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Social Capital Formation across Space: Proximity and Trust in European Regions

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Abstract

An extensive economics and regional science literature has discussed the importance of social capital for economic growth and development. Yet, what social capital is and how it is formed are elusive issues, which require further investigation. Here, we refer to social capital in terms of "civic" capital and "good culture," as rephrased by Guiso, Sapienza, and Zingales and Tabellini. The accumulation of this kind of capital allows the emerging of regional informal institutions, which may help explaining differences in regional development. In this article, we take a regional perspective and use exploratory space and space–time methods to assess whether geography, via proximity, contributes to the formation of social capital across European regions. In particular, we investigate whether generalized trust, a fundamental constituent of civic capital and an ingredient of economic development, tends to be clustered in space and over time. From the policy standpoint, the spatial "path dependence" of regional trust may contribute to the formation of "spatial traps" of social capital and act as a further barrier to regional economic development and convergence.

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Introduction

An increasing literature links social capital to economic development and growth. This literature praises the ability of social capital to reduce transaction costs and allow complex transactions without the need for legal contracts and enforcement, "multiply" the contribution of factor endowments, facilitate financial transactions, investment, and innovative activity. More generally, social capital enhances market efficiency and improves the quality of public institutions and private organizations.[1] A copious literature provides evidence that social capital is also important to explain differences in regional development (see Putnam 1993; Beugelsdijk and van Schaik, 2005; Beugelsdijk and Smulders 2009; Tabellini 2010).

The agreement on the positive effects of social capital solicits a better understanding of how this is accumulated and how it can be fostered. In this respect, the economics literature has lamented how vagueness around the definition of social capital has led to confusion about how social capital is measured and it is accumulated (Durlauf 2002). In particular, social capital is generally seen as a relational concept, so that its formation should depend on human and social interactions. However, different interpretations are given on the role of these interactions.

Some authors, such as Coleman (1988), consider primarily networks as the channel of transmission. In this literature, social capital is seen as the number of connections of an individual within the network. Along these lines, Woolcock (1998) distinguishes between different types of social capital depending on the strength of ties between people in the network. Bonding social capital denotes ties between immediately close people, such as family or close friends. Bridging social capital characterizes ties between similar, but not immediate, people, such as those belonging to the same community. Linking social capital connects people more dissimilar and outside the community, allowing network members to reach greater variety of resources. In the economics literature, this interpretation is criticized for lacking an appropriate theory of investment and depreciation needed for social capital to be considered as "capital" (see Solow 1995 and Durlauf 2002), but also for its limits to explain the historical persistence of social capital (see Guiso, Sapienza, and Zingales 2011).

Other authors consider social capital as those intangible features, such as norms, values, trust, beliefs, and shared identity, forming the basis of a community. These cultural traits are passed within an intergenerational framework, where parents decide which values to pass onto their heir strategically and depending on their perception of the external environment. In equilibrium, this process generates path dependence, reinforcing favorable or unfavorable initial conditions, and determining economic development through better institutions (Tabellini 2008). This theory provides a process of investment in social capital and is able to explain the historical persistence of cultural traits. The accumulation or decumulation of social capital may depend on positive or negative historical events, whose effects are replicated over time by the intergenerational process of transmission.

In this interpretation of social capital, refined into the narrower concept of civic capital, what matters is not simply how an individual acquires civic capital, but how the community does (see Guiso, Sapienza, and Zingales 2008, 2011). While the above literature stresses the role of space in terms of social interactions within the community, the robust empirical evidence on the ability of social capital to explain regional differences in development calls for further investigation into the spatial dimension of social capital and in particular its spatial diffusion. Along these lines, Durlauf and Ioannides (2010) and Blume et al. (2010) discuss the parallels between the social interaction models and spatial econometrics models, calling for further integration between the two. Such integration may also lead to integrating the network theory and social values and beliefs theory of social and civic capital.

The role of space for the diffusion of social capital can be theorized in a number of ways. In particular, the set of cultural traits defining social norms, values, and beliefs will also be transmitted through networks. To the extent that the formation of cultural traits will depend on human interactions, the strength of these ties will depend on transaction costs, which are typically directly related to distance (see Westlund 1999). As a consequence, Rutten, Westlund, and Boekema (2010, 869) argue that "*to the extent that social relations are spatially sticky, so are norms and values*."

Rutten, Westlund, and Boekema (2010), further, underline how agglomeration forces also imply a concentration of people with more similar cultural traits. Moreover, they highlight how preserving ties over long distances requires benefits to be large and maintained over time. Ties at shorter distances can be maintained also in the presence of smaller benefits, so that proximity should imply denser social relations and transmission of cultural values. Interestingly, they also note how the spatial dimension of social capital requires consideration for both "space" and "time."

According to Westlund, Rutten, and Boekema (2010), the relationship between space and social capital can occur in a horizontal continuous space marked by distance, a horizontal discontinuous space marked by borders, and a hierarchical space with discontinuities due to multiple levels of markets and governance. This particular interpretation allows a role for geography in mapping values and beliefs across communities as a function of proximity. Hence, the interest for assessing the relationship between space and cultural ties and monitoring this relationship over time.

Along these lines, this article focuses on the role of space for the spatial diffusion of social capital. Specifically, we investigate the extent of spatial association of "generalized trust," one of the fundamental cultural traits identified by Guiso, Sapienza, and Zingales (2011) and Tabellini (2008, 2010) for economic development. Generalized trust is in sharp contrast with the "amoral familism" of Banfield (1958), where optimistic and selfish behavior are considered moral outside the restricted network of family and friends. In agreement with Weber (1905), who sees the diffusion of generalized morality as a prerequisite for the emancipation from a feudal to a democratic society, Guiso, Sapienza, and Zingales (2006) point out that individuals with high "personalized" trust (i.e., trusting only selective persons or institutions) are more likely to free ride on others.[2] Moreover, the trusting attitude and trustworthiness of a community and the trust between communities, more than other cultural traits, rest on economic and social relations built over time.

In this article, the relationship between space and generalized trust is assessed by employing both static and dynamic spatial exploratory data methods (exploratory space data analysis [ESDA] and Exploratory Space–Time Data Analysis [ESTDA]) over a measure of "generalized trust" for the nomenclature of territorial units for statistics 2 (NUTS 2) regions of Europe.[3] This kind of analysis allows investigating the role of proximity for the diffusion of trusting attitude along more dimensions. First, it allows assessing the extent of spatial association of such attitude. Second, it allows incorporating both time and space into the spatial diffusion of social capital by investigating the time persistence of the spatial stickiness of a social value like generalized trust. Focusing on proximity and controlling for national effects, we are also able to assess the discontinuities and hierarchical structure theorized by Westlund, Rutten, and Boekema (2010). The identification of regional transitions also allows comparing the regional economic features of regions changing their spatial trusting attitude. Finally, a spatial Markov analysis allows assessing the distribution of trust across regions and changes in such distribution, conditional on the distribution of trust in neighboring regions. Such space–time analysis helps assessing the regional "spatial path dependence" of generalized trust.

