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Firm innovation and generalized trust as a regional resource

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Abstract:

Generalized trust within regions represents an important firm resource. We provide empirical evidence on the impact of trust among people in regions on innovation using two distinct data sets. The first one contains firm-level data and is used to analyze how trust affects firm-level innovation in small and medium sized enterprises (SMEs). The second data set is used to analyze the trust-innovation relationship within regions. It allows us to capture innovation in the form of patents and explore spatial patterns. Our observation period ranges from 2004 to 2019. We apply a multilevel approach, panel data models as well as spatial techniques. The results show that generalized trust has a positive impact on a firm's innovativeness, which is particularly strong for small and medium-sized firms and in regions with relatively low levels of trust.

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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 (Putnam, 1995; Westlund and Adam 2010; Brockman et al., 2018), thereby facilitating an open innovation culture. 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 (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 trust and innovation (Laursen et al., 2012; Landry et al., 2002; 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 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 survey data from a single region, which does not allow the application of panel data and spatial 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 knowledge, thereby ignoring innovation based on the doing-using-interacting mode (DUI, see Jensen et al., 2007; Thomä, 2017, Runst and Thomä, 2021). Similarly, Akçomak and Ter Weel (2009), and Akçomak and Müller-Zick (2018) exclusively focus on patents and their data sets are purely cross-section. 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 panel data and a large number of geographic regions. We also contribute to this novel empirical literature by using different empirical approaches. First, we apply 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). Second, we also examine the relationship between trust and innovation at a single level by aggregating firm-level data on innovation at the regional level. This procedure allows us to control for regional characteristics by including region fixed effects and permits utilizing the spatial structure of our data by applying spatial panel regression techniques and geographically-weighted regressions.

We contribute to the RIS literature by quantitatively analyzing the effects of regional trust on firm- and regional-level innovation. Our main data set contains 91 planning regions within Germany between 2004 and 2019. We combine four 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 and Förderkatalog 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 small and medium-sized firms (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.

Apart from the RIS 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 Week (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

On the one hand, social capital can be conceptualized in the form of networks of social connections. In this view, it generates resources for individuals or firms that are either positioned within a dense network of strong ties (Coleman, 1988) or whose social ties are weaker but more far reaching (Granovetter, 1973). On the other hand, social capital can be conceptualized as generalized trust among people. Here, trust is a relational component of social capital (Nahapiet and Ghoshal, 1998) and it refers to a psychological state that comprises the intention to accept vulnerability based upon positive expectations of the intentions or behavior of others (Rousseau et al., 1998). It is developed at the individual level, but it can be generalized at an institutional level in an organized system (Zucker, 1986). Such a system can be a region that inherits traditions of fostering trust, interactions and thereby future cooperation (Putnam, 1993). The expectation of fair play – according to a commonly-accepted set of rules – should be 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). For example, there is evidence that individuals in high trust countries are more likely to cooperate in public goods games (e.g., Henrich et al., 2010). 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) 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 and economic growth are linked to firm innovation remains an under explored issue.

2.2. Regional trust as a firm resource

The innovation literature proposes that firm innovation is not a linear but rather an interactive and collective process, including many individuals and organizations (Schumpeter, 1911). These individuals are embedded in a system of innovation, which can be defined at many different levels (e.g. global, national, regional, technological, sectoral) that overlap to some extent (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, 2020 and Ruhrmann et al., 2021).

A regional innovation system (RIS) comprises firms, organizations, a supporting infrastructure, and a minimum governance capacity or quality of institutions (Edquist, 1997). Firms interact with each other and the organizations within the system based on a set of rules, e.g. laws, social norms, and trust (Cooke et al., 1997). These interactions in turn shape the system structure and cause a continuous evolution of the RIS (Kashani and Roshani, 2019). The system emerges through the formation of new institutions and 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 stability of the competitive and innovation processes over time (Asheim et al., 2011; Martin and Moodysson, 2013; Hipp and Binz, 2020). In fact, empirical studies find that the regional configuration of innovative firms, financial organizations (such as venture capital) and other actors, as well as the institutions governing the transactions between these actors are becoming increasingly important for firm success. There seem to be positive feedback loops (or increasing returns to scale) and innovative regions continue to be more successful than their less innovative neighbors (Moretti, 2012). As a result, we can observe increasing regional disparities driven by the differing innovation capacities (Feldman et al., 2021).

Firm learning is dependent on the external structure of the RIS (Cooke et al., 1997), as well as its own DUI capacity (Jensen et al., 2007; Runst and Thomä, 2021), and absorptive capacity (Cohen and Levinthal, 1989, 1990). In its classic presentation, a firm's knowledge about how to produce, solve problems, and acquire new knowledge within its ecological niche are embodied in its routines, thereby serving as repositories of knowledge (Nelson and Winter, 1982).

Moreover, firms rarely innovate in isolation. Instead, they interact with other organizations to develop new products and technologies. Maskell and Malmberg (1999: 179) state that "learning processes are inherently interactive in nature and generally characterized by uncertainty". 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). We expect trust to be an integral component in producing and diffusing knowledge, as it fosters interaction, knowledge exchange and cooperation within regions (Cooke et al., 1997; Cooke, 2001; Westlund and Adam, 2010).

However, one may ask why an aggregate phenomenon such as generalized trust within a region should affect the cooperation behavior of individuals and subsequently the innovativeness of firms. Institutions such as laws and social norms govern social interactions (Edquist, 1997). Generalized trust within a region becomes institutionalized as people identify locally anchored commonalities (e.g. same competencies, language or history) (Zucker, 1986) and share the same interest of cooperation (Cooke et al., 1997; Nahapiet and Ghoshal, 1998; Romanelli and Khessina, 2005). We argue that trust constitutes a regional resource that embodies this institutional repository of collective experiences, norms and values by which people interact with each other. It serves as a mental heuristic based on which people expect fair play and enter into a cooperative action, which increases the likelihood of future innovation. 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) or in experimental settings such as public goods games as trust-based cooperation at the individual level correlates with the generalized trust of a region (e.g., Henrich et al., 2010).

H1: Generalized trust within regions increases the likelihood of firm innovation.

However, the opportunities and risks associated with innovation cooperation are not distributed equally. SMEs rely on cooperative innovation more than larger firms because they lack essential technological and business-related in-house capacities (Cooke et al., 1997). Thus, they require cooperation 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 regional cooperation partners, and SMEs are likely to engage in such cooperative ventures (Hervás-Oliver et al., 2021; Aragón Amonarriz et al., 2017), they should especially benefit from higher regional levels of trust.

Moreover, SMEs are likely to be disproportionately burdened because they lack the specialized legal departments to set up comprehensive contractual arrangements to safeguard cooperation (Doh and Kim, 2014). High levels of generalized trust compensate for this deficiency as firms negotiate and act based on the assumption of fair play, implicitly drawing on the regional resource of trust. Thus, we expect the relationship between trust and firm innovation to be strongest in the case of SMEs.

In addition, SMEs rely on their DUI capacities (Jensen et al., 2007; Thomä, 2017) more frequently than larger firms. The tacit knowledge involved is spatially less mobile, its acquisition is a slower process, driven by personal interaction and repeated exchanges, whose frequency and quality can be increased by higher levels of generalized trust (Lundvall et al., 2002; Tödtling and Kaufmann, 2001). In addition, incremental learning in SMEs is generated by practical problem-solving, often on a trial-and-error basis. Higher levels of trust should facilitate such an iterative process, especially if multiple parties across firms are involved.

