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For a cross-section of 123 European regions, we find evidence for a positive effect of generalized trust on regional innovation activity. We aim to identify causal effects by using instrumental variables from climate and soil data, drawing from recent literature on the effects of climate on historic trust levels. The popular explanation for spatial clustering of innovation by "interregional knowledge spillovers" is also tested. It is found that spatial clustering of innovation activity can be better explained by a positive influence of trust on innovation and spatial clustering of trust.

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1 Introduction

Beginning with Putnam et al. (1993), there have been numerous studies on the effects of social capital on institutions and economic outcomes.[1] For example, it has been discussed how generalized, impersonal trust may decrease transaction costs of economic exchange and increase the number of potential exchange partners (Durlauf & Fafchamps, 2005). Among others, Beugelsdijk & Schaik (2005) and Tabellini (2010) show empirically how differences in social capital can be related to differences in economic outcomes at the European regional level.

There are several definitions of social capital. For this work, social capital is defined as the effects of generalized (i.e. impersonal) trust. In the literature, the concept of generalized trust has mostly been associated with positive aggregate welfare effects, such as decreased information asymmetries and internalised externalities between groups ("bridging social capital"), as opposed to "particularized trust", i.e. "group-specific trust", which has been associated with insider-outsider effects and generally ambiguous or even negative aggregate welfare effects ("bonding social capital") (Durlauf & Fafchamps, 2005; Bjørnskov, 2007). In the rest of this paper, "social capital" and "trust" are used synonymously with the term "generalized trust".

Recently, the literature has discussed the role of social capital for innovation processes: Anselin et al. (1997) already point to the role of regional innovation networks (the "regional knowledge infrastructure") in regional innovation processes. Hauser et al. (2007) find that social capital plays an important role in the diffusion of tacit knowledge within regions. Akçomak & ter Weel (2009) argue that due to the usually high risk associated with financing innovation projects, regional differences in trust constitute an essential factor in regional innovation processes, and provide empirical evidence for this for a sample of European regions. A few other empirical studies find positive causal effects of regional social capital on regional innovation activity (Barrutia & Echebarria, 2010; de Dominicis et al., 2013).

Identifying causal effects of trust on other aggregate variables is problematic for several reasons: first, available measures for trust are based on survey data, which may be subject to measurement bias.[2] Also, there may be feedback effects from economic or institutional development on regional trust, making trust endogenous.[3] Consequently, in empirical studies about effects of trust, there have been numerous

[1]Most notably, Knack & Keefer (1997) and Zak & Knack (2001) have found evidence for growth effects of social capital across countries. Iyer et al. (2005) have found growth effects of social capital for US-regions.

[2]Note that survey based measurement of generalized trust at the European regional level is based on only about several hundred cases per region on average, which could aggravate measurement error.

[3]Measured generalized trust may be influenced by other variables that affect innovation activity, such as human capital.

attempts to find suitable instruments. For example, in their cross-country study on economic effects of social capital on economic growth, Knack & Keefer (1997) take the percentage of the largest ethnolinguistic group as an instrument for trust, arguing that the more ethnically fragmented a society, the lower the level of trust. Estimating effects of trust on regional income levels, Tabellini (2010) takes indicators of historical institutional quality in European regions as instruments, arguing that good institutions are favorable for social capital in the long run. Akçomak & ter Weel (2009) take early literacy rates and university founding dates, arguing that early spread of education had lasting effects on regional trust, as it helped to spread persistent cultural values of cooperation. Bjørnskov & Méon (2010) propose the language attribute ”tu-vous-differentation“ as an instrument for trust, arguing that the use of a polite form is an expression of strong cultural values of social hierarchies, which in turn are related to low trust. In their cross-country study on the effects of social capital on welfare state institutions, Bergh & Bjørnskov (2011) take the average temperature in the coldest winter month as an instrument for social capital, arguing that severe winters forced people to rely on the help of strangers, which promoted development of values of impersonal cooperation.

The approach of taking current variables (such as ethnic fractionalization) as instruments may be most problematic with regard to instrument validity, since simultaneity is likely to be an issue, meaning that these variables are likely to be codetermined with other relevant variables. On the other hand, more recent variables may constitute stronger instruments. The approach of taking past structural or institutional variables (such as university founding dates) as instruments is less likely to suffer from problems of validity, since these variables are determined earlier, which makes them less likely to exert other important direct or indirect effects on the dependent variable. However, these variables are still man-made and may have been subject to other historic influences that may also have affected the dependent variable. This can be illustrated by the study of Guiso et al. (2008), who show that early medieval free city state status of Italian cities had a long lasting effect on current trust, and that through this channel continues to determine growth rates of Italian regions today, even though the institution “free city state” has long disappeared. In such a context, “medieval free city state” is not a valid instrument if there are other historical factors (say, historic regional economic prosperity) that can be argued to have substantially affected both the instrument (“free city state”) and the dependent variable (say, current regional economic prosperity).

The appeal of taking natural environmental variables (such as winter temperature) as instruments lies in nature’s exogeneity: in the context of empirical models in the social sciences, which deal with anthropogenic phenomena, natural variables are exogenous by definition. If natural environmental factors can be found, that can be argued to have been historically promotive for the development of a regional culture of generalized trust, and that are irrelevant for other variables that affect the dependent variable, then these variables are theoretically strong and valid instruments for trust.

The basic idea that the natural environment does not by itself explain development, but has a strong indirect effect on development through its effects on institutions that are favorable for development, has been formulated by Rodrik et al. (2004). In a theoretical and empirical analysis, Durante (2009) claims that climate has had a lasting effect on regional trust: in pre-industrial Europe, where formal insurance institutions were non-existing or non-accessible to farmers, the degree of regional climatic risk determined the need for farmers to collectively deal with harvest risk, this in turn spurred the development of larger social networks that extended beyond the (large) family, thus favoring the development of impersonal, generalized informal norms of cooperation.

In this paper, we argue that regional generalized trust, as measured by European wide surveys, has a causal effect on regional innovation activity, since it helps the diffusion of tacit knowledge in the region (Hauser et al., 2007) and decreases transaction costs in dealing with the high risk that is typically involved in innovation projects (Akçomak & ter Weel, 2009; Durlauf & Fafchamps, 2005). To identify a causal effect, we pursue an instrumental variables approach. For this, we take up the basic idea of the natural environment's exogenous influence on institutions by Rodrik et al. (2004) and the idea of using natural environmental variables as instruments for generalized trust as in Bergh & Bjørnskov (2011). Drawing from Durante (2009), instruments are taken from a set of climate and soil attributes that are argued to be suitable instruments for trust on a European regional level.

The paper proceeds as follows: first, the empirical model is formulated. Then, natural environmental variables are proposed and discussed as suitable instruments for generalized trust. Then the employed data for European regions is described. Finally, the estimates from the model are presented and discussed.

