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# Spatial Heterogeneity in the Effect of Regional Trust on Innovation

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**Abstract**

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

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

## 1. Introduction

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

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

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

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

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

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

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

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

## 2. Generalized trust and regional innovation

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

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

*Why trust is more important in some regions than others*

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

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

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

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

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

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

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

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

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

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

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

## 3. Data and methods

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

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

Our main independent variable GEN_*TRUST* is derived from three survey questions in the ESS that measure trust on a scale from 0 to 10.[2] These questions are part of the survey every other year. We aggregate individual responses to the survey questions at the regional level. By applying a principal component analysis (PCA) to the three trust items, we obtain a single indicator for generalized trust. Tables A.1 and A.2 in the appendix display the Eigenvalues and Eigenvectors from the PCA. We use the predicted scores of the first component as our final measure of generalized trust, on which all three items load strongly and positively, thereby generating average scores for each region. For missing years (odd years), we use lagged values. We also drop a region's value if the number of individual responses is lower than 50. We use the third lag of this variable in our regression analysis as it takes some time until the facilitating effects of trust can measured in terms of patent output. The geographical distribution of the average trust score is depicted in figure 1 (right panel). Regions in northern and central Europe have the highest scores of generalized trust, while trust levels are lowest in eastern and southern European regions. This pattern corresponds to expectations as the former socialist countries in particular display lower trust values and there is evidence with respect to an east-west split in trust at the micro level. Individuals from formerly socialist regions display markedly lower solidarity in experimental trust games (Ockenfels and Weiman, 1999; Brosig-Koch et al, 2011). Similarly, Putnam et al. (1992) have pointed to the persistently lower social capital and trust in southern Italian regions such as Sicily, a result that is mirrored by our data. The variable *LOW_TRUST* is equal to one if a region has trust values below the median of this variable.

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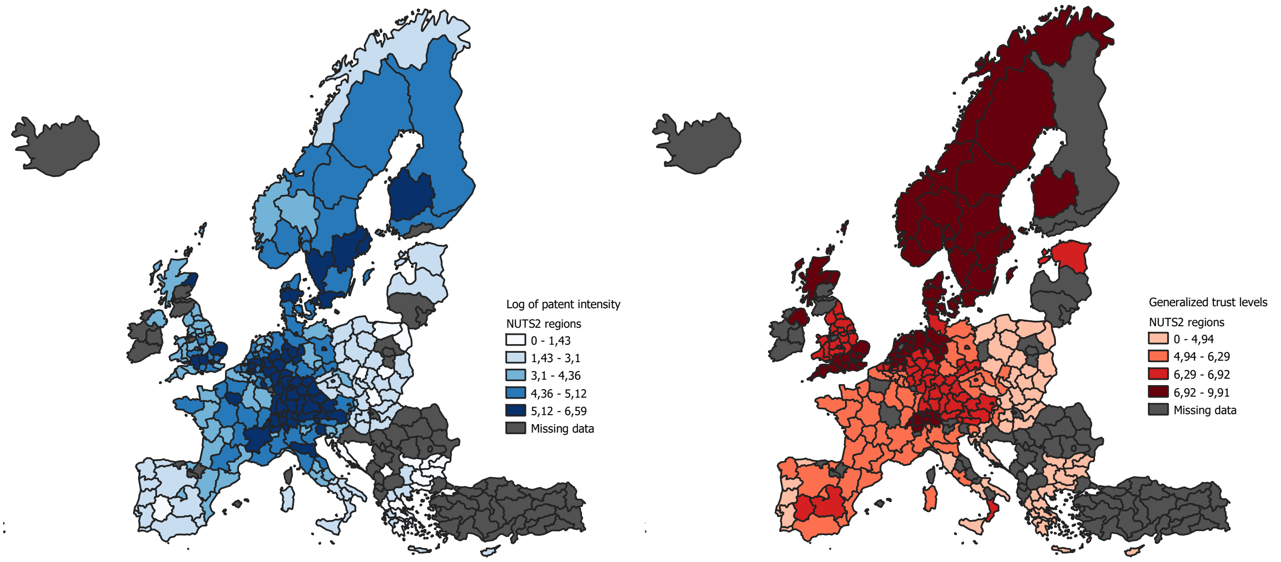
[1] Each inventor is assigned a patent share that is equal to the inverse of the number of inventors of a patent.