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

As we suspect the trust-innovation relationship to differ by firm size, and firm size differs by region, the strength of the trust-innovation relationship can be expected to be non-uniform across space, where RIS that host a large share of smaller firms are more likely to benefit from higher levels of trust. Thus, we move from the firm- to the regional level. Just as RIS may differ in their composition of firms (and firm sizes), they also differ along additional margins, such as the level of trust. Some studies provide evidence for a non-linear effect of trust (Echebarria and Barrutia, 2013; Roth, 2009). For example, firms may particularly benefit from an increase in trust when the trust level is relatively low. If trust exceeds a certain minimum level necessary to sustain cooperation and learning however, further increases in trust may have lower, or even negative, returns. It follows that the trust-innovation relationship will be relatively larger when regional trust levels are low.

H3: The trust-innovation relationship is non-uniform across space.

3. Trust and innovation in German regions

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).

While East Germany's formal institutions became part of the FRG's economic system, the informal institutions and the level of generalized trust were particularly marked 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). However, trust related to norms and values such as solidarity (Brosig-Koch et al., 2011), locus of control (Runst, 2013), and openness to new experiences as well as extroversion also differ between regions and especially compared to East Germany, which is constantly marked by lower levels (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 the regions (Cantner et al., 2019). The number of patent applications varies between the 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 stronger 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

To test our hypotheses we use two distinct data sets. Data set 1 uses firm level data to test our first two hypotheses. It allows us to include several firm level control variables and to restrict the sample to the group of SMEs. Data set 2 exclusively focusses on the regional level, allowing us to validate the results obtained from the firm data for the first two hypotheses. Moreover, we use the regional data to analyze hypothesis 3, which posits a non-uniform size of the trust-innovation relationship across space.

4.1. Data set 1 – firm-level innovation

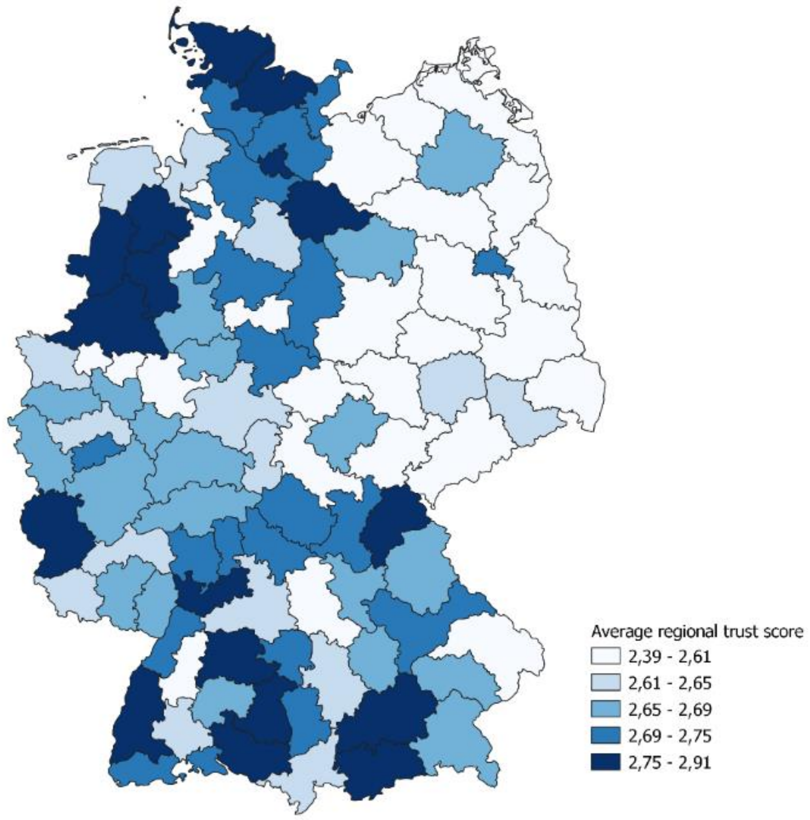
Data set 1 combines four different data sources. First, the MIP, which constitutes the German version of the Community Innovation Survey (CIS) of the European Commission. The MIP contains information on innovation activities and the characteristics of German firms. Second, we use the GSOEP, which entails a broad set of data on social and economic behavior in Germany such as satisfaction with work, feelings of anger or 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 more than 700 regional indicators from Europe and Germany. Finally, the Förderkatalog provides information on governmental firm funding. All databases provide data on a yearly basis. Our observation period is from 2004 to 2019, 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. In all specifications, we drop regions with fewer than 100 observations, which leaves us with 91 regions in our main specifications. 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 (see figure A.3. in the appendix). Intrapolating the aggregated trust variable allows us to generate a larger time series, as all other variables are available for all years between 2004 and 2019. 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) and a minimum of 100 trust observations per region. 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 analysis we also use trust values from current 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.



In one specification, we also include the weighted mean of trust of all neighbors of a region, i.e. spatially lagged trust (W_TRUST).

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 often considered more likely to successfully exploit novel knowledge (Srholec, 2009). R&D indicates whether a firm invested in activities related to R&D because they determine firm innovation (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). An indicator for the engagement in cooperation activities (COOP) is used as cooperation is assumed to be important for innovation activities (De Faria et al., 2010). The question on cooperation activity is only part of the MIP survey every two years. We approximate missing years by using previous year values. 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 they differ in their innovative activities and outcomes (Pavitt, 1984; Malerba, 2002). We control for remaining structural differences between German states using an indicator of the state in which a firm is located (STATE). Finally, we include the respective year in the analysis (YEAR) to account for time effects.

The RIS literature provides ample evidence for 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 the region's per capita income, and UNEMP the regional unemployment rate to control for the economic structure of the region and potential agglomeration effects (Schmutzler and Lorenz, 2018). We include a region's aggregate amount of cumulative funds for innovation from the government (FUNDS) to control for the influence of innovation subsidies within a region (Broekel et al., 2017). STUDENT_UNI and STUDENT_FH uses the number of students at universities and universities for applied sciences as an indicator of regional human capital (Pfister, 2021). Table 1 provides the descriptive statistics of the variables. Our final sample comprises 38,080 firms in the observation period from 2004 to 2019.

Table 1. Descriptive statistics, data set 1 (firm level)

Variable	Description	Mean	SD
INNO	1 if firm introduced an innovation, 0 if not	0.502	0.500
TRUST	average trust score in t-1	2.664	0.104
W_TRUST	spatially lagged trust score of neighboring regions	2.654	0.070
EXP	1 if firm exports, 0 if not	0.518	0.500
R&D	1 if firm performs R&D, 0 if not	0.375	0.484
SIZE	Natural log of number of employees	3.792	1.697
COOP	1 if firm cooperates for innovation, 0 if not	0.196	0.397
SECTOR	1-21 for different sectors		
STATE	1-16 for German states		
POP_DEN	Natural log of inhabitants per square kilometer	5.708	0.942
GDP	GDP per capita	32.857	10.034
UNEMP	Unemployment rate	8.073	3.817
STUDENT_UNI	Students at universities per 10k inhabitants	0.031	0.026
STUDENT_FH	Students at applied universities per 10k inhabitants	0.010	0.010
FUNDS	Cumulative funds for innovation from the government in million	1055.396	1993.690

Sources: MIP; GSOEP, INKAR, Förderkatalog, N=38,080

4.2. Data set 2 – regional innovation data

The distinguishing feature of the second data set is its exclusive regional focus, which allows us to apply spatial regression techniques. Furthermore, we use an alternate dependent variable, namely the annual log number of innovative firms per region (LOG_INNO). This variable allows us to aggregate firm-level data on innovative firms at the regional level. The Pearson correlation coefficient for the population and the number of firms in the MIP is higher than 0.8 for most years, indicating a representative data set with respect to its geographic distribution.

