARE where N=1309, MICRO_SHARE/MICRO where N=1708, LARGE_SHARE where N=1309 and LAGGING where N=1927. The sample is an unbalanced panel of 223 European NUTS2 regions observed over the period 2005 to 2018. The number of observations per year varies between 95 and 174.

The variable *LAGGING* is based on a cluster analysis, which we perform to identify types of regions in terms of their innovation properties. We include the variables *GDP*, *PATENTS* and *R&D* in a cluster analysis, first using hierarchical clustering (Ward's linkage) to guide our choice of the number of clusters, and second partition-clustering (Kmeans) to obtain the final cluster solution. This two-step procedure combines the advantages of both methods and allows us to both identify the optimal number of clusters and fine-tune the final solution (Hair et al., 1998). To account for the panel structure of our data, we cluster at six different points in time (2002, 2005, 2008, 2011, 2014, 2017).

The dendrograms as well as the standard cluster stopping rules (Calinski/Harabast pseudo F, Duda/Hart Je(2)/Je(1), Duda/Hart pseudo T-squared) support our choice of a three-cluster solution in most cases. Table A3 in the appendix presents the final cluster results by displaying averages of clustering and validation variables by category and the significance of cluster differences using Kruskal-Wallis equality-of-populations rank test with ties. We identify a three-cluster solution, one group with relatively low values of GDP, *PATENTS*, *R&D* and *EDUCATION* (lagging regions), one group with intermediate values of these variables and one group with relatively high values of GDP, *PATENTS*, *R&D* and *EDUCATION* (leading regions). The variable *LAGGING* is equal to one if a region belongs to the first group. Figure A1 in the appendix illustrates the geographic position of the different region types. The lagging regions can mainly be found in the eastern and southern parts of Europe, while the few leading regions are located in central and northern Europe. The remaining regions belong to the intermediate cluster.

To analyze our data and evaluate the hypotheses above, we apply several techniques. First, we perform GWR (Brunsdon et al., 1996; LeSage, 2004) to reveal the potential spatial heterogeneity in the relationship between trust and innovation. This method builds distance-weighted sub-samples for each region, including neighboring regions that are closer and excluding regions beyond a certain distance. It therefore produces region-specific coefficients for each region. While GWR permits us to identify the general existence of spatial heterogeneity, it also has one limitation: as the sub-samples of neighboring regions are fairly similar, the trust coefficients of neighboring regions must also be similar, thereby generating a coefficient map with smooth transitions between regions.

We also apply panel data techniques (fixed effects models with cluster-robust standard errors) to analyze the hypothesized determinants of spatial heterogeneity. The equation of our baseline model has the following form:

$$PATENTS_{it} = \beta_0 + \beta_1 GEN\_TRUST_{it-3} + \sum_{j=2}^{k} \beta_j X_{jit} + \alpha_i + e_{it}$$

$PATENTS_{it}$ represents the natural logarithm of patent intensity of region i at time t. β_0 is the model's overall intercept and β_1 the coefficient of our main independent variable GEN_TRUST_{it-3}. The term $\sum_{j=2}^{k} \beta_j X_{jit}$ contains all control variables and their respective coefficients. The unobserved time-invariant effects are covered by α_i and e_{it} is the error term of the model. We include a quadratic trust term to test for non-linearity of the trust-innovation relationship (H1). We also divide the sample in lagging/intermediate/leading regions, regions with lower or higher institutional trust, as well as regions that are above or below the median share of micro firms (also SMEs and large firms), and run the regression for each of these sub-samples (H2-H4). The final model combines all previous specifications by creating interaction terms. For example, the coefficient for the variable LOW_TRUST#GEN_TRUST estimates the effect of trust on innovation in regions with below-median trust values.

4. Results

4.1 Spatial heterogeneity of the trust-innovation relationship

The results of the GWR are displayed in figure 2. The dot color indicates the size of the trust coefficient, and a darker hue of red signifies a larger magnitude. Generally speaking, regions can be divided into a north-western and south-eastern half, with the latter displaying larger coefficients. Thus, there is evidence in support of spatial heterogeneity in the trust-innovation relationship. Moreover, a side-by-side comparison of the GWR coefficient map and the trust distribution in figure 1 indicates that regions with lower trust values – which are also located in the south and east – are indeed more likely to benefit from trust than higher-trust regions. The same is true with respect to institutional indicators, which are also lower in the east and south (see Figure A1 in the appendix). Finally, the share of micro firms is larger in the south and east and they are generally classified as lagging innovation regions, all of which can be read as tentative support for hypotheses one to four. Figure A1 in the appendix depicts the maps for the geographical distribution of the share of micro firms, institutional trust and leading, intermediate and lagging regions.

Figure 2. Local coefficients from geographically weighted regression

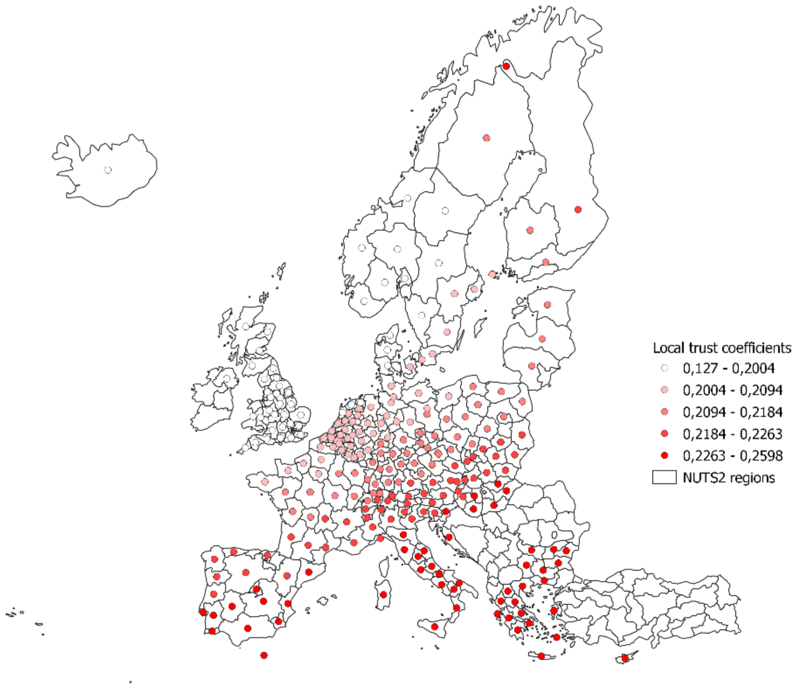


Table 2 summarizes the first set of regression results. In the baseline specification (column 1), the trust coefficient is small to moderate in size and statistically significant at the ten percent level. A one standard deviation increase in trust is associated with a 3.9% increase in innovation output. Thus, there is some evidence of a general (i.e. non-heterogeneous) trust-innovation relationship across all regions in the sample. The coefficients of the control variables are mostly in line with expectations. R&D expenditure, GDP as well as education are positively and significantly related to innovation. Surprisingly, population density is negatively related to innovation, a counter-intuitive finding that can already be observed in Lee (2017) but which may nevertheless point to one or more omitted variables.

In the following, we focus on spatial heterogeneity, starting with a quadratic trust specification (column 2). Both the trust and trust squared coefficient are different from zero (significant at the 1 percent level). A visual representation of the curve of predicted patent output as well as estimated trust coefficients at different levels of trust can be found in figure A2 in the appendix. We can see that an increase in trust only positively affects innovation in regions with lower levels of trust (where GEN_TRUST<6.19), and we observe negative trust coefficients when the level of trust is above this value. For example, when trust is equal to 3, the magnitude of the estimated coefficient is quite large (15%). This result therefore speaks in favor of hypothesis 1, stating that the trust-innovation relationship is more pronounced in lower-trust regions and even negative in high-trust regions. The negative impact of trust in regions with above-median levels of trust may be an artifact of the imposed quadratic functional form. To further investigate, we generate an above- and a below-median trust sub-sample (see table A4 columns 9 and 10 in the appendix). We find a positive trust effect in the latter but no evidence of a negative trust effect in the former.

Columns 3-5 display regression results for lagging, intermediate and leading innovation regions, respectively, as identified by the cluster analysis. We only find a significant effect of trust on innovation for the sample of leading regions where the trust coefficient is negative. The coefficient on trust for the sample of lagging and intermediate regions is insignificant. Although there seem to be differences in the relationship between trust and innovation between lagging and leading regions, the results do not support the hypothesis that trust is particularly important for innovation in lagging regions.

In columns 6 and 7, we utilize a measure for institutional trust (obtained from the ESS survey), splitting the sample into high and low institutional trust regions (using the median of this variable to split the sample). In line with hypothesis 4, we find evidence that trust is more important for innovation in regions with low levels of institutional trust. The coefficient of trust is only significant for the sample of low-trust regions and is of larger magnitude compared to the coefficient in the baseline regression in column 1.

Table 2. Baseline regression results, lagging regions and institutional trust

	(1) Baseline linear	(2) Baseline quadratic	(3) Lagging regions	(4) Intermediate regions	(5) Leading regions	(6) Institutional trust low	(7) Institutional trust high
GEN_TRUST	**0.039***	**0.269*****	**0.028**	**-0.024**	**-0.065****	**0.055****	**-0.029**
R&D	0.279***	0.265***	0.074	0.081	0.013	0.162*	0.195*
EDUCATION	0.039***	0.036***	0.080***	0.011***	0.023**	0.043***	0.013***
GDP	0.010*	0.010*	0.082***	0.012*	0.012	0.042***	0.006
POP_DENS	-2.544***	-2.352***	-1.931*	-0.072	0.566	-3.482***	-1.069**
GEN_TRUST^2		**-0.022*****					
Constant	14.702***	13.281***	8.273*	4.553	1.008	17.764***	9.585***
Observations	1942	1942	672	1045	210	965	977
R^2	0.259	0.272	0.488	0.110	0.306	0.395	0.137

*Notes: * / ** / *** denote p-values of 0.1 / 0.05 / 0.1 respectively. Regions are assigned to lagging and leading regions by a cluster analysis using R&D, GDP and PATENTS as cluster variables.*

The regression results in table 3 correspond to hypothesis 3, in which it is argued that small-firm regions should benefit more strongly from trust than larger-firm regions. An increase in trust in regions with an above-median SME share is associated with a 14.9% increase in patenting (significant at the one percent level). Conversely, the trust coefficient is not different from zero in regions with below-average SME shares (columns 1 and 2). We can further sharpen the interpretation of the results by looking at regions with an above- or below-average share of micro enterprises (columns 3 and 4). In regions with many micro firms, the coefficient is equal to 0.088 and significant at the one percent level. In regions with few micro firms, it is again not different from zero. Finally, regions with many large firms do not seem to benefit from trust, whereas firms with few large firms display a positive and significant trust coefficient of 0.101 (columns 5 and 6). Overall, the evidence speaks in favor of hypothesis 3.

Table 3. SME analysis

	(1) SME high	(2) SME low	(3) Micro high	(4) Micro low	(5) Large high	(6) Large low
GEN_TRUST	**0.149*****	**0.058**	**0.088*****	**-0.049**	**-0.021**	**0.101*****
R&D	0.434***	0.262**	0.287**	0.184**	0.371***	0.182
EDUCATION	0.052***	0.024**	0.030***	0.018***	0.025**	0.041***
GDP	0.019*	0.019	0.016*	-0.010	0.005	0.058**
POP_DENS	-3.717***	-2.328*	-3.898***	-0.286	-1.672**	-4.783***
Constant	19.249***	13.456**	19.289***	5.748	12.467***	21.694***
Observations	655	654	854	854	655	654
R^2	0.505	0.221	0.428	0.119	0.225	0.393

*Notes: * / ** / *** denote p-values of 0.1 / 0.05 / 0.1, respectively. The assignment of regions into the sub-samples micro high, micro low, large high, large low, SME high and SME low is based on the employment share in the respective size groups. Micro firms have up to nine employees, SMEs between ten and 249 and large firms more than 249 employees. If a firm has an above-average share of micro firms, it is assigned to the micro high sub-sample. The assignment to the other sub-samples works accordingly.*

Finally, we combine all previous specifications in table 4 by creating binary variables for micro firm (and SME) regions (with an above-median share of micro/SME firms), regions with lower institutional trust, and low generalized trust regions. We use the binary variable for micro firm regions instead of SME firm regions in our main specifications because we have less data on SME employment. However, the results are also robust when using the binary variable for SME firm regions (specification 2). We do not use a variable for lagging regions because the analysis in table 2 does not provide evidence of a positive relationship between trust and innovation in lagging regions. We also include an interaction term of the binary measures and the generalized trust variable (e.g. GEN_TRUST X INST_TRUST). The results in column 1 of table 4 are in line with H1 (low trust) and H3 (small firms) but no longer support H4 (institutions). In terms of magnitude, a one standard deviation increase in general trust increases patenting by 8.6% in micro firm regions and by 11.5% in regions with low general trust. However, one should note that the general trust coefficient is negative. Therefore, more than a single standard deviation increase in micro firms would be required to generate an overall positive trust impact. By contrast, in low-trust regions, a one standard deviation increase would be sufficient to generate a net positive outcome. Similarly, we see a similar picture when we exchange micro for SME regions, although the magnitude of the trust relationship becomes larger still (column 2). A single standard deviation increase in trust in an SME region is already sufficient to generate an overall positive net effect. Moreover, the effect size in low-trust regions rises to 17.4%.

Building on this result, we generate a dummy variable that takes the value of one if a region displays below-median trust and an above-median share of micro firms and zero otherwise (columns 3). A total of 506 observations can be characterized by such a confluence of circumstances. We find a highly significant and quite sizable effect of trust on patenting (16.6%). Finally, we generate a dummy variable that takes the value of one if the former conditions apply in addition to also exhibiting below-median levels of institutional trust (column 4). The trust effect rises further, which represents evidence for H4. The specification yields a trust coefficient of 0.2. A total of 443 observations are characterized by low levels of general trust, low levels of institutional trust, and high shares of micro firms. In two unreported specifications, we repeat the analysis from columns 3 and 4 by using SME share instead of micro firm shares, finding almost identical results.

In summary, we find evidence for H1 (low trust) and H3 (micro firms and SMEs), where the magnitude of the effect is larger in the case of H1 than H3. We could not find a significant effect of trust on innovation in lagging regions (H2), and there is only partial evidence of a positive trust effect in regions with low levels of institutional trust (H4).

Table 4. Combining arguments for spatial heterogeneity

	(1) Interactions MICRO	(2) Interactions SME	(3) Interactions MICRO & Trust	(4) Interactions MICRO & Trust & Institutions
GEN_TRUST	-0.084***	-0.071**	-0.064**	-0.037
MICRO	-0.505**			
BAD_INST	-0.056	-0.115	-0.246	
LOW_TRUST	-0.610*	-0.978***		
MICRO# GEN_TRUST	**0.086*****			
LOW_INST_TRUST#GEN_TRUST	**0.018**	**0.021**	0.050	
LOW_TRUST#GEN_TRUST	**0.115****	**0.174*****		
R&D	0.288***	0.292***	0.286***	0.281***
EDUCATION	0.037***	0.035***	0.037***	0.039***
GDP	0.006	0.016*	0.006	0.005
POP_DENS	-2.337***	-3.383***	-2.288***	-2.214***
SME		-0.789***		
SME# GEN_TRUST		**0.093*****		
MICRO_LOW_TRUST			-0.900***	
MICRO_LOW_TRUST#GEN_TRUST			**0.166*****	
MICRO_LOW_TRUST_INSTITUTIONS				-0.988***
MICRO_LOW_TRUST_INSTITUTIONS#GEN_TRUST				**0.200*****
Constant	14.435***	19.606***	14.125***	13.564***
Observations	1708	1309	1708	1708
R^2	0.327	0.400	0.324	0.328

*Notes: * / ** / *** denote p-values of 0.1 / 0.05 / 0.1, respectively. The variable MICRO_LOW_TRUST is equal to 1 if a region has above-median shares of micro firm employment and below-median trust values and is equal to 0 otherwise. Similarly, the variable MICRO_LOW_TRUST_INSTITUTIONS is equal to 1 if a region has above-median shares of micro firm employment, below-median trust values and below-median values of institutional trust and is equal to zero otherwise.*

4.2 The effective range of trust

In this section, we analyze the effective range of trust by generating co-patent categories based on the average distance between inventors. We use the centroid coordinate of NUTS3 regions of all inventor residential locations to calculate the average distance of all inventor pairs within a patent. We then split the distribution of the average within-patent distances at the 25th percentile (with an inventor distance of zero, i.e. they are located within the same NUTS3 region) median (with an inventor distance of 41.05 km) and the 75th percentile (with an inventor distance of *152.82* km), generating four inventor distance categories as a result of this partition.

Table 5 displays the result of regressions in which the dependent variables record the number of (fractionally counted) patents within a distance category. We find that generalized trust only affects (co-)patenting in the case of local inventor cooperation, where all cooperating inventors are located within the same NUTS3 region. An increase in trust by one standard deviation is associated with a 4.8% increase in patenting. The trust coefficient cannot be distinguished from zero in any other distance band, suggesting that the positive effects of dense social networks play out within a small geographic space. In other words, trustful cooperation is largely an intra-regional phenomenon, and the average distance between co-inventors must be less than 41.05 km for trust to be an effective facilitator of cooperation and innovation. This finding ties in with research on localized knowledge spillover. The analysis of patent citation distances reveals that innovation in most technology classes strongly benefits from inventor co-location (Murata et al., 2014; Kerr and Kominers, 2015). The latter paper states that the between-distance of firms must not exceed 75 miles for spillover processes to be effective, and spillover and clustering is most pronounced at very small distances below 40 miles, which corresponds well with our findings in table 5.

Table 5. Distance analysis

	(1) All co-patents	(2) No distance	(3) Small distance	(4) Medium distance	(5) Large distance
GEN_TRUST	**0.031**	**0.048****	**-0.006**	**0.008**	**0.007**
R&D	0.305***	0.281***	0.156***	0.103*	0.175***
EDUCATION	0.036***	0.015*	0.024***	0.029***	0.033***
GDP	0.002	0.004	0.010	0.013*	0.001
POP_DENS	-1.672***	0.832	-1.105*	-1.863***	-1.747***
Constant	10.062***	-3.026	5.697**	10.182***	9.817***
Observations	1942	1942	1942	1942	1942
R^2	0.282	0.153	0.051	0.113	0.211

Notes: * / ** / *** denote p-values of 0.1 / 0.05 / 0.1, respectively. Co-patents are defined as patents with more than one inventor. The distance of co-patents is measured by the mean distance between the centroids of each co-inventor NUTS3 residence of the respective patent. Each co-patent is then assigned to one of the four distance categories "no distance "(=0 km, same NUTS3 for all inventors), "small distance" (>0km and <41.05km), "medium distance" (>41.05km and <152.82 km), "large distance" (>152.82 km).

4.3 Robustness analysis

We address the modifiable areal unit problem (MAUP) – according to which different levels of aggregation can produce different results – by re-running the interaction model from table 4, column 1 at the NUTS1 instead of the NUTS2 level. The corresponding coefficients – which can be found in table A4, column 1 – confirm the previous findings. Generalized trust positively affects patenting in micro firm regions and low-trust regions. The effect size in low-trust regions becomes considerably larger at the NUTS1 compared to the NUTS2 level. As before, there is no trust effect in regions with low levels of institutional trust. Another specification (column 2) uses the third lag of R&D instead of present values, again confirming the previous results.

As an alternative measure to our institutional trust derived from the ESS, we can utilize the index of economic freedom (Heritage Foundation, 2022), which has previously been employed as an indicator of institutional quality (e.g. Williamson, 2009), but which is only available at the national level. The results (columns 3 and 4) support H4 in a similar manner as specifications 6 and 7 of table 2. The coefficient of trust is positive and significant for the sample of regions with lower levels of institutional quality and is negative and significant for regions with higher levels of institutional quality.

