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Firm innovation and generalized trust as a regional resource

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A B S T R A C T

Generalized trust represents an important regional resource for a firm. 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 on firm innovation in German regions. Our observation period ranges from 2004 to 2018. A trust measure is generated by using survey data from the German Socio-Economic Panel, firm-level data is obtained from the Mannheim Innovation Panel 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, and in small and medium-sized enterprises, especially those that operate in the doing-using-interacting mode of innovation (DUI) with an emphasis on employee freedom and creativity.

1. Introduction

The current open innovation debate highlights trust as an essential resource of a firm to engage in collaboration and the creation of new or improved products and technologies (Wyrwich et al., 2022). In general, one can distinguish two types of trust: Generalized trust refers to a situation in which a person expects honest behavior of other people, without further specification of the type of person or subject matter (Robbins, 2016; Fukuyama, 1995). It fosters interaction and increases the exchange of information and cooperation (Becattini, 1990; Putnam, 1995, 2000; Westlund and Adam, 2010; Brockman et al., 2018). In contrast, relational trust refers to particular people and circumstances (Hardin, 2002; Robbins, 2016). There is evidence that general expectations about the trustworthiness of others carry over into specific interactions (Robbins, 2016; Ockenfels and Weimann, 1999).

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; Doloreux and Porto Gomez, 2017). These contributions suggest that the high degree of theoretic significance assigned to this topic is warranted, especially with regard to the role of small and medium-sized enterprises (SMEs) and learning modes therein (e.g. Cooke et al., 1997). 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), we need to better understand the link between generalized trust and firm innovation.

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. 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

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lower-tech knowledge, thereby ignoring the doing-using-interacting (DUI) mode of innovation (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 extend the literature as follows: First, we posit that generalized trust and firm innovation exhibit a diminishing returns relationship. The argument of diminishing returns is derived from the lack of openness and knowledge inflow from outside of the focal region because firms within high trust regions may rely on existing and productive relationships within their own region at the expense of forming new or far reaching ones (see Fitjar and Rodríguez-Pose, 2013). Second, we hypothesize that trust is particularly relevant for innovation in SMEs, which lack internal capacities in contrast to larger firms (e.g., Rammer et al., 2009; Doh and Kim, 2014; Jensen et al., 2007). Third, we argue that the trust-innovation relationship is most beneficial for SMEs that operate under a DUI mode, by relying on the knowledge and creativity of their employees (Runst and Thomä, 2022; Thomä, 2017).

We test these hypotheses by selecting a more encompassing measure of innovation, a multilevel model (MLM), which includes firm-level panel data and a large number of geographic regions. As the RIS concept suggests, a multilevel structure is inherent to innovation processes (Srholec, 2010; Cooke, 2001; Fernandes et al., 2020). 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. Our results support not just diminishing returns to trust in the bottom half of the trust distribution but an inverted U-shaped effect. In addition, we provide robust evidence on the particular importance of generalized trust for SMEs, especially those that operate in a DUI mode, emphasizing employee independence and creativity.

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. Akçomak 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 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 mechanism, 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; Trigilia, 2001; 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). If an individual trusts a specific person (or type of persons) with regard to concrete subject matter, trust can be said to be relational, which is distinct from generalized trust in others (Hardin, 2002; Robbins, 2016). There is evidence that generalized and relational trust are causally connected (Sapienza et al., 2013; Robbins, 2016; Ockenfels and Weimann, 1999; Henrich et al., 2001). For example, individuals in high trust countries/regions are more likely to cooperate with others in public goods games (e.g. Ockenfels and Weimann, 1999; Henrich et al., 2001) or in regions with entrepreneurial communities (Mickiewicz et al., 2019).

Trust can be seen as an outcome of and indicator for dense social networks. While it is theoretically conceivable that trust is the cause of dense social networks, we do not differentiate between the two cases but treat trust and high network density as co-occurring phenomena, as suggested by Putnam (1993).

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 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.