However, to test the robustness of our results we also use the number of patents (PATENTS) per region as a dependent variable. Patents could not be used as a dependent variable in Data set 1 because the MIP does only provide information on patent activities of firms for some of the years in our observation period. Patent information can be obtained from the German Patent and Trademark Office (DPMA).[1] 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.

Analogous to data set 1, we include regional data from the German INKAR database and the Förderkatalog (GDP per capita, unemployment shares, the share of large companies, self-employment, and funds) as well as regional trust values based on SOEP data. Table 2 provides an overview of the regional variables. Data is available for the years from 2005 to 2018.

Table 2. Descriptive statistics, data set 2 (regional level, planning regions)

Variable	Description	N	Mean	SD
LOG_INNO	Natural log of number of innovators per region	1,599	2.987	.7347
PATENTS	Fraction patent count per 10,000 inhabitants	1,344	5.462	3.809
TRUST	Average trust score in t-1	1,536	2.667	0.113
W_TRUST	spatially lagged trust score of neighboring regions	1,536	2.671	0.069
GDP	GDP per capita	1,344	31.160	8.369
UNEMP	Unemployment rate	1,344	7.530	3.738
LOG_POP_DEN	Natural log of inhabitants per square kilometer	1,344	330.002	501.318
Self_EMP	Self-employed individuals per 1k working individuals	1,440	110.472	16.57192
Share of…				
Small (10-50 employees)	in % of all companies	960	87.897	10.384
Medium (50-250 employees)		960	19.810	3.207
Large (above 250 employees)		960	3.119	0.805
STUDENT_UNI	Students at universities per 1k inhabitants	1,246	0.031	0.026
STUDENT_FH	Students at applied universities per 1k inhabitants	1,246	0.010	0.010
FUNDS	cumulative funds for innovation from the government in million	1,632	5.140	1.320

Sources: INKAR database, GSOEP, DPMA

4.3. Methods

Firms' innovative activities are embedded in the regional system, which is hierarchically organized (Srholec, 2011; Cooke, 2001; Fernandes et al., 2020). Here, 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 thus an appropriate approach to analyze data with a nested structure, e.g. firms within regions. MLMs relax the independence assumption. It allows us to analyze the effects of regional characteristics on firm-level outcomes (Srholec, 2010) and decomposes the hierarchical heterogeneity in the dependent variable. We apply MLM, with multiple measurements of innovation of different firms (level 1) nested in regions (level 2). We did not choose to conduct a three-level MLM with time as level 1, firms as level 2 and regions as level 3 given the low number of time periods (16 years).

The panel data set also allows us to apply fixed effects models to account for time invariant regional characteristics. Due to the binary nature of our dependent variable, we have several observations of firms in our data set that are innovative or not innovative in all years. These time-invariant observations are dropped from the estimation in the fixed-effects model, which reduces our sample sizes (see Tab. A.4 in the appendix). Since firms

[1] See https://register.dpma.de/

seem to exhibit somewhat different characteristics, we only run this model as a robustness check and instead rely on multilevel and random effects estimations. Nevertheless, our main results remain stable in the fixed effects estimation.

In contrast to our firm-level data set, the regionally aggregated MIP-innovation data and the patent data set include a metric dependent variable (i.e. the number of innovators and the annual number of patent applications per 10,000 inhabitants), which varies from year to year, allowing us to employ (region) fixed effects regressions in addition to controlling for region characteristics and year fixed effects.

In our regional data, we consider a number of spatial panel regression techniques. Following LeSage and Pace (2009), we start from the general nesting spatial model (GNS), which includes spatially lagged dependent (W_Trust) and independent variables (W_X) as well as a spatially lagged error term (also see Kelejian and Prucha, 2007), after which we drop spatial variables if their coefficients are not significantly different from zero. We generate a contiguity spatial weights matrix of order one, based on a spectral row normalization. Finally, we run geographically weighted regressions (see Brundson et al., 1996; LeSage, 2004), in which distance weighted subsamples of all regions are used to produce local coefficient estimates for each point in space. This technique permits us to identify heterogeneity in the trust-innovation relationship across space as each local model may yield different coefficients.

5. Results

5.1. Trust and firm innovation at the firm level

Table 3 shows the multilevel regression results for the full sample as well as the analysis of SMEs. Specification (1) reports the empty MLM results, which enables estimating the variability of firm innovation between regions, as indicated by the interclass correlation coefficient (ICC). Its size of 0.017 indicates that 1.7 % of the variability in innovation exists between regions, while most of the variability occurs across firms. Specification (2) reports the coefficients of the MLM, regressing innovation on regional trust and the firm-level covariates. Trust has a positive and significant (5 percent level) impact on the probability of being an innovator. A one-point increase in the trust level is associated with a 5.8 percentage point increase in the likelihood of being an innovator. Put differently, a one standard deviation increase in trust leads to an increase in the likelihood of innovation by about 0.6 percentage points. The coefficients on all firm-level covariates are significant and have the expected signs. Including regional level covariates in specification (3) does not significantly change the results. The impact of trust on innovation remains almost the same in terms of its magnitude and is still significant at the 10 percent level, supporting the results of previous studies (Laursen et al., 2012; Doh and Acs, 2010; Akçomak and Müller-Zick, 2018; Akçomak and Weel, 2009). Specification (4) not only includes the trust level of the region i in which the firm is located but also the spatially weighted mean of the neighboring regions j. The coefficient of trust in region i is comparable to the coefficient in previous specifications while the trust level of neighboring regions does not seem to have an impact on innovation, indicating that only trust in the immediate vicinity of firms affects firm innovation. Specification (5) adds a quadratic trust term. The coefficient on the quadratic term is negative and significant, indicating an inverted U-shape relationship. A simple back-of-the-envelope calculation2 suggests that the maximum of the inverted U-shape relationship between trust and innovation is reached when trust is close to its mean (maximum = 2.741, mean = 2.667). 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).

Finally, 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 (6) reports the results including all firm- and regional-level covariates for the sample of large firms. The coefficient on trust becomes insignificant. By contrast, when running the same regression model for the sample of SMEs (Specification 7), the coefficient on trust is of a similar size compared to the full sample and statistically significant indicating that trust is especially important for SMEs.

[2] 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.

Table 3. Multilevel regressions (2MLM, data set 1, firm level, binary dep. var.: INNO)

	(1) Empty	(2) Firm level	(3) Baseline	(4) Neighbors	(5) Trust squared	(6) Large	(7) SMEs
TRUST		**0.058****	**0.054***	**0.056***	**1.617****	**0.717**	**1.535***
W_TRUST				**0.047**			
TRUST^2					**-0.295****	**-0.144**	**-0.278***
EXP		0.032***	0.032***	0.032***	0.032***	0.001	0.036***
R&D		0.372***	0.372***	0.372***	0.372***	0.256***	0.383***
SIZE		0.022***	0.022***	0.022***	0.022***	0.025***	0.021***
COOP		0.106***	0.106***	0.106***	0.105***	0.103***	0.101***
SECTOR		Yes	Yes	Yes	Yes	Yes	Yes
STATE		Yes	Yes	Yes	Yes	Yes	Yes
YEAR		Yes	Yes	Yes	Yes	Yes	Yes
POP_DENSITY			-0.011	-0.010	-0.013*	0.015	-0.016**
GDP			0.001	0.001	0.001	-0.001	0.001
UNEMP			0.001	0.001	0.001	-0.004	0.002
FUNDS			-0.000	-0.000	-0.000	0.000	-0.000
STUDENT_UNI			0.143	0.168	0.142	0.397	0.140
STUDENT_FH			-0.221	-0.276	-0.238	-1.657	-0.195
Constant	-0.020	-0.419	-0.158	-1.174	-14.909**	-8.400	-13.815*
Var(constant)	0.056	0.005	0.005	0.004	0.005	0.134	0.006
Observations	38,080	38,080	38,080	38,080	38,080	3,250	34,830
No. of groups	91	91	91	91	91	90	91
ICC	0.017	0.002	0.001	0.001	0.001	0.039	0.002

*Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01 respectively. The table displays marginal effects. 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. Trust and firm innovation aggregated to the regional level

Next, we perform regression analyses based on the MIP firm data, aggregated to the regional level of planning regions, permitting us to more conveniently apply spatial econometric techniques. These methods allow us to analyze the interrelationships between different RIS as well as examining the spatial distribution of the effect of trust on innovation. As the dependent variable LOG_INNO is metric and time-variant, this data set allows us to perform panel regressions with region fixed effects.