Columns 5 to 8 constitute a different way of analyzing the effective range of trust by measuring co-patents between inventors who are located in different countries (column 4, international), within the same country but not in the same NUTS1 region (column 5, national), within the same NUTS1 region but not in the same NUTS2 region (column 6), or within the same NUTS2 region. As before, trust only affects patenting at the smallest geographic level, when inventors are located in the same NUTS2 region.

5. Conclusion

In this paper, we have analyzed the effect of generalized trust on regional innovation in Europe. We use trust items from the European Social survey, patent information from the OECD RegPat database, and several sources for additional control variables. We argue that the trust-innovation relationship is heterogeneous across geographic space, and identify four plausible reasons for spatial heterogeneity.

First, we identify a sizable trust-innovation relationship in regions with low levels of trust. Once a medium level of trust is reached, the relationship no longer holds. Thus, there are diminishing returns to trust. We argue that non-cooperative strategies are more likely to succeed in higher-trust environments, counteracting the positive effects of more trust. Moreover, higher trust levels can lead to excessive reliance on in-group cooperation at the expense of seeking new connections and new knowledge. However, there is no evidence of a negative trust-innovation relationship in high-trust regions.

Second, it is known that smaller firms lack in-house resources and are therefore required to engage in cooperative partnerships. They also tend to lack the legal capacities for formalized contract, which again leads to more frequent informal relationships. Cooperation – and especially informal cooperation – can be facilitated by higher levels of generalized trust. Third, trust could serve as a partial substitute for formal institutions, where legal enforcement via state-run organizations can be replaced by informal relationships built on trust. However, while there is some evidence to support such a notion, our empirical findings are not consistent on this point and the question must remain open for future analysis.

Fourth, previous research suggests that cooperation is more important in lagging than leading regions. However, we do not find a consistent effect of trust on patenting in lagging innovation regions.

Our overall results support the general hypothesis of spatial heterogeneity in the trust-innovation relationship. Our paper is therefore in line with recent findings (Hervás-Oliver et al., 2021; Filippopoulos & Fotopoulos, 2022). It is also consistent with the literature on regional systems of innovation (see Edquist, 1997), which highlights qualitative differences in the way in which innovation systems operate, and underlines the need for place-sensitive economic policies. However, according to our results, the leading-lagging region distinction – which is so prominent in Hervás-Oliver et al. (2021) and Filippopoulos and Fotopoulos (2022) – does not seem to play a major role when it comes to the trust-innovation relationship.

Finally, we address the effective distance of generalized trust, finding that the trust impact is highly localized. It only seems to operate when patent holders are located in the same NUTS2 or NUTS3 region but not when they are further apart. Given that the build-up of trust is highly dependent on repeated and face-to-face personal relationships, the small effective distance seems to be quite plausible. This result may nevertheless limit the potential innovation and growth-enhancing effects of generalized regional trust, as it seems to suggest that trust-based networks cannot relay knowledge across larger geographic distances, somewhat reducing these networks' role in the diffusion of knowledge between leading and lagging regions. Instead, trustful networks facilitate the exploitation of existing regional innovation capacities by supporting cooperation and the (re-)combination of various pieces of local knowledge within regions.

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Appendix

Table A1. Eigenvalues from PCA

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	**2.72433**	**2.56789**	**0.9081**	**0.9081**
Comp2	.156443	.0372142	0.0521	0.9603
Comp3	.119229	.	0.0397	1.0000

Notes: N=2632

Table A2. Eigenvectors from PCA

Variable	**Comp1**	Comp2	Comp3	Unexplained
Help	**0.5754**	-0.7032	0.4178	0
Trust	**0.5815**	-0.0076	-0.8135	0
Fair	**0.5752**	0.7110	0.4045	0

Notes: N=2632

Table A3. Three-cluster solution

Variable	Overall mean	Lagging	Intermediate	Leading	χ^2	
PATENTS	4.185	2.728	4.892	5.366	992.523	***
GEN_TRUST	6.169	4.836	6.866	6.987	847.096	***
R&D	2.595	1.769	2.97	3.376	824.333	***
EDUCATION	27.683	22.577	29.209	36.492	498.806	***
GDP	26.366	17.36	28.665	44.061	1425.219	***
POP_DENS	5.022	4.596	5.048	6.284	414.569	***
INST_TRUST	5.062	4.222	5.472	5.703	721.551	***
INST_QUALITY	68.218	65.928	69.343	70.756	329.957	***
SME_SHARE	0.165	0.142	0.169	0.213	250.356	***
MICRO_SHARE	0.072	0.077	0.067	0.077	56.964	***
LARGE_SHARE	0.084	0.054	0.083	0.178	499.767	***
MICRO	0.5	0.618	0.391	0.608	64.433	***
LAGGING	0.349	1	0	0	1926.000	***
LOW_INST_TRUST	0.497	0.863	0.329	0.157	574.725	***
LOW_TRUST	0.497	0.906	0.283	0.243	695.105	***
observations		*672*	*1045*	*210*		

Sources: OECD; Eurostat, ESS, Office for National Statistics (UK), Heritage Foundation, European Spatial Planning Observation Network.

*Notes: The variables PATENTS, R&D, and GDP (printed in bold) are used for clustering. The statistical significance of mean differences across clusters is estimated using Kruskal-Wallis equality-of-populations rank test with ties (***significance level of 1 percent).*

Table A4. Robustness analysis 1

	(1) Interact. N1	(2) Interact R&D (t-3)	(3) Instit. quality low	(4) Instit. quality high	(5) Inter-national	(6) National	(7) N1	(8) N2	(9) Low trust	(10) High trust
GEN_TRUST	**-0.104****	**-0.094*****	**0.064****	**-0.047****	**-0.009**	**0.002**	**-0.009**	**0.054****	**0.058***	**-0.008**
MICRO	-0.305	-0.546**								
BAD_INST	0.177	0.014								
LOW_TRUST	-1.366***	-0.685*								
MICRO#GEN_TRUST	**0.078****	**0.094*****								
LOW_INST_TRUST#GEN_TRUST	**-0.018**	**0.007**								
LOW_TRUST#GEN_TRUST	**0.321*****	**0.127****								
R&D	0.403**		0.184*	0.102	0.109*	0.143***	0.012	0.296***	0.201**	0.135**
EDUCATION	0.056***	0.036***	0.047***	0.009*	0.019***	0.030***	0.025***	0.024***	0.038***	0.011**
GDP	0.013	0.009	0.053***	0.004	0.010*	0.004	0.002	0.007	0.044***	0.011**
POP_DENS	-2.432**	-2.080***	-4.135***	-0.831	-1.248**	-1.615***	-0.872	0.252	-3.453***	-0.501
R&D (t-3)		0.279***								
Constant	13.782***	13.163***	20.461***	8.892***	7.099***	8.955***	5.337	-0.140	17.663***	6.651**
Observations	623	1656	848	853	1942	1942	1942	1942	965	977
R^2	0.489	0.338	0.404	0.110	0.118	0.125	0.083	0.147	0.387	0.106

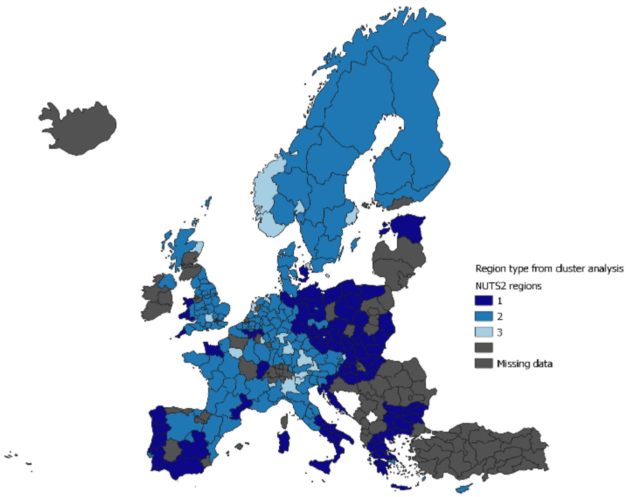
Notes: * / ** / *** denote p-values of 0.1 / 0.05 / 0.1, respectively. Specification 1 reruns the regression including the interaction terms of trust with the dummy variables MICRO, BAD_INSTITUTIONS and LOW_TRUST but use NUTS1 regions instead of NUTS2 regions as the level of observation. Descriptive statistics for the variables on level NUTS1 can be found in table A5 in the appendix. Specification (2) uses the third lag of R&D intensity instead of its current value as research projects usually take time to yield innovation. Specification 3 and 4 re-run specifications 6 and 7 of table 3 but use an alternative indicator for institutional quality. Specifications 5-8 re-run the distance analysis of table 4 but instead of using distances between NUTS3 centroids we use the belonging of inventors to NUTS2 regions to assign patents to the groups of within N2, within N1, national or international co-patents. Instead of using a quadratic trust term to analyze whether trust is more important in regions with low levels of trust, specifications 9 and 10 split the sample in observations with below- (specification 9) and above-median values of trust (specification 10).

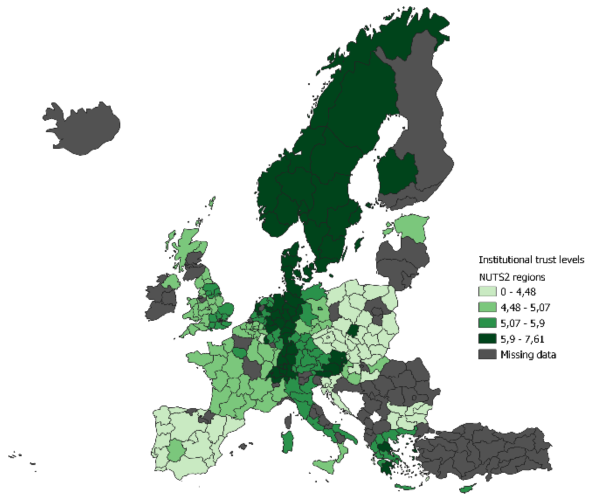
Table A5. Descriptive statistics (NUTS1)

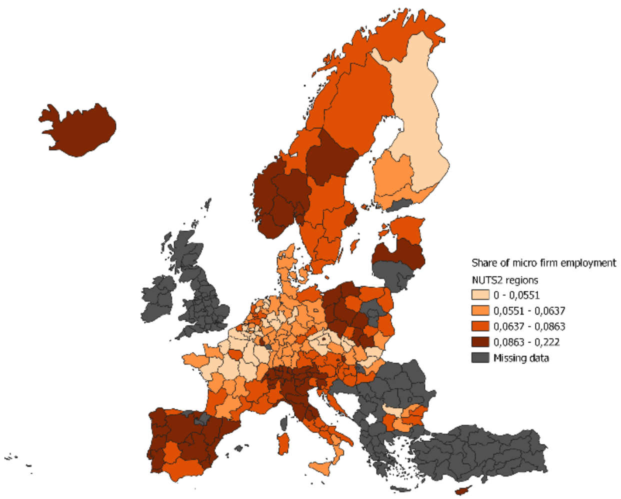
Variable	Description	Mean	Std. Dev.	Min	Max
PATENTS	Natural log of patent intensity	4.164	1.489	-0.824	7.055
GEN_TRUST	Regional level of generalized trust	4.775	1.607	0	8.931
R&D	Natural log of R&D intensity	3.557	1.032	0.437	5.517
EDUCATION	Share of people with tertiary education	28.336	7.666	10.077	49.3
GDP	GDP per capita in thousands	26.717	9.702	7.848	66.3
POP_DENS	Natural log of population density	5.085	1.212	1.689	8.916
INST_TRUST	Regional level of institutional trust	5.012	0.975	2.166	7.476
INST_QUALITY	Heritage index of economic freedom	68.225	4.778	58	79.9
SME_SHARE	Employment share in SMEs (<250)	0.175	0.055	0.043	0.327
MICRO_SHARE	Employment share in micro-sized firms (<10)	0.075	0.026	0.009	0.197
LARGE_SHARE	Employment share in large firms (>249)	0.094	0.056	0.009	0.311
MICRO	Dummy variable equal to 1 if region has above-average employment share in micro-sized firms	0.501	0.5	0	1
LAGGING	Dummy variable equal to 1 if region was assigned to lagging cluster in cluster analysis	0.444	0.497	0	1
LOW_INST_TRUST	Dummy variable equal to 1 if region has below-average level of institutional trust	0.499	0.5	0	1
LOW_TRUST	Dummy variable equal to 1 if region has below-average level of generalized trust	0.498	0.5	0	1

Sources: EPO; Eurostat, ESS, Office for National Statistics (UK), European Spatial Planning Observation Network. N=691, except for the variables INST_QUALITY where N=624, SME_SHARE where N=441, MICRO_SHARE / MICRO where N=623 and LARGE_SHARE where N=441. The sample is an unbalanced panel of 85 European NUTS1 regions observed over the period 2005 to 2018. The number of observations per year varies between 43 and 75.

Figure A1. Regional levels of the share of micro-sized employment, institutional trust and the region type from the cluster solution



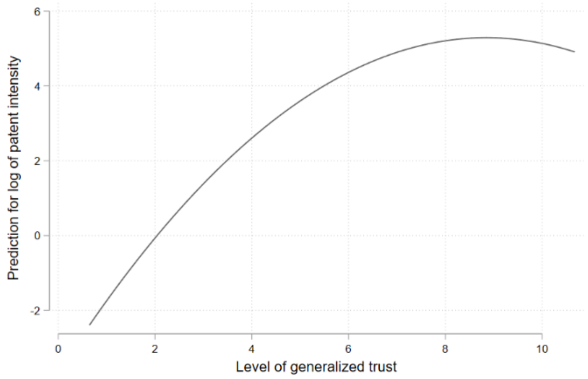




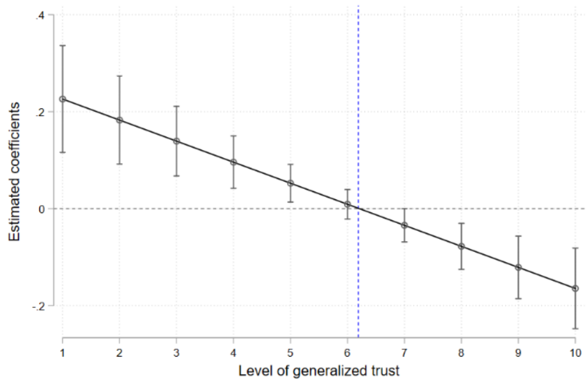
Source: Eurostat for SME data, ESS for institutional trust data, aggregated by the regional level (European NUTS2 regions). The depicted values for the share of micro-sized employment and institutional trust are averages over the years 2005 to 2018. The map for the cluster solution depicts the assignment to the two clusters in 2018. Regions that changed from lagging to leading regions have green borders and those that changed from leading to lagging regions have red borders.

Figure A2: Visual representation of the quadratic trust specification (based on table 2, column 2)

Predicted probabilities



Coefficients at different levels of trust



Notes: The horizontal line in the right panel denotes the average level of trust across all regions, i.e. is 6.183. The horizontal line simply signifies the zero line.

Chapter 4

From automation to databased business models: digitalization and its links to innovation in small and medium-sized enterprises

From automation to databased business models: digitalization and its links to innovation in small and medium-sized enterprises

Jörg Thomä & Thore Sören Bischoff

Abstract

In order to provide a better basis for measuring the complex interplay between digital technologies, competences and innovation, the present paper examines the digitalization-innovation link in small and medium-sized enterprises (SMEs). Starting from a review of the fourth edition of the Oslo Manual, a qualitative content analysis of interview data on innovating German SMEs is conducted to derive a category system that covers the multidimensional relationship between digitalization and firm-level innovation. Its empirical application confirms the heterogeneity of innovating SMEs with regard to digital transformation. While some SMEs are slow to find their way into digitalizing their innovation processes, others have started to use new digital technologies for efficiency reasons in the sense of "doing the same with less", while still others are aligning their entire business model with the requirements of digital environments based on the innovation principle of "doing something new". The paper concludes with implications for innovation measurement, managers, policy and research.

JEL: D22; O31; O32; O33

Keywords: Digitalization; Digital innovation; Innovation measurement; Qualitative content analysis; SMEs

1. Introduction

Digitalization is expected to have a profound impact on firm-level innovation (Teece, 2018; Nambisan et al., 2019; Bogers et al., 2022), which is one reason why supporting small and medium-sized enterprises (SMEs) to use digital technologies is one of the current policy concerns in the context of digital transformation (OECD, 2019; 2020). Digitalization changes innovation processes in a variety of ways, leading to a complex interplay between the use of digital technologies, corresponding competences and innovation at the company level, a topic that has only recently entered into the focus of innovation research (e.g. Ciarli et al., 2021; De Paula et al., 2022). A better understanding of this multidimensional digitalization-innovation link is crucial; for example, to explain how smaller firms are adapting and recombining digital technologies, know what competences they are using for digital-based innovation, or assess the extent to which digitalization is more of a driver of SME innovation or an innovation outcome in itself.

Several studies have been published on the digitalization behaviour of SMEs (e.g. Fauzi and Sheng, 2020; Saura et al., 2021; Soluk and Kammerlander, 2021) or specific aspects of the digitalization-innovation link in smaller firms (e.g. Coreynen et al., 2017; Bouwman et al., 2019; Taura and Radicic, 2019; Ben Arfi and Hikkerova, 2021; Soluk, 2022). However, at present, there is no overall picture on the multidimensional aspects of the digitalization-innovation link in SMEs. However, this would be a prerequisite for innovation policy to meet the need of smaller firms for targeted support in coping with the digital transformation.

Measuring the digitalization-innovation link in SMEs therefore provides a vivid example of the general need for developing adequate indicators on the use (or planned use) of new technologies and practices in firms, so that it can be assessed how this influences their innovation activity (Gault, 2013). In this regard, the fourth edition of the Oslo Manual (OECD/Eurostat, 2018; in the following: OM 2018) was a milestone. For the first time, a broad variety of digitalization-relevant aspects has been compiled from the perspective of innovation measurement. Numerous indications are given in loose order throughout the OM 2018; for example, on the role of digital technologies in both product and business process innovation, the classification of software development and database activities as potential innovation activities, the key importance of digital competences as a driver of innovation or the relevance of external market factors in triggering digital-based innovation. Thus, in a sense, the OM 2018 is a “real treasure trove” for delving deeper into the interdependencies between digital technologies, corresponding competences and firm-level innovation. However, a review of the OM 2018 on these different links in the relationship between digitalization and innovation as well as its systematic transfer and validation in empirical innovation studies is still missing. Moreover, several relevant main and sub-dimensions of the digitalization-innovation link are not or only partly addressed in the OM 2018, such as the within-firm drivers of digital-based innovation, the impact of external non-market factors or the overall relevance of digital-based innovation activities for the economic performance of companies.

Against this background, this paper explores the question of how digital technologies, competences and innovation are linked in SMEs. The resulting contribution to the literature is a better understanding of the multidimensional role digitalization plays in innovation activity at the company level. To this end, we start our empirical analysis based on a review of the OM 2018 by identifying a first set of potential links between digitalization and firm-level innovation. The system of content categories that we are developing on this basis forms the first step of a qualitative content analysis (QCA) of interview data from a sample of 49 innovating German SMEs. This serves the purpose of empirically validating the category system developed based on the OM 2018 and adjusting or expanding it via inductive reasoning. The result is a differentiated set of thematic areas that depicts the complex relationship between digital technologies, corresponding competences and SME innovation in its various facets. To complete this picture, we examine how these different categories relate to each other and use the derived category system to analyse – in the sense of a basic validity test – which groups of SME innovators can be distinguished in terms of their capability to use digital technologies in their innovation activities.