2 Method

2.1 Empirical Model

To estimate the causal effect of social capital on innovation activity on a regional level, a standard knowledge production function is considered. Our baseline model follows Griliches (1979)[4] in assuming a theoretical determination of innovation ac-

[4]Compare OÕhuallachain & Leslie (2007) and Niebuhr (2010)

tivity of the following form, adding a measure of social capital, SC:

$$ln(P_i) = \alpha_0 + \alpha_1 ln(SC_i) + \alpha_2 ln(RD_i) + \alpha_3 ln(HC_i) + \sum_k \alpha_k C_{ki} + u_i \tag{1}$$

This specification assumes innovation activity in region i, which is measured by the natural log of the number of patent applications, P, to be a function of regional per capita expenditures on research and development, RD, and a measure of regional human capital, HC.[5] Following the usual procedure in the literature, the variables RD, HC, and SC are included with time lags in order to alleviate problems of simultaneity and because the effects are assumed not to occur instantaneously but to constitute a process that takes several month to several years. Regional control variables C_k are population density and country dummies. Country dummies are included to account for differences in national economic and innovation policies as well as differences in the quality of national institutional characteristics such as quality of the judicial system.[6] We provide a description of our variables in section 3.

Survey based measures such as generalized trust suffer from measurement error. Also, there may be feedback effects on regional trust, for example from aggregate human capital, making trust endogenous. Both issues will lead OLS estimates to be biased.[7] To deal with this, a 2-stage-least-squares model is estimated with geographic instruments for generalized trust, where the model for the first stage can be described as:

$$ln(SC) = \gamma_0 + \sum_j \gamma_j Z_j + \sum_m \delta_m X_m + v \tag{2}$$

The included instruments are denoted by X_m. The (excluded) natural environmental instruments Z_j comprise climate, soil, and topographic variables that are discussed below. Since cultural cooperative norms have spread across space over centuries of economic and cultural exchange, neighboring region's natural characteristics can also explain a regions' historical trust. Therefore we add to the set of instruments

[5]Note that there are known potential problems embedded in the standard knowledge production function: for example, OÕhuallachain & Leslie (2007) have noted that the implicit assumption of *R&D* being an exogenous (choice) parameter, may not be adequate, and that in fact, it may be more reasonable to assume that regional structural parameters, that are not as easily altered, are the driving force and the relatively more exogenous causing factors behind both patent applications and *R&D* expenditures. OÕhuallachain & Leslie (2007) propose an ad-hoc approach to deal with this problem of simultaneity by excluding *R&D* from the equation and instead to include only "regional structural parameters". Therefore, as a robustness check all models were re-estimated without *R&D*. This does not change the basic results, neither for the non-spatial nor for the spatial model specifications.

[6]Note that there is no measure of current within-country formal institutional differences available. It is therefore assumed that within-country institutional differences are solely driven by differences in regional social capital.

[7]See Wooldridge (2010).

spatially lagged versions of each of the natural environmental variables (for the choice of the matrix defining the spatial weights used to calculate these lags see below).

We also want to test if innovation activity is correlated with innovation activity in neighboring regions through interregional knowledge spillovers (Bottazzi & Peri, 2003; de Dominicis et al., 2013). To test for this, the baseline model is extended by including spatially lagged expenditures for research and development to explicitly model interregional knowledge spillovers. To avoid confounding interregional knowledge spillovers with other interregional spatial relations, we also allow for spatial autocorrelation of the residuals. This augmented model is described by equation 3 (Anselin, 1988).

$$log(P) = \alpha_0 + \alpha_1 log(SC) + \alpha_2 ln(RD) + \alpha_3 ln(HC) + \alpha_4 \mathbf{W} ln(RD) + \sum_k \beta_k C_k + \rho \mathbf{W} u + \epsilon \quad (3)$$

The spatial weighting matrix W is an inverse distance matrix with a 300km cutoff. It is both used to calculate the lagged versions of our instruments and to model interregional knowledge spillovers as described in the equation above. At least regarding the spatially lagged instruments, the matrix W leads to a spatial specification without a clear theoretical preconception about the true nature of the spatial relations, as usual in the applied spatial econometric literature. To the degree that the assumptions about the spatial relations, as resembled by matrix W, are inappropriate, we may introduce bias (Pinkse & Slade, 2010). However, we pursue this strategy in order to contrast our findings with the results from similar models in the literature. Regarding knowledge spillovers, we can refer to Bottazzi & Peri (2003), who find no interregional knowledge spillovers in Europe beyond a distance of 300km.

2.2 Natural Environmental Instruments for Trust

Durante (2009) argues that due to the lack of access to functioning formal insurance markets for farmers in the pre-industrial rural economy, a natural environment characterized by high climatic uncertainty meant that there where high benefits for these rural societies to develop generalized cooperative norms to deal with climatic risks, for example by developing informal rules of mutual assistance. Durante (2009) also argues that climatic uncertainty might have affected cooperative values because it favored economies of scale in cooperative irrigation and drainage activities, forcing people to cooperate and to develop rules of cooperation. Also, Durante (2009) argues that access to sea and rivers and natural terrain obstacles to movement could have influenced the exposure to other populations and therefore could have determined the degree to which people interacted with and developed cultural norms of cooperating with strangers. Finally, Durante (2009) claims that due to a strong persistence of cultural values, historical trust levels largely persist until today. This last claim is supported by recent literature that suggest long-term persistence of culture. Most notably, the study by Guiso et al. (2008) cited above provides empirical evidence for long term persistence of cultural values. The arguments in favor of this view of cultural persistence are supported by a growing theoretical economic literature on the genesis and intergenerational transmission of cultural values (Bisin & Verdier, 2010). For example, Tabellini (2008) has analysed in an economic intergenerational investment model, how cultural values and their evolvement over time may be explained by investments of parents into their offspring's cultural values, how these investment choices interact with external norm enforcement institutions and parents' expectations of future transactions of their offspring, and how in such a setting path dependencies may arise, that could explain large and long-lasting differences in culture. Empirically, Durante (2009) shows that European regions with higher interannual variation in temperature and rainfall show higher levels of trust today, controlling for country fixed effects and indicators of early institutional development.

We categorize the different arguments made by Durante (2009) as risk-management arguments, scale effects arguments, and costs of cultural exchange arguments. We argue that the theoretical case for natural environmental variables being valid instruments for current trust in estimations of the effect of trust on current regional innovation activity rests on three critical assumptions: a) the natural environment has shaped culture substantially, b) culture has been sufficiently persistent and c) the natural environmental variables do not affect regional innovation activity substantially via other channels.