The trust variable (TRUST) affects the number of innovators positively and significantly in all models (Specification 1-8) (see Table 4). When using current trust instead of lagged trust, effect sizes are slightly smaller but consistently significant across specifications (see Table A.4 in the appendix). None of the covariates have a consistent effect on innovation across all specifications. Dropping all regions with trust levels higher than the mean increases the effect size of the trust coefficient (Specification 2). Similar to our firm-level findings, the evidence points to a stronger trust-innovation relationship when regional trust levels are low. Thus, we include a squared trust term in our regional regression (Specification 3), which is negative and significant. The maximum of the inverted U-shape relationship between trust and innovation is again reached when trust levels are close to their mean values.

Restricting the sample to regions with above-average shares of self-employment also increases the impact of trust on innovation (Specification 4). Trust seems to be particularly beneficial for innovation activity in the presence of entrepreneurial dynamism, which can also be interpreted as a strong presence of smaller firms.

Following Akçomak and Müller-Zick (2018), we also include the interaction terms Trust x GDP and Trust x Unemp (Specification 5 & 6). The coefficient of trust-GDP interaction is negative and statistically significant. This suggests that the higher GDP, the lower is the impact of trust on innovation. The size of the trust coefficient further increases. When we exclude the regions with an above average share of large firms (Specification 6), the size of the trust coefficient further increases.

Finally, we perform spatial regressions. The trust coefficient remains significant in the GNS model (Specification 7) although it is likely overparameterized, which is why we drop insignificant variables in specification 8. The size of the trust coefficient is similar to our baseline model. After dropping all variables whose coefficients are not significantly different from zero, we obtain the final spatial model (Specification 8), containing the spatial lag of funds, and the lagged number of innovators. Again, the coefficient for trust is significant and similar in size as in the baseline model.

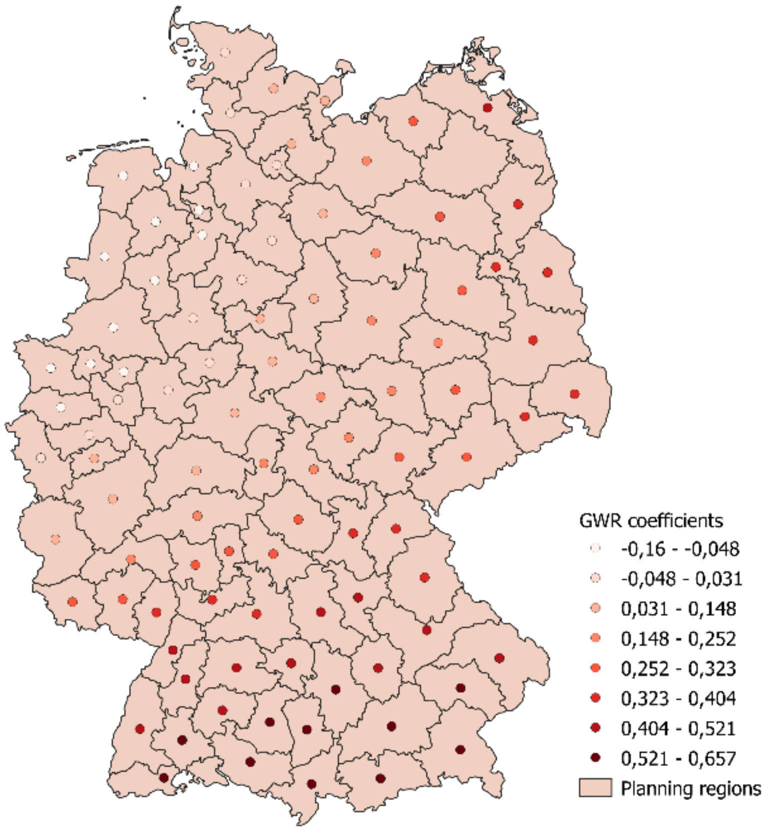
Table 4. Panel regression results (data set 2, dep. var.: LOG_INNO, regional level).

	(1) Baseline	(2) Low Trust	(3) Trust Squared	(4) High self-employment	(5) Interaction	(6) SMEs	(7) GNS	(8) Constrained
TRUST	**0.339*** **	**0.506** **	**0.857*** **	**0.777*** **	**1.000*** **	**1.320** **	**0.304** **	**0.317** **
Trust^2			**-0.972***					
UNEMP	0.004	0.019**	0.007	0.001	0.063	0.040	0.007	0.003
POP_DENSITY	-0.003***	-0.003**	-0.003***	-0.002*	-0.003***	-0.009	-0.003***	-0.003***
GDP	-0.005	-0.003	-0.003	-0.006	0.057*	0.141**	-0.013*	-0.011
STUDENTS_UNI	0.441	1.324	-0.060	5.313	0.154	-0.633	0.731	0.956
STUDENTS_FH	-5.980**	-11.548***	-5.007*	-3.908	-5.480*	-14.734**	-4.921*	-5.496*
FUNDS	0.000	0.000**	0.000	0.000	0.000*	0.000	0.000*	0.000*
TRUST x GDP					-0.023**	-0.049**		
TRUST x UNEMP					-0.022	0.005		
		Spatial Variable Coefficients						
TRUST							-0.445	
UNEMP							-0.005	
POP_DENSITY							-0.003	
GDP							0.004	
STUDENT_UNI							-0.519	
STUDENT_FH							-2.149	
FUNDS							0.000***	0.000***
Innovators (W_Y)							0.016	0.065
Error							0.043	
constant	2.708***	1.878***	1.665***	0.526	0.933	0.162	0.218***	0.218***
N	1,128	753	1,128	576	1,128	526	1,128	1,128
R^2	0.439	0.493	0.442	0.431	0.443	0.393		

*Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01 respectively. The number of units is 94 planning regions. There is no trust information for two additional planning regions. All specifications contain region- and year fixed effects. The results are robust when using current trust instead of lagged trust (see table A.4 in the appendix). SMEs are defined as firms with fewer than 250 employees and specification (7) drops all regions with an above average share of large non-SMEs.*

In the final step of the analysis, we conduct geographically weighted regressions, using the baseline model from Table 4. Iterating through all regions, the algorithm includes all regions within a certain distance from that region, regenerating a local model for each region i. Figure 2 displays the regression coefficients of the trust variable for each region. A darker color denotes a larger coefficient size. The effect of trust on innovation is stronger in the eastern and southern part of Germany and weaker in the northwestern regions. The regression results above suggest that the trust-innovation relationship is stronger when trust levels are low. Thus, the strong trust-innovation relationship in the East is likely due to its lower trust values (see Figure 1). By contrast, the southern parts of Germany are characterized by higher trust values, and the strong trust-innovation relationship therefore requires an additional explanation. Our results in Table 4 suggest that areas with a higher share of self-employed individuals as well as regions with a higher share of SMEs particularly benefit from higher trust levels. As both, self-employment and the share of SMEs are larger in the southern states of Baden-Württemberg and Bavaria, the cartographic results are in line with the findings from the regression above.