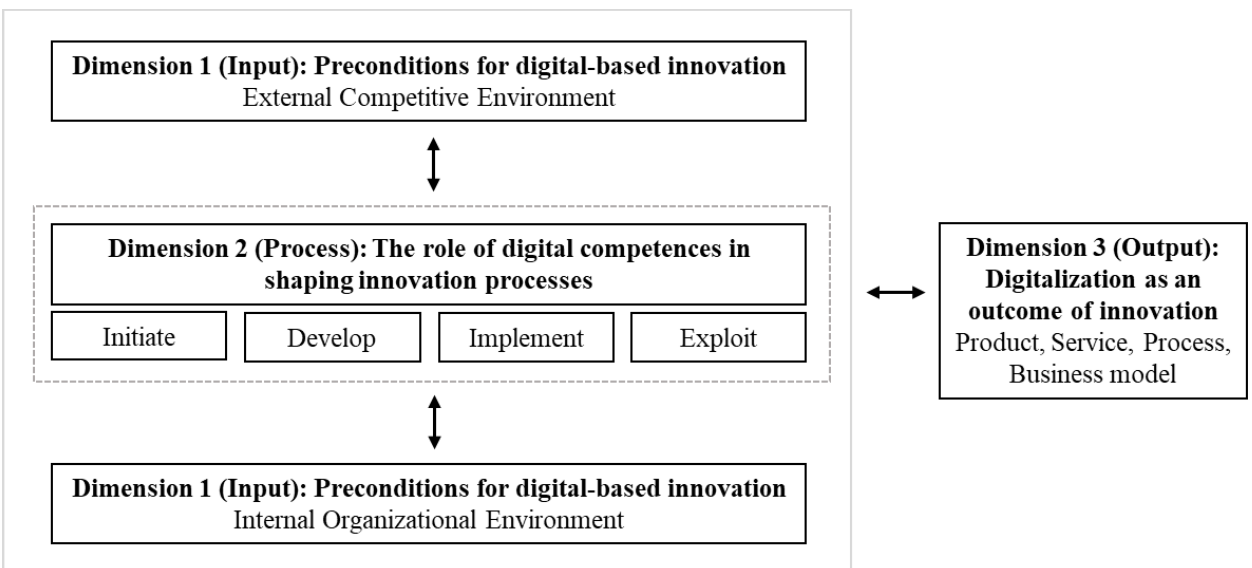
In this way, the results of our paper provide several indications for innovation measurement (for an overview of the literature, see Dziallas and Blind, 2019) – either by showing where innovation indicators can be targeted in the future to (quantitatively) measure the digitalization-innovation link at the company level, or, more concretely, where future revisions of the Oslo Manual could start in order to further improve the guidelines for measuring the multidimensional relationship between digitalization and innovation. Our paper can thus help managers, researchers, and policymakers alike who are interested in the role of digitalization in the context of firm-level innovation.

The remainder of this paper is organized as follows. In Section 2, we discuss our theoretical framework of the digitalization-innovation link in SMEs. Section 3 presents our interview data on digitalization activities of innovating SMEs and describes the steps of the QCA. The empirical results are described in sections 4 and 5. Finally, in Section 6 we summarize our results and conclude with implications for innovation measurement, managers, policy and further research.

2. Theoretical background

Based on the Input-Process-Output model developed by Agostini et al. (2020) to describe key aspects of the digitalization-innovation link and the conceptual framework of digital innovation proposed by Kohli and Melville (2019), we assume that the complex interplay between digital technologies, corresponding competences and SME innovation has three basic, interrelated dimensions (Figure 1). The first dimension relates to the input side of innovation by taking into account the fact that a success of digitally driven innovation requires both an organisational willingness to recognise opportunities and an equipment with resources and capabilities (i.e. a conducive internal organizational environment). Digital technologies are dynamic and complex and therefore often entail significant adjustments to a company's organisational culture, decision-making processes, strategies, resources, staffing and communication processes (Agostini et al., 2020). Therefore, due to their limited resource base, SMEs in particular are often only willing to use digital technologies if they consider them necessary in economic terms. Accordingly, they usually carefully weigh the costs and benefits of their use, often approaching the potential efficiency benefits of digitally enabled automation as a first step (Horváth and Szabó, 2019; Somohano-Rodríguez et al., 2020; Gartner et al., 2022). Naturally, SME owners play an important role here – either as inhibitors or as promoters of the use of digital technologies. At the same time, employees are of central importance when it comes to making the digital transformation a success in the early phases of the innovation process and thus creating the necessary organisational conditions for digital-based innovation within the firm (Kohli and Melville, 2019; Agostini et al., 2020).

Figure 1. Theoretical framework of the digitalization-innovation link in SMEs



Source: Own compilation based on Kohli & Melville (2019) and Agostini et al. (2020)

In addition to these internal drivers, various external factors also are a precondition for digital-based innovation at the company level (i.e. the external competitive environment, see Figure 1). This is particularly important for the digital transformation of innovating SMEs, as smaller firms – due to their resource and capability constraints – are often dependent on impulses from their external environment when it comes to the potential use of digital technologies and practices (Fauzi and Sheng, 2020). On the one hand, this refers to basic external conditions such as the industry or the market context of a company, which can determine whether and to what extent digital technologies are required for innovation. On the other hand, the digital transformation influences the way companies and other actors in the innovation system interact and learn with each other. For example, digitalization has changed the nature of external knowledge flows, raising urgent questions; for example, in terms of the appropriability of digital innovation results (Teece, 2018; Miric et al., 2019; Butticè et al., 2020) or regarding the interplay of digital technologies and open innovation practices (Brunswicker and Schecter, 2019; Shaikh and Levina, 2019; Pershina et al., 2019). All these aspects fall within the scope of the external competitive environment as part of the first dimension of the relationship between digitalization and SME innovation.

The second dimension relates to the enabling function of digital competences and related knowledge-based activities throughout the entire innovation process – i.e. from initiation, development and implementation to commercial exploitation of digital-based innovations (Figure 1). It has been shown that dynamic capabilities for digital transformation can have a profound influence on innovation processes in SMEs (Parida and Örtqvist, 2015; Cannas, 2021; Soluk and Kammerlander, 2021). Digital technologies and related competences can enable the creation of new or significantly improved products, processes and business models. Moreover, they promote cooperation, coordination and communication within the company and with external partners such as customers – which opens up a wealth of opportunities for interactive learning. For example, the ability of employees to participate in innovation can be increased through the within-firm spread of digital communication technologies, digitally supported knowledge management and the development of data analysis skills. The resulting demands on the company's internal competence base are correspondingly high (Kohli and Melville, 2019; Agostini et al., 2020).

At the same time, the digital components of innovative products or services are often only possible when certain preconditions are met in the company, such as IT resources, digital skills or a digital strategy. This explains, for example, Teirlinck's (2018) finding that there is close link between the internal development of software and in-house R&D activities in certain SMEs. Another example: According to Saura et al. (2021), information from digital databases is relevant for innovating SMEs if they are able to translate their database capabilities into a new digital marketing strategy for product sales. Especially in customer-focused SMEs, collecting and analysing data can help establish a data-driven approach to innovation that enables continuous improvement of products or services based on customer feedback and provides the opportunity to build and maintain close digital-based relationships with customers. For this to succeed, a company must combine the digital and physical aspects of its innovation process as optimally as possible. SMEs in particular, whose innovation mode is relatively strongly based on face-to-face interaction and person-embodied experiential knowledge (Thomä and Zimmermann, 2020; Runst and Thomä, 2022), therefore face the challenge of maintaining the innovation-promoting balance of human and technology in a digitally supported innovation process when building digital competences.

The third dimension of the digitalization-innovation link (Figure 1) relates to the role of digital technologies for product and process innovation outcomes in SMEs (e.g. Taura and Radicic, 2019; Eiteneyer et al., 2019; Ardito et al., 2021; Ben Arfi and Hikkerova, 2021) and the implementation of new forms of business models enabled by digital technologies (e.g. Bouwman et al., 2019; Rachinger et al., 2019). On this output side of innovation, two basic types of innovation outcomes can be distinguished from a theoretical point of view (Agostini et al., 2020). One is based on the principle of “doing the same with less”. Here, innovation consists of reducing operating costs through new or significantly improved business processes and protecting a company's profit margin from competitors' price pressure. On the other hand, innovations based on the principle of “doing something new” by using digital technologies to introduce new or significantly improved products or services can increase the company's revenue growth, lead to more lucrative and higher-growth market segments or enhance customer satisfaction. In this context of digital-based product innovation, a continuous reconfiguration of the company's business model is often crucial (e.g. in the context of the use of digital platforms). For SMEs in particular, digital technologies theoretically offer the opportunity not only to benefit from one of these two different types of innovation outcomes, but also to combine the advantages of both underlying principles (Gartner et al., 2022). This is because traditionally, small innovating firms have had to choose between a cost leadership and a differentiation strategy to gain a competitive advantage. Digital technologies now potentially enable SMEs to reduce their costs while simultaneously increasing the value of their market offerings through differentiation.

3. Data and methods

3.1 Interview data

Our sample is based on interview data from a previous research project on learning and innovation in SMEs (see Alhusen et al., 2021).[5] During this project, a broad exploratory interview survey was conducted, which addressed, among other things, the digitalization activities of the responding SME innovators. With the help of a semi-structured interview guideline (Table A3 in the appendix), a total of 49 interviews with SME owners and managers took place between February 2018 and October 2018. In accordance with the commonly-used definition applied by

[5] The project was entitled “Indicators for the Doing-Using-Interacting-Mode in SMEs (InDUI)”, funded by the German Federal Ministry of Education and Research, Grant Number 16IFI005. We are grateful to have been given the opportunity to analyse the interview data collected during the InDUI project. We would especially like to thank the interviewers, namely Harm Alhusen, Tatjana Bennat, Martin Kalthaus, Stefan Töpfer and Tina Wolf.

the European Union, an upper threshold of 249 employees was used to identify the survey participants. The average firm size in the interview sample amounts to 49.7 employees, while the interviews lasted 64.9 minutes on average (Table A2).

During the process of data collection, several steps were taken by the corresponding researchers to ensure data validity (for more details, see Alhusen et al., 2021). Since the purpose of the exploratory interview survey was not to collect a representative sample of innovating SMEs but rather the handpicked identification of different relevant cases, a purposive sampling strategy was chosen. Based on extensive web search, suggestions made by regional innovation consultants, the examination of innovation award results and snowball sampling, a number of innovating SMEs were identified. In this context, special care was taken to ensure that SMEs from various industries and business contexts were sampled to account for the heterogeneity of smaller firms in terms of innovation. Moreover, three German regions were selected for the empirical survey (Table A2). In our case, this geographical sample has the advantage that different regional economic and innovation structures are covered. For example, the region of Jena is characterized by manufacturers of optical products that are currently strongly implementing digital transformation processes, while e.g. the SME respondents from the urban area of Hanover often came from the information and communication technology (ICT) sector and thus naturally have a close connection to digitalization. On the other hand, the region of Göttingen has a long tradition in manufacturing meteorological instruments, with digital measurement technology currently being an integral part of product and process automation in corresponding companies. The fact that the heterogeneity of innovating SMEs in terms of sector and company context was taken into account in the previous project when compiling the interview sample therefore has the benefit for us that the role of digital transformation for SME innovation can be very broadly examined.

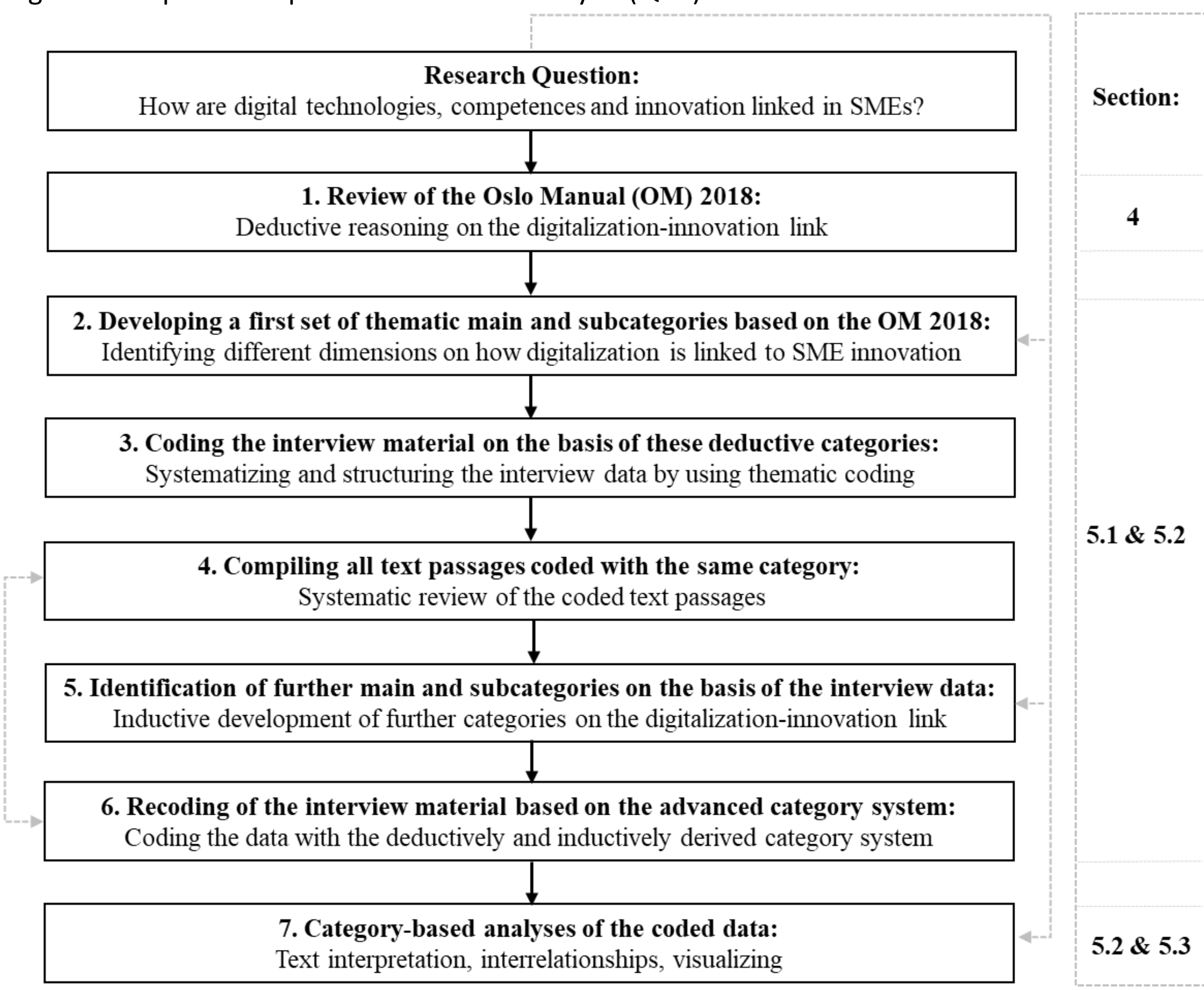
Furthermore, as the former project’s primary research interest laid in conducting an exploratory investigation into the innovation activities and learning processes of the sampled SMEs, the interview guideline was only used to roughly structure an interview talk to enable a high degree of flexibility and openness in collecting information from respondents. Because of this, the topic of digitalization came up at various points in the interviews – either by the interviewees themselves or through specific queries by the interviewers regarding certain digitalization aspects relevant to innovation.

The willingness of respondents to provide information was supported by promising anonymity for all interviewees. For this reason, each respondent is assigned a unique number, on the scale I1 to I49 (Table A2). Moreover, before starting with the interview stage, a pilot phase was conducted to test and adapt the interview guideline. Finally, to allow for a computer-assisted empirical analysis of the collected interview data, the interviews were recorded and later transcribed by a professional transcription service provider who was not part of the research team.

3.2 Qualitative content analysis

We use qualitative content analysis (QCA; Mayring, 2000; Kuckartz, 2014) to empirically identify the multidimensional relationship between digitalization and firm-level innovation according to various main and sub-categories. For this purpose, we apply and combine both deductive and inductive reasoning to obtain an overall picture of the various facets of the digitalization-innovation link in SMEs. MAXQDA was used throughout the qualitative data analysis. The methodological approach and the respective steps are shown in Figure 2. On the right side of Figure 2, an additional column is added indicating in which sections of the present paper the results of each step can be found.

Figure 2. Steps of the qualitative content analysis (QCA)



Notes: Own compilation based on Mayring (2000); Kuckartz (2014).

Starting from our research question, the first step of the QCA is a review of the OM 2018 on the potential links between digitalization and firm-level innovation. On this basis, a deductive formulation of different thematic categories is conducted. For this purpose, we reformulated the identified aspects from the OM 2018 review shown in Table A1 (Appendix) as main and sub-categories through which a first structuring of the interview data in terms of content could be achieved (Steps 2 and 3). The transcripts were read through from this perspective, striking passages were marked and memos were written. Most importantly, all of the interview material was coded along the deductive OM 2018 categories. In steps 4 to 6, all text passages coded in the interview transcripts with the same category were compiled and reviewed. This served to allow a further differentiation of the categories after finishing the first part of the coding process. Memos and the markings of important text passages were used at this point for a continuous reconsideration of chosen codifications and to create a solid basis for the later interpretation of the category system. Moreover, based on the interview material we inductively derived further main and sub-categories with relevance to the digitalization-innovation link in SMEs that extend beyond the OM 2018. If necessary, the categories deductively derived from the OM 2018 were adapted and modified in light of the evidence from the interview data. As a result, the QCA led to an advanced category system in which all of the interview material was coded one further time to achieve a finer content structuring of the interview material.

Since further categories or the need to revise existing ones could arise at any time during the coding process, steps 4 to 6 were conducted several times, which implies that the interview data has been analysed on a recurring basis (dashed line on the left side of Figure 2). Through the entire coding procedure, the material was always first completely coded by the same member of our research team to avoid potential problems due to insufficient intercoder reliability. Only in a second step did another researcher check the coding in each case so that potential disagreements in terms of coding preferences could be discussed and solved. At this point, special care was taken regarding the straightforward interpretation of text passages and their allocation to certain categories. Finally, Step 7 of the QCA refers to the presentation and discussion of the final empirical results. This includes a category-based interpretation of the final category system and an analysis of the interrelationships between different sub-categories.

4. Empirical results I: Review of the OM 2018

Table A1 in the appendix summarizes the various digitalization aspects discussed in five chapters of the OM 2018 from an innovation measurement perspective. The first one (Chapter 3) is about the definition of various types of innovation outcomes by considering the digital transformation. The relevance of digitized information is shown from the perspectives of product and business process innovation activity. In the case of defining product innovation, this means that the renewal or improvement of goods in terms of integrated software or the degree of their digital nature as well as the digitalization of services are explicitly addressed in the revised manual. The definition of business process innovation now also covers the adoption and modification of digital technologies within firms "to codify processes and procedures, add functions to existing processes and enable the sale of processes and services" (OECD/Eurostat, 2018: 72-73). Digital-based business process innovations are therefore to be found along the full range of business functions, such as production, service delivery or marketing. Business model innovations in response to the digital transformation are defined in the OM 2018 as typically involving either the digitalization of a firm's products or business processes, or both (for example, in the course of switching to digital business processes to sell or deliver products).

Chapter 4 of the OM 2018 discusses the role of software development and database activities. The manual lists these two – along with seven other areas (including R&D, employee training, marketing, etc.) – as innovation activities if they contribute to product, business process or business model innovation. While digitalization can potentially play a role in different types of innovation activities, it holds central importance in firms that take steps in data development activities (including software) in their pursuit of innovation. Software development constitutes an innovation activity, for example, when software is integrated in existing products or services to renew or improve them. Digital database information holds relevance when its use results in product or business process innovations.

Furthermore, in line with our theoretical framework of the digitalization-innovation link in SMEs (Section 2), the OM 2018 emphasizes "the enabling, general purpose nature of digital technologies and data analytics" (OECD/Eurostat, 2018: 118). Thus, digital competences are described in Chapter 5 as a key business capability with high relevance for innovation activities. This includes the use of digital technologies, the existence of in-house capabilities required for it and the availability of data management competences, whereas in each case the digital skills of the workforce are deemed to be highly important (see Table A1).