As natural environmental instruments for trust, we propose regional averages of interannual standard deviation of rainfall during growing season months, interannual standard deviation of temperature during growing season months, soil water capacity, soil heterogeneity within a 30km radius, standard deviation of terrain elevation within a 30km radius, the share of regional area higher than 800m above sea level.

Note that we are not the first to use instrumental variables from natural environmental characteristics. As mentioned above, Bergh & Bjørnskov (2011) have used climate characteristics. Also, note that we are not the first to use soil and other terrain characteristics as instrumental variables: Combes et al. (2010) have used soil and terrain characteristics as instruments for population density in a different context. Following their argumentation, we also consider the possible influence of soil and terrain on population density in our instrumental variable specifications (see below).

We now discuss these suggested variables with regard to their theoretical effect on historical trust levels and with regard to their validity in the following paragraphs.

One general objection against taking natural environmental variables to instrument for trust in estimating the effect of trust on innovation could relate to effects of the natural environment on agricultural productivity. We argue that the share of the agricultural sector in production today is comparatively small in all of the regions in our sample, while the share of the agricultural sector in innovation activities is likely to be even smaller.

A further objection, as already mentioned above, could relate to population density: in particular, soil characteristics and topographic measures, some of which similar, some different than the soil and terrain characteristics that we propose as instruments for trust, have previously been used as instruments for population density (Combes et al., 2010). Therefore we consider it necessary to also consider population density as an endogenous variable and to instrument for it in our IV-specifications. For the same reason, we add a measure of natural suitability for agriculture[8] to the first stage to explain population density, and which we calculate from climate and soil characteristics.[9]

Another objection could relate to effects of the natural environment on quality of life, such as climatic attributes that are correlated with the amount of sunshine. We argue that effects of natural characteristics on quality of life are theoretically and empirically unresolved and that it seems plausible to assume that such effects, if there are any, are dependent on preferences, and that therefore no region in Europe has notable climate and / or topography related disadvantages regarding its innovation potential.

Objections regarding instrument validity could also relate to effects on transport costs. We argue that the regions in our sample today are sufficiently connected by transport infrastructure as well as by communication technology to make geographic impediments (such as terrain ruggedness) a negligible factor for current innovation processes.

As climate related instruments for social capital, referring to Durante (2009), we take interannual variability of precipitation and interannual variability of temperature, arguing that high climatic risk has favored development of large-scale

[8]For descriptions of our variables see section 3

[9]Note however, that there is in fact also a compelling argument why suitability for agriculture may also be a determinant of trust itself: suitability for agriculture could be interpreted as a proxy for the share of the commons; the less suitable the land for crops, the (relatively) more important become pasture and foresting. In the spirit of Durante's arguments, as the management of common pool resources requires institutions of cooperation, this could have favored the evolution of cooperative cultural traits. The reader is referred to Ostrom (1990) for the most prominent theoretical analysis and historic case studies of institutional arrangements of common pool resource management.

cooperation. We also argue that the soils' capacity to retain water has affected the exposure of the soil to climatic risk. The higher the available soil water capacity, the smaller the compromising effects of periods without (or with too much) rain, the smaller the need to cooperate both in irrigation, drainage, and / or any other climate risk-pooling activities.

As another instrument, we propose a measure of regional soil heterogeneity. We argue that for neighboring communities with very different soils, it ceteris paribus was more profitable to specialize in certain crops or pasture that the particular communities' soil had a comparative advantage for. Since specialization makes production dependent on trade with neighboring communities, regional heterogeneity of soils favored the development of larger, impersonal networks and therefore favored the development of impersonal cooperative norms. We can also assume that different types of climate shocks (i.e. too much / too little rain, too high / too low temperatures) affected different soils differently, making neighboring communities' risk less correlated, so that a high degree of regional soil heterogeneity c.p. increased the local benefits of cooperation by increasing the benefits of risk-pooling between neighboring communities.

The case studies by Ostrom (1990) suggest that specific characteristics of the high mountains favored the development of a local agricultural economy that was naturally dominated by a large share of common resources: high meadows and forests that could only be used seasonally and cooperatively, and the need to cooperate to cope with natural dangers specific to mountain regions (Ostrom, 1990). To capture "high mountain" topography, we propose the share of the region's area above a certain elevation cutoff. Topography also matters for the "costs of cultural exchange"-argument made by Durante (2009), stating that geographic obstacles made it costly to interact with neighboring communities. Therefore, we also include a measure of local variability of land elevation, measuring "terrain ruggedness".

3 Data

The sample consists of 123 European regions of comparable size and for which data was available. In the system of European regional classification ("Nomenclature d'Unités Territoriales Statistiques (NUTS)", depending on data availability and the number of survey respondents per region, the regions are either of NUTS1 regions (Austria, Belgium, France, Germany, Netherlands, and the United Kingdom)[10], or

[10]For example, for Germany, the number of respondents in the survey data that was employed (see below) was below 100 for many NUTS2 regions. For Austria and the Netherlands, suitable survey data actually was available at the NUTS2-level, however, due to the comparatively small geographical size of NUTS2 regions in these countries, NUTS1 regions where taken instead to improve comparability in the context of this study.

of NUTS2 regions (Czech Republic, Spain, Finland, Hungary, Ireland, Italy, Estonia, Poland, Portugal, Slovak Republic, and Sweden)[11]. For small countries where subnational data was not available, the whole country was included as a region (Denmark, Estonia, and Luxembourg).[12] Since the theoretic foundation for the geographic instruments used in the analysis refers to rural regions, all regions that are practically solely comprised of urban area were excluded.[13] From the countries included, some regions had to be excluded due to data availability. A list of all 123 regions that were finally included in the analysis is shown in table 6.3 on page 23. The variables used in our analysis are described in table 1.

Table 1: Generalized Trust and Innovation: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Patents/1M Inh.'01	78.291	106.573	0.168	637.186
Trust (ESS2 and 3)	4.768	0.767	2.864	6.755
Students Lvl 5-6 '99	0.139	0.05	0.012	0.28
R.D. p.c.'00	231.405	216.08	13.217	944.64
Pop.Density '99	158.525	133.051	3.325	861.942
Std.Dev.Prec.GSM	32.491	8.289	21.01	65.457
Soil AWC	131.456	28.957	68	190.692
Elev.800m	9.551	15.424	0	71.38
Std.Dev.Elevation	129.166	107.203	3.908	417.35
Soil Heterogen.	0	1	-2.24	2.122
Suitab. Agric.	0	1	-1.808	2.335
N	123			

Data on patent applications, expenditures on research and development, the share of students in tertiary education and population density are from the Eurostat regional database.[14] For a graphical representation of the regional patent application data see figure 1 on page 10. Distribution of patent activity is strongly spatially clustered: the northern and western European countries (the upper cluster) can be clearly separated from the southern and eastern European countries (the lower

[11]For the Czech Republic, the factually lowest statistical regional level below the country level is the NUTS2-level.