Figure 2. Geographically weighted regression results



5.3. *Robustness checks*

To test the robustness of our firm-level results, we first apply a logistic random effects regression at the regional level instead of an MLM (Table 5). The ICC of the empty MLM suggests that there is only little variability of firm innovation between regions. This might lead to the conclusion that accounting for the multilevel structure of the data is not that important and one could also apply single level models. Doing so for the baseline model without the quadratic trust term (Specification 1) slightly changes the results, as the coefficient on trust becomes insignificant. However, including the quadratic trust term again leads to a positive effect of trust on innovation, which decreases for higher trust values (Specification 2). Next, we apply a fixed effects model to account for unobserved firm characteristics (Specification 3). As argued above, the sample size significantly declines, which is why we did not opt to use fixed effects in our main models. Following Kitazawa (2012), coefficients are reported as semi-elasticities. The results again indicate an inverted U-shape relationship between trust and innovation.

Specifications 4 and 5 rerun the SME analysis using multilevel techniques but with a different definition 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 on innovation is only significant for the SME sample. Finally, we examine whether the effect of trust on innovation remains the same when using current trust instead of lagged trust (Specification 6). The coefficient of trust is still positive and significant and the coefficient on the quadratic term is negative and significant.

Next, to check the robustness of our regional-level results in Table 4, we perform additional regressions in which PATENTS (i.e. the number of patents per 10,000 inhabitants) represents the dependent variable (table 6). 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 0.88 patent per 10,000 inhabitants. Put differently, a one standard deviation increase in trust leads to an additional 0.12 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. None of the control variables is significant over all specifications. 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 particularly affect innovation when trust levels are relatively low. 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.

Table 5. Logit and multilevel regressions (data set 1, firm level, binary dep. var.: INNO)

	(1) RE Baseline	(2) RE trust squared	(3) FE trust squared	(4) MLM large	(5) MLM small	(6) Trust same year
TRUST	**0.050**	**1.603****	**11.191****	**1.989**	**1.545***	**1.645****
TRUST^2		**-0.293****	**-2.054****	**-0.371**	**-0.279***	**-0.301****
Constant	-3.748***	-21.819***		-23.585	-13.910*	-18.204***
Var(constant)				0.049	0.005	0.005
Observations	38,080	38,080	17,881	5,927	32,153	38,875
No. of groups	12,685	12,685	3,815	91	91	91
ICC	NA	NA	NA	0.015	0.002	0.001

*Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01 respectively. The table displays marginal effects except for specification 3. The results of the fixed effects model are reported as semi-elasticities (Kitazawa 2012). SMEs are defined as firms with fewer than 250 employees. Large firms are defined as firms with 250 or more employees. This table reports only coefficients for the trust variables. However, all specifications control for the same control variables as the main models in table 3. When using trust values of the same year in specification 6, the observation period changes to 2003 to 2018.*

Table 6. Panel regression results (data set 2, dep. var.: PATENTS, regional level)

	(1) Baseline	(2) Low Trust	(3) SME
TRUST	**0.876***	**2.666*****	**1.725****
GDP	0.175***	0.053	0.260***
UNEMP	-0.060**	-0.106***	-0.004
POP_DENSITY	-0.006***	0.003	-0.038***
STUDENTS_UNI	288.373	-82.083	1766.967
STUDENTS_FH	9.444	11.393	18.698
constant	-0.571	-4.259	-0.947
GDP			
Students			
Patents (W_Y)			
constant			
N	1,150	458	598
R^2	0.406	0.424	0.418

** / ** / *** 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 planning regions. SMEs are defined as firms with fewer than 250 employees.*

6. Discussion

Our findings have important implications for the innovation literature, including studies concerning RIS and SME and economic growth. First, we show a positive relation between generalized trust between people in regions and firm innovation (Hypothesis 1), which remains robust across all our specifications by using a broad or narrow innovation variable or considering firm and regional levels. This finding is important when investigating possible influencing factors of RIS and open innovation (Brockman et al., 2018; Rakas and Hain, 2019; Fernandes et al., 2020). 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 inputs or patents as proxies for innovation (e.g., Laursen et al., 2012). Trust not only has an influence on STI-based innovation – which is typically measured by the number of patents – but it also influences DUI innovation in a moderate manner. 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. In a similar vein, restricting the sample to regions with above-average shares of self-employment leads to a stronger trust-innovation relationship, which is supported by the literature (e.g., Romero and Martínez-Román, 2012). Moreover, introducing a squared trust term shows that this effect becomes negative at a certain level of trust, as found by Echebarria and Barrutia (2013).

Second, we find that the trust-innovation relationship is stronger for SMEs (Hypothesis 2). Based on these results, one could argue that firm size 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 – particularly in a DUI fashion – and compensate for their lacking resources (Aragón Amonarriz et al., 2017; Hervás-Oliver et al., 2021; Thomä, 2017). Our results show that stronger trust-innovation relationships hold for regions with a higher share of SMEs. I.e. for Germany it is the strongest in the eastern and southern regions, which are characterized by smaller firms, higher shares of self-employment, and – in the case of East Germany – lower levels of trust (Hypothesis 3).

Third, the spatial regression results suggest that while innovation spillovers occur across regions, trust only operates at the regional level (and not supra-regional levels), underlining its role as a facilitator of personal relationships and the learning that results from these interactions. Our findings thus tie in with previous research addressing the most effective distance for firm cooperation. Parrilli and Heras (2016) summarize their own and the findings of Fitjar and Rodríguez-Pose (2013) by stating that global DUI cooperations and then regional STI and global STI cooperations are relevant for technological innovations, while regional DUI cooperations are not. Germany is a larger country with a higher population density than Norway or the Basque country analyzed by the authors. It hosts larger regional ecosystems of firms, associated with a potentially higher value of regional interaction. Parrilli and Heras (2016) themselves acknowledge that their sample is taken from “a rather geographically-circumscribed region (…), in which relationships with other national or international partners face some historic and political constraint…”. Thus, regional DUI may play a larger role in fostering innovation in German SMEs.

It is also conceivable that supra-regional cooperation facilitates innovation but that it is qualitatively different from regional cooperation, whereby only the latter benefits from higher levels of trust, whereas supra-regional cooperation requires different supporting mechanism altogether, such as contractual arrangement, sound formal institutions, etc.

Future research could build on our findings and should examine other countries or regions. Like 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, albeit for which it is difficult to obtain data on firm innovation. Finally, we found persistent patterns of generalized trust in our longitudinal setting, although trust can also be reduced by appropriation (Brockman et al., 2018) or inefficient institutions, which in turn negatively affect innovation (e.g., Aragón Amonarriz et al., 2017). Further research might even extend the observation period used in this study.

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 the 91 German planning regions during the observation period from 2004 to 2019.

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 that serves as a future template based on which people interact with each other, which increases the likelihood of future innovation. 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 channels in a DUI-based innovation mode. Moreover, the effect of trust on innovation is stronger in regions with relatively low levels of trust. Trust among people in neighboring regions (i.e. at the supra-regional level) is not relevant for firm innovation, which is likely caused by different regionally anchored norms and values based on which people trust and interact with each other.