The OM measurement guidelines also account for the fact that the digital transformation affects the way in which firms and other actors in the innovation system are interacting and learning with each other. Thus, the role of digital-based knowledge flows in innovation activities and their potential effects for a firm's cooperative and competitive environment are described in the OM 2018's Chapter 6 as another dimension of the digitalization-innovation link (Table A1). Finally, Chapter 7 of the OM 2018 discusses the measurement of external market factors driving digital-based innovation. Such drivers described in the OM 2018 are the digital nature of a firm's market, the influence of customers and users on the incentive to engage in digital-based innovation, the role of suppliers as a source of digital technologies/competences and the relevance of online sources through which firms can find new ideas and information for innovation. Throughout this discussion, the role of digital platforms is assigned strong importance, reflecting not least their high innovation potential for SME (Kenney et al., 2019; Ben Arfi and Hikkerova, 2021).

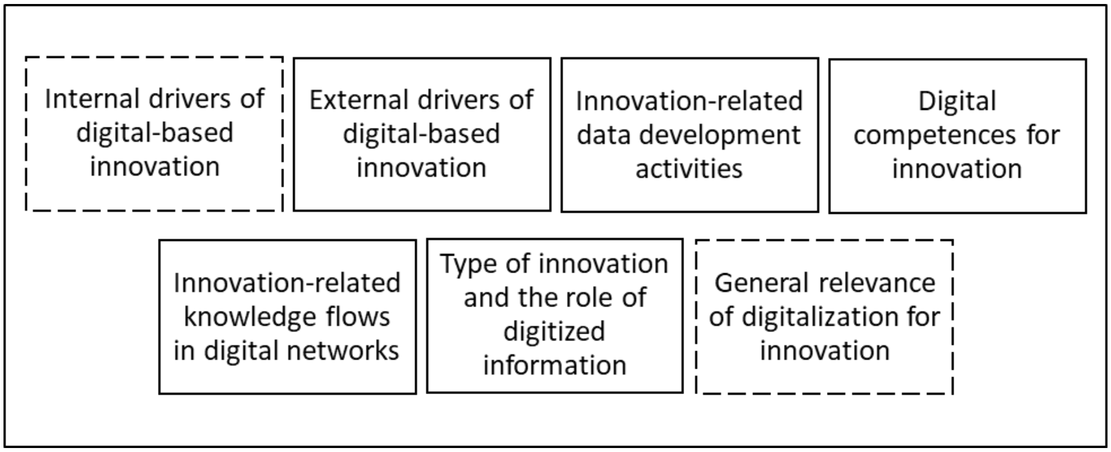
5. Empirical results II: Interview data

5.1 Main categories of the digitalization-innovation link in SMEs

Five of the main categories derived fully or partly relate to the OM 2018 (see Figure 3), two of which belong to Dimension 1 of our theoretical framework presented in Section 2 (“External drivers of digital-based innovation”, “Innovation-related knowledge flows in digital networks”). Two of these main categories belong to Dimension 2 (“Digital competences for innovation”, “Innovation-related data development activities”) and one to Dimension 3 (“Type of innovation and the role of digitized information”).

On this basis, we developed a first set of deductive categories. However, while coding the interview material along these five main categories, we encountered several relevant text passages for the digitalization-innovation link that could not be assigned to any of them. Thus, detached from the OM 2018, we inductively developed two additional main categories under which the corresponding text passages could be summarized and coded. As a result, our final category system comprises seven main categories (see Figure 3). First, the “Internal drivers of digital-based innovation” category covers a number of within-firm organizational determinants of the digitalization-innovation link and thus relates to Dimension 1 of our theoretical framework (see Section 2). Second, the “General relevance for innovation” category comprises several passages of the interviews describing how SME representatives reflect the perceived overall impact of the digital transformation on their business and innovation model. Correspondingly coded interview material thus lies somewhere between Dimension 1 and 2 of our theoretical framework of the digitalization-innovation link in SMEs.

Figure 3. Deductive and inductive development of the main categories



Notes: Main categories with solid lines are fully or partly derived from the OM 2018; while main categories with dashed lines are only derived from the interview data.

Finally, in case of the "External drivers of digital-based innovation" category, we started with Chapter 7 of the OM 2018 (which deals with external market factors that drive digital-based innovation) to derive our deductive categories. However, the interview material indicates that other, non-market impulses from the external environment also play a role for a firm's decision to engage in digital-based innovation activities. As such – in extending the OM 2018 – for example, collaborations with universities or the role of informal networks are also covered by this main category.

5.2 Description of the subcategories

For each of the seven main categories, we developed a set of sub-categories in accordance to the procedure described above (see Figure 2). Table A4 in the appendix presents the final category system in detail, including the labels of the main and sub-categories and the definitions of the categories used for guiding the coding process. In each case, exemplary quotes taken from the interview material are given for illustration. Moreover, the total number of coded segments within the interview transcripts are added for each sub-category.

The main category of "Internal drivers of digital-based innovation" is divided into four sub-categories. A number of SME respondents reflected on the (potential) benefits of digital-based innovation activities in terms of *automation and increased efficiency* (e.g. I5, I7, I20, I42). In several cases, the pursuit of automation and efficiency benefits to optimize internal business processes was the firm's starting point for engaging in digitalization (e.g. I16, I49). Members of more digitalized companies tended to emphasize the importance of a *business culture* that is conducive to learning and digital-based innovation (e.g. I1, I5, I7, I20). Interviewees from both less and more digitalized companies frequently mentioned the role of *employees*. It emerges that employees are generally important for the within-firm implementation of the digitalization-innovation link. Especially younger employees are reported to trigger digitalization at the company level (e.g. I22, I26, I32). Regarding the input side of digital-based innovation, a number of interviewees also emphasized the gatekeeping role of the *business owner/entrepreneur* in bringing in new ideas about the innovation potential of digitalization and convincing sceptical employees to adapt to corresponding digital technologies and practices (e.g. I5, I9, I26, I32, I39). However, it also emerges that the business owner can constitute a barrier to successful digitalization processes due to ignorance and refusal of the need to use digital technologies (e.g. I43).

Regarding the main category of "External drivers of digitalization", our interview data confirms that *customers* play a multifaceted role for the digitalization-innovation link. They can clearly drive digital-based innovation efforts. A number of SMEs report that they integrated digital technologies in their products or services to create an innovative benefit from their customers' perspective (e.g. product improvements through the integration of software applications – I8). In terms of process innovation, the QCA's results show that digital technologies have opened up new possibilities for SMEs to interact with their customers (e.g. through data collected via sensors in new products – I32). The exchange with *suppliers* is another external precondition for digital-based innovation, in particular when larger-sized suppliers push smaller firms to adapt to new digital standards and integrate them into their digital supply chains (I17).

Furthermore, several SME interviewees report that they monitor their *competitors* to ascertain which digital technologies and practices have proven useful under similar market conditions, which then often provides the impetus for digital-based innovations that are new to the firm. On the other hand, SMEs that have adopted a digital-based business model often did so to gain a competitive advantage over their rivals (e.g. by creating a digital sales channel as a distinguishing feature – I12) or because they were literally forced to do so by competitors with a digital business model.

In terms of cooperation activities, digital technologies are reported relatively often to be either means or purposes of formal and informal *firm networks* in which some of our SME interviewees are engaged, with firms from either the same industry or other sectors. *Trade fairs and trade magazines* are another external driver of digital-based innovation activities in SMEs. A number of SME interviewees report visiting trade fairs (or reading trade magazines) to obtain knowledge inputs about new digital technologies and their potential applications in practice. Several interviewees also consider *digital platforms, websites and databases* as valuable sources for finding new ideas to improve their products and processes.

Besides these market factors, other external factors also prove important for the digitalization-innovation link. The SME interviewees relatively frequently use their contacts with *universities and institutes* to recruit young employees with advanced digital skills. However, apart from such recruitment purposes, research projects on digitalization in cooperation with universities or other external research institutes are often seen critically by the SME representatives, because such efforts are perceived to be too time-consuming, bureaucratic and not sufficiently productive in terms of economic benefit. A further external non-market factor that drives digital-based innovation activities is *regulations and norms*. Our SME interviewees report that this factor can be a barrier as well as a driver of digitalization (for example, in case of the EU General Data Protection Regulation – I22, I34). Finally, it has been shown that public *funding* can be a further external driver for the digitalization-innovation link in SMEs.

Regarding the main category "Innovation-related data development activities", the QCA's results confirm that *database activities* are an integral part of innovation activities in SMEs (e.g. when databases are used to avoid the potential loss of critical innovation-related knowledge – I39, I40, I45, open up new opportunities for interactive learning within the company – I34, or serve as a basis for continuous improvement of products and processes – I49). Several firms in our interview sample also refer to the *development of software* in the context of their innovation activity, which shows how important software has now become for the creation of new or improved products, services or processes for various SMEs.

Several sub-categories have been identified in the main dimension of "Digital competences for innovation". Competences in *data protection* is the first in this regard. Our interview data shows that conducting digital-based innovation activities requires adequate management of privacy and cybersecurity risks (e.g. I18, I33). For obvious reasons, *training activities* are another content category in the digitalization-innovation context. On the one hand, this concerns the digital support of innovation-related training programs (e.g. I49). On the other hand, it is more common that this sub-category refers to the ongoing need in innovating SMEs to keep employees up to date on new digital technologies and practices in the workplace (e.g. I26, I30, I43, I47). The interview material further shows that competences for creating and sustaining *digital internal connections* are essential for the conduct of business process innovation; for example, by organizing within-firm communication flows more efficiently through the use of digital tools. Such a digital integration within and across different business functions can facilitate the collection and exchange of new innovation-related ideas between people and departments of a company (e.g. I49). Besides digital internal connections, a firm's competences in *digital external connections* also often form a basis for innovation. Several SME interviewees report that they now communicate mainly digitally with their suppliers and customers. For example, some firms have integrated suppliers into their digital organizational system (I49) or use digital external connections to their customers for after-sales service or web marketing (I17, I19, I38).

Another area of digital competences relates to *knowledge management*. A number of firms in our sample emphasize the importance of experiential knowledge for innovation, which needs time to accumulate and is often held by older employees or employees in key positions. In order to secure this knowledge for the company in the longer term and be less dependent on specific employees, the digital storage of such know-how is perceived as crucial for firm innovativeness by several respondents (e.g. I15, I16, I35, I37, I49). *Data analytics for innovation* is another part of an SME's digital competence portfolio. The use of data analytic tools in firms can be important for introducing product novelties or driving business process innovation. For example, an SME from the service sector (I17) offers improved building automation to its customers by not only collecting user data via a digital instrumentation and control system but also in being able to analyze this data to offer comprehensive remote maintenance functions.

Unsurprisingly, digital competences at the company level are closely linked to the *use of digital technologies*. The corresponding sub-category is specifically about the use of new digital tools and methods in innovating SMEs. Hence, we included all text passages that mention electronic tools, systems, devices or other digital technologies to "generate, store, process, exchange or use digital data" (OECD/Eurostat, 2018: 121). While some firms employ basic digital ICT to benefit from automation, other firms use more advanced digital technologies to connect and integrate various business activities and functions or to tailor products and services to customer needs (e.g. I16, I18, I36, I39, I40). Finally, the sub-category of *digital capabilities and skills* reflects on the in-house capabilities for digitalization. For example, some SME interviewees have their own IT department, an own mission statement with guiding values on the company's digital transformation, a separate budget for costs in electronic data processing or emphasize the digital qualifications of certain people in the firm (e.g. I1, I21, I23, I32, I47).

The first sub-category of the main dimension "Innovation-related knowledge flows in digital networks" refers to the fact that several SME interviewees use digital technologies for external *interactions and exchanges* to ensure efficient knowledge flows. Our interview material reveals that firms can face different challenges when exchanging innovation-related knowledge with external actors via digital channels (e.g. in terms of complying with security standards – I34, or managing the risk of information or knowledge loss when using digital technologies in collaboration activities – e.g. I4, I14, I23, I34, I49). It is therefore unsurprising that some respondents also reflect on the role of *trust* in external digital networks. For example, SMEs interviewees state that while it is perfectly fine to communicate with customers or other external partners through digital channels, it remains best in case of critical questions to meet face-to-face to solve innovation-related problems (I21, I26, I35). In addition, there are questions of appropriability arising in terms of *diffusion and exclusion*. Especially for SME interviewees from the ICT sector, open source constitutes an important element of software development. Therefore, for example, most software firms in our data are opposed to software patents (e.g. I4, I23).

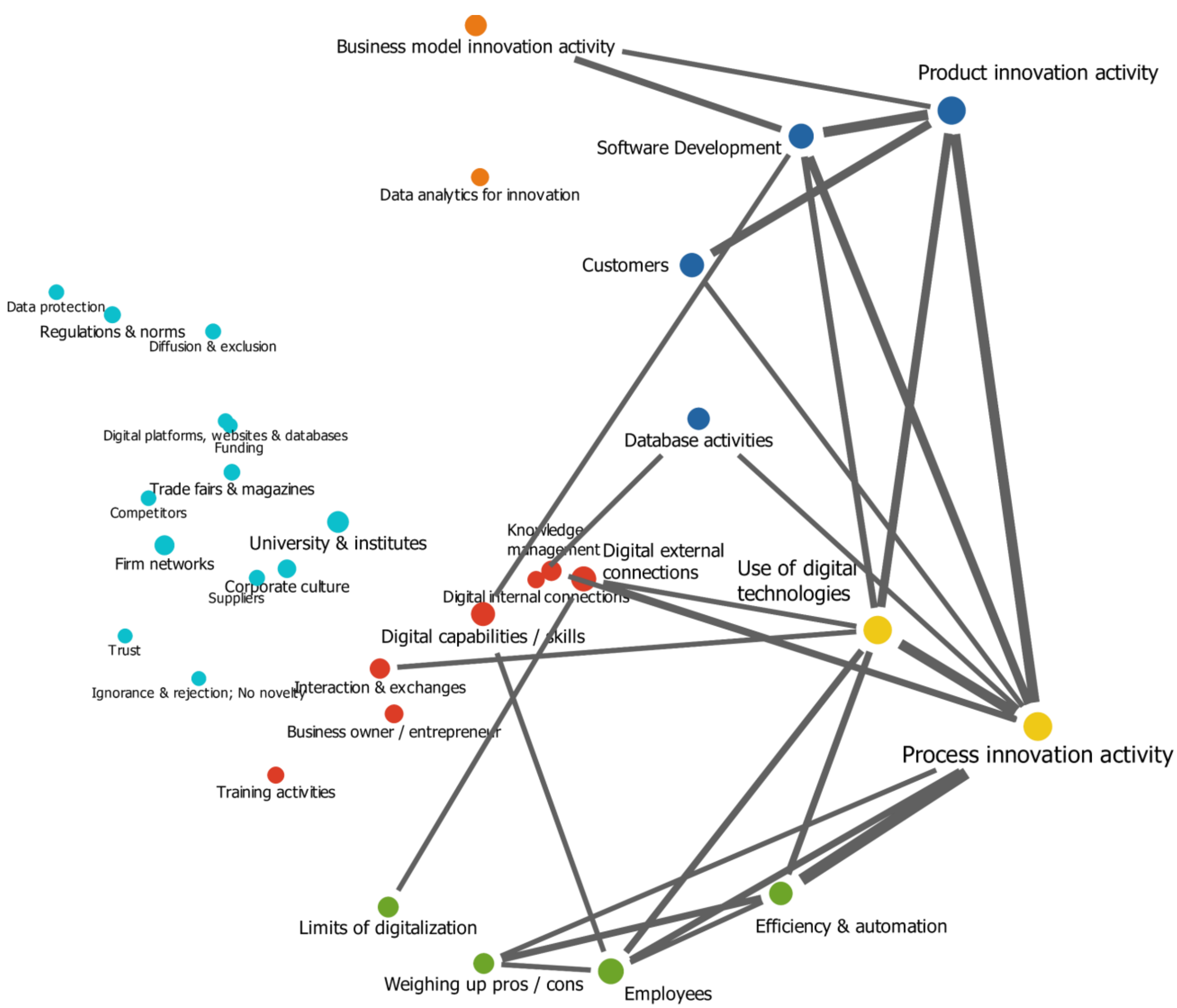
The sixth main category – labelled "Type of innovation and the role of digitized information" – has already been touched on couple of times in the above discussion. The description of the other sub-categories confirms that digitalization can either be a competence factor that drives innovation in SMEs, or it can itself constitute an innovation outcome. In this regard, we make no distinction whether the digital-based innovation activity has taken place in the past, is recently completed, currently not yet completed or being considered potentially for the future by the SME respondents. The sub-category of *process innovation activity* refers to the use of digital technologies during the implementation of new or significantly improved business processes (e.g. I18, I25, I47). On the other hand, digitalization is linked to *product innovation activity* when digitized information forms a distinct part of new or significantly improved products or services. For example, a number of manufacturing SMEs in our sample report that their recent product improvements are based on the implementation of software applications or sensors (e.g. I8, I31, I49). Digitalization activities can also result in *business model innovation*. Text passages with codes on this sub-category refer to an SME's experiences with digital business models, e.g. by implementing the digital transformation of the company's products or business functions in an all-encompassing sense (I17, I18, I22, I23, I32) or switching to a business model for digital market environments (I6, I11, I33, I47, I49).

Finally, the interviewees also reflected about the "General relevance of digitalization for innovation". The corresponding results show a number of reasons why innovating SMEs may still refrain from more intense digitalization activities or why they do not attribute them much relevance in terms of innovation. For example, some companies tend to ignore or even reject the current digitalization trend (*ignorance & rejection; no novelty*), because they see no need to use new digital technologies as they assume that their business model will work successfully without further digital transformation. Some say that digitalization, in a sense, is past history for them and therefore not innovative from their perspective (e.g. I19, I25, I38). A larger number of respondents refers to *limits to digitalization* that occur because either certain business processes still require human interaction or certain people-related barriers within or external to the firm are hindering the implementation of more advanced digital technologies and practices (e.g. I8, I19, I20, I27, I45, I47). Finally, several SME respondents report that they are *weighing up the economic pros and cons* before taking further digitalization steps. This reflects the typical resource constraints of smaller companies, which means that many SMEs tend to prefer to rely on established standards due to risk considerations rather than trying out new but hitherto hardly tested digital technologies (e.g. I3, I7, I21, I29, I47).

5.3 Interrelationships between the sub-categories

To further delve into the various connections between individual sub-categories, a code map has been created to visualize how closely different categories are related to each other in terms of content from the SME respondents' perspective (Figure 4). In the code map, each category is symbolized by a circle, with the distances between two categories reflecting how similar the corresponding topics have been mentioned by an SME interviewee (measured by the proximity of codes in each interview document). The more codings to which a category has been assigned in the data, the larger its circle will be. Moreover, colors are used to highlight the affiliation to six groups of categories. The grouping and coloring of the categories are undertaken by MAXQDA based on a hierarchical cluster analysis (unweighted average linkage) of the positions on the code map. In the case of overlapping codes at a text segment, the connecting lines between two categories are shown when there are at least 25 times intersections in the interview data, since this allows highlighting the most relevant associations between the codes of those text passages that are more distant from each other in an interview document. The more interrelationships that have been measured in this way, the thicker the connecting lines are displayed.

Figure 4. Code map – sub-categories positioned according to their similarity within the same interview document



In line with the theoretical framework presented in Section 2, the code mapping results show the complex interplay between digital technologies, competences and innovation in SMEs. Digital competences and related knowledge-based activities such as database activities or software development (i.e. Dimension 2 of our theoretical framework) are central when it comes to the link between digitalization and SME innovation (mainly red circles, partly also blue and orange). For obvious reasons, this is especially true for the use of digital technologies as the "spider in the web" with which everything is connected, both in terms of competence factors that drive innovation and as a specific component of different types of innovation outcomes. It is interesting that the business owner is to be found in the area of innovation-related digital competences, which may point to his or her gatekeeping function in the context of SME innovation (on this issue, see Runst and Thomä, 2022).