This analysis may have interesting implications for the debate on regional development. To the extent that generalized trust is an important determinant of growth, the clustering of regions with high levels of trust and regions with low levels of trust may favor the formation of clubs of convergence toward better or worse economic equilibria. At the regional level, the spatial stickiness of values and beliefs may imply that while "trust abundant" regions surrounded by similarly "trust abundant" regions will tend to strengthen their position, "poorly trusting" regions next to other "poorly trusting" regions may end up stuck in a "spatial social capital trap."[4]

The rest of the article is organized as follows. The next section introduces the related theoretical and empirical literature on social capital and trust. The third section describes the data and illustrates the intensity of generalized trust of European regions. The fourth section presents the methodology and the fifth section discusses the results. The final section draws some concluding remarks from the analysis.

Related Literature

Social Capital, Trust, and Development

Following the early contributions of Banfield (1958), Coleman (1988), and Putnam (1993), a growing body of literature has considered social capital in general, and trust in particular, as critical for economic development and growth. In this literature, generalized trust is seen as a complementary factor endowment (Fukuyama 1995) that not only lowers transaction costs but also allows transactions otherwise impossible, even in the presence of an advanced legal system. Hence, societies endowed with a higher level of trust require lighter legal systems (Aghion et al. 2010). According to Cersosimo and Nisticò (2008), trust acquired in social relations is the foundation of social capital.[5]

The empirical literature investigates the impact of social capital and trust for economic development at both the country and regional level. For example, in country-level studies, Knack and Keefer (1997) and Zac and Knack (2001) use survey-based measures of social capital, in terms of trust, civicness, and associational membership, finding a positive impact of trust and civicness, but not membership, on growth.[6] La Porta et al. (1997) find that greater trust increases judicial efficiency and reduces government corruption, two key institutional determinants of growth. Guiso, Sapienza, and Zingales (2004) associate social capital to international economic exchanges.

At the regional level, given the importance of human interactions for its accumulation, social capital can be likened to the "second nature" advantages of geography, such as agglomeration externalities, emphasized by the recent contributions in new economic growth, new economic geography, and evolutionary economic geography theories. According to this literature, these advantages will be stronger at the regional rather than national scale (Glaeser, Kallal, and Scheinkman 1992) because of the greater ease of information, ideas, and knowledge exchange between agents due to proximity.

In his seminal contribution, Putnam (1993) argues that social capital, intended as the extent of civic engagement in the community, enhances the quality of institutions, which in turn determine growth. Differences in social capital are considered as the main determinant of the different development of Southern and Northern Italian regions (Putnam, Leonardi, and Nanetti 1993). Beugelsdijk and van Schaik (2005) investigate fifty-four NUTS 1 Western European regions and find that regional growth differentials are positively related to social capital measured in terms of associational activity using data from the 1990 European Values Study (EVS). They also underline that it is the intensity of involvement in network relationships that stimulates regional economic growth.[7]

De Dominicis, Florax, and de Groot (2013) construct a measure of social capital as the principal component of indicators of opinion leadership, daily newspaper readership, life satisfaction, and trust taken from the Eurobarometer. They find evidence that both social capital and geographical proximity are important determinants of European regions' innovative output. Basile, Capello, and Caragliu (2011) find empirical evidence of the importance of social proximity for knowledge spillovers.

Defining and Measuring Social Capital and Trust

Given the strong evidence on the positive effects of social capital and trust, understanding how they are accumulated is particularly important. This, however, requires an operational definition of social capital. As mentioned above, the literature is, unfortunately, far less unanimous when it comes to defining and, hence, measuring social capital. Traditional measures of social capital are complicated by measurement errors and by a general lack of reliable information (Durlauf 2002). Solow (1995) highlights in particular how, in order to be considered as "capital," social capital needs a process of accumulation (investment) or decumulation (depreciation) and it needs to be comparable across communities (countries/regions).[8]

According to economic theory, this process of investment is intergenerational (i.e., vertical transmission): individuals acquire preferences relevant for their economic outcomes, and critical beliefs about the world, from their parents and from socialization (i.e., oblique transmission, see Bisin and Verdier 2000; Bisin, Topa, and Verdier, 2004). Along these lines, Tabellini (2008) considers social capital as the set of cultural traits of an individual, or a community, which can "*affect economic development both directly, or indirectly through better functioning institutions*." These cultural traits are transmitted within an intergenerational framework, where parents strategically decide which values to pass onto the heir depending on their perception of the external environment. This strategic complementarity is critical to understand how some communities may end up in low-trust equilibria and others in high-trust equilibria. If parents believe that others are not trustworthy, they will teach their children that you can never be too careful, otherwise they will pass the belief that most people can be trusted. This process generates path dependence, reinforcing favorable or unfavorable initial conditions, and can explain the strong historical persistence of cultural traits and development: events occurred centuries ago, may influence current social capital and current regional differences in economic development, even under the same formal institutions (Tabellini 2010). In this direction, along the lines of Putnam (1993), Guiso, Sapienza, and Zingales (2006, 2008) concentrate on the narrower concept of "civic capital," defined as "*those persistent and shared beliefs and values that help a group overcome the free rider problem in the pursuit of socially valuable activities*." Guiso, Sapienza, and Zingales (2011), further, explain how this definition fits the requirements of Solow (1995) and can easily be incorporated in the model of Tabellini (2008). Importantly, unlike other capitals, such as human capital, civic capital is the result of a social process of investment and requires individual values and beliefs to be shared by other members of the community. Over time, this process determines the "civicness" of a community. Building on this definition of social capital, Tabellini (2010), argues how over the course of history these cultural traits help shaping not only formal institutions at the national level but also informal ones at the local or community level. In turn, this process may help explaining different economic outcomes even under the same formal institutions. Such perspective is particularly interesting in a regional setting, as it may help explaining why some communities decumulate social capital and end in underdevelopment, while others accumulate social capital and prosper. Empirically, Tabellini (2010) provides evidence of the role of these cultural traits for the economic development of Western European NUTS 1 regions. Given its formalization within an explicit economic theory and its implications for the longterm persistence of development and underdevelopment, here we concentrate on civic capital and consider generalized trust as its fundamental component.