Like other studies in this field (Cantner et al., 2019; Fritsch and Wyrwich, 2014), we find that these patterns persist over time, challenging innovation and economic policies today. Policy-makers aim to supporting 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 that became institutionalized as policy or political demands began to form new institutions (Cooke et al., 1997). These historical processes led to different processes of economic development and distinct regional settings that cannot be easily reproduced nor influenced via the regional resource of trust. Especially for regions with distinct histories such as in the case of 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 low levels of trust 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.

References

Aiello, F., Bonanno, G., Rossi, S.P., 2020. How firms finance innovation. Further empirics from European SMEs. Metroeconomica 71(4), 689-714.

Akçomak, İ. S., Müller-Zick, H., 2018. Trust and inventive activity in Europe: causal, spatial and nonlinear forces. The Annals of Regional Science 60(3), 529-568.

Akçomak, I. S., Ter Weel, B., 2009. Social capital, innovation and growth: Evidence from Europe. European Economic Review, 53(5), 544-567.

Algan, Y., Cahuc, P., 2010. Inherited Trust and Growth. American Economic Review 100, 2060-2092.

Algan, Y., Cahuc, P., 2014. Trust, growth, and well-being: New evidence and policy implications. In Handbook of economic growth (Vol. 2, pp. 49-120). Elsevier.

Aragón Amonarriz, C., Iturrioz, C., Narvaiza, L., Parrilli, M.D., 2017. The role of social capital in regional innovation systems: Creative social capital and its institutionalization process. Papers in Regional Science 98, 35-51.

Asheim, B.T., Boschma, R., Cooke, P., 2011. Constructing Regional Advantage: Platform Policies Based on Related Variety and Differentiated Knowledge Bases. Regional Studies 45, 893-904.

Audretsch, D.B., Feldman, M.P., 1996. R&D spillovers and the geography of innovation and production. The American economic review 86, 630-640.

Brockman, P., Khurana, I. K., Zhong, R.I., 2018. Societal trust and open innovation. Research Policy 47(10), 2048-2065.

Broekel, T., Brachert, M., Duschl, M., Brenner, T., 2017. Joint R&D Subsidies, Related Variety, and Regional Innovation. International Regional Science Review 40, 297-326.

Broekel, T., Rogge, N., Brenner, T., 2018. The innovation efficiency of German regions - a shared-input DEA approach. Review of Regional Research 38, 77-109.

Brosig-Koch, J., Helbach, C., Ockenfels, A., Weimann, J., 2011. Still different after all these years: Solidarity behavior in East and West Germany. Journal of Public Economics 95, 1373-1376.

Bstieler, L., Hemmert, M., Barczak, G., 2015. Trust Formation in University-Industry Collaborations in the U.S. Biotechnology Industry: IP Policies, Shared Governance, and Champions. Journal of Product Innovation Management 32, 111-121.

Brunsdon, C., Fotheringham, A.S., Charlton, M., 1996. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. Geographical Analysis 28, 281-98.

Cantner, U., Dettmann, E., Giebler, A., Guenther, J., Kristalova, M., 2019. The impact of innovation and innovation subsidies on economic development in German regions. Regional Studies 53, 1284-1295.

Cantner, U., Giebler, A., Günther, J., Kristalova, M., Meder, A., 2018. Innovation cooperation in East and West Germany: a study on the regional and technological impact. International Journal of Computational Economics and Econometrics 8, 242.

Carl, N., Billari, F.C., 2014. Generalized trust and intelligence in the United States. PloS one, 9(3), e91786.

Chesbrough, H.W., 2003. Open innovation: the new imperative for creating and profiting from technology. Harvard Business School Press, Boston, Mass.

Christensen, C. M., Bower, J.L., 1996. Customer power, strategic investment, and the failure of leading firms. Strategic management journal, 17(3), 197-218.

Cohen, W., Levinthal, D.A., 1989. Innovation and Learning: The Two Faces of R&D. Economic Journal 99(397), 569-596.

Cohen, W., Levinthal, D.A., 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly (35)1, 128-152.

Coleman, J.S., 1988. Social capital in the creation of human capital. American journal of sociology 94, 95-120.

Cooke, P., 2001. Regional Innovation Systems, Clusters, and the Knowledge Economy. Industrial and Corporate Change 10, 945-974.

Cooke, P., Clifton, N., Oleaga, M., 2005. Social capital, firm embeddedness and regional development. Regional Studies 39, 1065-1077.

Cooke, P., Gomez Uranga, M., Etxebarria, G., 1997. Regional innovation systems: Institutional and organisational dimensions. Research Policy 26, 475-491.

De Faria, P., Lima, F., Santos, R., 2010. Cooperation in innovation activities: The importance of partners. Research policy 39(8), 1082-1092.

Doh, S., Acs, Z.J., 2010. Innovation and Social Capital: A Cross-Country Investigation. Industry and Innovation 17, 241-262.

Doh, S., Kim, B., 2014. Government support for SME innovations in the regional industries: The case of government financial support program in South Korea. Research Policy 43(9), 1557-1569.

Doloreux, D., Porto Gomez, I., 2017. A review of (almost) 20 years of regional innovation systems research. European Planning Studies 25, 371-387.

Echebarria, C., Barrutia, J. M., 2013. Limits of social capital as a driver of innovation: an empirical analysis in the context of European regions. Regional Studies 47(7), 1001-1017.

Edquist, C. (Ed.), 1997. Systems of innovation: technologies, institutions, and organizations, Science, technology and the international political economy series. Pinter, London; Washington.

Eickelpasch, A., Fritsch, M., 2005. Contests for cooperation—A new approach in German innovation policy. Research Policy 34, 1269-1282.

Feldman, M., Guy, F., Iammarino, S., 2021. Regional income disparities, monopoly and finance. Cambridge Journal of Regions, Economy and Society 14(1), 25-49.

Fernandes, C., Farinha, L., Ferreira, J. J., Asheim, B., Rutten, R., 2021. Regional innovation systems: what can we learn from 25 years of scientific achievements?. Regional Studies 55(3), 377-389.

Fitjar, R. D., Rodríguez-Pose, A., 2013. Firm collaboration and modes of innovation in Norway. Research policy 42(1), 128-138.

Freeman, C., 1994. The economics of technical change. Cambridge journal of economics, 18(5), 463-514.

Fritsch, M., Slavtchev, V., 2007. Universities and Innovation in Space. Industry and Innovation 14, 201-218.

Fritsch, M., Wyrwich, M., 2014. The Long Persistence of Regional Levels of Entrepreneurship: Germany, 1925-2005. Regional Studies 48, 955-973.

Fulbrook, M., 2011. A History of Germany 1918-2008 The Divided Nation.

Goldstein, H., 2003. Multilevel statistical models, London: Arnold.

Granovetter, M.S., 1973. The Strength of Weak Ties. American Journal of Sociology 78, 1360- 80.

Grillitsch, M., Trippl, M., 2014. Combining knowledge from different sources, channels and geographical scales. European Planning Studies 22 (11), 2305-2325.

Günther, J., 2004. Innovation cooperation: experiences from East and West Germany. Science and Public Policy 31, 151-158.

Günther, J., Stegmaier, J., Sunder, M., Trocka, D., 2008. Aktuelle Trends: Innovationstätigkeit in Ostdeutschland ungebrochen. Wirtschaft im Wandel 9, 347.

Henrich, J., Heine, S.J., Norenzayan, A., 2010. The weirdest people in the world? Behavioral and brain sciences 33(2-3), 61-83.