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). 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. By accessing generalized trust in regions, it is a key intangible asset that enables firms to generate new or improved products and technologies in the realm of open innovation and achieve a competitive advantage (Brockman et al., 2018). However, given the risks attributed to open innovation (ibid.; Brunswicker and Chesbrough, 2018), we still lack knowledge on the outcome and mechanisms that link trust among people in regions to firm-level innovation, and its particular role for SMEs and DUI innovation remains largely neglected. We therefore elaborate on the importance of generalized trust for firm, SME and DUI innovation by using the RIS concept in the following section.

2.2. *Regional trust as a firm resource*

Firm learning and innovation is, among 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 Jane 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, nonconformance 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. However, in contrast to analytic (STI-based) knowledge supporting radical innovation, the exchange of synthetic (DUI-based) knowledge in these interactions mainly enables incremental and user-driven innovation, which is especially relevant in lower-tech settings (Rammer et al., 2009; D'Ambrosio et al., 2019; Carayannis et al., 2008). "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., 2001; Ockenfels and Weimann, 1999). 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, higher levels of trust and social cohesion may produce diminishing returns (McFadyen and Cannella Jr, 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. McFadyen and Cannella Jr (2004) argue, for example, that there is a danger that individuals in dense social networks become more alike in what they know, reducing the informational value of the network. If firms operate within tied and tested business networks they may neglect to cultivate links with potential partners outside the network, which may hinder the absorption of external knowledge. For example, interactions along the value chain, that are related to the procurement of inputs or customer requests, can generate an impetus for learning and innovation as a by-product of interaction, when technological knowledge is exchanged or hitherto unknown customer needs become apparent. Lock-in effects can result if firms remain within their established network and too few weak-tie and far-reaching connections – the value of which has been demonstrated before (Fitjar and Rodríguez-Pose, 2013) - are being created through which external knowledge enters the regional system. In addition, while increases in generalized trust at lower levels can lead to improved human capital, information sharing and lower transaction costs, it may no longer translate into more innovation outcome after it has reached a certain level. Especially when it comes to costly innovation projects, there are limits to the transaction cost reducing effects of generalized trust. Apart from that, the risks associated with collaboration and open innovation practices such as appropriation and opportunism have been brought forward multiple times (Brockman et al., 2018; Brunswicker and Chesbrough, 2018), and might also explain a diminishing return relationship between generalized trust and firm innovation.

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 Jr (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 when regional trust levels are high. While the aforementioned empirical results suggest an inverted U-shape relationship between trust and innovation – with negative returns after a certain level of trust has been reached - the theoretical basis for a negative impact is tenuous. We therefore hypothesize that there are diminishing returns of generalized trust:

H1. Generalized trust within regions and the likelihood of firm innovation exhibit a diminishing returns 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.

H2.A. Generalized trust particularly affects SME innovation, as opposed to innovation in larger firms.

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 STI mode. According to Alhusen et al. (2021: 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 (Alhusen et al., 2021).

If the firm is embedded within a community characterized by dense network connections and a high degree of trust, one can argue that it will be easier 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 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. 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.

Nevertheless, the necessity of geographic proximity suggested by repeat interactions and learning by doing has been challenged empirically. Fitjar and Rodríguez-Pose (2013) show that far reaching DUI-interactions are related to more innovation in a sample of Norwegian firms, whereas local DUI-interactions are not. However, with reference to H1, we note that Norwegian regions exhibit some of the highest trust values in Europe and it can be suspected that further increases in trust (and local cooperation) will not noticeably affect cooperation and innovation. DUI companies particularly depend on the experiential knowledge of employees, relying on employee freedom and creativity in the process of innovation (see Runst and Thomä, 2022; Thomä, 2017). It can be argued that generalized trust supports the independent and unsupervised actions of employees, allowing them to experiment and incrementally improve products or services. In that sense, higher regional trust levels translate into a different leadership style, where owner/ managers are more willing to give up some hierarchical control in order to create an internal culture of independent creativity.

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. 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 STI firm.

H2.B. Generalized trust particularly affects SMEs operating under the DUI mode.

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 and Weimann, 1999).

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 extroversion 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 an authoritarian regime reduces the likelihood of future cooperation (Wyrwich et al., 2022).