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

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

Figure 1. Regional levels of patent intensity and generalized trust




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

We use the natural logarithm of R&D intensity (*R&D*), the share of people with tertiary education (*EDUCATION*), GDP per capita in thousands (*GDP*) and the natural logarithm of the population density (*POP_DENS*) as control variables, following a knowledge production function approach (Lee, 2017). To test the hypotheses concerning the spatial heterogeneity in the trust-innovation relationship, we create additional binary variables. *MICRO* is equal to one if a region has an above-median share of micro-sized firm employees among the total population. Similarly, SME and LARGE are equal to one if the share of SME or large-firm employees is above the median, where micro firms have up to nine employees, SMEs up to 249 and large firms more than 249 employees. The data on total employment by size category can be obtained from the ESPON (2022) project 'Small and Medium-Sized Enterprises in European Regions and Cities.' The data is available for 2008 and 2014, and – depending on the country – at either the NUTS2 or NUTS3 level. As the variable values do not seem to fluctuate between years, we linearly intrapolate and extrapolate to fill the missing years of the panel structure.

Table 1. Descriptive statistics

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

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

The variable *LAGGING* is based on a cluster analysis, which we perform to identify types of regions in terms of their innovation properties. We include the variables *GDP*, *PATENTS* and *R&D* in a cluster analysis, first using hierarchical clustering (Ward's linkage) to guide our choice of the number of clusters, and second partition-clustering (k-means) to obtain the final cluster solution. This two-step procedure combines the advantages of both methods and allows us to both identify the optimal number of clusters and fine-tune the final solution (see Hair et al., 1998, p. 498). To account for the panel structure of our data, we cluster at six different points in time (2002, 2005, 2008, 2011, 2014, 2017) The dendrograms as well as the standard cluster stopping rules (Calinski/Harabast pseudo F, Duda/Hart Je(2)/Je(1), Duda/Hart pseudo T-squared)) support our choice of a three-cluster solution in most cases. Table A.3 in the appendix presents the final cluster results by displaying averages of clustering and validation variables by category and the significance of cluster differences using Kruskal-Wallis equality-of-populations rank test with ties. We identify a three-cluster solution, one group with relatively low values of GDP, *PATENTS*, *R&D* and *EDUCATION* (lagging regions), one group with intermediate values of these variables and one group with relatively high values of GDP, *PATENTS*, *R&D* and *EDUCATION* (leading regions). The variable *LAGGING* is equal to one if a region belongs to the first group. Figure A1 in the appendix illustrates the geographic position of the different region types. The lagging regions can mainly be found in the eastern and southern parts of Europe, while the few leading regions are located in central and northern Europe. The remaining regions belong to the intermediate cluster.

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

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

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

$PATENTS_{it}$ represents the natural logarithm of patent intensity of region $i$ at time $t$. $\beta_0$ is the model's overall intercept and $\beta_1$ the coefficient of our main independent variable $GEN\_TRUST_{it-3}$ . The term $\sum_{j=2}^{k} \beta_j X_{jit}$ contains all control variables and their respective coefficients. The unobserved time-invariant effects are covered by $\alpha_i$ and $e_{it}$ is the error term of the model. We include a quadratic trust term to test for non-linearity of the trust-innovation relationship (H1). We also divide the sample in lagging/intermediate/leading regions, regions with lower or higher institutional trust, as well as regions that are above or below the median share of micro firms (also SMEs and large firms), and run the regression for each of these sub-samples (H2-H4). The final model combines all previous specifications by creating interaction terms. For example, the coefficient for the variable LOW_TRUST#GEN_TRUST estimates the effect of trust on innovation in regions with below-median trust values.