Hervás-Oliver, J. L., Parrilli, M. D., Rodríguez-Pose, A., Sempere-Ripoll, F., 2021. The drivers of SME innovation in the regions of the EU. Research Policy 50(9), 104316.

Hipp, A.; Ludwig, U.; Guenther, J., 2021. Unable to innovate or just bad circumstances? Comparing the innovation system of a state-led and market-based economy. Bremen Papers on Economics & Innovation 2111, 1-26.

Hipp, A., Binz, C., 2020. Firm survival in complex value chains and global innovation systems: Evidence from solar photovoltaics. Research Policy 49, 103876.

Hornych, C., Schwartz, M., 2009. Industry concentration and regional innovative performance: empirical evidence for Eastern Germany. Post-Communist Economies 21, 513-530.

Hox, J., 2002. Multilevel analysis: Techniques and applications. Mahwah, NH: Lawrence Erlbaum Associates.

Jensen, M.B., Johnson, B., Lorenz, E., Lundvall, B.Å., 2007. Forms of knowledge and modes of innovation. Research Policy 36(5), 680-693.

Kashani, E. S., Roshani, S., 2019. Evolution of innovation system literature: Intellectual bases and emerging trends. Technological Forecasting and Social Change 146, 68-80.

Kelejian, H. H., Prucha, I.R., 2007. HAC estimation in a spatial framework. Journal of Econometrics, 140(1), 131-154.

Kitazawa, Y., 2012. Hyperbolic transformation and average elasticity in the framework of the fixed effects logit model. Theoretical Economics Letters 2(2), 192-199.

Knack, S., Keefer, P., 1997. Does Social Capital Have an Economic Payoff? A Cross-Country Investigation. The Quarterly Journal of Economics 112, 1251-1288.

Landry, R., Amara, N., Lamari, M., 2002. Does social capital determine innovation? To what extent? Technological Forecasting and Social Change 69, 681-701.

Laursen, K., Masciarelli, F., Prencipe, A., 2012. Regions Matter: How Localized Social Capital Affects Innovation and External Knowledge Acquisition. Organization Science 23, 177-193.

LeSage, J.P., Pace, R.K., 2009. Introduction to spatial econometrics. Chapman and Hall/CRC.

LeSage, J.P., 2004. A family of geographically weighted regression models. In Advances in spatial econometrics (pp. 241-264). Springer, Berlin, Heidelberg.

Lichter, A., Löffler, M., Siegloch, S., 2021. The long-term costs of government surveillance: Insights from stasi spying in East Germany. Journal of the European Economic Association 19(2), 741-789.

Luke, A., 2004. Multilevel Modelling. London: Sage.

Lundvall, B.A., 1992. National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning. Pinter, London.

Lundvall, B.Å., Johnson, B., Andersen, E.S., Dalum, B., 2002. National systems of production, innovation and competence building. Research Policy 31(2), 213-231.

Malerba, F., 2002. Sectoral systems of innovation and production. Research Policy 31(2), 247-264.

Martin, R., Moodysson, J., 2013. Comparing knowledge bases: on the geography and organization of knowledge sourcing in the regional innovation system of Scania, Sweden. European Urban and Regional Studies 20, 170-187.

Maskell, P., Malmberg, A., 1999. Localised learning and industrial competitiveness. Cambridge Journal of Economics 23, 167-185.

Moretti, E., 2012. The new geography of jobs. Houghton Mifflin Harcourt.

Nahapiet, J., Ghoshal, S., 1998. Social Capital, Intellectual Capital, and the Organizational Advantage. Academy of Management Review 23, 242-266.

Nelson, R.R., Winter, S.G., 1982. The Schumpeterian tradeoff revisited. The American Economic Review, 72(1), 114-132.

Obschonka, M., Wyrwich, M., Fritsch, M., Gosling, S.D., Rentfrow, P.J., Potter, J., 2019. Von unterkühlten Norddeutschen, gemütlichen Süddeutschen und aufgeschlossenen Großstädtern: Regionale Persönlichkeitsunterschiede in Deutschland. Psychologische Rundschau 70, 173-194.

Parrilli, M.D., Heras, H.A., 2016. STI and DUI innovation modes: Scientific-technological and context-specific nuances. Research Policy 45(4), 747-756.

Pavitt, K., 1984. Sectoral patterns of technical change: towards a taxonomy and a theory. Research Policy 13, 343-373.

Pfister, C., Koomen, M., Harhoff, D., Backes-Gellner, U., 2021. Regional innovation effects of applied research institutions. Research Policy, 50(4), 104197.

Putnam, R., 1993. Making Democracy Work. Civic Traditions in Modern Italy. Princeton University Press, Princeton.

Putnam, R.D., 1995. Bowling alone: America's declining social capital. Journal of Democracy 6(1), 65-78.

Rabe-Hesketh, S., Skrondal, A., 2014. Multilevel and Longitudinal Modeling Using STATA, 3rd edn. College Station, TX: Stata Press.

Rakas, M., Hain, D.S., 2019. The state of innovation system research: What happens beneath the surface?. Research Policy, 48(9), 103787.

Rodríguez-Pose, A., 2013. Do Institutions Matter for Regional Development? Regional Studies 47(7), 1034-1047.

Romanelli, E., Khessina, O.M., 2005. Regional Industrial Identity: Cluster Configurations and Eco-nomic Development. Organization Science 16, 344-358.

Romero, I., Martínez-Román, J. A., 2012. Self-employment and innovation. Exploring the determinants of innovative behavior in small businesses. Research Policy 41(1), 178-189.

Rousseau, D.M., Sitkin, S.B., Burt, R.S., Camerer, C., 1998. Not So Different After All: A Cross-Discipline View Of Trust. Academy of management review 23, 393-404.

Roth, F., 2009. Does too much trust hamper economic growth?. Kyklos 62(1), 103-128.

Ruhrmann, H., Fritsch, M., Leydesdorff, L., 2021. Synergy and policy-making in German innovation systems: Smart Specialisation Strategies at national, regional, local levels? Regional Studies 1-12.

Runst, P., 2013. Post-socialist Culture and Entrepreneurship. American Journal of Economics and Sociology, 72(3) 2013, 593-626.

Runst, P., Thomä, J., 2021. Does personality matter? Small business owners and modes of innovation. Small Business Economics, 1-26.

Schmutzler, J., Lorenz, E., 2018. Tolerance, agglomeration, and enterprise innovation performance: a multilevel analysis of Latin American regions. Industrial and Corporate Change 27(2), 243-268.

Smith, A., 1776 [1991]. An Inquiry into the Nature and Causes of the Wealth of Nations. David Campbell Publishers Ltd., London. Book 4, Ch. 2.

Snijders, T., Bsoker, R., 2012. Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling, 2nd edn. Thousand Oaks: Sage Publications Ltd.

Schumpeter, J.A., 1911. The Theory of Economic Development. Harvard University Press, Cambridge.

Srholec, M., 2009. Does foreign ownership facilitate cooperation on innovation? Firm-level evidence from the enlarged European Union. The European Journal of Development Research 21(1), 47-62.

Srholec, M., 2010. A multilevel approach to geography of innovation. Regional Studies 44(9), 1207-1220.

Srholec, M., 2011. A multilevel analysis of innovation in developing countries. Industrial and Corporate Change 20(6), 1539-1569.

Storper, M., 1997. The regionalized world: territorial development in a global economy. Guildford Press, New York.

Strambach S., Klement, B., 2012. Cumulative and combinatorial micro-dynamics of knowledge: the role of space and place in knowledge integration. European Planning Studies 20 (11), 1843-1866.