To the left of the digital competences categories are various internal and external drivers of digital-based innovation (light blue dots), which often provide the first impetus for building up digital competences (i.e. Dimension 1 of the theoretical framework). Furthermore, the code map confirms the fact that the use of new digital technologies is closely related to process innovation activity in SMEs at the output side (yellow circles; Dimension 3). This shows that digitalization in innovating SMEs is strongly associated with new or improved business processes. In this respect, employees are closely involved as both drivers and possible inhibitors (green circles). The efficiency motive also fits into this connection between the employee level and process innovation activity. This suggests that digital-based process innovation is primarily aimed at improving efficiency of the company's operations through an automation of tasks that humans used to do. The interview data shows that in this context SMEs face the ongoing challenge of weighing up the economic pros and cons of further digitalization steps and testing the associated limits.

Relatively unrelated to this nexus of input drivers, digital competences, automation benefits and process innovation activity is the conduct of digital-based production innovation (dark blue circles; Dimension 3) and – closely related to this – of digital business model innovation (orange; Dimension 3), suggesting that some of the SMEs in our interview sample have already reached a more advanced level of digitalization maturity. As expected, software development and product innovation activities are closely interlinked, which confirms that the integration of software elements has become a key feature of new or improved products and services (Figure 4). Moreover, customers often are strongly involved in such digital-oriented product innovation activities. This probably also explains the closer relationship with database activities, as digitally stored information on customers is becoming increasingly important for analyzing customer preferences during the innovation process (OECD/Eurostat, 2018). The same applies with regard to the proximity to competences in innovation-related data analytics, which are an important prerequisite for the successful adoption of digital-based business models (orange).

5.4 A basic test of validity

The observed interrelationships between the sub-categories already indicate that there is a dichotomy between digital-based process innovation on the one hand and digitally driven product/business model innovation on the other, reflecting the conceptual distinction discussed in Section 2 between digital-based innovation outcomes based on the principle of "doing the same with less" and those based on the principle of "doing something new". To illustrate the category system's potential for innovation measurement, we therefore conducted a basic test of validity. To this end, we leave the within-document level of analysis and switch to an across-company perspective so that different groups of the 49 innovating SMEs in our sample can be compared with each other based on a set of explanatory variables. For this purpose, the innovating SMEs in our sample are clustered according to their digital competences (eight sub-categories) and related knowledge-based activities (i.e. the sub-categories database activities and software development) by using the MAXQDA's Document Map Tool. We have chosen these cluster variables because both theoretically (Section 2) and against the background of the empirical results above, it can be assumed that the digital competence portfolio of an SME (i.e. Dimension 2 of our theoretical framework) is likely to be a main driver of variability between firms in terms of the digitalization-innovation link.

The assessment of similarity between individual companies is based on the basic occurrence of codes in the companies' interview transcripts, as the absolute frequency of codes could be biased by the specifics of each interview situation and does not necessarily tell us something about the similarity of two companies. For the same reason, we use the Jaccard algorithm as a similarity measure. This only considers the co-occurrence of codes in different documents as similarity and neglects a joint non-occurrence of codes.

According to the document map's results, a three-cluster solution fits the data quite well (Table 1).[6] The first cluster consists mainly of companies with only a few codes for the subcategories considered, indicating that the members of this group have relatively weak digital competences. A closer look at the cluster results (Table 1) shows that the percentage of companies with digital competences and related knowledge-based activities is only below average in the case of the first cluster, with the exception of digital external connections. This indicates that the respective companies have so far only taken first steps in digitalizing their innovation processes by using basic digital communication technologies to improve their interactions with external partners such as customers and suppliers. This interpretation is consistent with the results in Table A5 in the appendix, where the other subcategories that were not used for clustering are employed to create descriptive cluster profiles. Accordingly, on both the input and output side of digital-based innovation (i.e. Dimension 1 and 3 of the theoretical framework), members of the first cluster are

[6] The visual grouping of the surveyed SMEs according to their digital competences (document map) is available from the authors upon request.

less likely to be represented in the respective subcategories. Against this background, we refer to this first group of SME innovators as “Beginners in digital-based innovation”.

The second cluster of innovating SMEs includes companies that have already built up some competence portfolio in terms of digital-based innovation (see Table 1). According to the cluster results, they are above average in terms of database activities, training, digital internal connections, knowledge management and the use of new digital technologies, indicating a strong focus in the area of digital improvement of internal business processes (i.e. Dimension 2 and 3 of the theoretical framework). The cluster profiles with regard to the other subcategories confirm this. The efficiency & automation motive and the associated weighing of economic advantages and disadvantages of further digitalization is relatively likely for the second group, often stimulated by visits to trade fairs, reading the trade press and suggestions from suppliers (which relates to Dimension 1). At the same time, the likelihood of digital-based product or business model innovation is rather low in this group (see Table A5), which is why we name the second cluster as “Digital-oriented process innovators”.

Table 1. Clustering of innovating SMEs according to their digital competences

	Sample mean	**Cluster 1 (N=9)**	**Cluster 2 (N=16)**	**Cluster 3 (N=24)**
Database activities, number of firms (%)	24 (49.0)	1 (11.1)	**9 (56.3)**	**14 (58.3)**
Software development, number of firms (%)	24 (49.0)	1 (11.1)	0 (0.0)	**23 (95.8)**
Data protection, number of firms (%)	10 (20.4)	2 (22.2)	0 (0.0)	**8 (33.3)**
Training activities, number of firms (%)	17 (34.7)	1 (11.1)	**10 (62.5)**	6 (25.0)
Digital internal connections, number of firms (%)	17 (34.7)	2 (22.2)	**7 (43.8)**	8 (33.3)
Digital external connections, number of firms (%)	34 (69.4)	**9 (100.0)**	7 (43.8)	18 (75.0)
Knowledge management, number of firms (%)	24 (49.0)	0 (0.0)	**10 (62.5)**	**14 (58.3)**
Data analytics for innovation, number of firms (%)	13 (26.5)	0 (0.0)	4 (25.0)	**9 (37.5)**
Use of digital technologies, number of firms (%)	35 (71.4)	5 (55.6)	**15 (93.8)**	15 (62.5)
Digital capabilities / skills, number of firms (%)	30 (61.2)	0 (0.0)	11 (68.8)	**19 (79.2)**
N = number of firms (Share of sample in percent)	49 (100.0)	9 (18.4%)	16 (32.7%)	24 (49.0%)
Cluster label		Beginners in digital-based innovatio n	Digital-oriented process innovator s	Digital pro-duct/busine ss model innovators

Notes: Percentages that are relatively high above the sample mean are marked in bold.

The third and largest cluster contains the companies with the most developed digital competences in our sample. Compared to the other two clusters, SMEs in this group put a relatively high emphasis on database activities, software development, data protection, knowledge management, data analytics and digital capabilities / skills (see Table 1). The cluster profiles confirm that the companies in this group have a strong commitment to combine digital technologies and corresponding competences with their innovation activity (i.e. they are integrating all three dimensions of the theoretical framework), which is why the question of the pros and cons of digitalization hardly arises anymore (Table A5). This is illustrated by the fact that they are likely to maintain a distinct culture of information and knowledge sharing, experimentation and informal exchange in the context of their digital-based innovation activities (business culture) and that these firms attribute high importance to the role of employees and owners for the successful within-firm implementation of the digitalization-innovation link.

In addition, their external market environment and their involvement in external knowledge flows, networks and interactions with external partners are strongly shaped by the digitalization, which is why it can be assumed that their business model is fully or largely aligned with the requirements of digital innovation. This is exactly what the cluster profiles show with regard to the output side of innovation: The introduction of digital-based product or business model innovations is comparatively very likely in case of the third group (see Table A5). Therefore, we choose “Digital product/business model innovators” as the cluster label for the third group of SMEs. Overall, we interpret these clustering results as an indication that the category system developed in this paper has predictive validity.

6. Discussion and conclusion

Digitalization is one of the main trends that affects innovation today. In this context, there remains considerable room to improve our understanding of the complex interplay between digital technologies, competences and firm-level innovation. Against this background, the present paper empirically examines the role of digitalization in the context of SME innovation to provide a basis for better measuring the digitalization-innovation link at the company level. This is theoretically rooted in a three-dimensional understanding of the digital transformation of innovating SMEs: as an innovation-promoting input factor, as a competence factor shaping the innovation process and as an output of a firm’s innovation activity in itself.

Using the fourth edition of the Oslo Manual as a starting point for a qualitative content analysis (QCA) of interview data on innovating SMEs, a category system is derived that covers the multi-dimensional relationship between digital technologies, competences and SME innovation along seven main categories and 32 sub-categories. The potential of this category system from an innovation measurement perspective was tested by using it to identify, in an exploratory manner, different groups of innovating SMEs with regard to digital transformation. The corresponding results confirm that there are three groups of “digitalizers” among innovating SME. First, beginners in digital-based innovation that use basic digital technologies for communication with external partners such as customers or suppliers. Second, digital-oriented process innovators who are using new digital technologies and practices to achieve efficiency and automation benefits by improving their internal business processes. Third, digital product/business model innovators that are strongly investing in the digitalization of their products and services and often already have extensive experience regarding the adoption of digital-based business models. In light of these results, we conclude that the derived category system has predictive validity – demonstrating its relevance for future revisions of the Oslo Manual.

Hence, there is a great variety of SMEs in terms of the possible links between digitalization and innovation. While some SMEs are slow to find their way into digitalizing their innovation processes, others have started to use new digital technologies for efficiency reasons in the sense of “doing the same with less”, while still others are aligning their entire business model with the requirements of digital environments based on the innovation principle of “doing something new”. This also indicates the potential that the derived category system offers from the perspective of managers and innovation policy. Our results illustrate how strongly the innovation activities of SMEs are already shaped by the digital transformation, and, at the same time, they show at which different points at the company level the digitalization-innovation link can be influenced.

However, there are also certain limitations associated with this paper. Of course, the potential weaknesses of qualitative research apply. For example, even though this was not the objective of our study, it remains unclear how strong the relative weight of the three different groups is in the overall population of innovating SMEs. Something similar applies regarding the interpretation of causal relationships between the different dimensions of the digitalization-innovation link in SMEs. Several of our arguments regarding the multidimensional relationship between digital technologies, competences and innovation should therefore be interpreted with caution regarding causal inference. This also points the way for future research efforts. A promising approach would be to bridge the gap to quantitative innovation measurement by developing concrete indicators for the individual main and sub-categories and systematically evaluating them based on quantitative innovation surveys. This is already happening to some extent. For example, starting with the survey year 2019, the new guidelines of the OM 2018 for defining product and business process innovations by taking into account digital aspects have been implemented in the German CIS (Mannheim Innovation Panel). However, to better understand the multidimensional relationship between digitalization and firm-level innovation highlighted in this paper and, for example, to verify our findings, further efforts in this direction are needed.

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Appendix

Table A1. The Oslo Manual 2018 on digitalization and its potential links with firm-level innovation

OM 2018	Main topic	Content
Chapter 3	The link between digitalization and different types of innovation	- Defining product innovation regarding digitized information (including pure digital products and supporting business processes that require ICT or web/software development) - Defining business process innovation with respect to the firm-level adoption and modification of digital technologies - Discussing digital-based business model innovation and their relationship with product and business process innovations
Chapter 4	Data development activities along with software as a potential innovation activity	- Software development and database activities are given as an example for innovation activities at the company level - Software development is an innovation activity when used to develop new or improved business processes or products - Database activities are an innovation activity when analyses of data on the properties of materials or customer preferences are used for innovation
Chapter 5	Digital competences for innovation	- Digital competences are defined as a distinct part of the wider technological capabilities of a firm (due to the general purpose nature of digital technologies and data analytics) - Three components of innovation-related digital competences are to be distinguished: - (1) a firm’s use of different digital technologies (e.g. advanced digital tools and methods; digital platforms) - (2) a firm's in-house capabilities for using digital technologies (IT resources, digital skills, digital strategy/vision) - (3) a firm’s data management competences, including the acquisition of external data analytics services (e.g. database management systems, data mining tools, machine learning, user behavior analysis or real time data analysis)

Table A1. (continued)

Chapter 6	Digital-based knowledge flows with relevance to innovation	- Knowledge flows and exchanges between firms and other actors in the innovation system nowadays often are strongly supported or facilitated by digital information and communications technology (ICT) - This affects both a firm's cooperative and competitive interactions with other firms or institutions (e.g. decentralized collaboration models supported by digitalized knowledge)
Chapter 7	External market factors as drivers of digital-based innovation	- External market factors can have a major impact on a firm's incentives for digital-based innovation activities - Major drivers of how a firm's external market environment can influence innovation in terms of digitalization are: (1) The nature of a firm's markets (notably with respect to the role of digital platforms, the existence of main competitors with digital business models or in terms of geographical coverage and the role of digital marketing) (2) The influence of customers and users (is there a demand for digital-based innovation?) (3) Suppliers as an important source of digital technologies/competences (4) Online sources to find ideas and information for innovation (the use of external business websites, searchable repositories or databases in the pursuit of innovation)

Source: OECD/Eurostat (2018)

Table A2. Detailed information on the SME interviews

No. of interview	Industry	Position of interviewee	Region	Number of employees	Duration of interview (minutes)
1	Professional, scientific and technical activities	CEO	Goettingen	12	104
2	Mining and quarrying	CEO	Goettingen	3	66
3	Construction	Executive	Goettingen	10	73
4	Information and communication	CEO	Goettingen	61	96
5	Manufacturing	CEO	Goettingen	16	73
6	Wholesale and retail trade; repair of motor vehicles and motorcycles	CEO	Goettingen	20	67
7	Manufacturing	Executive	Goettingen	143	64
8	Manufacturing	CEO	Goettingen	50	71
9	Information and communication	CEO	Goettingen	1	76
10	Transporting and storage	CEO	Goettingen	3	63
11	Manufacturing	Executive	Goettingen	91	40
12	Manufacturing	CEO	Goettingen	100	64
13	Wholesale and retail trade; repair of motor vehicles and motorcycles	CEO	Goettingen	1	78
14	Professional, scientific and technical activities	CEO	Goettingen	7	69
15	Manufacturing	CEO	Goettingen	33	80
16	Manufacturing	CEO	Goettingen	24	84
17	Professional, scientific and technical activities	CEO	Goettingen	12	58
18	Manufacturing	Development	Goettingen	103	75
19	Other services activities	CEO	Hanover	4	60
20	Construction	CEO	Hanover	120	70
21	Professional, scientific and technical activities	CEO	Hanover	4	64
22	Information and communication	CEO	Hanover	35	55
23	Information and communication	CEO	Hanover	5	70
24	Human health and social work activities	CEO	Hanover	30	33
25	Manufacturing	CEO	Hanover	46	85
26	Manufacturing	CEO	Hanover	26	64
27	Manufacturing	CEO	Hanover	12	44
28	Manufacturing	CEO	Hanover	15	90

Table A2. (continued)

29	Agriculture, forestry and fishing	CEO	Hanover	104	40
30	Manufacturing	CEO	Hanover	17	87
31	Manufacturing	CEO	Hanover	170	42
32	Information and communication	CEO	Hanover	7	66
33	Wholesale and retail trade; repair of motor vehicles and motorcycles	CEO	Hanover	14	74
34	Manufacturing	CEO	Jena	70	92
35	Manufacturing	CEO	Jena	170	150
38	Manufacturing	CEO	Jena	23	29
39	Manufacturing	CEO	Jena	97	39
40	Manufacturing	CEO	Jena	58	35
41	Manufacturing	CEO	Jena	50	17
42	Manufacturing	CEO	Jena	200	89
43	Wholesale and retail trade; repair of motor vehicles and motorcycles	CEO	Jena	5	26
44	Manufacturing	CEO	Jena	25	49
45	Manufacturing	CEO	Jena	33	32
46	Information and communication	CEO	Jena	10	12
47	Manufacturing	Executive	Jena	140	70
48	Manufacturing	CEO	Jena	25	89
49	Manufacturing	Executive	Jena	150	109
			Mean	**49,7**	**64,9**

Source: Alhusen et al. (2021)

Table A3. Interview guide

Category	**Questions**
Firm characteristics	Interviewee demographics (position, time spend in the firm, previous positions in the firm, education); firm demographics (founding year, legal status, chamber association, number of employees, revenue, sector, main product); market environment (position in the value chain, main customers, geography of sales)
New innovations within the last three years	Which novelties have you introduced within the last three years (product, process, social, marketing, innovation)?
The role of formal knowledge	Do you conduct formal research?; Do you cooperate with universities (in research projects)?; What is the role of high-skilled labor for your firm?; Do you use patents?
Process improvements	Do you achieve cost reduction or quality improvements over time?; If yes, how? (Learning curve effects); Have you introduced new machines?; How did learning occur?; Which employees are important for improvements?
Importance of implicit knowledge and employee skills	How is knowledge produced at the firm level?; Are there individual employees who possess key knowledge?; How to do you preserve tacit knowledge competencies within the firm?
Knowledge exchange within the firm	How do you exchange knowledge and experience within the firm, in particular regarding your production?; Do you use heterogeneous teams?
Customer relations and exchange	How do customers influence your product innovations or your product improvements?; Which channels do you use to communicate with your customer?; Do you customize products according to customer wishes?; Do you use new modifications of your product developed by your customer?
Competitor relations and exchange	Do you exchange ideas and resources with your competitors?; How do competitors influence your innovative capacity?; How do you communicate with competitors?
Other actors influence on innovations	Do other actors like suppliers, banks and governmental institutions influence your innovative capacity?; How do you exchange with other actors?
The role of digitalization	How relevant is digitalization for your firm?; What are barriers to more innovation?; Is digitalization influencing innovations within your firm?; If yes, how?
Expertise change and unlearning	Have the required competencies changed in your firm within the last ten years?; How have work routines changed?; Have you actively unlearned competencies?; Has this influenced your innovative capacity?