In measuring social capital and trust, the literature has mostly adopted three approaches: outcome-based measures, experiments, and surveys.[9] For example, in agreement with his theory of social capital, Putnam (1993) proxied the attitude toward cooperation, social behavior and free riding, civic awareness, and civic engagement with the number of local cooperatives and the participation in nonprofit organizations, tax compliance, littering, and queuing. In agreement with Putnam's theory of social capital, early studies used mostly measures of associational density. These were then extended depending on data availability to include other variables, such as voluntary work, political participation, census turnout, crime rates, teenage pregnancies, and blood donations. However, this approach has been criticized on the grounds that social capital is already present whenever one tries to measure it through the outcome-based approach (DiPasquale and Glaeser, 1998).

Social capital and trust can also be measured in the controlled environment of laboratory experiments. These are relatively cheap and probably allow more accurate measurement of the type of trust one intends to consider. However, they may lack external validity (Glaeser et al. 2000) and their results may not be easily extended outside the experiment. Levitt and List (2007) also suggest that when in the laboratory, individuals may modify their behavior and respond in order to please the experimenter. Last, but not least, many studies have employed surveys to measure social capital. The survey-based approach has found extensive applications, especially in economics (see, e.g., Alesina and La Ferrara 2002; Glaeser, Laibson, and Sacerdote 2002). Surveys, such as the World Values Surveys (WVS) and the EVS are also used by Guiso, Sapienza, and Zingales (2004, 2006, 2008) and Tabellini (2010) to match the definition of civic capital we borrow in this study. Like the others, this approach is not free from criticisms, as doubts are raised about the way people respond or interpret questions, potentially leading to measurement errors. These errors are likely to be correlated with individual characteristics, a problem that is probably mitigated when data are aggregated.

Surveys, however, also present considerable advantages. They provide direct measures of trust readily available for a large number of countries and regions, satisfying Solow's requirement in terms of comparability. Similarly, major surveys are now available for a number of waves, allowing comparability over time. For these reasons, and given the purposes of this article, here we rely on survey data to measure trust at the regional level. In line with the theory of civic capital, and for the reasons illustrated in the introduction, we consider, in particular, generalized trust or trust toward the others in general.

The Role of Space on Social Capital Formation

Rutten, Westlund, and Boekema (2010) highlight how the interpretation of social capital in terms of social norms, values, and beliefs, which are generated through social interactions, allows an extension of the role of space for social capital. They underline, in particular, the role of geography in terms of distance: shorter distances imply lower costs of interaction, so that denser social relations will be easier at close proximity. Further, agglomeration forces will tend to concentrate people who have greater scope for cooperation. While proximity will be necessary to sustain weak ties, social relations at greater distance will be sustained only if benefits are large and maintained over time. For this reason, they underline the importance of considering the spatial dimension of social capital also along the time dimension. We would also add that, since social capital and trust require investment in relationships, proximity may reduce the informational costs of this investment. Westlund, Rutten, and Boekema (2010) discuss three possible approaches to the relationship between space and social capital: a horizontal continuous space, where social relations diminish with distance in a not necessarily linear way, a horizontal space where borders introduce discontinuities in the transmission of social capital, and a hierarchical space where discontinuities are due to the presence of multiple levels of markets and governance. Barriers and discontinuities should promote bonding social capital but limit the formation of bridging social capital. The existence of hierarchies should imply that the civic capital of a community may depend on the influence of international, national, and regional factors.

LeSage and Ha (2012) consider migration as a possible channel through which geography can influence social capital. They underline how the relational nature of social capital often leads researchers to consider it as a place-based phenomenon. For this reason, the role of migration has been often ignored (among the others by Putnam 2000). LeSage and Ha argue, on the other hand, that migration may involve members of a society with higher levels of human capital and higher propensity to participate in social and civic organizations. If migrants maintain these attitudes, they are likely to change positively the social capital of their community of destination. At the same time, however, it implies that considering social capital as place-based is too simplistic. In their interpretation, geography may, again, play a role in terms of distance: while close migration should be consistent with maintaining strong ties, far migration should imply weak ties. In terms of trust, longer distance migration may also imply that the destination community is also culturally more distant making migrants less trusting. The opposite would be true for close-distance migration. LeSage and Ha consider a social capital index, based on associational density and civic participation, for US counties and apply spatial regression methods to investigate the impact of migration on social capital. They find evidence of a positive effect of migration on social capital, concluding that social capital cannot be considered just as place based.

Generalized Trust in European Regions

As mentioned above, following Guiso, Sapienza, and Zingales and Tabellini, we rely on survey data to measure generalized trust. The most comprehensive and widely used international social surveys are the WVS, the EVS, and the European Social

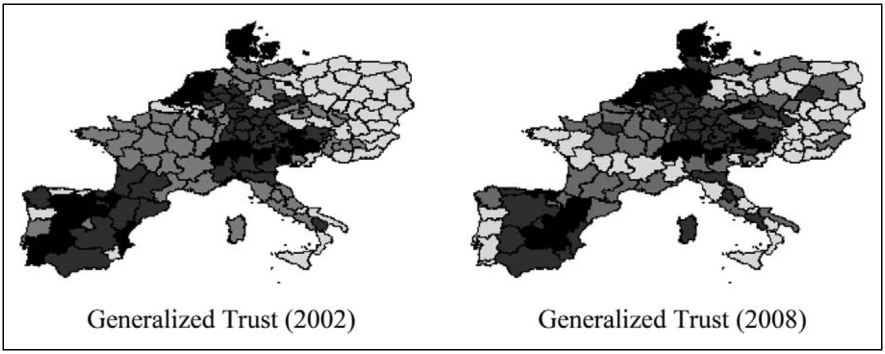

Figure 1. Spatial distribution of trust. *Note*: These figures present the quartiles distribution of Generalized Trust at the NUTS-2 level, with darker colors indicating higher levels of trust. Data for Italy and Luxembourg in 2008 are from the 2004 wave.

Survey (ESS). However, compared to the other surveys, the ESS allows greater precision in the calculation of the regional trusting attitude and intensity. Unlike other surveys where trust is a dichotomous variable, the ESS expresses trust using values between 0 and 10. Moreover, the sampling stratification of the ESS seems to guarantee more representativeness at the intranational NUTS-2 level than other surveys. Please refer to the data Appendix for further details.

Following the standard convention in the literature to measure generalized trust, we specifically exploit question A.8 of the "core" section of the questionnaire that is present in all four rounds of the ESS considered here (2002, 2004, 2006, 2008):

> Using this card, 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.