4. Data and methods

4.1. Data sources

Our data set combines three different data sources. First, the MIP 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 and M&As, 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 with the German component of the CIS. Second, we use the GSOEP, which is one of the largest and longest-running multidisciplinary household surveys worldwide by interviewing >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 to include further regional control variables. The INKAR database contains >700 regional indicators from Europe and Germany. Our observation period is from 2004 to 2018, as the GSOEP does not provide information on trust before that period.

4.2. Core variables – innovation and trust

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 annually.

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 >1000 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. Fig. 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.

Fig. 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.

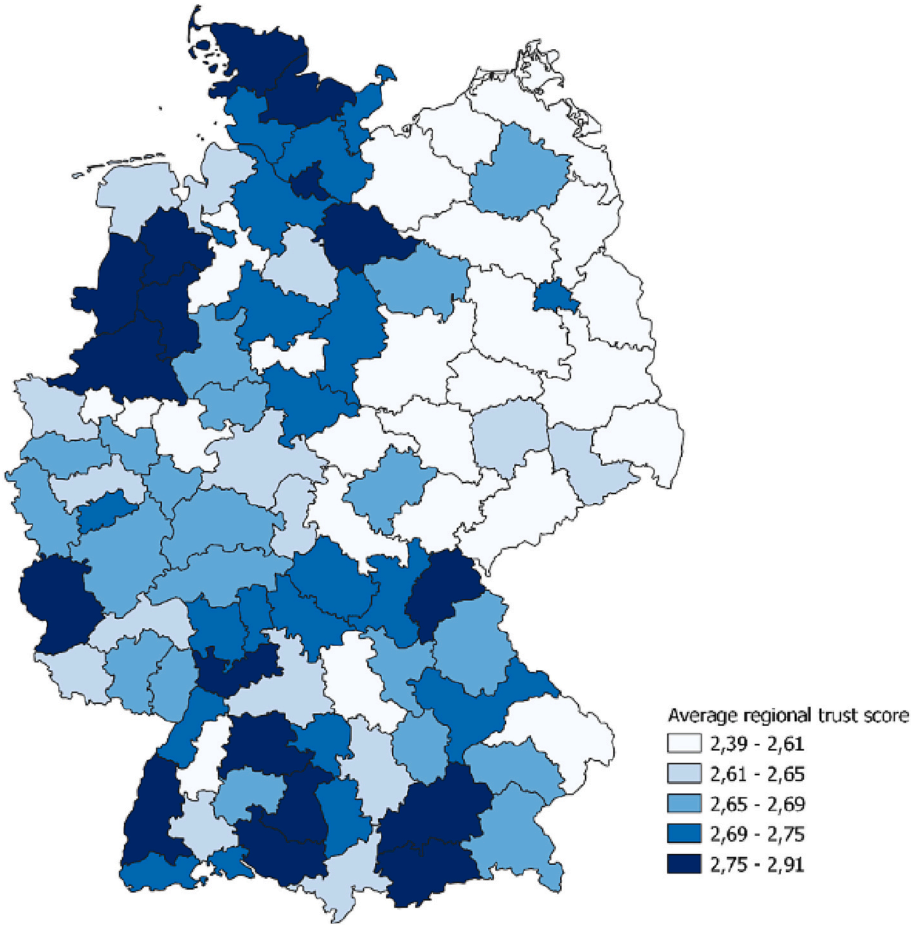

Fig. 1. Regional levels of trust in German spatial planning regions.
Source: GSOEP, aggregated to regional levels (German planning regions). The depicted values are averages over the years 2003, 2008, 2013 and 2018, which is also why minimum and maximum values on the map differ from the descriptive statistics in Table 2. The minimum and maximum values in Table 2 refer to individual year observations.

4.3. Control variables

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. On the other hand, SMEs benefit from their smaller size by making more flexible and faster decisions, which is crucial for innovation. 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.

4.4. Cluster analysis

To identify different modes of learning and innovation, including patent protected STI innovation as well as DUI type innovations, we

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 2178 and 4175. Table A1 displays the correlation coefficients between all variables.