Source: Alhusen et al. (2021)

Table A4. Detailed category system including definitions and exemplary quotes

Main category	Sub-categories	Definition	Exemplary quotes (no. of interview in brackets)	Coded segments
Internal drivers of digital-based innovation	Efficiency & automation	Basic digital technologies are employed to exploit benefits of automation and increased efficiency	“Autonomous Industry 4.0 means – we have just made our first experiences with co-bots – that we are simply experimenting and getting a few things started. We also have automated machines and we have robots in use. We don’t consider this to be Industry 4.0, but rather we simply want to use automation.” (I47)	62
	Corporate culture	A culture of information and knowledge sharing, experimentation and informal exchange facilitates digital-oriented innovation activities	“R&D is second nature to us. We could do a workshop every day, every weekend, and build a new sensor. So now this weekend it's happening again, because I was at the trade fair yesterday and said I have an idea, we have to try something out. And now we're going to sit down this weekend, spend a whole Saturday together and solder a new sensor. Then I have a certain product idea and we'll just try it out.” (I32)	34
	Employees	Employees are essential for the successful within-firm implementation of the digitalization-innovation link	“So, the CNC machining, of course, we have different types of software at our company to program machines. [...] We have found that the younger employees cope much better with the new software than older ones. I don't even know how many we’ve tested. The newer employees are much more comfortable with this type of programming task, probably also because of the training they have received. [...] Older employees have great problems using the software, as they don't grasp the complex interrelationships like younger people do.“ (I26)	75
	Business owner / entrepreneur	Owners/entrepreneurs are a main driving force of digitalization in terms of bringing in new ideas and perspectives	“My father was actually always one who always looked ahead, always going further and further. He always wanted to grow, it wasn't that he was reluctant. But where he always resisted was an online store. For example, this he didn't want to do at all, which, in turn, has been on my mind ever since I took over the company, thinking about how I want to implement it, which, as I said, I've already started to do.” (I43)	35

Table A4. (continued)

External drivers of digital-based innovation	Regulations & norms	Regulations and norms can be a barrier as well as a driver of digitalization	"Or now, for example, the GDPR *[General Data Protection Regulation],* a great thing. So, I'm totally happy about that topic, because of all the compliance constraints you can impose on the customer and say: Watch out, you have to comply with data protection. Don't mess around. That's positive, so the customer is closely guided and there's nothing better, legal constraints are the best thing ever." (I4)	25
	Public funding	Public funding can support innovation-related digitalization activities at the company level	"To drive digitalization here, in order to optimize business processes, reduce errors, save money and things like that, we also have an innovation program from the NBank *[i.e. the development bank for the German federal state of Lower Saxony],* to which we applied for funding, which was later approved, and we are just initiating digital processes here at a high speed, it's fantastic!" (I25)	15
	Universities & institutes	Enhancement of digital skills through recruitment of university graduates and cooperation with universities and other external research institutes	"But instead we have people, who come from the university, who can then operate with advanced tools due of their training. One of the most important ones was someone who came from the FHDW. That is the university of applied sciences that we have here in Hanover, which offers dual training. [...] And then we had a working student for half a year, who was well versed in information technology, he really boosted us here. [...] So he helped us a lot with our digital processes." (I25)	52
	Firm networks	Formal and informal exchange with firms from the same industry and firms from other sectors	"As we are a rather small team, everyone brings something in at some point. When university graduates join us, it's often the employees through whom they who come to us, or you hear from them from friendly companies. If these firms use a new software and say it's particularly great, than we would also try something like that, but we don't have a formalized process in this regard." (I17)	42
	Trade fairs & trade press	Knowledge inputs for digital-based innovation activities through trade fairs and trade magazines	"But the real reason, or a very big reason, to go to a trade fair is, of course, to look around: What's there? [...] What didn't interest me at all in the past, because it was unimportant to me, is actually the most important thing for me today: observing what others are doing in terms of software. [...] What can the other companies do, what do they offer? What do small start-up companies offer and so on. That is interesting to me because that is, let's say, determining our future efficiency." (I44)	23

Table A4. (continued)

	Suppliers	Suppliers are often closely involved in digitalization processes of SMEs	"Where before you still did it mechanically, you now of course convert to all the digital things, so that in the end the difficulty arises there [...] that you then take that and turn it into a meteorological product. In other words, where you used to focus on electronics, you now focus on information technology, because now the product has to cope with the external conditions so that it works outside. [...] simply also shaped by the market and what is happening at the IT companies." (I8)	20
	Digital platforms, websites & databases	Engagement in markets with digital platforms; Information acquisition through external websites and online databases	"Internet search is a big thing for us, of course, because in this way we can see what works and what doesn't." (I23)	16
	Competitors	Trying to achieve a competitive advantage over rivals by using advanced digital tools and methods	"For example, we are now offering for the first time, and this is also our vision, the connection between a sensor with another sensor. This means that one sensor orders the goods and automatically a driverless transport system drives off and brings the goods to the production line. There is no longer a human being in between, this is classic Industry 4.0, this is where we belong. Many of our competitors are highly interested in this, I have to be careful not to tell too much, that's exactly where we are pushing forward." (I32)	17
	Customers	Customers as a driving force of digital-based product innovation; usage of digital technologies to open up new ways to communicate with the customer side	"Customers are a large, a very large one. In computer production, I'd say it's 90 percent, where impulses come from the customer side, and in software, I've already mentioned a percentage figure, but I've already forgotten it. So there really is a large proportion that is brought in by the customers. Sometimes the customer has to co-finance this, sometimes we say it's so brilliant that we can sell it to others as a new module, and then it's practically a real research output." (I37)	67

Table A4. (continued)

Innovation-related data development activities	Database activities	Using digital databases to identify potential market opportunities or as tool for knowledge management	"Our business processes very often deal with our own system, that is, they start right at the beginning. Data is stored on how precise an optic is [...]. Measurement data is entered into the system, also production data and coating data. So practically everything, the entire documentation of this optics production works via our own data management system." (I49)	56
	Software development	Software development forms an integral part of in-house R&D, or it is part of non-R&D-based innovation activity	"In terms of software, I would say 70 percent of what we do in software development for our own product is R&D, if you want, because it's always about the creation of new modules. So we're constantly developing that and maybe 30 percent are customizations for customers where I would say that's just normal service, but 70 percent are new modules or new workflows." (I37)	71
Digital competences for innovation	Data protection	Managing internal data protection; using external data protection services	"So we train our people to be scrum masters, or I could appoint someone as a data protection officer now, if it wasn't better for this one to come from extern. And yes, that's how we make sure that we somehow keep people up to date with the latest knowledge, that we always bring the latest knowledge into the company, on the one hand from the outside and then distribute it within the company, but that's actually the art of the whole thing." (I18)	17
	Training activities	Training activities based on digital technologies as well as training to support digital competences	"As I said, we provide training in the technical area primarily through our own learning workshop, so we do a lot of things there. By now, we also have an online tool for further training activities. All colleagues receive a number of work packages via this digital-based training system, so we don't have to send our people to somewhere else, but can train them online ourselves." (I49)	25

Table A4. (continued)

	Digital internal connections	Digital integration within and across business functions	"In terms of internal organization, we have been pushing ahead with, how shall we say, digitalization in our company for some years now. Our vision is the digital control of the entire production process, so according to this vision we control everything from ordering to purchasing to financial accounting via a software and operate it in such a way that we can also handle quality management, i.e. customers complaints, everything via it, so that we can afford to have such a flat corporate structure." (I40)	27
	Digital external connections	Interaction with external partners using digital communication technologies	"There is, well, in the past the orders came by post or fax. So now there's nothing, everything just comes by e-mail. Or with the customers, there's a, I don't know how it's called, but a platform where we pick up the orders directly, yes." (I41)	71
	Knowledge management	Using digital methods of knowledge management to share, protect and reuse of experience-based knowledge	"[…] if someone drops out, it's not like the tapes stand still, because we don't have them in that sense. [...] we are now using platforms that are actually available on every computer and through which our employees have access from everywhere and can generate their things accordingly. That makes us a little less susceptible when an employee leaves the company and then it's over. That is not the case." (I14)	44
	Data analytics	Using internal or external competences in data analytics	"[…] at the trade fairs, we have individual customer contact worldwide. They say, gee, I bought this product from you, but I don't like this, or this, or that. And this should be a bit stronger there, this should be a bit slimmer or more handy. [...] more ergonomic. We collect all that information. We do customer surveys, we ask our customers. These questions are then evaluated at every trade fair. [...] Evaluated in a very targeted manner [...] with failure mode and effects analyses, which we also do here." (I30)	31
	Use of digital technologies	Use of different digital technologies	"Digitalization plays a big role because we use a digital customer list, we use digital X-ray technology. Now recently we also fabricate digital models, also communication runs digitally. And that is why this is a very central tool for us." (I24)	90

Table A4. (continued)

	Digital capabilities / skills	In-house capabilities for using digital technologies (IT resources, digital skills, digital strategy)	"I am actually in the area of calculation, but my main area is Building Information Modeling, i.e. digital construction, which is on the rise right now. I'm also a bit involved in other digitalization activities of our company. I'm responsible for the web presence, the intranet presence, our own app, which we have for about a year now, and generally responsible for, let's say, process digitalization." (I20)	65
Innovation-related knowledge flows in digital networks	Interactions & exchanges	Use of digital technologies for more efficient knowledge exchange	"Touchscreens and other such tools are really only operating elements for us, at the moment, and now there are, for the future, as I said, these small digital pads [...] that are still to come, there is a communicative level that should improve, that should of course also stimulate the exchange of ideas, should develop fast communication, that one is simply faster, is more nimble, and can also solve things faster. You can also exchange ideas better." (I42)	44
	Trust	The role of trust in digital-based communication	"There is this discussion, this dispute, or first of all this assumption that everything that can be digitalized will be digitalized. So... I think that's only partly true, but on the other hand, you can clearly handle this exchange/network a bit via Facebook and social media, but that's somehow different than when you meet in person from time to time and sit together and exchange and talk to people face to face in real life, that simply builds trust." (I21)	13
	Diffusion & exclusion	Issues relating to the tradeoff between diffusion and knowledge protection (e.g. open-source vs. proprietary software)	"This means that our software is also open, so other sensor manufacturers can also jump in, so to speak. Simply this, not to limit ourselves, but to go beyond company boundaries [...], to create a supply chain from the manufacturer to the supplier. That first has to grow in people's minds, but that's exactly the step we're taking right now […]." (I32)	25

Table A4. (continued)

Type of innovation activity and the role of digitized information	Process innovation activity	Adoption and modification of digital technologies during the implementation of new or significantly improved business processes	"[…] it's all about innovation, I would say. I mean, in recent years, of course, [...] the development of additive, so-called additive manufacturing came up. In other words, 3D printing, not only of plastics, which we already have been doing for 20 or 25 years, but now also of metals." (I45)	92
	Product innovation activity	Digitized information forms a distinct part of new or significantly improved products and services	"And now there is a software for the new product range, an app where you have a nice little interface where you can activate all kinds of additional functions. And you can also do a system check, initial error analyses and so on. For example, if the customer has a problem somewhere, he can use the app to call it up, do a system check, and we can sometimes immediately determine what might not be working." (I38)	89
	Business model innovation	Experiences with digital business models, e.g. by integrating digitalization in a company's products or business functions in an all-encompassing sense or by switching to a databased business model by using e-commerce or digital platforms	"Actually, we are only digital. [...] This is reflected in the fact that when there is power blackout or if something happens to our network, everybody stands around or is outside. Those who can smoke, they smoke, otherwise no one has anything to do then. So without computers, nothing works. But digitalization in our company means, yes, what does it actually mean? That all information is stored digitally, that means in databases, that means ERP software, we have developed our own. All information is stored there; it can no longer be in people's heads, it has to be reproducible somewhere in databases, the whole customer and supplier management anyway, but also more and more specialist knowledge in various forms. So we have certain tools that are used, especially in software development, where certain information is stored so that it will still be available in a year's time, Ok? We have also an Issue-Tracking-System. Therefore, nothing really works in our company without software tools. The only thing I still treat myself to is a paper calendar on my desk." (I37)	53

Table A4. (continued)

General relevance of digitalization for innovation	Ignorance & rejection; No novelty	Opinion not to be affected by the digital transformation; Digitalization is not perceived as "novel"	"Let me start with the simplest story of digitalization, namely my business processes. So, I have an end-to-end computer system through which I manage everything. By far not everyone has that so far. I acquired it in 1999." (I45)	13
	Limits of digitalization	Problems with the external infrastructure; internal resistance to digitalization; ongoing relevance of personal, face-to-face contacts with customers etc.	"We try to do that, of course, but the human factor cannot be avoided. When you go into our production, not everything is automated, but the human must actually first place an optic in the machine and have it processed accordingly. He simply presses the button, but employees are still involved in many steps, which is why this is still a human-driven story." (I49)	47
	Weighing up economic pros / cons	Several SMEs are aware of digitalization potentials but are weighing up economic advantages and disadvantages of digitalization	"We don't have a proper database so far where customers are automatically assigned to a salesperson. Everything is still done a bit manually. Of course, that's anything but optimal. But then you have to say that a reasonable software package for our company costs almost 100,000 euros, which then can display everything, right? The business relationship, the customer relationship, the production relationship, if it can display and connect all these topics, you can calculate about 10,000 euros per employee, which would be about 100,000 euros in our case. Of course, this is an investment where you have to, say, you first have to find your way into the market and then you can think about it. But I think you have to do it in due time. Because if you miss the ship, at some point you can no longer catch up." (I3)	47

Table A5. Across-cluster percentages for sub-categories not used for clustering

Sub-categories	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Total**
Efficiency & automation	9.7%	41.9%	48.4%	100%
Corporate culture	0.0%	30.8%	69.2%	100%
Employees	11.8%	29.4%	58.8%	100%
Business owner / entrepreneur	5.3%	31.6%	63.2%	100%
Regulations & norms	15.4%	7.7%	76.9%	100%
Funding	10.0%	50.0%	40.0%	100%
University & institutes	0.0%	38.1%	61.9%	100%
Firm networks	13.0%	21.7%	65.2%	100%
Trade fairs & magazines	7.7%	38.5%	53.8%	100%
Suppliers	0.0%	37.5%	62.5%	100%
Digital platforms, websites & databases	0.0%	38.5%	61.5%	100%
Competitors	8.3%	33.3%	58.3%	100%
Customers	7.7%	30.8%	61.5%	100%
Interaction & exchanges	12.0%	28.0%	60.0%	100%
Trust	16.7%	33.3%	50.0%	100%
Diffusion & exclusion	11.1%	33.3%	55.6%	100%
Process innovation activity	14.3%	31.4%	54.3%	100%
Product innovation activity	12.9%	16.1%	71.0%	100%
Business model innovation activity	5.3%	26.3%	68.4%	100%
Ignorance & rejection; No novelty	14.3%	71.4%	14.3%	100%
Limits of digitalization	13.8%	31.0%	55.2%	100%
Weighing up pros / cons	15.0%	45.0%	40.0%	100%
Total sample share	**18.4%**	**32.7%**	**49.0%**	**100%**
Cluster label	**Beginners in digital-based innovation**	**Digital-oriented process innovators**	**Digital pro-duct/business model innovators**	

Chapter 5

Beauty attracts the eye but personality captures the heart … of digital transformation in crafts SMEs

Beauty attracts the eye but personality captures the heart … of digital transformation in crafts SMEs

Thore Sören Bischoff, Anita Thonipara & Kilian Bizer

Abstract

Digital transformation determines the long-term viability of SMEs but poses particular challenges for crafts SMEs due to their lack of resources and their individualized products and services. We argue that the unique personality of a crafts owner is a missing link in the literature on the firm-level drivers of digitalization. Using the Big Five personality model, data of 554 crafts SMEs and quantitative methods, our results provide evidence that the personality traits of extraversion and openness are particularly beneficial for overall digitalization in crafts companies. Furthermore, we show that different personality traits are important at different maturity levels of digitalization and that the effect of personality on digitalization is to some extent mediated by the owner's local embeddedness.

JEL: O31; O32

Keywords: Digital transformation; Crafts; Personality; Big Five; SMEs

1. Introduction

As the so-called "fourth revolution", digitalization has disrupted markets, business models and society. Making efficient and effective use of information technologies determines a company's success, competitiveness and long-term viability (e.g. Bharadwaj, 2000; de Massis et al., 2018; Soluk and Kammerlander, 2021; Yoo et al., 2010). While larger companies have more financial and human resources to adopt new technologies, resources are often limited in small and medium-sized companies (SMEs) (de Massis et al., 2018). In this context, it is important to understand how SMEs deal with the digital transformation and which dynamic capabilities, barriers or enablers support or hinder them (Soluk and Kammerlander, 2021). SMEs from the crafts sector, in particular, are likely to face systematic disadvantages in digitalization due to their small company size, a lack of resources and management capacities, as well as their individualized products and services, which upon first glance do not lend themselves to automation (Ghobakhloo et al., 2022; Kocak and Pawlowski, 2022; Matt et al., 2020; Sasaki et al., 2021). Nevertheless, digitalization also offers unprecedented opportunities for craft-based SMEs, such as access to the global market and the ability to increase the efficiency of business processes (Sasaki et al. 2021). In order to promote digital transformation in crafts SMEs it is important to understand its unique drivers.

Previous research agrees that digitalization is an iterative process starting with digital awareness and exploration and evolving up to the digital transformation of the whole organization and changes in the company's business model (Garzoni et al., 2020; Kane et al., 2022; Soluk and Kammerlander, 2021). The scholars argue that SMEs go through a process of maturity as digital transformation proceeds, and different dynamic capabilities are needed depending on the level of a company's digital maturity. Previous research has identified various managerial capabilities (e.g. managerial IT capabilities) as drivers of digital transformation in SMEs (Adner and Helfat, 2003; Crupi et al., 2020; Garzoni et al., 2020; Ghobakhloo et al., 2022; Kocak and Pawlowski, 2022; Li et al., 2018; Matt et al., 2020; Sasaki et al., 2021). However, the impact of the business owner and his / her personality on the digital transformation process in SMEs has been neglected. In a sector such as the crafts, which is characterized by mainly owner-centered small companies with a dominance of personal working relationships, it is very likely that the unique personality of the business owner is a missing link in the literature on the firm-level drivers of digital transformation. We therefore investigate which role the owner's personality traits play for digital transformation in crafts SMEs using quantitative methods. We also address the question of which personality traits of the owner are important at which stage of digitalization.

The Big Five personality model provides a useful framework to examine the impact of an owner's personality traits on digital transformation in crafts SMEs (see e.g. Runst and Thomä, 2022 for a recent study examining the influence of the Big Five personality traits of small business owners on the technological innovativeness of craft SMEs). We, therefore, use a sample of 554 owners of crafts SMEs in Northern Germany and use factor analyses as well as regression analyses. First, we apply factor analysis to derive indicators for different maturity levels of digitalization. We then use linear regression models with cluster-robust standard errors at the county level to evaluate our hypotheses.

Our results suggest that the owners' personality traits of extraversion and openness positively affect the overall digitalization level in crafts SMEs in our sample. In addition, the analysis of different maturity levels of the digitalization process shows that extraversion and neuroticism are particularly important in early stages of the digitalization process, whereas openness is critical for higher stages of digitalization. The results of this paper contribute to the literature on the micro-foundations of the digital transformation process in craft and extends prior work by shedding light on the importance of owners' personalities for the digital transformation process in crafts SMEs. As drivers of digitalization in crafts SMEs have been largely neglected to date, this paper offers a valuable contribution to the broader field of craft-based venturing.

The remainder of this paper is structured as follows: Section 2 presents the theoretic framework and derives the hypotheses that will be tested. Section 3 introduces the methods used and describes the sample specifics. Section 4 presents the results, whereas section 5 discusses the results and draws a conclusion.

2. Theory and hypotheses

2.1 Digital transformation of SMEs in the crafts sector

Digital transformation is defined as an "organizational transformation that integrates digital technologies and business processes in a digital economy" (Liu et al., 2011: 1730). While the industrial and large parts of the services sector as well as generally larger companies seem to benefit directly from digitalization (Moeuf et al., 2017; Rüßmann et al., 2015), digitalization in the crafts sector does not seem to harmonize promptly and technological development seems to contradict the core characteristic of craftsmanship. Nevertheless, digitalization is associated with a number of challenges and advantages for the crafts sector. While some suggest that increasing digitalization and automation makes typical crafts work obsolete (Akerman et al., 2015; Thonipara et al., 2022) others argue that digitalization paves the way for crafts firms to access the global market (Galloway et al., 2011; Grimes, 2005; Sasaki et al., 2021). However, in both cases only companies that are able to adapt and make effective and efficient use of digital technologies will be able to remain successful and competitive in the future (Bharadwaj, 2000; Soluk and Kammerlander, 2021). Therefore, it is important to understand the unique determinants of digitalization in crafts SMEs.

Drivers of digitalization in the crafts sector, in particular, have not been subject to the literature. However, there is a comprehensive literature on the drivers of digital transformation in SMEs addressing the particular characteristics of SMEs and the challenges that they face due to their small firm size and limited resources. Scholars agree that digital transformation in SMEs is an evolutionary path comprising the different stages that a company goes through (i.e. the concept of digital maturity, see Brodny and Tutak, 2021; Jones et al., 2021; Mittal et al., 2018; Rodrigues-Espindola et al., 2022). Garzoni et al. (2020) argue that digital transformation comprises four stages: (1) "digital awareness", (2) "digital enquirement", (3) "digital collaboration" and (4) "digital transformation". Kane et al. (2022) similarly define the four stages as (1) "exploration of digital transformation", (2) "development of digital initiatives", (3) "digital maturity" and (4) "digital organization".