The regional measure of "generalized trust" is constructed, using survey weights, as the weighted average of responses to the above question for the 182 NUTS 2 regions of sixteen European countries. The use of weighted data mitigates some of the problems affecting survey data, as reported by Faiella (2010). The NUTS 2 level is convenient since it provides greater geographical disaggregation and because most EU policies are framed at this level. The data can be directly downloaded from the ESS website.[10]

Figure 1 presents the regional intensity of generalized trust for the 2002 and 2008 waves of the ESS (see data Appendix), with darker colors denoting regions where citizens are more trusting toward the others. Interesting indications come from these pictures. First, generalized trust seems unevenly distributed across European regions. Denmark, Belgium, the Netherlands, and Switzerland seem to be, overall, the countries with the highest levels of trust. Central-Eastern Europe and part of Italy are dominated by low-trust regions. It is worth noting, however, that differences in the level of trust do not just emerge across countries but also within countries (intranationally). Further, both clusters of regions with high levels of trust and clusters with low levels of trust seem to emerge. Again, these are both intranational and international. This is particularly evident by looking at France, Germany, Italy, Spain, and Portugal. This pattern confirms the idea that communities tend to share values with their neighbors. To some extent, this regional dimension seems to overcome the national dimension, as regions share common values also across national borders. This evidence corroborates the view that disaggregating the data at the regional level may yield interesting information, otherwise hidden at the national level.

Generally, regions with high (low) levels of trust tend to be located closer to other regions with high (low) levels of trust. While this spatial pattern seems stable over time, some changes in trusting attitude can also be spotted. This issue is going to be investigated later in the article.

Methodology

Spatial Association

In order to assess the degree of regional spatial association of "trust," we first employ basic ESDA techniques. In particular, we first compute a simple global spatial statistic, such as the Global Moran's I (see Anselin 1995):

$$I = \frac{\Sigma_i \Sigma_j w_{ij}(x_i - \bar{x})\ \left(x_j - \bar{x}\right)}{m_2 \Sigma_i \Sigma_j w_{ij}}, \tag{1}$$

where $w_{ij} = 1$, if region i is contiguous to region j, and vice versa; $\bar{x}$ is the average and $m_2 = \Sigma_i (x_i - \bar{x})^2 / n$ is the second moment of the target variable, x_i. Contiguity in equation (1) can be either "queen contiguity," that is, where two regions are considered "neighbors" if they share at least one border or a vertex, or "rook contiguity," that is, where only shared borders are considered. Elements of the weighting matrix are row standardized.[11] Moran's I gives a first measure of the overall degree of linear association between variable x and the neighboring regions' values of x, indicating whether the observed spatial pattern is clustered, dispersed, or random. Generally, values of Moran's I closer to $+1$ indicate stronger positive spatial autocorrelation, or clustering, values closer to -1 stronger negative spatial autocorrelation, or dispersion.[12]

In a second step, we calculate the local indicators of spatial association (LISA), which allow the decomposition of Global Moran's I, and consider the graphic counterpart, that is, the Moran's scatterplot (see Anselin 1993, 1996). Local Moran's I for observation i may be defined as:

$$I_i = \frac{(x_i - \bar{x})}{m_2} \sum_j w_{ij} \left(x_j - \bar{x}\right). \tag{2}$$

Clearly, Local Moran's I and Global Moran's I are linked, as shown by Anselin (1995), who proves that the sum of Local Moran's I is proportional to Global Moran's I; the numerator of equation (1) is the sum of equation (2) across i, while the denominator is equal to the factor of proportionality γ:

$$\gamma = m_2 \sum_i \sum_j w_{ij}. \tag{3}$$

Moran 's scatterplot (see Anselin 1993) cross-plots the values of variable X of a region against the values of X spatially weighted by contiguity, WX, according to the position on the four quadrants identified by the averages of X and WX. The position of each region can be determined with respect to its level of variable X and the weighted average of X for its neighbors. Four positions are possible: in the I quadrant (North–East, High–High [HH]) are located regions with high values of X surrounded by neighbors with high values of X; in the II quadrant (North–West, Low–High [LH]) are located regions with low levels of X surrounded by neighbors with high values of X; in the III quadrant (South–West, Low–Low [LL]) are positioned regions with low levels of X surrounded by neighbors with similarly low levels of X; finally, in the IV quadrant (South–East, High–Low [HL]) are found regions with high values of X surrounded by neighbors with low values of X. Under positive spatial association, the mass of points will be concentrated on quadrants I and III (HH and LL). The slope of the linear interpolation of the points on a Moran's scatterplot is the Global Moran's I.

ESTDA

The ESDA analysis gives a static representation of the degree of spatial association of our variable of interest. As mentioned above, however, important questions arise with respect to the spatial dynamics of trust and the probability of spatial change, that is, regions changing their trusting attitudes in relation to the trusting attitudes of neighbors. Hence, we further perform an ESTDA. Formally, following Rey (2001), Rey, Murray, and Anselin (2011) and Sastré-Gutiérrez and Rey (2010), the LISA for location i at time t is:

$$L_{it} = \frac{z_{it} \sum_j w_{ij} z_{jt}}{\sum_i z_{it}^2}, \tag{4}$$

where z_{it} is the value of our target variable at location i at time t, expressed in terms of deviations from the mean. The approach can be best understood by looking at the trusting attitude of regions and their neighbors in successive Moran scatterplots, that is, the transitions of points between the four quadrants of HH, HL, LH, LL spatial combinations of trusting attitude, as represented in Figure 2. Changes in the neighboring regions level of trust with no changes in regional values will be reflected in vertical shifts from quadrants II to III or from I to IV, and vice versa. Changes in regional values of trust with no changes in

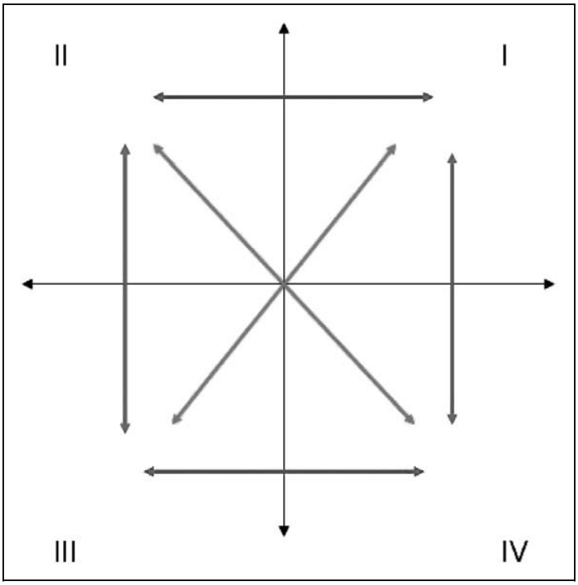

Figure 2. Interpretation of transitions.

neighboring regions' values will be reflected in horizontal shifts, from quadrant II to I or from IV to III, and vice versa. Instead, changes in the trusting attitude of a region and its neighbors will be associated with movements from I to III and II to IV.