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. $N = 1440$. Regional variables are collected yearly on the level of German planning regions. 94 regions are included in the analysis. Table A1 displays the correlation coefficients between all variables.

follow Thomä (2017) who applies clustering methods, using a number of variables from the MIP panel. Information on whether a company engages in in-house R&D represents a standard measure of formalized learning within an STI framework. Moreover, a set of Likert-type questions on company competencies exist in the 2011 wave that reveal more tacit components of learning and innovation. They record (1) whether a company has the capability to detect customer needs, (2) to find technological solutions, (3) to provide space for trial and error learning, and (4) whether it delegates responsibility and (5) creativity to employees. It also records (6) whether there are internal incentivization systems or (7) internal competition, (8) whether there is cooperation between different company departments, (9) a strong relationship with external partners, (10) speed in implementing ideas, or (11) quick adoption of external innovations.

First, we apply a factor analysis to reduce the eleven competency items and identify three latent underlying variables with an eigenvalue above one (see Table A2). Factor F1 represents the domain of "employee freedom and creativity" as these are the two variables with the highest factor loadings. Employee incentivizing also seems to be associated with factor 1, albeit less importantly. There are two to three variables that load highly on the second factor "speed and adaptation" (F2), i.e. the speed of idea implementation, the capacity to adopt external ideas and to detect customer needs. Finally, the third factor (F3) is related to "management practices", such as employee incentivization and competition between departments.

Second, the three factors as well as the R&D dummy – which constitute innovation input measures - enter into the clustering procedure. We apply a hierarchical method, using Ward's linkages and squared Euclidean distances. The dendrogram in conjunction with standard cluster-stopping rules (Duda et al., 2001) suggests a 5-group solution (see Table A3) that resembles the one found by Thomä (2017). The first cluster (C1) contains the highest R&D shares but also displays above average values for the three competency factor scores. Table A3 also displays means of variables not used for clustering but for validating the cluster solution.

The share of innovative companies and companies with R&D is particularly large in C1 (89% and 99 % respectively), as the share of companies that report having introduced a radical innovation (59 %). Moreover, the share of companies relying on patent protection (44 %) and the average number of employees is higher than in any other group. We therefore assign the label "STI" to group (C1). In contrast, there are three DUI groups (C2-C4) that report some innovative success despite the absence of R&D or patenting. Each of these groups displays a different mix of competency factors. C2 display below average scores in F1 (employee freedom and creativity), a slightly below average score in F3 (management practices), and above average scores in F2 (speed and adaptation). Thus, firms in group C2 are likely innovative due to their ability to quickly absorb and implement external technological developments. We therefore call them "DUI adopters". C3 displays above average scores in all three factors but particularly in F1, which relates to employee freedom and creativity, and F3, offering efficient management practices. They thus represent the "DUI independent creators". Group C4 somewhat resembles C3 in that it also seems to be driven by employee creativity and freedom. However, it displays below average scores in F2 and F3, and is less successful in its innovation output, which indicates the "DUI beginners". Finally, there is a "low learning group" (C5) which exhibits low competency scores and less innovation output. In order to utilize the panel structure of the MIP data, the innovation mode classified in the year 2011 is retained in the four subsequent years.

4.5. A multi-level model

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). Fig. 2 illustrates the hierarchical structure of our 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:

$$\mathrm{INNO}_{tij} = \gamma_{0ij} + \delta_{.ij}\mathrm{Year} + e_{tij}$$

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.