For each stage of digital transformation, different barriers or drivers work against or towards digitalization (Soluk and Kammerlander, 2021). Soluk and Kammerlander (2021) conducted comprehensive qualitative research on barriers and enablers and the associated dynamic capabilities for each of the digital transformation stages. They suggest that in early stages of digital transformation paternalism is a barrier to digitalization whereas cash opportunities are a driver in SMEs. This impedes or fosters the dynamic capabilities of effective strategic decision-making as well as the ability to recognize and work with new information. In later stages of the digital transformation, an inconsistent understanding of digital transformation poses a main barrier, whereas a digital strategy and a common understanding of digital transformation are the main drivers in SMEs. They foster or impede the ability to renew the firm, the employee's ability to learn quickly as well as strategic partnerships. For all stages of digital transformation, Soluk and Kammerlander (2021) find that employees' resistance to digital transformation is the main barrier and early success stories of digital transformation are a main driver, both of which foster or impede reorganization of routines and brand management.

Apart from this comprehensive investigation into barriers, drivers and capabilities and their role in digital transformation, there is literature suggesting that the owner's commitment, personality and engagement with the company are main drivers of innovation or the implementation of technologies or processes in small companies (Garzoni et al., 2020; Michaelis et al., 2022; Rau et al., 2019). Scholars from the dynamic managerial capabilities theory argue that digital transformation in SMEs is driven by the owners, whereby the success depends on the owner's capabilities (Adner and Helfat, 2003; Li et al., 2018). For example, scholars suggest that IT capabilities, the ability to mobilize and exploit IT-based resources are a driver of innovation and hence digital transformation of SMEs (Bharadwaj, 2000; Limaj et al., 2016; Mohd Salleh et al., 2017; Pavlou and el Sawy, 2006). On the other hand, scholars from the field of family-led SMEs emphasize the meaning of the owner's character as well as their long-term commitment in the community based on the community's values for the longevity of successful companies (Glynn & Navis, 2013; Sasaki et al., 2019; Selznick, 1957). This is also emphasized by Crupi et al. (2020), who argue that establishing external relationships and being externally embedded are critical factors for digital transformation in SMEs by encouraging knowledge exchange.

Against this background, the role of the owner's commitment and characteristics for a company are particularly important in companies in the crafts sector, as entrepreneurs in this sector bring characteristics different from the usual image of entrepreneurship (Thurnell-Read, 2021). They invest emotion and identity and measure success not only "in sales, turnover and profit but in personal fulfilment, interpersonal affinities and […] contentment" (Thurnell-Read, 2021: 48). As a study conducted by Runst and Thomä (2022) recently found, the owner's personality has a significant effect on firm innovations in crafts SMEs. Although this study did not focus on digital transformation, it prompts the question concerning the role that the owner's personality and local embeddedness play for digital transformation in the crafts sector, a sector which is traditionally rather "low-tech". This question has not been addressed in the literature to date and is the subject of this paper.

2.2 The impact of the owner's personality on digitalization in SMEs

The impact of the crafts owner's personality on digital transformation in crafts SMEs has not been investigated to date. However, it is known from the innovation literature, that an owner's personality traits play a decisive role for innovation in (crafts) SMEs (Marcati et al., 2008; Runst and Thomä, 2022). Both Marcati et al. (2008) and Runst and Thomä (2022) make use of the Big Five personality model to investigate the impact of the owner's personality traits on innovation. The model provides a useful framework to group personality traits and represents a psychology-based model to measure personality traits. The Big Five personality traits are biologically based traits that have a genetic fundament and are therefore considered to be stable throughout a person's lifetime (Obschonka and Stuetzer, 2017). They comprise extraversion, conscientiousness, openness, agreeableness, and neuroticism[7] (Digman, 1990; Obschonka and Stuetzer, 2017; Runst and Thomä, 2022).

"Extraversion" is characterized by a preference for social interaction. An owner with higher extraversion scores is rather active, sociable, communicative and outgoing (Iqbal et al., 2021; Runst and Thomä, 2022). As these owners promote in-firm communication, they lay the foundation for an exchange of information and knowledge (Jensen et al., 2007; Runst and Thomä, 2022). According to Iqbal et al., (2021) higher levels of extraversion correlate with a higher level of technology acceptance and Runst and Thomä (2022: 4) suggest that extravert owners are more likely to "monitor their external environment for novel ideas from customers or suppliers".

"Openness" or rather "openness to experience" is characterized by being open to gaining new experiences and being curious about and interested in different things and ideas (Mewes et al., 2022; Runst and Thomä, 2022). Owners with a high level of openness appreciate new ideas and foster "an innovation-friendly learning environment" (Runst and Thomä, 2022: 4) in which employees feel comfortable expressing themselves freely which again fosters

[7] A description of the five personality traits can also be found in the appendix.

innovation according to Runst and Thomä (2022). As in the case of extraversion, Iqbal et al. (2021) suggest that openness correlates with higher levels of technology acceptance.

"Agreeableness" is characterized by trust in employees, being helpful, cooperative and appreciating employees' ideas (Barrick and Mount, 1991; Iqbal et al., 2021). An owner with high levels of agreeableness tends to defer to others when social conflicts arise. He / she has a forgiving attitude and assigns less relevance to one's own opinion (Barrick and Mount, 1991; Runst and Thomä, 2022). Runst and Thomä (2022) argue that although a high level of agreeableness can promote cooperation and hence innovation, it can also hamper innovation as "high levels of agreeableness can also lead to conflict avoidance behavior, thereby strengthening the status quo" (Runst and Thomä, 2022: 4).

"Conscientiousness" is characterized by being self-controlled, well organized, engaging in long-term planning and being on time (Iqbal et al., 2021; Runst and Thomä, 2022). An owner with high scores of conscientiousness is most likely characterized as hard-working, following rules and having a will to achieve (Barrick and Mount, 1991). According to Marcati et al. (2008), it is negatively correlated with creativity and innovativeness. For digital transformation, conscientiousness could have a mixed effect: on the one hand, owners with high conscientiousness scores could have high ambitions to reach a digitalization goal, while on the other hand, obeying rules could hamper digital transformation due to their complexity.

"Neuroticism" is characterized by frequently experiencing negative emotions such as anger, worries, sadness, guilt or hopelessness. Owners with high levels of neuroticism are emotionally less stable or have less emotional control. Iqbal et al. (2021) suggest that neurotic individuals consider information system growth as both a stressful and threatening process. For digital transformation in crafts SMEs this suggests that neuroticism would have a negative impact.

These five personality characteristics are deeply rooted and broadly accepted as grouping different facets of personality in the psychological literature (John et al., 2008). While the use of the Big Five personality traits to explain entrepreneurship in general already exists (e.g. (Marcati et al., 2008; McCrae and Costa, 2008; Obschonka and Stuetzer, 2017; Runst and Thomä, 2022), the Big Five personality traits have not been brought into a relationship with digital transformation in SMEs. However, two papers have used the Big Five personality traits to explain innovation in SMEs, both of which serve as a foundation for this paper because digitalization is often associated with innovation (Agostini et al., 2020). Marcati et al. (2008) use a small sample of SME owners and find suggestive effects that openness and extraversion correlate with innovativeness. Beyond this – and more suitably for the crafts sector – Runst and Thomä (2022) use a sample of 1,928 crafts SMEs and quantitative methods to investigate the impact of the owner's personality traits on innovation. Their findings clearly point towards the critical role of the small business owner's personality in driving firm-level innovation, particularly openness and extraversion. They argue that owners who have high levels of these characteristics are more likely to draw novel ideas from the environment outside the company or foster innovation within the company by living an open communication culture and exchanging knowledge and ideas within the company. An open character of the owner also encourages employees to express their own innovative ideas.

2.3 Hypotheses

Against this background and given the above evidence, we expect personality traits of crafts owners to exert a major influence on a crafts SME's digital transformation. In particular, we expect that – as in the case for innovation in crafts SMEs in general (Runst and Thomä, 2022) – openness and extraversion play a driving role for digital transformation in crafts SMEs.

H1: The personality of the owner of crafts SMEs affects the firm's digitalization level.

H1a: Extraversion positively affects the digitalization activity of a company.

H1b: Openness positively affects the digitalization activity of a company.

As the literature on digital transformation in SMEs suggests that digital transformation is an iterative process comprising different stages of digitalization, we are further interested in exploring whether different stages of digitalization require different types of personality traits in crafts SMEs (H2). We expect different personality factors to be important depending on the maturity level of a company's digitalization. For example, in the case of digital communication technologies, one could expect more extravert owners to use them to engage more intensively in social interaction with external partners. Another example is craft owners who need to be particularly open to new experiences to become active regarding complex Industry 4.0 technologies with a high degree of innovative novelty.

H2: The effect of personality on digitalization differs based on the level of digital maturity within the company.

The aforementioned literature on drivers of digital transformation in SMEs suggests that an owner's local or – more generally – external embeddedness is a driver of digital transformation. Although this could be an interesting area of research for digital transformation in SMEs in the crafts sector on its own, we are interested whether the owner's local embeddedness serves as a mediator for extraversion. One could argue that extravert owners tend to establish networks and are more likely locally embedded. Therefore, the following third hypothesis will be tested:

H3: The effect of an owner's extraversion on digitalization is mediated by the owner's local embeddedness.

3. Data and methods

3.1 Data collection and sample specifics

In order to obtain suitable data to test our hypotheses, we conducted a comprehensive online survey between April, 25 and May, 12 2022. The survey was presented and discussed with experts from the crafts chambers in advance to ensure the use of comprehensible language. In cooperation with eight crafts chambers of northern Germany (Lower Saxony and Mecklenburg-Western Pomerania), the questionnaire was sent out to all officially registered crafts firms included in the official e-mail distribution list of the crafts chambers. These companies are typically small, with only 1-19 employees, and an average turnover per employee of around 110,000 Euros (Statistisches Bundesamt (Destatis), 2021). We received answers from 554 craft firms that fully answered the questionnaire.

The questionnaire covered questions about general firm characteristics, the importance of digitalization in different business areas, the drivers of digitalization, the importance of digital communication and recruiting channels, as well as questions regarding the personality of the company's owner. A detailed version of the questionnaire is included in the appendix (table A1). Table 1 presents the items in the questionnaire that covered digitalization in different business areas and the variables that we derived from them. The respondents could rate the importance of digitalization in the different business areas on a five-point scale.

We use a simple arithmetic mean of all items as the dependent variable in our baseline model. In the next step, we apply PCA to all digitalization items. We retain the first three factors as the first two factors have Eigenvalues greater than one and the Eigenvalue of the third factor is almost equal to one. Afterwards, we use varimax rotated factor loadings to identify factors, which are more distinctive in terms of the items that load strongly on them. This approach helps to identify different areas of digitalization. We retain three distinctive factors for which we display factor loadings in table A2. Table 1 displays the items and the resulting factors. We named the first factor digital communication and organization because the items "digital communication within the firm and to outside actors", "software implementation for business processes" and "cloud applications" load strongly on this factor while the other items do not. The second factor is called digital sales and products as only the items "digital sales channels" and "digital products" load strong on this factor. The final factor is called digital production because only the items "digital connections and data exchange between systems, processes and products" as well as "automated production technologies" have high factor loadings for this factor.

One can view these factors as representations of different stages in the digitalization process of a firm. As shown in the literature review, this process often starts with the implementation of digital communication and organization tools, followed by the introduction of digital sales channels. Finally, digital production technologies often represent the highest level of digitalization within a firm. We use the factor scores of these factors as dependent variables in our analysis to evaluate whether personality has different effects on different stages of the digitalization process. As a robustness test, we also use the arithmetic mean of the respective items as dependent variables for different digitalization areas.

Table 1. Digitalization items and variables

Items in the questionnaire (Respondents indicated importance on a five-point scale)	Variables for specific fields of digitalization
Digital communication within the firm and to outside actors	Digital communication and organization
Software implementation for business processes	
Cloud applications	
Digital sales channels	Digital sales and products
Digital products	
Digital connections and data exchange between systems, processes and products	Digital production
Automated production technologies	

3.2 Personality

There are different methods to measure the Big Five personality characteristics, such as including a set of ten or 44 established questions on a person's personality, which can be clearly connected to personality traits (for more information see Rammstedt and John, 2007). For this paper, we rely on the BFI-10 set of ten established questions on a person's personality on a seven-point Likert scale (see Rammstedt and John, 2007). Although there are longer sets of questions to measure the Big Five personality traits (e.g. see BFI-44), the BFI-10 can be used in surveys with limited length and it retains reliability and validity (Rammstedt and John, 2007). Each Big Five trait relies on two questions (see table 2) on a person's personality on a seven-point Likert scale and is calculated using the mean values of the two questions. As indicated in table 2, for each trait one item enters this calculation with a reversed scale because higher values of the answers to these questions express lower levels of the respective trait. In a final step, we standardize the variables for the empirical analysis.

Table 2. Big Five and BFI-10

Big Five personality traits	BFI-10 Items
Extraversion	I am rather reserved. (reversed scale) I am outgoing, sociable.
Agreeableness	I trust others easily, believe in the good in people. I tend to criticize others. (reversed scale)
Conscientiousness	I tend to be lazy. (reversed scale) I do my tasks thorough.
Neuroticism	I am relaxed. (reversed scale) I get easily nervous.
Openness	I have few artistic interests. (reversed scale) I have active imagination.

In order to test hypothesis 3 on the mediating effect of local embeddedness in the relation between personality and digitalization, we include a question asking about the importance of the owner's involvement in local associations and networks on a five-point scale. Finally, we include several firm- and region-specific control variables such as firm size, age of the owner, perception of competition, broadband availability at the company site, digitalization training for employees, sector affiliation, distance to the main customers as well as an indicator for whether the firm is located in a rural area or city. The descriptive statistics for all variables can be found in table 3 and a correlation matrix is included in the appendix (table A3).

Table 3. Descriptive statistics

Variable	Description	Mean	SD	Min	Max
Digitalization (mean)	Level of digitalization calculated as arithmetic mean	2.078	0.636	1	4
Digital communication (PCA)	Importance of digital communication derived from PCA	0.029	1.398	-2.889	2.636
Digital sales (PCA)	Importance of digital sales derived from PCA	-0.021	1.227	-1.338	3.820
Digital production (PCA)	Importance of digital production derived from PCA	-0.020	1.156	-1.176	3.449
Digital communication (mean)	Importance of digital communication calculated as arithmetic mean	2.606	0.830	1	4
Digital sales (mean)	Importance of digital sales calculated as arithmetic mean	1.665	0.789	1	4
Digital production (mean)	Importance of digital production calculated as arithmetic mean	1.699	0.827	1	4
Local embeddedness	Importance of local embeddedness of owner for the firm	3.065	1.152	1	5
Extraversion		-0.000	1.007	-3.147	1.654
Agreeableness		-0.014	1.005	-2.767	2.475
Conscientiousness	Standardized personality scores	-0.011	1.013	-4.926	1.142
Neuroticism		-0.023	0.988	-1.916	3.144
Openness		-0.021	1.012	-2.992	1.640
Size	Firm size in number of employees	14.908	33.469	0	500
Age owner	Age of the owner in number of years	50.484	9.884	25	80
Competition	Perception of competition	2.628	0.848	1	4
Broadband	Dummy for availability of broadband at company	0.673	0.469	0	1
Training	Dummy for offering digitalization training	0.353	0.479	0	1
Sector	Indicator for nine different sectors	3.211	2.329	1	9
Distance to customer	Indicator for distance to main customers (1=up to 20km, 2=up to 50km, 3=over 50km)	1.783	0.699	1	3
Region type	Indicator for region type (1=city, 2=region with urbanization, 3=rural region)	2.126	0.718	1	3

3.2 Model

To analyze the relationship between digitalization and the Big Five personality traits we use a linear regression analysis with cluster-robust standard errors at the county level. First, we regress the digitalization score (mean of all digitalization items) on the Big Five personality traits and all control variables to test hypothesis 1. Second, we subsequently use the factor scores for the factors of digital communication and organization, digital sales and products and digital production from the PCA as dependent variables to test hypothesis 2.

In order to test hypothesis 3, we conduct a mediation analysis with a series of regressions (Judd & Kenny, 1981). First, we regress the variable measuring local embeddedness on the Big Five personality traits. As local embeddedness is measured as an ordinal variable with five distinctive characteristics, we use ordinal logistic regression. If hypothesis 3 is valid, we should find a positive and significant correlation between local embeddedness and extraversion. Afterwards we use the same regression equation as in our baseline model but also include local embeddedness as an explanatory variable. If there is a mediating effect of local embeddedness in the relationship between extraversion and digitalization, the coefficients on extraversion and openness should decrease compared to the baseline model.

4. Results

4.1 Relationship between digitalization and personality

We first evaluate hypothesis 1 concerning whether the owner's personality has an influence on the overall digitalization level of the company using linear regression techniques. More specifically, we test whether the levels of extraversion and openness are positively related to digitalization. Our baseline model in column 1 of table 4 includes all Big Five personality traits as well as all control variables. We find a positive and significant effect of the owner's extraversion and openness on the firm's overall digitalization level. An increase of one standard deviation in the level of extraversion translates into an increase in the digitalization level of 0.066. Similarly, a one standard deviation increase in the level of openness increases the digitalization level by 0.065. Both effects are highly significant, and we therefore find evidence for our first hypothesis. Neuroticism has a weak positive and significant impact on digitalization, albeit with the effect being small. The remaining personality traits do not have significant effects on the digitalization level. All control variables have the expected signs. Firm size, competition, digitalization training and the distance to main customers are all positively and significantly related to digitalization, whereas the age of the owner and being located in a rural area have a negative and significant effect on the overall digitalization level. Broadband availability has no impact on digitalization, which is probably due to the fact that most regions have access to broadband internet.

Table 4. Regression analysis

	(1) Baseline score	(2) Digital communication	(3) Digital sales	(4) Digital production
Extraversion	**0.066*** **	**0.193*** **	**0.095* **	-0.000
Agreeableness	-0.004	-0.021	-0.002	0.003
Conscientiousness	-0.006	-0.055	0.020	0.035
Neuroticism	**0.041* **	**0.092* **	0.003	0.086
Openness	**0.065*** **	0.067	**0.110* **	**0.137** **
Size	0.002**	0.005**	-0.000	0.005***
Age owner	-0.010***	-0.020***	-0.015***	-0.007*
Competition	0.100***	0.239***	0.053	0.136***
Broadband	0.012	0.021	0.071	-0.039
Training	0.452***	0.878***	0.666***	0.501***
Sector	Yes	Yes	Yes	Yes
Distance to customer (up to 20km reference)				
Up to 50km	0.030	0.011	0.101	0.036
More than 50km	0.253***	0.369**	0.285*	0.523***
Region type (City reference)				
Region with urbanization	-0.040	-0.187*	0.051	-0.001
Rural region	-0.173**	-0.507***	0.017	-0.218
Constant	-0.104	0.141	-0.073	-0.377
N	554	554	554	554
R^2	0.297	0.257	0.158	0.236

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Columns 2-4 of table 4 present the results of the analysis of hypothesis 2 where we evaluate whether different personality traits are important at different stages of the digitalization process. We first use the variable on digital communication and organization, which we derived from PCA with varimax rotated factor loadings. Compared to the baseline regression, we find that extraversion is again positively and significantly related to digital communication, while we no longer find a significant impact of openness on digital communication. We thus can state that for rather basic digitalization steps in the area of communication and organization, being extravert is more important than being open. Surprisingly, we also find a significant and positive impact of neuroticism on digital communication and organization. However, the effect is rather small and close to insignificance. The remaining coefficients on the control variables have the same signs as in the baseline model in column 1.