## 4. Results

### *4.1. Spatial heterogeneity of the trust-innovation relationship*

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

Figure 2. Local coefficients from geographically weighted regression

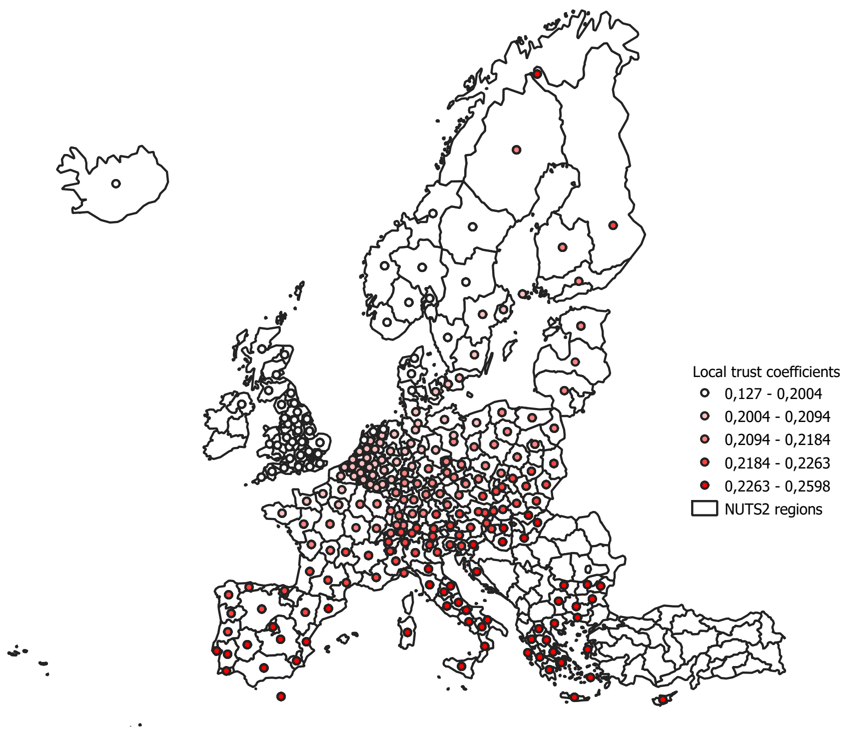


Table 2 summarizes the first set of regression results. In the baseline specification (column 1), the trust coefficient is small to moderate in size and statistically significant at the ten percent level. A one standard deviation increase in trust is associated with a 3.9% increase in innovation output.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

In the following, we focus on spatial heterogeneity, starting with a quadratic trust specification (column 2). Both the trust and trust squared coefficient are different from zero (significant at the 1 percent level). A visual representation of the curve of predicted patent output as well as estimated trust coefficients at different levels of trust can be found in figure A2 in the appendix. We can see that an increase in trust only positively affects innovation in regions with lower levels of trust (where GEN_TRUST<6.19), and we observe negative trust coefficients when the level of trust is above this value. For example, when trust is equal to 3, the magnitude of the estimated coefficient is quite large (15%). This result therefore speaks in favor of hypothesis 1, stating that the trust-innovation relationship is more pronounced in lower-trust regions and even negative in high-trust regions. The negative impact of trust in regions with above-median levels of trust may be an artifact of the imposed quadratic functional form. To further investigate, we generate an above- and a below-median trust sub-sample (see table A.4 columns 9 and 10 in the appendix). We find a positive trust effect in the latter but no evidence of a negative trust effect in the former.