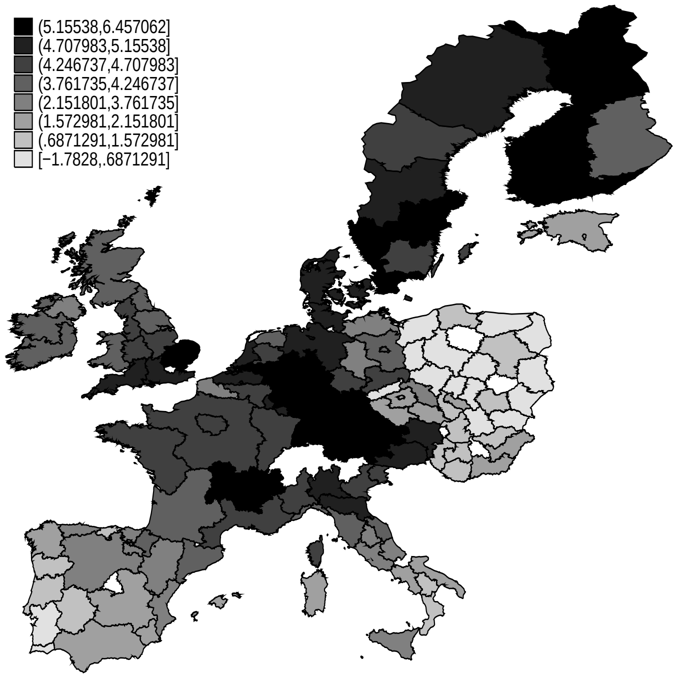
[12]However, since all of our specifications include country fixed effects, omitting these regions has no effect on the results.

[13]The excluded urban regions are: AT13 (Vienna), BE1 (Brussels), CZ01 (Prague), DE3 (Berlin), DE5 (Bremen), DE6 (Hamburg), ES30 (Madrid), FR1 (Paris, Ile-de-France), HU10 (Budapest), PT17 (Lisbon), SE11 (Stockholm), SK01 (Bratislava), UKI (London). Our results are not sensitive to including these urban regions regarding the size and significance of the estimated effects. However, in the instrumental variable estimations, including these urban regions leads to somewhat increased indications for weak identification and underidentification of our geographic instruments.

[14]Eurostat (2011)

cluster), with some exceptions such as the north Italian regions. This spatial autocorrelation is confirmed by the Morans' I statistic reported in figure 3 on page 20.

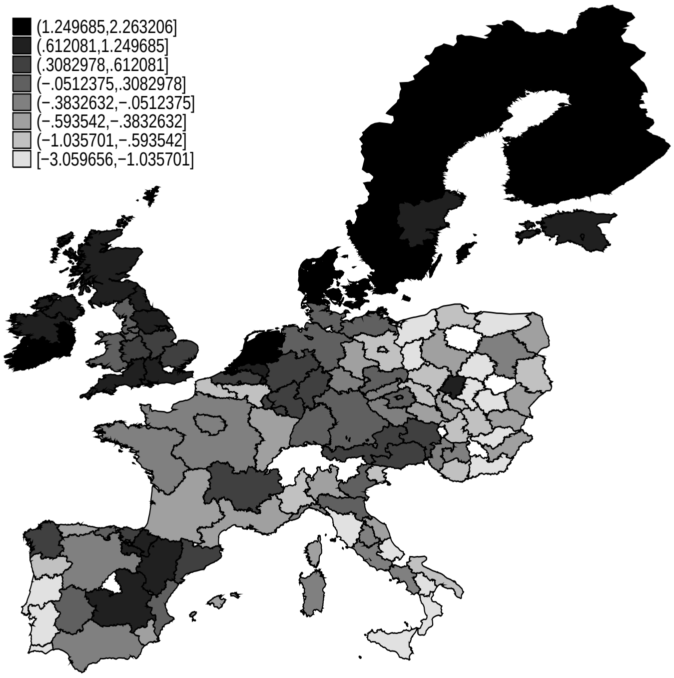
Figure 1: Log of Regional Patent Applications per 1M Inhabitants
Source: Eurostat (2011)



Survey data on social capital is from the European Social Survey (ESS). The European Social Survey is a biennial multi-country survey covering over 30 nations, co-funded by the European Commission, with the first round conducted in 2002/2003. The data is available free of charge for academic purposes. The core module of the survey includes questions on social and public trust.[15] To measure generalized trust, the following question from the ESS was used: "generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please tell me on a score of 0 to 10, where 0 means you can't be too careful and 10 means that most people can be trusted." Answers to this question were aggregated to the regional level to measure the regional degree of generalized trust.[16] For a graphical representation of the aggregated values see figure 2 on page 11. Figure 2 reveals strong spatial clustering of the trust variable. The Scandinavian regions and the regions of the Netherlands are at the top of the distribution, followed by the United Kingdom, some (northern and central) Spanish regions, then Austria, Germany, some regions in northern Italy and France, and at the bottom

[15]ESS (2004).
[16]Answers from waves 2 and 3 of ESS (2004) were used.

Figure 2: Generalized Trust, log of regional averages
Source: ESS (2004) (waves 2 and 3)



of the distribution we have southern Spain, the eastern European regions, southern Italy, and Portugal. The spatial autocorrelation of the trust variable is confirmed by the Moran's I statistic and the corresponding graphical representation in figure 4 on page 20.

The climate data come from the CRU TS 1.2 data-set.[17] This climate raster data set consists of 1200 monthly grids of each observed climate variable, for the period 1901-2000, and covers the global land surface at 10 ° degree resolution (which for Europe, is about 15 kilometers). It comprises daily mean temperature, minimum and maximum temperature, diurnal temperature range, precipitation, wet day frequency, frost day frequency, vapour pressure and cloud cover. In generating the employed climate variables from the original raw data, the same procedure as described in Durante (2009) has been applied.[18] For a graphical representation of the interannual standard deviation of temperature see figure 5 on page 21, for interannual standard deviation of rainfall see figure 7 on page 22.

All employed soil data is from the Harmonized European Soil Database (ESDB) by the European Commission (EC, 2004).[19] It is a dataset available as both 1km x

[17]This dataset was previously used by Durante (2009) to explain variation in trust levels across European regions (see the discussion above). See Mitchell & Jones (2005) for the original source.

[18]For all calculations of climate, soil, and elevation data, the software package ESRI ArcGIS was used.

[19]Note that Combes et al. (2010) have used soil data from the ESDB as instrumental variables for population density.