We next use the variable on digital sales and products as our dependent variable in column 3. We find similar effects of the personality traits as in our baseline model. Extraversion and openness are again positively related to digital sales and products. However, the coefficients are only significant at the 10% level. Most of the effects of the control variables remain similar to the baseline model, although we no longer find significant effects of firm size, competition and being located in a rural area on digitalization. This means that for firms advancing in digital sales and products, firm size, competition and the location of the firm are less important compared to digitalization in other business areas.

Finally, we analyze the effects of personality traits on digital production, which constitutes the most advanced stage of digitalization in our analysis. We find that openness is the only personality trait that has a positive and significant impact on digital production. The coefficients on the control variables have the same sign and are similarly significant as in the baseline model, except for being located in a rural area, where we no longer find a significant impact.

To conclude, our analysis provides evidence that the level of extraversion and openness of the owner have a positive impact on the overall digitalization level of the company. However, when considering different stages of the digitalization process, we gain a more detailed picture of which traits are important for different digitalization stages. While extraversion is more important in the early stages of digitalization, such as introducing digital technologies for communication and organization, openness is important when it comes to introducing advanced digital technologies in the areas of data exchange and automated production technologies.

4.2 Mediation analysis for local embeddedness

We next test hypothesis 3 concerning whether the effect of extraversion on digitalization is mediated by the local embeddedness of the owner by implementing a series of regression models (Judd and Kenny, 1981). In the first step, we regress the local embeddedness variable on the Big Five personality traits to check whether there is a positive and significant relation between extraversion and local embeddedness. The results of this step provide evidence of such a relationship and are depicted in column 1 of table 5. The coefficient on extraversion is positive and highly significant. In the second step of the mediation analysis, we regress the overall digitalization variable on the Big Five personality traits and all control variables without the mediator, which replicates our baseline model (column 2 of table 5). In the third step of the analysis, we include the mediator local embeddedness in the regression. In case of a mediating role of local embeddedness, we should find a positive relation between the local embeddedness variable and digitalization as well as a smaller coefficient on extraversion compared to the model without the mediator. The results in column 3 of table 5 provide evidence of both requirements being fulfilled, hence supporting the validity of hypotheses 3. However, the coefficient of extraversion only slightly decreases, which means that although there seems to be a mediating role of local embeddedness in the relation between extraversion and digitalization, there is still a direct effect of extraversion.

Table 5. Mediation analysis

	(1) Local embeddedness	(2) Without mediator	(3) With mediator
Extraversion	**0.559*****	**0.066*****	**0.055****
Agreeableness	-0.010	-0.004	-0.006
Conscientiousness	-0.201**	-0.006	-0.000
Neuroticism	-0.012	**0.041***	0.038
Openness	0.134	**0.065*****	**0.061*****
Size		0.002**	0.002**
Age owner		-0.010***	-0.009***
Competition		0.100***	0.098***
Broadband		0.012	0.016
Training		0.452***	0.446***
Sector	Yes	Yes	Yes
Distance to customer (up to 20km reference)			
Up to 50km		0.030	0.033
More than 50km		0.253***	0.269***
Region type (City reference)			
Region with urbanization		-0.040	-0.039
Rural region		-0.173**	-0.176**
Local embeddedness (unimportant reference)			
Not very important			0.184
Important			0.100
Very important			0.198*
Extremely important			0.182
Constant		2.035***	1.862***
N	618	554	554
R^2		0.297	0.306

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Robustness analysis

Finally, we conduct some robustness checks to test the validity of our results. Columns 1-3 of table 6 replicate the regression analysis for the different stages of digitalization but also use alternative dependent variables. Instead of using factor scores from PCA with varimax rotated factor loadings, we simply use the arithmetic mean of the respective items that had large factor loadings for the different digitalization areas. These variables then only take into account the important items for the respective stage of digitalization and completely neglect the other items. The results confirm the overall result that extraversion is more important in early stages of the digitalization process while openness is more important in later stages. The coefficient on extraversion is larger and significant in the models using the variables for digital communication and organization as well as digital sales and products as dependent variables (column 1 and 2) compared to the baseline model. The effect of extraversion vanishes when using the variable for digital production as the dependent variable (column 3). The effect of openness is positive and significant in all three models, but considerably increases in size when looking at digital sales and products as well as digital production (columns 2 and 3).

Table 6. Robustness analysis

	(1) Digital communication score	(2) Digital sales score	(3) Digital production score
Extraversion	**0.235*****	**0.152***	0.104
Agreeableness	-0.002	-0.026	-0.006
Conscientiousness	-0.098	-0.035	0.023
Neuroticism	0.121	0.030	0.117
Openness	**0.115***	**0.193****	**0.209****
Size	0.008*	-0.000	0.010***
Age owner	-0.029***	-0.026***	-0.015**
Competition	0.329***	0.098	0.271***
Broadband	0.045	0.124	-0.029
Training	1.208***	0.981***	0.988***
Sector	Yes	Yes	Yes
Distance to customer (up to 20km reference)			
Up to 50km	0.019	0.168	0.051
More than 50km	0.505**	0.524**	0.943***
Region type (City reference)			
Region with urbanization	-0.256	0.077	-0.028
Rural region	-0.764***	0.038	-0.492**
N	567	562	569

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Discussion

The rise of information technologies has posed enormous challenges and opportunities for SMEs and will continue to do so. Although there is a growing body of literature on drivers of digital transformation in SMEs, it clearly lacks insights focused on crafts SMEs and neglects the role of owner’s personality for digital transformation. In a sector such as the crafts, which is characterized by mainly owner-centered small companies with a dominance of personal working relationships it is very likely that the unique personality of the business owner is a firm-level driver of digital transformation. This paper therefore contributes to the literature by shedding light on the effects of crafts owner’s personality traits on digital transformation as well as on different levels of digital maturity. We, therefore, use the Big Five personality theory to explain digital transformation in crafts SMEs by using survey data of 554 crafts firms and quantitative methods consisting of factor analyses and regression analyses. We find that the owner's personality traits of extraversion and openness positively affect the overall digitalization level in crafts SMEs in our sample. In addition, the analysis of different maturity levels of the digitalization process shows that extraversion is particularly important in early stages of the digitalization process, e.g. when digital communication and organization tools are used for the first time. Furthermore, this early phase of firm-level digitalization is also associated with a higher degree of neuroticism. While this may seem surprising upon first glance, this result can probably be explained by the fear of craft owners missing a new technological trend and the resulting motivation to take their first step into digitalization. Particularly in the crafts sector – as a traditional economic sector that tends to lag behind technologically – neuroticism in the sense of a fear of missing the boat is therefore likely to be an important early-stage driver of digitalization. Furthermore, extraversion also drives the evolution of SMEs in the craft sector towards a business model that focuses on digital sales. As this entails close interaction with external partners such as customers, stronger extraversion is automatically an advantage. By contrast, openness is most important in later stages of the digitalization process, when it comes to introducing advanced digital production technologies. Finally, we provide evidence that some part of the effect of extraversion on digitalization is mediated by the local embeddedness of the business owner. With these findings on the relationship between firm-level digitalization and the role of the owner's personality traits, this study contributes to the literature on the micro-foundations of the digital transformation process in craft SMEs and presents valuable insights for policy makers and management for the promotion of digital transformation in SMEs. As the literature has so far not examined the role of owners' personalities as a driver of digital transformation the results have to been seen as novel.

This study has limitations which presents avenues for further research. First, our sample is limited to a cross section of 554 crafts firms in Germany. Future research could apply this analysis to a sample of crafts SMEs in different countries and cultural settings. Furthermore, future research should validate in particular the impact of neuroticism on early stage digitalization as our results show positive effects, yet on a low significance level. Qualitative research could explore the mechanisms of the impact behind these personality traits. We moreover encourage future research to switch from a trait-oriented approach of the Big Five to a person-oriented approach (see e.g. Asendorpf et al., 2001; Gerlach et al., 2018). This approach focusses on different configurations of personality traits rather than their individual effects. It would be interesting to evaluate whether certain combinations of traits are important for digitalization or even have a leveraging effect, which has already been shown for entrepreneurship and innovation (Runst and Thomä, 2022).

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Appendix

Table A1. Survey questionnaire

A. General information about the business

1. Where is your company located (specification in postal code)? (open question)
2. Approximately how high is the proportion of highly qualified employees in your company (Bachelor professional degree or graduates from university/university of applied sciences)? (Open question)
3. How old is the managing director? (Open question)
4. To which trade/craft does your company belong? (Open question)
5. How many people were employed in your company on average in 2021 (including the owner)? (Open question)
6. When you think about your customers, where are the majority of them located? (Local (up to 20 km), Regional (up to 50 km), Supraregional (over 50 km))
7. What is the significance of the proximity to the urban area for your business? (Unimportant, Not very important, Important, Very important, Extremely important)
8. How is your company's turnover approximately divided by customer groups in 2021? (Total sum 100 %) (Private customers (%), Commercial customers (%), Public customers (%))
9. How do you assess the competitive pressure to which your company is exposed? (No competitive pressure, Low competitive pressure, Medium competitive pressure, High competitive pressure)

B. Digitization in the company

1. How widespread are the following application areas of digitization in your company? (None, Low, Medium, High)
    - Networking and data exchange between plants, processes, products (e.g. automatic error message)
    - Program-controlled production (e.g. 3D printing, milling technologies)
    - Digital sales channels (e.g. online stores, platforms)
    - Digital products
    - Software for business processes (e.g. enterprise resource planning systems, digital time recording, wikis)
    - Digital communication (e.g. with employees, customers, suppliers)
    - Cloud applications
2. How would you rate the level of digitization in your company compared to other companies in your industry? (Far below average, Rather below average, Average, Rather above average, Far above average)

3. Where does the impulse for digitization activities in your company come from? (Unimportant, Not very important, Important, Very important, Extremely important)

- Managing Director
- Employees
- Trainees
- Customers/clients
- Manufacturer/Supplier
- Competitors
- Universities, other scientific institutions
- Chambers of crafts, trade associations, guilds
- Trade press, media, Internet, trade fairs
- Laws and regulations

C. Infrastructure and communication channels

1. Which channels do you consider important to communicate with customers of your company? (Unimportant, Not very important, Important, Very important, Extremely important)

- Personal meetings
- Phone
- E-mail
- Messenger services (e.g. SMS, WhatsApp, Signal)
- Social media and platforms

2. Which channels do you consider important to search for new employees for your company? (Unimportant, Not very important, Important, Very important, Extremely important)

- Personal contacts
- Advertisements in magazines / newspapers
- Announcements on the own website
- Social media and platforms

3. Does your business have a broadband connection? (Yes, No)

4. Is the performance of your internet connection sufficient for the work in your business? (Yes, No)

5. How does a slow internet connection hinder your work? (Open question)

D. Digital competencies, education, and further training

1. Do you offer trainings in the area of digitization for you and your employees? (Yes, No)

2. To what extent do you agree with the following statement about vocational training: Previous educational content is outdated regarding digitization topics. (Fully agree, Partially agree, Neither, Partially disagree, Do not agree at all)
3. To what extent do you agree with the following statement about vocational training: In the future, entirely new digitization topics need to be included in the training. (Fully agree, Partially agree, Neither, Partially disagree, Do not agree at all)
4. Where are digitization topics missing in the training? (Open question)

E. Conclusion: Personal characteristics of the owner

1. Please indicate the extent to which the following characteristics apply to you as owner or manager. (If you are not the owner or managing director yourself, please provide information about them). (Do not agree at all, Disagree, Partially disagree, Neither, Partially agree, Agree, Fully agree)

- I am rather reluctant, reserved
- I easily give trust and believe in the good in people
- I am comfortable, I tend to inactivity
- I am relaxed, I do not let stress get me out of my stride
- I have little artistic interest
- I get out of myself, I am sociable
- I tend to criticize others
- I complete tasks thoroughly
- I easily get nervous and insecure
- I have an active imagination, I am fanciful

2. What is the significance of the owner's involvement at the local level for the business (e.g. in associations, networks, non-profit organizations or local politics)? (Unimportant, Not very important, Important, Very important, Extremely important)

Table A2. Factor loadings of PCA with varimax rotation to identify different areas of digitalization

Variable	Factor 1	Factor 2	Factor 3
Digital communication within the firm and to outside actors	**0.6058**	-0.0274	-0.0691
Software implementation for business processes	**0.5668**	-0.0390	0.0688
Cloud applications	**0.5403**	0.0478	-0.0309
Digital sales channels	-0.0510	**0.7342**	-0.0158
Digital products	0.0501	**0.6605**	-0.0120
Digital connections and data exchange between systems, processes and products	0.1084	0.1266	**0.5826**
Automated production technologies	-0.0544	-0.0645	**0.8061**

Table A3. Correlation matrix

	Digitalization (mean)	Digital communication (PCA)	Digital sales (PCA)	Digital production (PCA)	Digital communication (mean)	Digital sales (mean)	Digital production (mean)	Local embeddedness
Digitalization (mean)	1							
Digital communication (PCA)	0.868***	1						
Digital sales (PCA)	0.737***	0.455***	1					
Digital production (PCA)	0.663***	0.361***	0.308***	1				
Digital communication (mean)	0.860***	0.995***	0.445***	0.349***	1			
Digital sales (mean)	0.722***	0.442***	0.995***	0.285***	0.437***	1		
Digital production (mean)	0.710***	0.417***	0.366***	0.988***	0.395***	0.333***	1	
Local embeddedness	0.140***	0.153***	0.0824	0.0649	0.152***	0.0757	0.0776	1
Extraversion	0.127**	0.141***	0.125**	0.0121	0.126**	0.115**	0.0420	0.285***
Agreeableness	-0.00610	-0.0218	0.00907	0.00118	-0.0172	0.00274	0.00679	-0.00472
Conscientiousness	0.0260	-0.0152	0.0718	0.0369	-0.0287	0.0636	0.0527	-0.0360
Neuroticism	0.0155	0.0285	-0.0297	0.0283	0.0342	-0.0257	0.0146	-0.00711
Openness	0.0965*	0.0347	0.107*	0.108*	0.0356	0.101*	0.110**	0.0646
Size	0.209***	0.202***	0.0569	0.203***	0.205***	0.0507	0.206***	-0.0578
Age owner	-0.107*	-0.106*	-0.110**	-0.00712	-0.113**	-0.113**	-0.00884	-0.122**
Competition	0.174***	0.161***	0.0478	0.177***	0.164***	0.0487	0.175***	-0.0160
Broadband	0.0758	0.0699	0.0581	0.0404	0.0665	0.0605	0.0463	-0.00749
Training	0.403***	0.364***	0.281***	0.264***	0.361***	0.269***	0.286***	0.145***
Sector	0.0412	-0.00483	0.0831	0.0356	-0.00520	0.0843*	0.0383	0.0630
Distance to customer	0.160***	0.108*	0.0886*	0.187***	0.107*	0.0896*	0.184***	-0.0679
Region type	-0.109*	-0.156***	-0.00680	-0.0436	-0.160***	-0.00498	-0.0469	0.00536

Table A3. (continued)

	Extraversion	Agreeable-ness	Conscientiousness	Neuroticism	Openness	Size	Age owner	Competition	Broadband
Extraversion	1								
Agreeableness	-0.0119	1							
Conscientiousness	0.233***	0.00000142	1						
Neuroticism	-0.0783	-0.117**	-0.114**	1					
Openness	0.151***	0.132**	0.250***	0.00639	1				
Size	0.0652	0.00105	0.0542	-0.0789	-0.0382	1			
Age owner	-0.0342	0.00719	-0.0204	-0.0144	-0.0523	0.0623	1		
Competition	-0.0795	0.0134	0.0472	0.00161	0.0146	0.120**	-0.0245	1	
Broadband	-0.0115	-0.0504	-0.0358	0.0239	-0.00817	0.0218	-0.0182	-0.0832	1
Training	0.0623	0.0108	-0.0116	-0.0805	-0.0229	0.188***	0.0735	0.00838	0.153***
Sector	0.0727	0.0855*	0.0476	-0.0634	0.173***	-0.0405	-0.0608	0.144***	-0.0129
Distance to customer	0.0326	-0.0221	0.0458	-0.0699	0.0502	0.201***	0.0548	0.120**	-0.0232
Region type	0.00748	-0.0287	0.148***	0.0352	0.0731	-0.0211	-0.00264	0.00603	-0.140***

Table A3. (continued)

	Training	Sector	Distance to customer	Region type
Training	1			
Sector	0.0302	1		
Distance to customer	0.0890*	-0.140***	1	
Region type	-0.0830	0.0716	0.163***	1

Table A4. Big Five Personality Traits

Personality Trait	Description
Extraversion	Extraversion is characterized by a preference for social interaction. An owner with extravert personality trait is interested in communication, is sociable and active.
Agreeableness	Agreeableness is characterized by forgiving attitudes, trust in employees, appreciating employees' ideas and the belief in cooperation. When social conflicts arise, an agreeable person is likely to defer to others. Asserting the own opinion is of less relevance.
Conscientiousness	Conscientiousness is characterized by long-term planning, being on time. Owners who have high conscientiousness are hard-working, strictly follow rules and are comparatively risk averse.
Neuroticism	Neuroticism is characterized by frequently experiencing negative emotions (such as anger, worries, sadness, guilt or hopelessness). Owners with high neuroticism scores are considered emotionally less stable.
Openness	Openness is characterized by being open to make new experiences and appreciating new ideas as well as having an active imagination. Novelty and variety are preferred to routines and repetitions.

Source: Own elaboration, based on Runst & Thomä (2021, p.4)

Declaration of contribution to each paper of this cumulative dissertation (based on the CRediT taxonomy by Brand et al. 2015)[8]

1. ***Firm innovation and generalized trust as a regional resource***
   With: Ann Hipp, Petrik Runst
   Own contribution: 60%; conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – original draft, writing – review & editing, visualization
   Publication status: Earlier version published as ifh Working Paper, R & R Research Policy

2. ***Spatial heterogeneity in the effect of regional trust on innovation***
   With: Petrik Runst, Kilian Bizer
   Own contribution: 50%; conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – original draft, writing – review & editing, visualization
   Publication status: In publication as ifh Working Paper, submitting to Economic Geography

3. ***From automation to databased business models: digitalization and its links to innovation in small and medium-sized enterprises***
   With: Jörg Thomä
   Own contribution: 40%; conceptualization, methodology, software, validation, formal analysis, data curation, writing – original draft, writing – review & editing, visualization
   Publication status: Earlier version published as ifh Working Paper, submitting to Journal of Innovation & Knowledge

4. ***Beauty attracts the eye but personality captures the heart … of digital transformation in crafts SMEs***
   With: Anita Thonipara, Kilian Bizer
   Own contribution: 60%; conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – original draft, writing – review & editing, visualization
   Publication status: Earlier version published as ifh Working Paper, submitted to Technovation

05.02.2023

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[8] Brand, A., Allen, L., Altman, M., Hlava, M. & Scott, J., 2015. Beyond authorship: attribution, contribution, collaboration, and credit. Learned Publishing 28(2), 151-155.

Ph.D. program in Economics

Declaration for admission to the doctoral examination

I confirm

1. that the dissertation that I submitted "SME innovation in Regional Innovation Systems" was produced independently without assistance from external parties, and not contrary to high scientific standards and integrity,

2. that I have adhered to the examination regulations, including upholding a high degree of scientific integrity, which includes the strict and proper use of citations so that the inclusion of other ideas in the dissertation are clearly distinguished,

3. that in the process of completing this doctoral thesis, no intermediaries were compensated to assist me neither with the admissions or preparation processes, and in this process,

    - No remuneration or equivalent compensation were provided
    - No services were engaged that may contradict the purpose of producing a doctoral thesis

4. that I have not submitted this dissertation or parts of this dissertation elsewhere.

I am aware that false claims (and the discovery of those false claims now, and in the future) with regards to the declaration for admission to the doctoral examination can lead to the invalidation or revoking of the doctoral degree.

05.02.2023