These transitions can be associated with a matrix of Markovian probabilities, P^n, where the ijth entry, $p_{ij}^{(n)}$, gives the probability that the Markov chain starting in state i will be in state j after n steps. Each element of the matrix will give the probability of a movement type associated with the possible transitions between quadrants of the Moran's scatterplot. Values on the main diagonal of this matrix will indicate the probability of no spatial change. Off-diagonal values will reflect the probability of regional spatial change. Later, we will use these movement types to classify regions into regions improving their level of generalized trust in relation to their neighbors, regions worsening their level of trust, and regions maintaining their levels of generalized trust. This information will be used to compare regions in terms of a set of regional variables and investigate whether regions improving/worsening their trust levels experience similar macroeconomic conditions.

The ESTDA can be extended to consider spatial Markov transition probabilities conditional on neighbors belonging to different quartiles of the distribution of trust. This allows taking further into account the role of space and investigate whether the spatial stickiness of trust is greater if a region is surrounded by very low-trusting regions rather than very high-trusting regions.

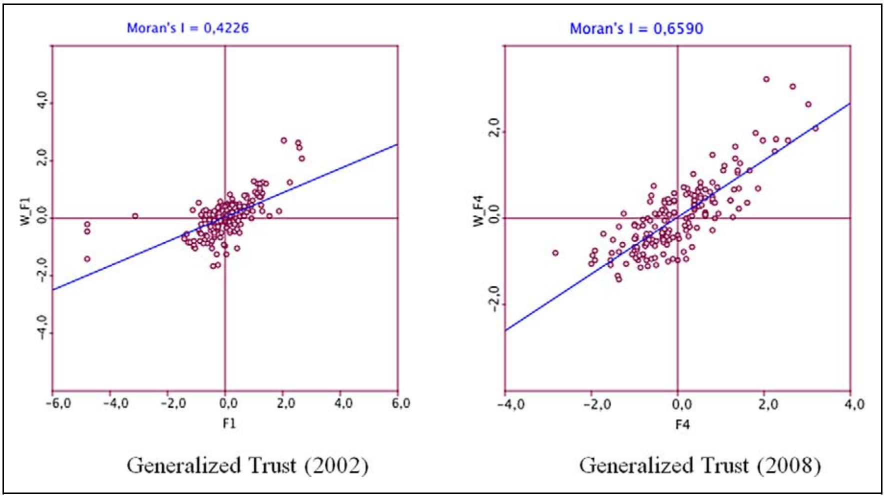

Figure 3. Moran scatterplots. *Note*: These figures present the Moran scatterplots of Generalized Trust. Data for Italy and Luxembourg in 2008 are from the 2004 wave.

Results

LISA Analysis

Figure 3 presents Moran scatterplots for the regional measure of "generalized trust."[13] These clearly show a degree of positive spatial association of regional trust levels, as it is evident from the large number of observations along the LL to HH direction and from the Moran's *I* statistics, increasing from around 0.42 in 2002 to 0.65 in 2008.[14] Interestingly, the degree of spatial association seems to increase over time, indicating a (positive or negative) contagion of trusting attitudes across regional borders.

Figure 4 further illustrates such degree of spatial association, by providing a geographic representation of the Moran's scatterplot. The figure highlights a number of LL (mostly in the Center-Eastern European countries and the Center-Southern Italy) and HH (mostly in the Center and North of continental Europe) clusters of trust. Interestingly, these clusters of regions lie both within the same country (e.g., Denmark or Italy) and across national borders (e.g., between the Netherlands and Belgium or France and Switzerland, the North of Italy, and Switzerland in 2002), indicating that the "forces" of regional proximity may be stronger than those of national borders, which in broad terms may include formal institutions and national cultural identity. This evidence, again, validates the initial quest for investigating the regional dimension of social capital. Interestingly, these clusters seem to be persistent over time. We further explore this issue in the next section.

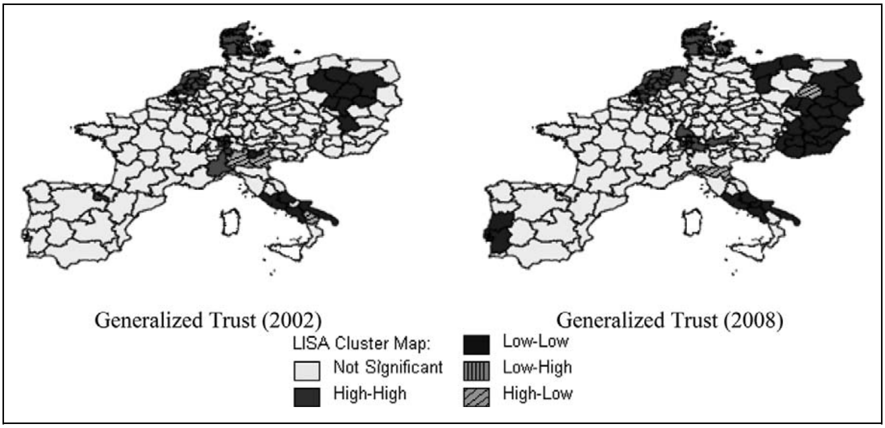

Figure 4. Spatial clusters. *Note*: These figures present the LISA cluster maps of Generalized Trust. Data for Italy and Luxembourg in 2008 are from the 2004 wave. LISA = local indicators of spatial association.