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

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

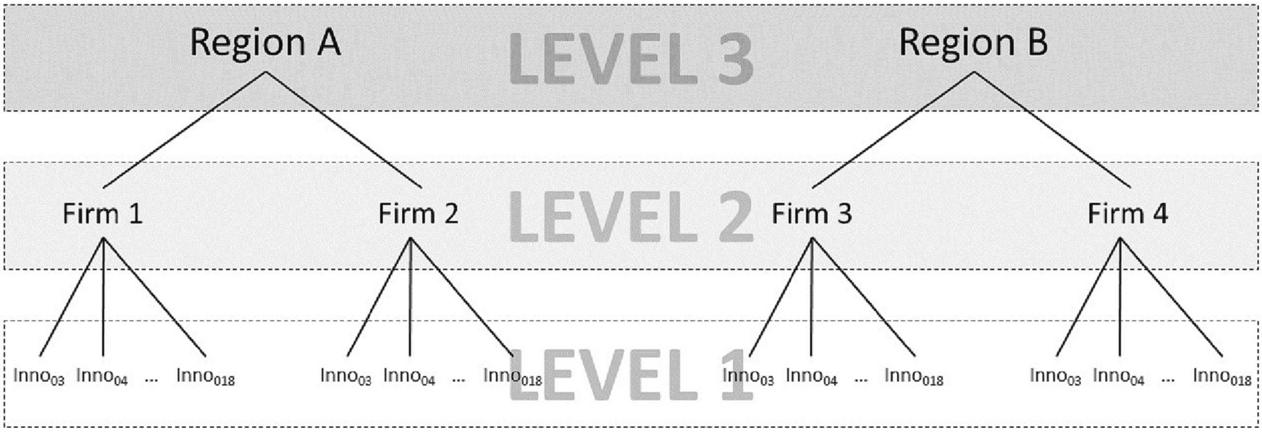

Fig. 2. Multilevel structure of the data.

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

	(1) Empty	(2) Baseline linear	(3) Baseline quadratic	(4) Low trust regions	(5) High trust regions	(6) Random slope	(7) Large	(8) SME
TRUST		0.427**	12.863**	1.163**	−0.651*	13.991**	−7.626	13.326**
TRUST^2			−2.340**			−2.546**	1.260	−2.409**
TRUST*R&D						−0.240		
EXP		0.436***	0.438***	0.480***	0.423***	0.435***	0.505**	0.459***
R&D		3.651***	3.654***	3.850***	3.727***	4.281***	3.868***	3.657***
SIZE		0.274***	0.274***	0.279***	0.277***	0.276***	0.529***	0.242***
EAST		0.050	0.041	0.038	0.059	−0.002	−0.124	0.074
SECTOR		YES	YES	YES	YES	YES	YES	YES
YEAR		YES	YES	YES	YES	YES	YES	YES
POP_DEN		0.026	0.019	−0.016	0.123**	−0.013	0.501***	0.003
GDP		−0.124	−0.094	−0.171	−0.271*	−0.020	−1.058**	−0.076
UNEMP		−0.013	−0.009	−0.005	−0.028*	−0.004	−0.119***	−0.007
STUDENTS		0.003**	0.003**	0.003*	0.001	0.003**	0.002	0.003**
Constant	−0.299***	−4.681***	−20.517***	−6.353***	−1.644	−22.165***	8.136	−21.174***
Var(constant level 2)	7.328	2.208	2.214	2.645	2.212	2.214	3.627	2.162
Var(constant level 3)	0.183	0.013	0.012	0.014	0.007	0.007	0.017	0.008
Cov(constant, R&D)						0.013		
Var(R&D)						0.044		
Observations	49,752	49,752	49,752	23,392	26,360	49,752	3980	45,772
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).

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 1000 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 (1–3, 6). 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 % 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 Ter 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. The coefficient of the quadratic term is negative and significant, indicating that the positive effect of trust decreases with increasing values of trust. 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. To further investigate whether there are negative returns to trust after a certain level, we split the sample into firms located in regions with below average values of trust (specification 4) and firms located in regions with above average values of trust (specification 5). In case of diminishing returns we should find a positive relationship between trust and innovation for the subsample of firms located in regions with below average values of trust, and a smaller or insignificant relationship for the subsample of firms located in regions with above average values of trust. The results of specification 4 support the finding that trust is particularly beneficial for firms in regions with relatively low levels of trust. The coefficient of trust is larger than in the baseline model (specification 2) and significant. In contrast, the coefficient of trust in specification 5 is negative and significant, indicating that the relationship between trust and innovation is negative for firms located in regions with relatively high values of trust. Overall, the results broadly support Hypothesis 1. In addition, they also indicate that there is an inverted U-shape relationship. Thus, there are diminishing returns in the bottom half of the trust distribution and negative returns to trust in the upper half of the trust distribution. Fig. A2 illustrates this inverted U-shape relationship based on the predicted values of our dependent variable from a regression of INNO und TRUST and TRUST squared.