1km and 10km x 10km raster datasets for a large number of soil attributes widely used in geological, geographical and agricultural sciences. A measure of regional soil heterogeneity was calculated to capture the uniqueness of each 10km x 10km soil raster cell within a 30km-radius.[20] We choose a 30km radius, arguing that this should be roughly close to the one day travel distance on flat land before the invention of modern means of transport: a one day travel distance seem like a plausible cut-off beyond which it would presumably have been more difficult to form and maintain social contacts in preindustrial societies. To make it less likely that the soil variables' exogeneity is impaired by human influence on soils, all soil-based measures are based on subsoil data where available.[21] The attribute "soil available water capacity" (soil AWC) is directly included in the ESDB as a derived soil attribute in 10km raster format. It was aggregated to the regional level using ArcGIS.

Land elevation data is from the Shuttle Radar Topography Mission's (SRTM) global high-resolution digital elevation dataset, a project led by the National Geospatial-Intelligence Agency (NGA) and NASA (Farr et al., 2007). To measure local variabilty of land elevation ("terrain ruggedness"), an elevation raster resolution of 1km x 1km is chosen. The "terrain ruggedness"-variable is calculated for each land cell of 1km by 1km for a radius of 30 km and averaged over all region's land cells (land-cells are matched to regions based on the location of their centroid). For the "high mountain"-variable, we take the share of the regions' area that is located at least 800m above sea level. 800m seems an appropriate cutoff, as there is negligible crop production above this height in Europe, which we take as an indicator of a large share of the commons, referring to Ostrom (1990). A measure of natural predisposition for agriculture using climate and soil data was calculated as described in detail in Ramankutty et al. (2002).[22] In some of our specifications we also instrument for regional human capital, for this we take the number of years that a university has had existed in the region in the year 1900. This is to capture "university tradition" and assumed to be an exogenous determinant of current human capital.[23]

4 Results

Given the spatial dimension of our data, we are confronted with the choice between using standard non-spatial multivariate regression and spatial regression models. The former ignores the spatial dimension of our data, which is potentially prob-

[20]For a description see section 6.1 on page 18.

[21]Note that for the soil dataset that is used, all subsoil attributes seem to be highly correlated with the corresponding topsoil attributes (EC, 2004).

[22]For our calculations this index was standardized to zero sample mean and unit sample variance.

[23]We thank Semih Akcomak for providing this variable.

lematic, given that there seem to be indications of spatial autocorrelation of both patents and trust, as described in the previous section, and given that such spatial autocorrelation can cause biased estimates (Anselin, 1988). In particular, the case for spatial dependence of interregional dependence of innovation activity has been made by the literature on interregional knowledge spillovers (de Dominicis et al., 2013; Bottazzi & Peri, 2003). However, as discussed above, modelling the spatial dimension in our data requires making assumptions about these spatial relations, and making such assumptions is problematic, since the nature of these relations is theoretically unknown, and the bias introduced by making inappropriate assumptions may be larger than the original bias incurred by ignoring spatial relations (Pinkse & Slade, 2010; Gibbons & Overman, 2012).[24] Since we have no theoretical preconception of which of these biases is likely to be larger in the present context, we decide to pursue both non-spatial and spatial specifications, to see if they lead to different results.

4.1 Non-Spatial Specifications

We first present our estimation of the baseline non-spatial model described by equation 1 on page 4. The results are shown in table 2. The first column (1) shows equation 1 estimated with OLS and country fixed effects. The coefficient for social capital is positive and significant, suggesting that innovation output is higher in regions with higher social capital, c.p. Since we have expressed both patents and social capital as their natural logarithms, the coefficients resemble elasticities, so that for instance we could quantitatively conclude that a one percent increase in our trust measure is associated with an estimated 0.33 percent increase in patent applications.

OLS coefficients will be biased downwards in the presence of measurement error (Wooldridge, 2010), which in fact is likely to be a problem with survey data on social capital, as we have discussed in section 2.1. Also, measured trust may be endogenous to other variables in our model, such as human capital. In the second column, we therefore instrument for social capital with the set of geographic instruments as described in section 2.1. Since we use climate and soil instruments, which could affect suitability for agriculture, and since we also use suitability for agriculture itself as an instrument for social capital, we alternatively assume population density to be an endogenous variable in column (2) (see section 2.1 for the discussion). All coefficients retain their sign and their significance in our instrumental variable regressions of column (2), supporting our OLS results. In column (3), we estimate the model with human capital assumed to be endogenous, i.e. we perform the same

[24]Spatial econometric methods suffer from a number of unresolved methodological problems, for a criticism see also Pinkse & Slade (2010); Gibbons & Overman (2012).

instrumental variables regression as in column (2), except that we additionally instrument for human capital. For this we add to our set of instruments the number of years that a university has had existed in the region in the year 1900 and the spatial lag of that variable, to capture "university tradition", as a largely exogenous source of variation for current human capital.[25] The coefficients in column (3) are positive and significant, also in line with our OLS results. Quantitatively, they are close to the coefficients from the previous specification in column (2). F-Tests of the joint

Table 2: Social Capital and Innovation: OLS and 2SLS

VARIABLES	(1) OLS Log Pat. 2001	(2) Baseline 2SLS Log Pat. 2001	(3) 2SLS Log Pat. 2001
Log Trust	0.3311***	0.6238**	0.6317***
	(0.115)	(0.278)	(0.234)
Log R&D p.c. 2000	0.7306***	0.6362***	0.6631***
	(0.116)	(0.106)	(0.092)
Log Share Students 1999	0.6264**	0.5431***	0.5612***
	(0.230)	(0.148)	(0.166)
Pop. Density 1999	0.2017**	0.4578***	0.3690***
	(0.080)	(0.171)	(0.090)
Observations	123	123	123
Adj R sqr	0.923		
Hansen J		0.423	0.504
Weak Id.		81.72	93.63
Underid. (Kleib-Paap LM)		0.180	0.284

Standard errors clustered at country level, *** p<0.01, ** p<0.05, * p<0.1
(1): Only social capital is instrumented
(2): Social capital and population density instrumented
(3): Social capital, population density, and human capital instrumented
All specifications include country fixed effects

significance of the employed instruments report values that are comfortably above the usual rule of thumb value of 10. Column (2) and (3) also report the Hansen J statistic's p-value, that for the case of clustered standard errors replaces the Sargan Test of overidentification; it is not significant here, suggesting that our instruments are in fact valid instruments, given that at least some of them are valid.[26] The Kleibergen-Paap Wald statistic for weak identification is above the critical value

[25] The spatial lag is included following the same basic arguments that we made above about the spread of cultural values across space: "university tradition" is assumed to have had a positive influence on human capital creation in the neighboring regions during the last century.

[26] A significant Hansen statistic would raise doubts about the validity of our instruments, as it would mean that our instruments are correlated with other regressors in our model.

suggested by Stock & Yogo (2002) for a maximum 10% bias, suggesting that our instruments should be sufficiently strong. The reported statistic for underidentification is insignificant (however just barely), suggesting that underidentification may be an issue.