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

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

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

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

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

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

Table 3. SME analysis

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

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

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

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

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

Table 4. Combining arguments for spatial heterogeneity

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

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

*4.2. The effective range of trust*

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

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

Table 5. Distance analysis

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

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

*4.3. Robustness analysis*

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

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

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

**5. Conclusion**

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

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

Second, it is known that smaller firms lack in-house resources and are therefore required to engage in cooperative partnerships. They also tend to lack the legal capacities for formalized contracts, which again leads to more frequent informal relationships. Cooperation – and especially informal cooperation – can be facilitated by higher levels of generalized trust.

Third, trust could serve as a partial substitute for formal institutions, where legal enforcement via state-run organizations can be replaced by informal relationships built on trust. However, while there is some evidence to support such a notion, our empirical findings are not consistent on this point and the question must remain open for future analysis.

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

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

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

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**Appendix**

Table A.1. Eigenvalues from PCA

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

*Notes: N=2632*

Table A.2. Eigenvectors from PCA

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

*Notes: N=2632*

Table A.3. Three-cluster solution

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

*Sources: OECD; Eurostat, ESS, Office for National Statistics (UK), Heritage Foundation, European Spatial Planning Observation Network.*
*Notes: The variables PATENTS, R&D, and GDP (printed in bold) are used for clustering. The statistical significance of mean differences across clusters is estimated using Kruskal-Wallis equality-of-populations rank test with ties (***significance level of 1 percent).*

Table A.4. Robustness analysis 1

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

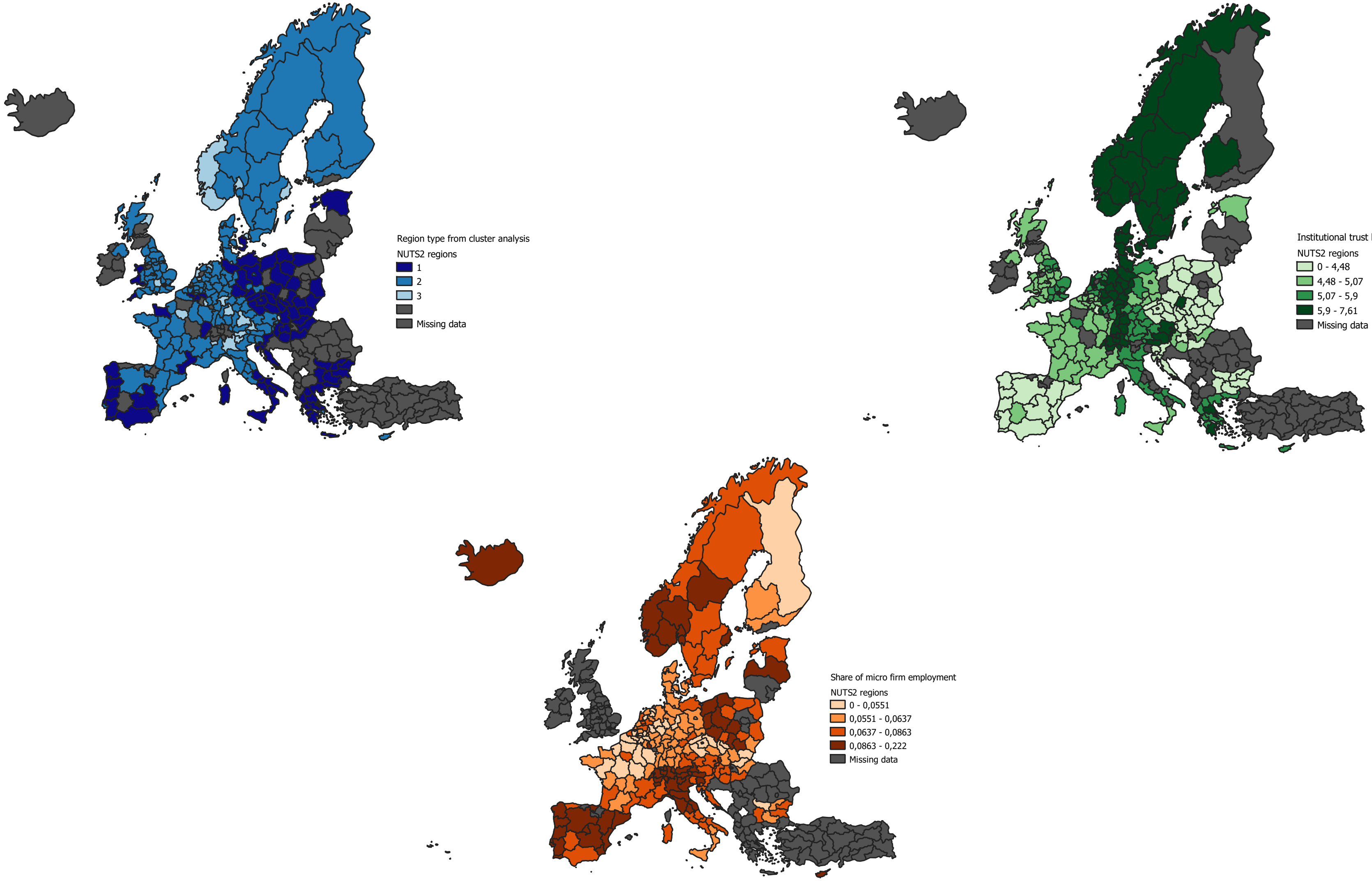
*Notes: * / ** / *** denote p-values of 0.1 / 0.05 / 0.1, respectively. Specification 1 reruns the regression including the interaction terms of trust with the dummy variables MICRO, BAD_INSTITUTIONS and LOW_TRUST but use NUTS1 regions instead of NUTS2 regions as the level of observation. Descriptive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