Space–Time Data Analysis

LISA Transition Probabilities. The above analysis identifies the presence of clusters in the trusting attitude of citizens across European regions in a given point in time. Given the importance of trust for economic growth and development, it may be important to assess how the evolution of trust in a region is influenced by the evolution of trust in neighboring regions. Hence, as a next step, we assess how regional trusting attitudes change over time conditional on proximity. In order to investigate this issue, we compute the LISA transition probabilities both unconditional and, in the next subsection, using a spatial Markov approach, conditional on the distribution of neighbors values. Further, we apply two types of controls to the analysis. First, we account for the possibility that trusting attitudes may change over time (thus across waves of the ESS) simply because of common time effects, such as positive or negative shocks affecting all regions alike (e.g., booms or busts in the global or European economic cycle). Second, we control for effects that are common to regions within a country, generally associated with the national border (e.g., national identity, formal institutions, etc ...). From the methodological standpoint, these controls are easily performed by replicating the standard analysis after "filtering" out wave and country effects. This can be achieved by taking the residuals of regressions of regional trust on wave and country dummies, as follows:[15]

$$x_{it} = \alpha_0 + \alpha_t \delta_t + \varepsilon_{it},$$

$$x_{it} = \alpha_0 + \alpha_i + \alpha_t \delta_t + \upsilon_{it},$$

where δ_t are wave-fixed effects, α_i are country-fixed effects, and ε_{it} and υ_{it} are the usual disturbances.

Table 1. LISA Transition Probabilities (2002–2008).

	No controls				Wave controls				Country and wave controls			
	HH	LH	LL	HL	HH	LH	LL	HL	HH	LH	LL	HL
HH	0.75	0.09	0.04	0.12	0.85	0.05	0.04	0.07	0.47	0.16	0.15	0.21
LH	0.17	0.67	0.16	0	0.23	0.50	0.25	0.02	0.26	0.38	0.29	0.07
LL	0.02	0.10	0.75	0.12	0.05	0.06	0.80	0.08	0.18	0.18	0.48	0.15
HL	0.13	0	0.17	0.70	0.30	0.06	0.32	0.32	0.32	0.08	0.30	0.30
Ergodic	0.27	0.17	0.32	0.24	0.45	0.10	0.36	0.09	0.31	0.20	0.31	0.18

Note: LISA = local indicators of spatial association; HH = High–High; LH = Low–High; LL = Low–Low; HL = High–Low.

In order to better capture the spatial dynamics of trust, we increase the temporal dimension to the four waves of the ESS. Unfortunately, this implies dropping for this part of the analysis two countries (Luxembourg and Italy), reducing the number of regions from 182 to 161 (see the data Appendix for further details).

Table 1 presents the LISA transition probabilities together with the ergodic probabilities. The latter refer to the steady state probability for a regular transition matrix and indicate whether the process has reached an equilibrium state. Also, they give an indication about how likely a transition is in the long run. The analysis is replicated for the data without controls and after controlling for wave effects and wave and country effects. This allows us to gauge the role of country effects beyond that of wave effect. Some results are worth mentioning. First, looking at the LISA probabilities without controls, we note the high probabilities on the main diagonal, indicating a high degree of spatial "stickiness." In general, there is very little probability of spatial change: regions with high (low) levels of trust will sit next to regions with high (low) levels of trust. This is also confirmed by the higher ergodic probabilities associated with the HH and LL columns. Very small probabilities are associated with spatial change, that is, off-diagonal elements of the matrix. Results are largely similar when we control for wave effects. Probabilities on the main diagonal are always larger than probabilities off-diagonal. There is a moderate increase in the probabilities associated with the main diagonal of the Moran scatterplot, that is, staying in HH or LL, and a moderate decrease in the probabilities associated with the secondary diagonal of a Moran scatterplot, that is, staying in LH or HL, indicating that these regions are now more likely to be in transition. With respect to the substantial increase in off-diagonal probabilities, it seems that starting from a position such as LH, a region is more likely to stay in LH or, alternatively, equally likely to become a high-trusting region (move to HH) or see a decline in the neighbors' trust (move to LL). If a region is in HL, it faces similar probabilities of staying in HL, of becoming less trusting (LL) or seeing neighbors become more trusting (HH). In all cases, controlling for wave effects, off-diagonal probabilities are always smaller than the long-run steady state, as indicated by the ergodic probabilities. Interestingly, controlling for both wave and country effects seems to dramatically reduce probabilities on the main diagonal, increasing the probability of spatial change (the off-diagonal elements). In some instances, these probabilities are larger than the ergodic steady state probabilities. This result implies that controlling for the effects of national borders, the possibility of spatial change substantially increases. In other words, national borders (and the forces they synthesize) seem to apply some degree of resistance to regional spatial change. Removing their effect reduces the probability of staying in the same cluster. However, this effect is at work not only on HH clusters but also on LL clusters. While the first can be considered a positive effect of national borders, the second clearly is not. From a European integration perspective, national borders seem to prevent the spreading of similar values and beliefs, and trust in this example.

In light of the importance of social capital and trust for regional economic development, it may be interesting to look at some of the macroeconomic features of regions making a spatial transition in the observed period, investigating in particular whether regions improving their levels of trust have different features from regions maintaining or losing trust. Clearly, a full investigation of the causes of spatial changes in trusting attitude requires consideration that goes beyond the scopes of this article. Interesting preliminary evidence, however, may be extracted by a simple descriptive statistical analysis.

In this direction, we first group regions by considering their type of movement, or transition, in the LISA-transition analysis for successive Moran's scatterplots. Within this framework, regions moving from the II (LH) or III (LL) quadrants to the I (HH) and IV (HL) quadrants can be considered as positive spatial trust movers who become more trusting. Regions moving in the opposite directions from quadrants I (HH) and IV (HL) to quadrants II (LH) and III (LL) are negative spatial trust movers who become less trusting. In all other cases, neighbors may change (e.g., vertical movements along the III–II direction and the IV–I direction), but regions are static over time and do not change their spatial position, remaining equally trusting. Hence, we group regions identified by the LISA-transition analysis into regions becoming more trusting, less trusting, or remaining equally trusting.

We then pool all transitions made between 2002 and 2004, 2004 and 2006, 2006 and 2008, and compare the macroeconomic features of regions making a positive, negative, or no transition, each time in reference to the rest of the sample, on the grounds of mean comparison tests of a set of variables extracted from the Eurostat Regio database. The set of variables is chosen upon both theoretical considerations and data availability issues and includes per capita gross domestic product (GDP) growth, changes in unemployment rate, changes in female and male unemployment, investment as a share of GDP, investment in research and development per inhabitant, variation in population in tertiary education, variation in reported mortality rates (crude death rate), changes in tourism arrivals. In principle, we would expect regions that have made the transition to higher trust levels to have experienced higher growth, lower unemployment, higher overall investment, higher investment in research and development and in human capital, as captured by the higher share

Table 2. Regional Macroeconomic Features and Spatial Trust Transitions Mean Comparison Tests.