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 6. 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 of the cross-level interaction is insignificant and does not provide evidence for a mediating role of R&D activity in the relationship between trust and innovation. We thus continue our analysis with the random intercept model of specification 3.

5.2. Trust and innovation in SMEs

Next, we analyze the effect of trust for large firms and SMEs, respectively, in order to test Hypothesis 2.A. Therefore, we divide the sample into firms with 500 and more employees (large firms) and firms with fewer than 500 employees (SMEs) according to the often used definition for the German context (IfM, 2023). Table 3 includes the multilevel regression results for the analysis of the sample of large companies (7) and SMEs (8) including all firm- and regional-level covariates. For the sample of large firms, the coefficient of trust becomes negative and insignificant (specification 7). 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 8), 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.

[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.

5.3. Trust and innovation in DUI-companies

One argument for the stronger effect of trust on innovation in SMEs vis-à-vis large companies is that SMEs more frequently innovate in the DUI mode compared to larger firms that often rely on the STI mode. To test this hypothesis (H2.B), we run the baseline model in column (2) of Table 3 separately for SMEs in the clusters of innovation modes described in chapter 4.4 (see Table 4). For ease of interpretation, we do not include the squared trust term. As the cluster variables are only available in the 2011 MIP-wave, and we therefore rely on an unbalanced sample of firms observed between 2011 and 2015, we apply a single level logistic random effects model. The shorter time period leads to insufficient firm-year-observations per regions for a multilevel setting.

Column (1) shows the results for the cluster of STI firms, column (2)–(4) for different clusters of DUI firms and column (5) for the cluster of low learning firms. The trust coefficient is only significant for DUI independent creators (see Table 4). The trust coefficient for this cluster is similar to the baseline model in Table 3 and is significant at the 5 %-level. These results provide partial evidence for Hypothesis 2.B, and indicate an internal component of trust, as opposed to its external effects (e.g. via cooperation). Specifically, it underlines the importance of trust in supporting employee freedom and creativity and via management practices, allowing employees to experiment and incrementally improve products or services.

5.4. Robustness checks

To test the robustness of our firm-level results, we first use current values of trust (specification 1 in Table 5) 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 of the third lag of trust becomes borderline insignificant ($p = 0.117$). 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 in Table 5, we again use our baseline model but

Table 4
Logistic random effects regressions for different firm clusters (marginal effects, dep. var.: INNO).

	(1) STI	(2) DUI adopters	(3) DUI independent creators	(4) DUI beginners	(5) Low learning
TRUST	0.061	−0.029	0.442**	0.019	0.179
EXP	0.035*	0.066**	0.041	−0.030	0.027
R&D	0.296***	0.455***	0.510***	0.348***	0.188***
SIZE	0.019***	0.030***	0.007	0.023**	0.036***
EAST	0.015	0.048	−0.045	0.008	−0.059
SECTOR	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES
POP_DEN	−0.007	−0.042*	−0.008	0.014	0.010
GDP	0.011	0.013	−0.064	−0.157*	−0.020
UNEMP	0.005	−0.008	−0.004	−0.011	0.005
STUDENTS	0.000	0.003***	−0.000	0.001	0.000
Observations	2318	1557	1152	1066	549

Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01 respectively. Clusters are generated using eleven competency variables from the MIP 2011 and a dummy variable on R&D activity. First, a factor analysis was applied to reduce the competency variables to three factors. Subsequently, the three factors as well as the R&D variable were used in a cluster analysis resulting in the five clusters (see Table A3) of firms used in this table. The sample size is smaller than in the overall sample because clusters are constructed based on firm competency items which are only available in the year 2011. We restrict the sample to SMEs with <500 employees. Coefficients are displayed as marginal effects.

Table 5
Multilevel regressions (3/2-MLM, binary dep. var.: INNO)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Trust (t)	Trust (t-2)	Trust (t-3)	Border	SME	Large	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	49,572	47,574	44,893	49,752	42,462	7290	49,752

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.

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 A4). Patents are a commonly used proxy to measure 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 as follows. 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 additional 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 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.A.