Table A.5. Descriptive statistics (NUTS1)

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

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

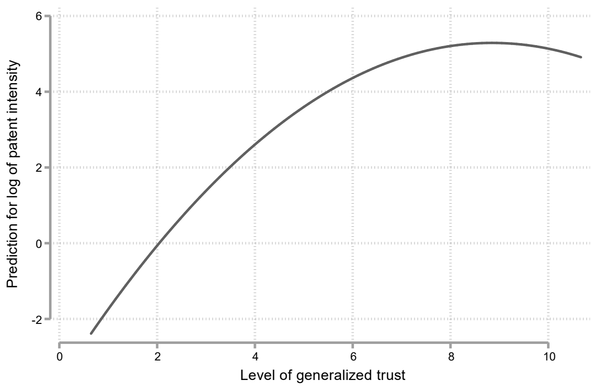
Figure A.1. Regional levels of the share of micro-sized employment, institutional trust and the region type from the cluster solution



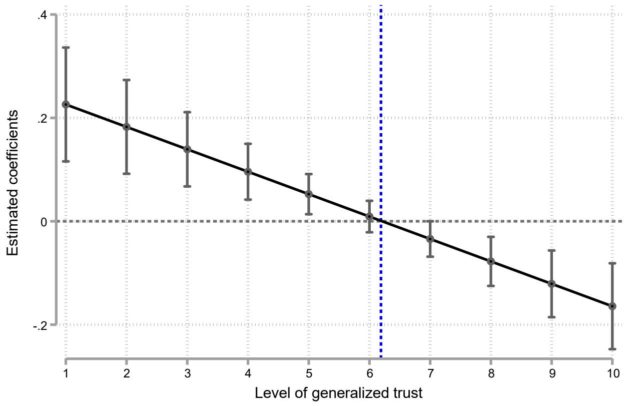

*Source: Eurostat for SME data, ESS for institutional trust data, aggregated by the regional level (European NUTS2 regions). The depicted values for the share of micro-sized employment and institutional trust are averages over the years 2005 to 2018. The map for the cluster solution depicts the assignment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

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

**Predicted probabilities**




**Coefficients at different levels of trust**




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