Sztompka, P., 1995. Vertrauen: Die Fehlende Ressource in der Postkommunistichen Gesellschaft, in: Nedelmann, B. (Ed.), Politische Institutionen in Wandel, Kiilner Zeitschrift Fur Soziologie Und Sozialpsychologie. pp. 254-276.

Tabellini G., 2008. Presidential address: institutions and culture. Journal of the European Economic Association 6, 255-294.

Thomä, J., 2017. DUI mode learning and barriers to innovation—A case from Germany. Research Policy 46, 1327-1339.

Tödtling, F., Kaufmann, A. 2001. The role of the region for innovation activities of SMEs. European urban and regional studies 8(3), 203-215.

Traunmuller, R., 2011. Moral Communities? Religion as a Source of Social Trust in a Multilevel Analysis of 97 German Regions. European Sociological Review 27, 346-363.

Veugelers, R., 1997. Internal R & D expenditures and external technology sourcing. Research policy, 26(3), 303-315.

Welter, F., Kautonen, T., Chepurenko, A., Malieva, E., Venesaar, U., 2004. Trust environments and entrepreneurial behavior - Exploratory evidence from Estonia, Germany and Russia. Journal of Enterprising Culture 12, 327-349.

Westlund, H., Adam, F., 2010. Social Capital and Economic Performance: A Meta-analysis of 65 Studies. European Planning Studies 18, 893-919.

Wyrwich, M., Steinberg, P. J., Noseleit, F., de Faria, P., 2022. Is open innovation imprinted on new ventures? The cooperation-inhibiting legacy of authoritarian regimes. Research Policy, 51(1), 104409.

Yoon, H., Yun, S., Lee, J., Phillips, F., 2015. Entrepreneurship in East Asian Regional Innovation Systems: Role of social capital. Technological Forecasting and Social Change 100, 83-95.

Zak, P.J., Knack, S., 2001. Trust and growth. The Economic Journal 111(470), 295-321.

Zucker, L.G., 1986. Production of trust: Institutional sources of economic structure, in: Staw, B.M., Cummings, L.L. (Eds.), Research in Organizational Behavior, 8. JAI Press, Greenwich, CT, pp. 1840-1920.

Appendix

Table A1. Correlation matrix of data set 1

	INNO	RD	EXP	SIZE	COOP	TRUST	POP_DEN	GDP	UNEMP	FUNDS	STUDENT _UNI	STUDENT _FH
INNO	1											
RD	0.609*	1										
EXP	0.308*	0.411*	1									
SIZE	0.272*	0.313*	0.289*	1								
COOP	0.363*	0.492*	0.268*	0.264*	1							
TRUST	0.010*	-0.014*	0.037*	0.040*	-0.029*	1						
POP_DEN	0.039*	0.033*	0.025*	0.059*	-0.003	0.337*	1					
GDP	0.009*	-0.012**	0.031*	0.067*	-0.039*	0.593*	0.509*	1				
UNEMP	-0.000	0.017*	-0.101*	-0.046*	0.031*	-0.525*	0.056*	-0.572*	1			
FUNDS	0.017*	0.007	-0.010*	0.023*	0.002	0.295*	0.498*	0.612*	-0.122*	1		
STUDENT_UNI	-0.009*	-0.007	-0.018*	-0.012**	0.021*	0.038*	-0.206*	-0.095*	0.002	-0.177*	1	
STUDENT_FH	-0.029*	-0.031*	-0.006	-0.016*	-0.020*	-0.034*	-0.288*	-0.049*	-0.086*	-0.206*	0.491*	1

* *$p < 0.1$*

Table A2. Correlation matrix of data set 2

	PATENTS	LOG_INNO	TRUST	GDP	UNEMP	LOG_POP_DEN	STUDENT_UNI	STUDENT_FH
PATENTS	1							
LOG_INNO	0.0829*	1						
TRUST	0.2067*	0.0416	1					
GDP	0.5562*	0.2903*	0.4679*	1				
UNEMP	-0.5864*	0.0845*	-0.4519*	-0.5717*	1			
LOG_POP_DEN	-0.0512*	0.4254*	0.1245*	0.3478*	0.1616*	1		
STUDENT_UNI	-0.0233	-0.1613*	0.1762*	0.0620*	-0.0591*	-0.0695*	1	
STUDENT_FH	-0.0074	-0.3714*	0.0111	0.0735*	-0.1098*	-0.1379*	0.3583*	1

* *$p < 0.1$*

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

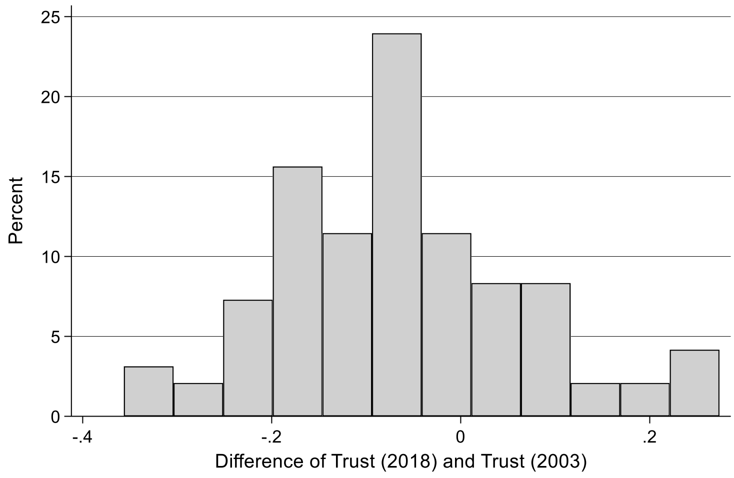


Table A3. Descriptive statistics, data set 1 (firm level) using fixed effects estimation

Variable	Mean	SD
INNO	0.458	0.498
TRUST	2.661	0.105
EXP	0.489	0.500
RD	0.306	0.461
SIZE	3.657	1.542
SECTOR		
COOP	0.144	0.351
STATE		
POP_DEN	5.676	0.951
GDP	32.565	10.135
UNEMP	8.220	3.908
STUDENT_UNI	0.031	0.027
STUDENT_FH	0.010	0.010
FUNDS	1056.972	2042.327

Sources: MIP; GSOEP, INKAR, Förderkatalog

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

	(1) Baseline	(2) Low Trust	(3) Trust Squared	(4) High self-employment	(5) Interaction	(6) SMEs
TRUST (current)	0.211*	0.350*	4.808*	0.729***	1.486**	2.750*
TRUST^2			-0.866*			
UNEMP	0.007	0.024***	0.012*	-0.003	0.129*	0.201
POP_DENSITY	-0.002***	-0.002*	-0.002***	-0.002	-0.002***	-0.001
GDP	-0.006	0.001	-0.004	-0.009	0.082	0.238**
STUDENT_UNI	-0.817	1.174	-1.139	4.983	-0.659	0.398
STUDENT_FH	-5.015*	-12.081***	-4.728*	-2.974	-5.383**	-17.499***
TRUST x GDP					-0.032	-0.086**
TRUST x UNEMP					-0.047	-0.061
constant	3.081***	1.167	-3.550	0.951	-0.342	-5.074
N	1,222	753	1,222	618	1,222	526
R^2	0.451	0.489	0.453	0.433	0.452	0.388

*Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01 respectively. The number of units is 94 planning regions. There is no trust information for two additional planning regions. All specifications use the current trust instead of lagged trust. All specifications contain region- and year fixed effects. SMEs are defined as firms with fewer than 250 employees.*