6. Discussion and conclusion

This paper provides novel empirical evidence on the link between generalized trust between people in regions and firm-level innovation. We combine knowledge from the social capital, innovation and economic growth literature and develop hypotheses on the impact of generalized trust within regions on the likelihood of firm level innovation with a particular focus on SMEs and the DUI mode of innovation. We test the relationship empirically for firms nested within the 94 German planning regions during the observation period from 2004 to 2018. Our findings have important implications for the innovation literature, including studies on RIS, SME innovation 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. However, somewhat surprisingly, this result suggests not just diminishing returns but detrimental effects of high trust values on innovation in high trust regions. After the innovation-enhancing effect of trust up to a trust value of 2.7 (trust is distributed between 2.28 and 3.05), it turns negative. We argue theoretically that, at higher regional trust levels, the trust-innovation relation weakens as firms become locked into a situation in which the benefits from increased human capital, information sharing and lower transaction costs are only marginal. In order for the trust effect to turn negative, however, a yet unidentified channel must exist. While our empirical result is corroborated by previous studies Echebarria and Barrutia (2013) on patents at the regional level, and McFadyen and Cannella Jr (2004) and Leenders et al. (2003) at the individual and team level), it is surprising from a theoretical point of view.

Second, we find that the trust-innovation relationship is stronger for SMEs (Hypothesis 2.A). Based on this result, 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 can 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).

[2] Patent information was 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 used 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.

Third, our results provide evidence that trust is especially beneficial for firms operating in the DUI mode of innovation (Hypothesis 2.B). However, we only find a positive and significant effect of trust on innovation for the cluster of DUI independent creators, in which firms practice employee-driven innovation activities and respective management practices. In contrast, the trust-innovation relationship seems to be less relevant for the STI-based, low learning, and other DUI groups. This result adds to previous studies that underline the role of employee freedom and creativity in DUI companies (e.g., Runst and Thomä, 2022).

However, this paper also has its limitations which could be addressed by future research: One might 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 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.

Another limitation of the paper concerns the causal interpretation of the relationship between trust and innovation. There might arise endogeneity problems due to reverse causality between generalized trust and innovation. We do not include instrumental variable regression but previous empirical research has already made the case for a causal effect of trust on regional patents (Akçomak and Ter Weel, 2009). Any other method for causal inference (DiD, SCM, discontinuity etc.) cannot be usefully employed in this case.

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.

Policy-makers aim to support regional innovation via different strategies such as smart specialization or short-term 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 historical processes that play out in the long run (Michalopoulos and Xue, 2021). These historical processes cause specific trajectories of economic development and distinct regional settings that cannot be easily reproduced nor directly 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). The long time horizons over which trust develops stand in conflict with the shorter time horizons of current policy making. Why we do not fully understand the process of building up trust, there are strong hints that suggest a positive association between trust and market-oriented institutions (Henrich et al., 2001; Lichter et al., 2021; Ockenfels and Weimann, 1999). We thus recommend that policy makers take note of very low trust levels as a disadvantage, view market-based societies as the most likely environment for nurturing generalized trust and structurally support respective institutions in the long run. 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.

CRediT authorship contribution statement

Thore Sören Bischoff: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft. **Ann Hipp:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing. **Petrik Runst:** Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A

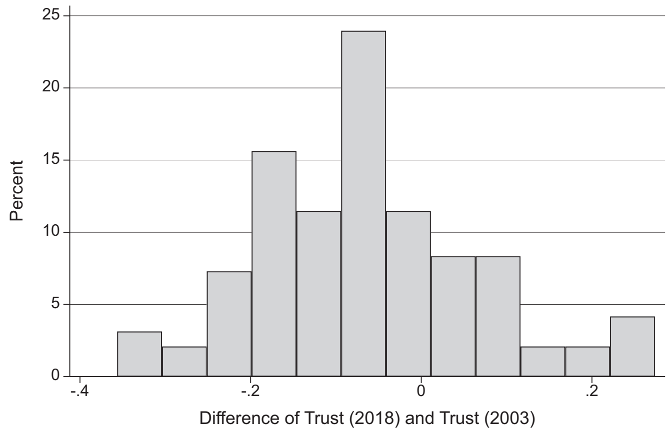

Fig. A1. Histogram of differences in regional trust levels over time.