	More trusting		Less trusting		Equally trusting	
Variable	Contrast	*SE*	Contrast	*SE*	Contrast	*SE*
Change in (log) of GDP per capita	0.016*	0.006	−0.003	0.005	−0.008	0.004
Change in unemployment rate	−0.301*	0.134	0.219	0.125	0.027	0.103
Change in female unemployment rate	−0.417*	0.148	0.172	0.139	0.129	0.114
Change in male unemployment rate	−0.212	0.139	0.266*	0.131	−0.053	0.107
Investment (as percentage GDP)	−0.088	0.287	0.338	0.278	−0.158	0.220
Investment in R&D per inhabitant	0.0429	0.0241	−0.0247	0.0223	−0.0084	0.0190
Change in (log) tertiary education	0.0146	0.0107	−0.0053	0.0099	−0.0051	0.0083
Change in (log) mortality	−0.0004	0.0021	−0.0012	0.0019	0.0011	0.0016
Change in (log) tourism arrivals	0.012*	0.005	−0.006	0.005	−0.002	0.004

Note: GDP = gross domestic product.
This table reports mean comparison tests of regional macroeconomic variables for regions grouped depending on their movement type across waves of the European Social Surveys. Variables are average changes over the year of transition (Δx_t) and the year preceding the transition (Δx_{t-1}).
*Denotes 5 percent significance level.

of people involved in tertiary education, lower mortality rates, and more tourism arrivals. The unemployment rate can be further separated into male and female unemployment to investigate where there are gender effects. Even though we expect more trusting regions to experience less unemployment in general, a reduction in female unemployment may be associated with greater improvements in the level of trust in society, compared to a reduction in male unemployment. Indeed, the greater employability of females could be associated with greater female emancipation (and the related decision to enter the job market) and less gender discrimination (a phenomenon in contrast with generalized trust).

Table 2 reports simple mean comparison tests for these variables across the three groups of regions identified from the LISA-transition analysis. This descriptive analysis returns interesting results that corroborate the importance to look at the relationship between trust and proximity. Indeed, we are able to identify how regions improving their spatial trust attitude also experience higher growth, reduced unemployment, and greater tourism flows. Interestingly, the reduction in unemployment is related to lower female unemployment and not male unemployment. This evidence could suggest potential gender effects on the evolution of social capital, a potentially interesting future line of research.

Next, we calculate Markov transition probabilities conditional on neighbors belonging to different quartiles of the distribution of trust.

Spatial Markov Transition Probabilities. Table 3 presents the spatial Markov transition probabilities conditional on the spatial distribution of trust, that is, probabilities to

Table 3. Spatial Markov Transition Probabilities.

No controls								
	(a) Neighbors bottom 25 percent				(b) Neighbors top 25 percent			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Q1	0.72	0.19	0.05	0.05	0.39	0.50	0.05	0.05
Q2	0.2	0.43	0.31	0.05	0.17	0.54	0.25	0.04
Q3	0	0.28	0.56	0.16	0.04	0.21	0.57	0.18
Q4	0.07	0.07	0	0.86	0	0	0.19	0.81
Country and wave controls								
	(c) Neighbors bottom 25 percent				(d) Neighbors top 25 percent			
Q1	0.43	0.41	0.07	0.09	0.28	0.50	0.22	0.00
Q2	0.25	0.25	0.39	0.11	0.35	0.35	0.13	0.17
Q3	0.29	0.25	0.29	0.17	0.31	0.22	0.22	0.25
Q4	0.12	0.00	0.29	0.59	0.16	0.29	0.24	0.32

transit to different quartiles of the distribution of trust conditional on the neighbors' quartile in the distribution of generalized trust.[16] For brevity, we only report the results for the original data without controls and for the data after controlling for wave and country effects. Indeed, the above discussion has highlighted the importance of the country effects. Also, for brevity and to make results more intelligible, we only present probabilities conditional on neighbors being either in the top or bottom 25 percent of the distribution of trust. Results for the other quartiles of the distribution are available upon request from the authors.

Probabilities in panels (a) and (b) of Table 3 refer to data without any control. As before, the probabilities of staying in the same quartile are larger than the probabilities of changing quartile. This result applies to both cases when neighbors are in the bottom and in the top quartiles of the distribution of trust. Some differences are worth mentioning between panels (a) and (b). First, the probability of staying in the first quartile (being low trusting) almost halves from 0.72 to 0.39 across the distribution of neighbors, suggesting substantial spillover effects. Interestingly, if a region is in the first quartile, Q1, it is more likely to become more trusting (move to the next quartile, Q2) if neighbors are highly trusting. A similar result applies if a region sits in the second quartile of the distribution of trust. On the other hand, if you are a high-trust region in Q4, you are very unlikely to change your attitude, independently of your neighbors trusting attitude. This seems to suggest that it is very difficult for high-trust regions to lose their trust attitude. In other words, without controlling for wave and country effects, the spatial distribution of trust seems to matter, where high trust seems to be mostly a place-based belief.

In panels (c) and (d), we repeat the analysis after controlling for wave and country effects. We know from Table 1 that country effects are relevant when it comes to the spatial distribution of trust. In Table 3 we can see how, again, the probabilities on the main diagonal, indicating no spatial change, are substantially lower when taking into account the country effects. If neighbors are in the bottom 25 percent, it is now more likely to improve on the trusting attitude, as it is easier to move from Q1 to Q2 and from Q2 to Q3. However, it is also easier than before to see regions in Q4 moving to Q3. If neighbors are in the top 25 percent, it is now even more likely a change from Q1, improving the trusting attitude to Q2 and Q3, but it is also easier to see regions starting in Q3 and Q4 and lose trust to Q1 and Q2, respectively. In general terms, there seems to be a decay process in the transition probabilities along the trust distribution: unsurprisingly, with few exceptions, it is easier to transit to the next lower or higher quartile than to farther away quartiles. This resembles a sort of spatial path dependence phenomenon, where trust emerges as a slow changing attitude. Also, and importantly, low-trust states are more difficult to get out from, especially if your neighbors are also low trust, than high-trust states. Finally, country effects seem to increase the resilience to regional spatial change and to changes in trusting attitude. When they are controlled for, movements along the distribution of trust are more likely. One could say that national institutions help maintaining the trusting attitude of citizens. Unfortunately, this is true for both low and high levels of trust, that is, formal institutions seem to matter for both the good and the bad.

Conclusions

In this article, we have empirically investigated the role of proximity in shaping trust across regions. In particular, we have employed ESDA and ESTDA to investigate the degree of spatial association and space–time evolution of generalized trust, measured using a question from the ESS, for NUTS-2 regions of continental Europe.