The results from the instrumental variables estimation suggest that generalized trust has a positive causal effect on current regional innovation activity. As we have discussed in section 2.1, the credibility of this claim rests on the assumptions that the natural environment has had a sufficiently strong effect on culture, that this culture has persisted, and that the natural environment did not and does not have any non-negligible effects on other variables that explain current regional innovation activity.

4.2 Spatial Specifications

We now turn to the results from our spatial model estimations, which should provide answers to the question of interregional knowledge spillovers, as found by de Dominicis et al. (2013); Bottazzi & Peri (2003), and if interregional knowledge spillovers and regional trust both independently explain a part of the innovation activity. A visual representation of trust and patent applications suggests that both variables are spatially autocorrelated. The Moran's I test statistic for spatial autocorrelation confirms this, as described above (see figures 4 and 3). To account for spatial dependencies between regions, we estimate variations of the spatial model described in equation 3 on page 5. As discussed, we have to be aware that the assumptions that need to be made about these spatial relations in order to specify these spatial models rest on inexact theoretical knowledge about these relations (such as the spatial weighting matrix W), and to the degree that they deviate from the true relations, will introduce bias (Pinkse & Slade, 2010).

The spatial model allows for both spatial autocorrelation of the residuals (the parameter ρ) and for research and development expenditures of neighboring regions to exert an effect on innovation activity.[27] The model in column (1) resembles a spatial specification of the knowledge production function without social capital: a spatial lag of the log of per capita spending on research and development is included. Such a specification is referred to as a spatial-autoregressive (SAR) model. Here, the spatial lag of R&D expenditures is found to be positive and significant. In similar studies, this is typically interpreted as the effect of neighboring regions' innovation activity on the region's own innovation activity, or "interregional knowledge spillovers" (Bottazzi & Peri, 2003).

[27] The employed spatial weights matrix is described and discussed in section 2.1.

Table 3: Social Capital and Patent Applications: Spatial Models

VARIABLES	(1) OLS	(2) OLS	(3) SARE	(4) SARE	(5) SARE-IV
Log(Trust)		**0.298*****		**0.273*****	**0.526****
		(0.106)		(0.102)	(0.262)
Log R.D.pc'00	0.741***	0.724***	0.703***	0.714***	0.695***
	(0.0970)	(0.0939)	(0.0863)	(0.0849)	(0.0981)
Sp. Lag logRD	**0.182****	**0.132**	**0.169***	**0.131**	**0.0723**
	(0.0873)	(0.0862)	(0.0884)	(0.0796)	(0.103)
Log.Shr.Stud.'99	0.653***	0.623***	0.614***	0.615***	0.588***
	(0.164)	(0.158)	(0.146)	(0.142)	(0.131)
Pop.Density '99	0.130	0.159*	0.144*	0.158**	0.263
	(0.0916)	(0.0891)	(0.0817)	(0.0794)	(0.168)
Constant	0.659	0.545	0.796	0.622	0.224
	(0.828)	(0.801)	(0.725)	(0.721)	(0.721)
rho			**0.859***	**0.371**	**0.164**
			(0.443)	(0.622)	(1.017)
Observations	123	123	123	123	123

SARE: ML-Estimator
SARE-IV: Robust SE, Soc. Cap. and Density instrumented
*** p<0.01, ** p<0.05, * p<0.1
Country fixed effects

Allowing for spatially autocorrelated residuals leads to a spatial-autoregressive model with spatial-autoregressive disturbances which is referred to as a SARAR or SARE model as in model (3) (Drukker et al., 2013b). As the specification in column (3) shows, allowing for spatially autocorrelated residuals by including the parameter ρ reduces the significance of our knowledge spillover parameter, suggesting that relevant spatially correlated variables where omitted in model (1).

When we add the trust variable, which we conjecture is such a relevant omitted variable, to model (1), which gives us model (2), we find that the significance of the spatially lagged per capita expenditures on research and development disappears, suggesting an alternative explanation for the phenomenon of high spatial clustering of innovation activity in Europe: generalized trust both affects regional innovation and is at the same time highly spatially autocorrelated.[28] This strongly autocorrelated variable, when omitted from spatial models explaining regional innovation with neigboring regions' innovation, causes the coefficient of neighboring regions innovation activity to turn significant, falsely suggesting interregional knowledge

[28]We argue in section 2.1 that it is theoretically plausible to assume spatial autocorrelation of cultural characteristics due to centuries of cultural relations between regions that decreased with distance.

spillovers.

Combining spatially lagged R&D-expenditures, the trust variable, and allowing for autocorrelated residuals (model 4), supports this claim that (spatially clustered) social capital, rather than interregional knowledge spillovers, seems to explain regional innovation activity.

The model in column 5 is a spatial-autoregressive model with spatial-autoregressive disturbances and further endogenous variables (Drukker et al. (2013a)), where social capital and density are assumed endogenous and are instrumented with our geographic instrumental variables. The results of this estimation support the results from the previous models.

5 Conclusion

We find empirical evidence that regional differences in generalized trust explain regional differences in innovation activity. For a cross-section of 123 European regions, the effects of trust were significant both for OLS estimation and for two-stage-least-square estimation employing soil and climate instruments for trust and population density.

The results from our spatial model specifications suggest that the usual explanation for clustered innovation activity by interregional knowledge spillovers may be flawed. Instead, a strong influence of generalized trust on innovation activity, combined with a strong spatial correlation of generalized trust, which is due to centuries of cultural influences between neighboring regions, provides a better explanation for the high spatial clustering of innovation activity that can be observed in Europe.

6 Appendix

6.1 Soil Heterogeneity Measure

The soil data is from the Harmonized European Soil Database (ESDB) maintained by the European Commission (EC, 2004). The measure of soil heterogeneity is designed to capture the uniqueness of each 10km x 10km soil raster cell within a 30km-radius. All soil attributes provided by the ESDB are described in detail in EC (2004). We select a subset of the soil attributes made available by this database according to the following criteria:[29] 1. classification according to derived physical, chemical or hydrogeological properties, 2. relevance for preindustrial agriculture, 3. exogeneity, i.e. degree of susceptibility to human influence, and 4. data coverage for the study area.