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
Factor loadings.

	F1	F2	F3	Uniqueness
	Employee freedom and creativity	Speed and adaptation	Management practices	
(1) Customer needs	0.39	0.43	0.09	0.57
(2) Tech. solutions	0.31	0.37	0.16	0.52
(3) Trial and error	0.31	0.28	0.22	0.62
(4) Responsibility	0.75	0.18	0.09	0.37
(5) Employee creativity	0.76	0.22	0.17	0.32
(6) Incentives employees	0.49	0.22	0.48	0.47
(7) Internal competition	0.24	0.23	0.53	0.58
(8) Cooperation	0.38	0.31	0.17	0.60
(9) External partner	0.15	0.33	0.17	0.71
(10) Implementation speed	0.28	0.67	0.14	0.42
(11) Adopt external innovations	0.23	0.66	0.17	0.47

Table A3
Clustering solution.

	C1	C2	C3	C4	C5
	STI	DUI adopters	DUI independent creators	DUI beginners	Low learning
F1	0.21	−0.43	0.56	0.29	−1.63
F2	0.30	0.33	0.16	−1.05	−0.97
F3	0.11	−0.10	0.27	−0.38	−0.31
R&D	0.99	0.00	0.00	0.03	0.03
SHARE_TERTIARY	25.74	15.59	25.69	26.54	17.77

(continued on next page)

Table A3 (*continued*)

	C1	C2	C3	C4	C5
	STI	DUI adopters	DUI independent creators	DUI beginners	Low learning
INNO	0.89	0.33	0.30	0.16	0.09
RADICAL	0.59	0.07	0.11	0.04	0.01
SIZE	279.46	113.13	101.16	82.65	78.39
PATENT	0.44	0.04	0.05	0.05	0.05
N	3435	2378	1773	1550	851

Notes: A hierarchical clustering procedure was applied (Ward's linkages with Euclidean distances), using the three factor scores (see Table A2) as well as a R&D dummy variable. Significant differences between all variable means exist across the five groups (Pearson's chi-squared test). The innovation mode classified in the year 2011 is retained in the four subsequent years and the resulting number of observations is displayed here.

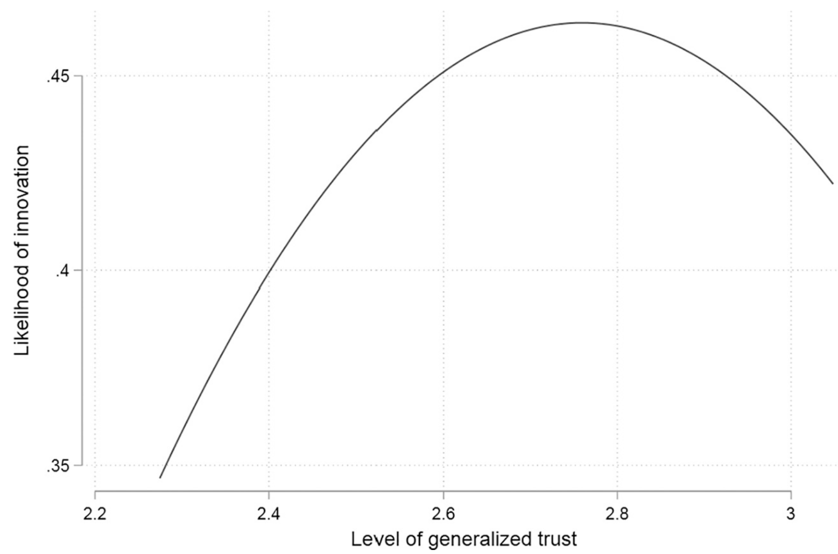

Fig. A2. Inverted U-shape relation between trust and innovation.
Notes: Prediction of INNO based on a linear regression of INNO on TRUST and TRUST squared.

Table A4
Panel regression results (data set 2, dep. var.: PATENTS, regional level).

	(1)	(2)	(3)
	Baseline	Low Trust	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.

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