A number of interesting results have emerged from the analysis. First, there is a degree of heterogeneity in the trusting attitude of the citizens of European regions. Differences in the level of trust arise both across countries (internationally) and within countries (intranationally). Similarly, clusters of regions with high levels and low levels of trust emerge both intranationally and across borders. Further, Moran scatterplots show that regional trust is characterized by positive, and increasing over time, spatial association.

Over time, the pattern of trust across European regions seems to be characterized by a strong persistence of spatial "stickiness" with low probability of spatial change: regions with high (low) levels of trust tend to stay next to regions with high (low) levels of trust. Interestingly, controlling for the effects of national borders, through country effects, increases the probabilities associated with spatial change. This provides evidence that national borders tend to increase the resistance to regional spatial change. This effect is at work not only on the resilience of high trust clusters, which may be a positive effect, but also on the resilience of low-trust clusters, which may be a negative effect. From a European integration perspective, this also implies that national borders still seem to be relevant in preventing a common European space of values and beliefs, and trust in this example.

Further, spatial Markov transition probabilities show substantial spillover effects in regional trusting attitudes: the probability of remaining low trusting almost halves if neighbors are high trusting. On the other hand, if you are a high-trusting region, at least in the short run, you are very unlikely to change your attitude, independently of your neighbors. In general terms, it seems possible to identify a decay of transition probabilities, or a sort of "spatial path dependence," along the trust distribution, as it is easier to transit to the next lower or higher quartile than to jump to farther away quartiles. Trust, after all, is a slow changing attitude and requires time to be built. Importantly, it is more difficult to exit a low-trust state, especially if your neighbors are also low trust, than to exit a high-trust state. Finally, country effects make spatial changes in regional (low or high) trusting attitudes more difficult, probably because they help maintaining the national trusting attitudes of citizens. Unfortunately, this is true for both low and high levels of trust, indicating that formal institutions matter in both the good and the bad sense.

In general, disaggregating trust at the regional level does seem to yield interesting information, otherwise hidden at the national level. From the policy standpoint, the existence of regional clusters of trust and their persistence over time may be a further obstacle to convergence, especially for poorly trusting regions trapped in poorly trusting surroundings, or "spatial traps of social capital." To the extent that social capital and trust are important determinants of development, regional policies should also take stock of this issue. Policies aiming at fostering trust should be enacted at different levels. At the regional level, they should reinforce those institutions that allow the accumulation of social capital and trust, such as schools, and encourage social interactions, such as the participation to civic organizations. Policies at the national level should try to foster shared common values and ensure the even distribution of the quality of formal institutions across regions, especially those needed for the respect of economic and social contracts. Finally, recalling that the NUTS 2 level considered here is also the one of interest for European regional policies, these could aim at making regions more "open" in terms of economic, institutional, and cultural exchanges, as greater "dialogue" between neighboring European regions may enhance the building of trust relationships. Future work could pursue a more thorough analysis of the determinants of regional trusting attitudes and identify more appropriate policies to break the vicious circles of low-trust clusters.

Data Appendix

The data used to measure generalized trust are based on question A8 from the four waves of the European Social Survey (ESS) available at the time of writing. Other international value surveys available are stratified at the country and not at the regional level, so that problems of representativeness may arise. In the ESS,

Table A1. ESS Data Availability and NUTS Representativeness by Country and Wave.

Country	2002	2004	2006	2008	Country	2002	2004	2006	2008
Austria	2	2	2[a]	n.a.	Luxembourg	3	3	n.a.	n.a.
Belgium	1	1	1[a]	1[a]	The Netherlands	3	3	3[a]	3[a]
Czech Republic	3	3	n.a.	2[a]	Poland	2	2	2	2
Denmark	3	3	3[a]	2[a]	Portugal	2	2	2	2
France	1	1	1	1[a]	Slovakia	n.a.	3	3[a]	3[a]
Germany	1	1	1[a]	1[a]	Slovenia	3	3	3[a]	3[a]
Hungary	2	2	2[a]	2	Spain	2	3	2[a]	2
Italy	2	2	n.a.	n.a.	Switzerland	2	2	2[a]	2[a]

Note: NUTS = nomenclature of territorial units for statistics.
This table reports the availability of data in the European Social Survey (ESS).
[a]Denotes when the NUTS representativeness is declared in the ESS documentation.

Table A2. Generalized Trust Descriptive Statistics (Data Set A).

				Quantiles				
Wave	*n*	*M*	*SD*	Minimum	.25	Median	.75	Maximum
2002	161	4.72	0.75	3.27	4.24	4.66	5.05	7.21
2004	161	4.73	0.75	2.86	4.24	4.80	5.11	6.90
2006	161	4.82	0.72	2.75	4.28	4.75	5.20	7.33
2008	161	4.88	0.76	2.67	4.32	4.77	5.25	7.24

Table A3. Generalized Trust Descriptive Statistics (Data Set B).

				Quantiles				
Wave	*n*	*M*	*SD*	Minimum	.25	Median	.75	Maximum
2002	182	4.70	0.77	1.63	4.26	4.66	5.06	7.21
2004	182	4.69	0.74	2.86	4.23	4.72	5.07	6.90
2006	182	4.76	0.72	2.75	4.27	4.69	5.14	7.33
2008	182	4.81	0.76	2.67	4.29	4.71	5.22	7.24

representativeness is at the regional level. Table A1 shows the level of stratification by wave and country and shows how, overall, the ESS guarantees reasonable regional representativeness, especially at the NUTS 2 level. However, as reported in Table A1, countries did not always participate to each wave. When only one wave is missing, such as Austria, the Czech Republic, and Slovakia, missing values have been interpolated using other available waves. In the case of Italy and Luxembourg, data are available only for the first two waves. In these cases, we have used the values of 2004 (the last available wave) for the computation of Global Moran's *I*, cluster maps, and Moran scatterplots in 2008. This data set (data set A), used for the ESDA, includes 182 observations for four waves. With respect to the computation of the transition probabilities (classic and spatial Markov), in order to incorporate more waves, we decided to drop Italy and Luxembourg and create a second data set (data set B) of 161 regions for the four waves. Given the geographical position of Italy at the southern border of Europe, its exclusion does not create "islands" in the analysis. The exclusion of Luxembourg does create a "hole" in the map. However, results are robust to merging Luxembourg with the closest value region, the Belgian "prov. Luxembourg." Tables A2 and A3 report descriptive statistics for our measure of generalized trust in the two data sets and show how excluding regions from data set B does not significantly changes the distribution of trust. Transition maps excluding Italy and Luxembourg are available upon request from the authors.

Authors' Note

The views expressed in this article are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Eurosystem or the Banca d'Italia.

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