To minimize susceptibility to human influence, subsoil attributes were preferred over topsoil attributes, where the choice was available, and all soil attributes termed "chemical" by ESDB were excluded.[30] The above criteria led us to include the following ESDB soil attributes in our calculation: depth to a gleyed horizon, depth to an impermeable layer, depth to rock, parent material (hydro-geological), dominant slope class, subsoil packing density, subsoil structure, dominant surface textural class, volume of stones. For each 10km x 10km landcell and for each included soil attribute, the share of landcells in a 30km-radius analysis window with the same

Table 4: ESDB Soil Attributes Used

ESDB Database Field	Description of Soil Attribute
DGH	Depth to a Gleyed Horizon
DIMP	Depth to an Impermeable Layer
DR	Depth to Rock
PMH	Parent Material Hydro-geological
SLOPEDO	Dominant Slope Class
PD-SUB	Subsoil Packing Density
STR-SUB	Subsoil Structure
TEXT	Dominant Surface Textural Class
VS	Volume of Stones

[29] In deciding whether the criteria were fulfilled, subjective judgement was applied and the attributes to be included were selected accordingly. The measure was calculated with the initial attribute selection according to predetermined rules described below, i.e. after calculating the index, no further adjustments were made, neither regarding attribute selection nor calculation rules.

[30] When subsoil attributes were available they were always used with the exception of "Dominant sub-surface textural class" which, due to only small gaps in data coverage and a very high correlation with "Dominant surface textural class", was replaced by the latter.

attribute value was calculated.[31] Our soil heterogeneity measure is the standardized average (zero sample mean and unit sample variance) of these shares. All calculations were made with ArcGIS^{TM}Spatial Analyst.

[31] For the sake of simplicity, ordinal information was not used in the calculations.

6.2 Figures

Figure 3: Regional Patent Applications, Moran's I

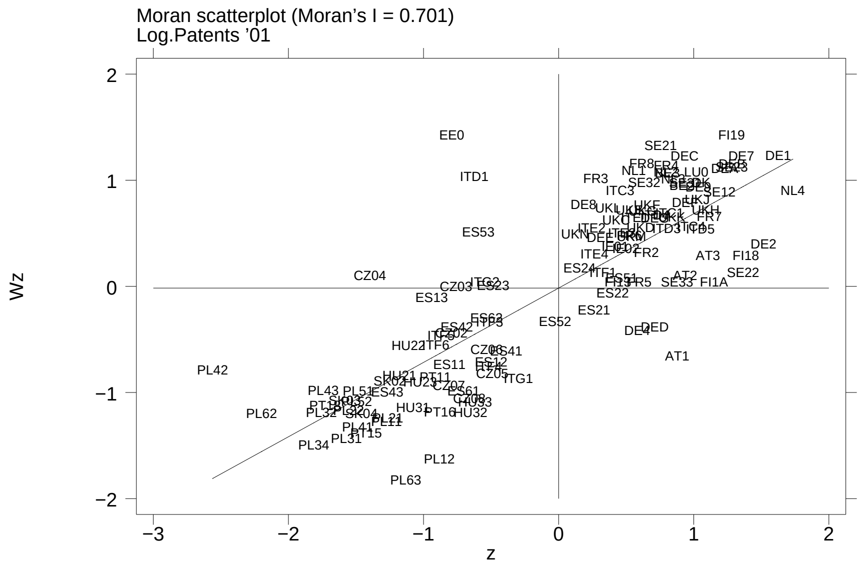


Figure 4: Generalized Trust, Moran's I

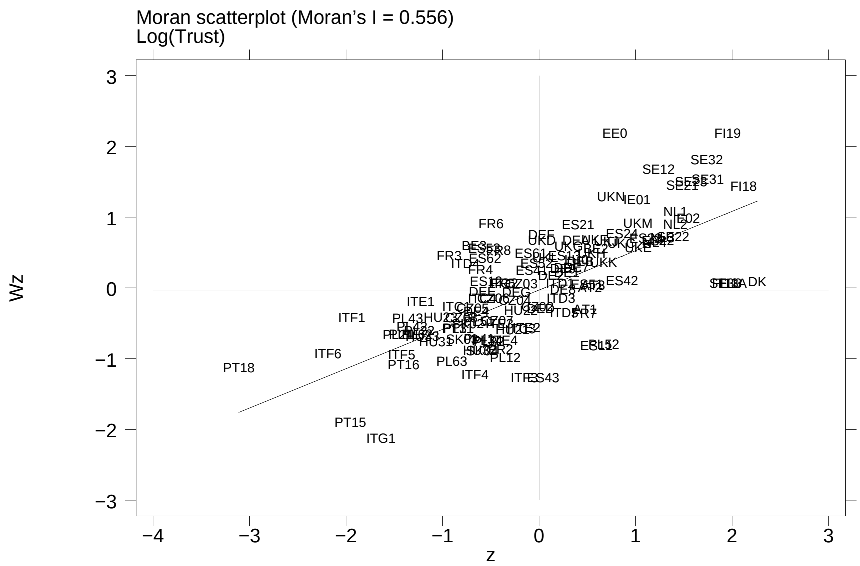


Figure 5: Interannual Standard Deviation of Temperature (Averaged over Growing Season Months, 1900-2000)
Source: CRU TS 1.2, own calculations as described in Durante (2009)

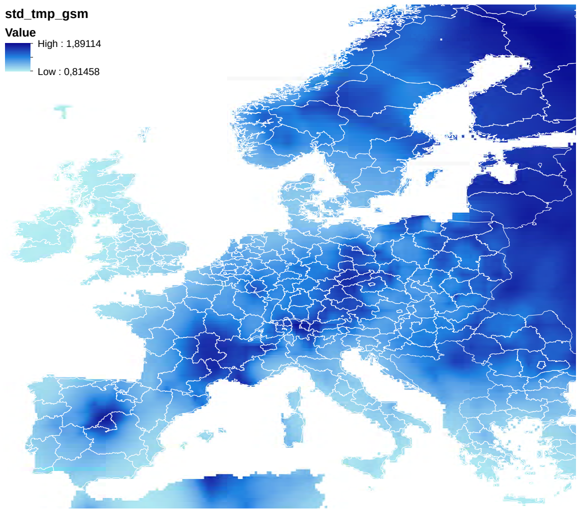


Figure 6: Soil Heterogeneity Index
Source: Harmonized European Soil Database (EC, 2004), own calculations as described on page 18

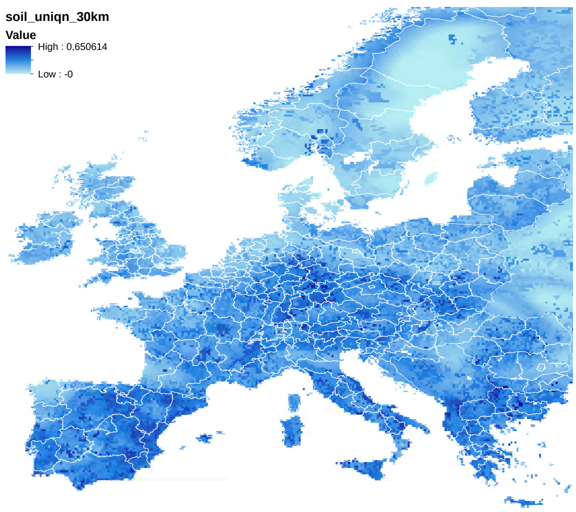
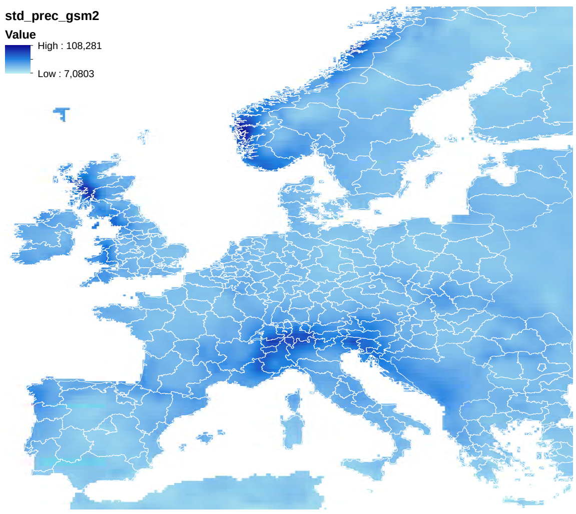


Figure 7: Interannual Standard Deviation of Rainfall (Averaged over Growing Season Months, 1900-2000)
Source: CRU TS 1.2, own calculations as described in Durante (2009)



6.3 List of Regions

Case ID	NUTS ID	Name of Region
1	AT1	OSTOESTERREICH
2	AT2	SUEDOESTERREICH
3	AT3	WESTOESTERREICH
4	BE2	VLAAMS GEWEST
5	BE3	REGION WALLONNE
6	CZ02	STEDNI ECHY
7	CZ03	JIHOZAPAD
8	CZ04	SEVEROZAPAD
9	CZ05	SEVEROVYCHOD
10	CZ06	JIHOVYCHOD
11	CZ07	STEDNI MORAVA
12	CZ08	MORAVSKOSLEZSKO
13	DE1	BADEN-WUERTTEMBERG
14	DE2	BAYERN
15	DE4	BRANDENBURG
16	DE7	HESSEN
17	DE8	MECKLENBURG-VORPOMMERN
18	DE9	NIEDERSACHSEN
19	DEA	NORDRHEIN-WESTFALEN
20	DEB	RHEINLAND-PFALZ
21	DEC	SAARLAND
22	DED	SACHSEN
23	DEE	SACHSEN-ANHALT
24	DEF	SCHLESWIG-HOLSTEIN
25	DEG	THUERINGEN
26	DK	DANMARK
27	EE0	EESTI
28	ES11	GALICIA
29	ES12	PRINCIPADO DE ASTURIAS
30	ES13	CANTABRIA
31	ES21	PAIS VASCO
32	ES22	COM. FORAL DE NAVARRA
33	ES23	LA RIOJA
34	ES24	ARAGON
35	ES41	CASTILLA Y LEON
36	ES42	CASTILLA-LA MANCHA
37	ES43	EXTREMADURA
38	ES51	CATALUNA
39	ES52	COMUNIDAD VALENCIANA
40	ES53	ILLES BALEARS
41	ES61	ANDALUCIA
42	ES62	REGION DE MURCIA
43	FI13	ITA-SUOMI
44	FI18	ETELA-SUOMI
45	FI19	LANSI-SUOMI
46	FI1A	POHJOIS-SUOMI
47	FR2	BASSIN PARISIEN
48	FR3	NORD - PAS-DE-CALAIS
49	FR4	EST
50	FR5	OUEST
51	FR6	SUD-OUEST
52	FR7	CENTRE-EST
53	FR8	MEDITERRANEE
54	HU21	KOZEP-DUNANTUL
55	HU22	NYUGAT-DUNANTUL
56	HU23	DEL-DUNANTUL

57	HU31	ESZAK-MAGYARORSZAG
58	HU32	ESZAK-ALFOLD
59	HU33	DEL-ALFOLD
60	IE01	BORDER, MIDLAND AND WESTERN
61	IE02	SOUTHERN AND EASTERN
62	ITC1	PIEMONTE
63	ITC3	LIGURIA
64	ITC4	LOMBARDIA
65	ITD1+2	TRENTINO-ALTO ADIGE
66	ITD3	VENETO
67	ITD4	FRIULI-VENEZIA GIULIA
68	ITD5	EMILIA-ROMAGNA
69	ITE1	TOSCANA
70	ITE2	UMBRIA
71	ITE3	MARCHE
72	ITE4	LAZIO
73	ITF1	ABRUZZO
74	ITF3	CAMPANIA
75	ITF4	PUGLIA
76	ITF5	BASILICATA
77	ITF6	CALABRIA
78	ITG1	SICILIA
79	ITG2	SARDEGNA
80	LU0	LUXEMBOURG
81	NL1	NOORD-NEDERLAND
82	NL2	OOST-NEDERLAND
83	NL3	WEST-NEDERLAND
84	NL4	ZUID-NEDERLAND
85	PL11	ODZKIE
86	PL12	MAZOWIECKIE
87	PL21	MAOPOLSKIE
88	PL22	LSKIE
89	PL31	LUBELSKIE
90	PL32	PODKARPACKIE
91	PL34	PODLASKIE
92	PL41	WIELKOPOLSKIE
93	PL42	ZACHODNIOPOMORSKIE
94	PL43	LUBUSKIE
95	PL51	DOLNOLSKIE
96	PL52	OPOLSKIE
97	PL62	WARMISKO-MAZURSKIE
98	PL63	POMORSKIE
99	PT11	NORTE
100	PT15	ALGARVE
101	PT16	CENTRO (PT)
102	PT18	ALENTEJO
103	SE12	OESTRA MELLANSVERIGE
104	SE21	SMALAND MED OARNA
105	SE22	SYDSVERIGE
106	SE23	VASTSVERIGE
107	SE31	NORRA MELLANSVERIGE
108	SE32	MELLERSTA NORRLAND
109	SE33	OEVRE NORRLAND
110	SK02	ZAPADNE SLOVENSKO
111	SK03	STREDNE SLOVENSKO
112	SK04	VYCHODNE SLOVENSKO
113	UKC	NORTH EAST (ENGLAND)
114	UKD	NORTH WEST (ENGLAND)
115	UKE	YORKSHIRE AND THE HUMBER

116	UKF	EAST MIDLANDS (ENGLAND)
117	UKG	WEST MIDLANDS (ENGLAND)
118	UKH	EAST OF ENGLAND
119	UKJ	SOUTH EAST (ENGLAND)
120	UKK	SOUTH WEST (ENGLAND)
121	UKL	WALES
122	UKM	SCOTLAND
123	UKN	NORTHERN IRELAND

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