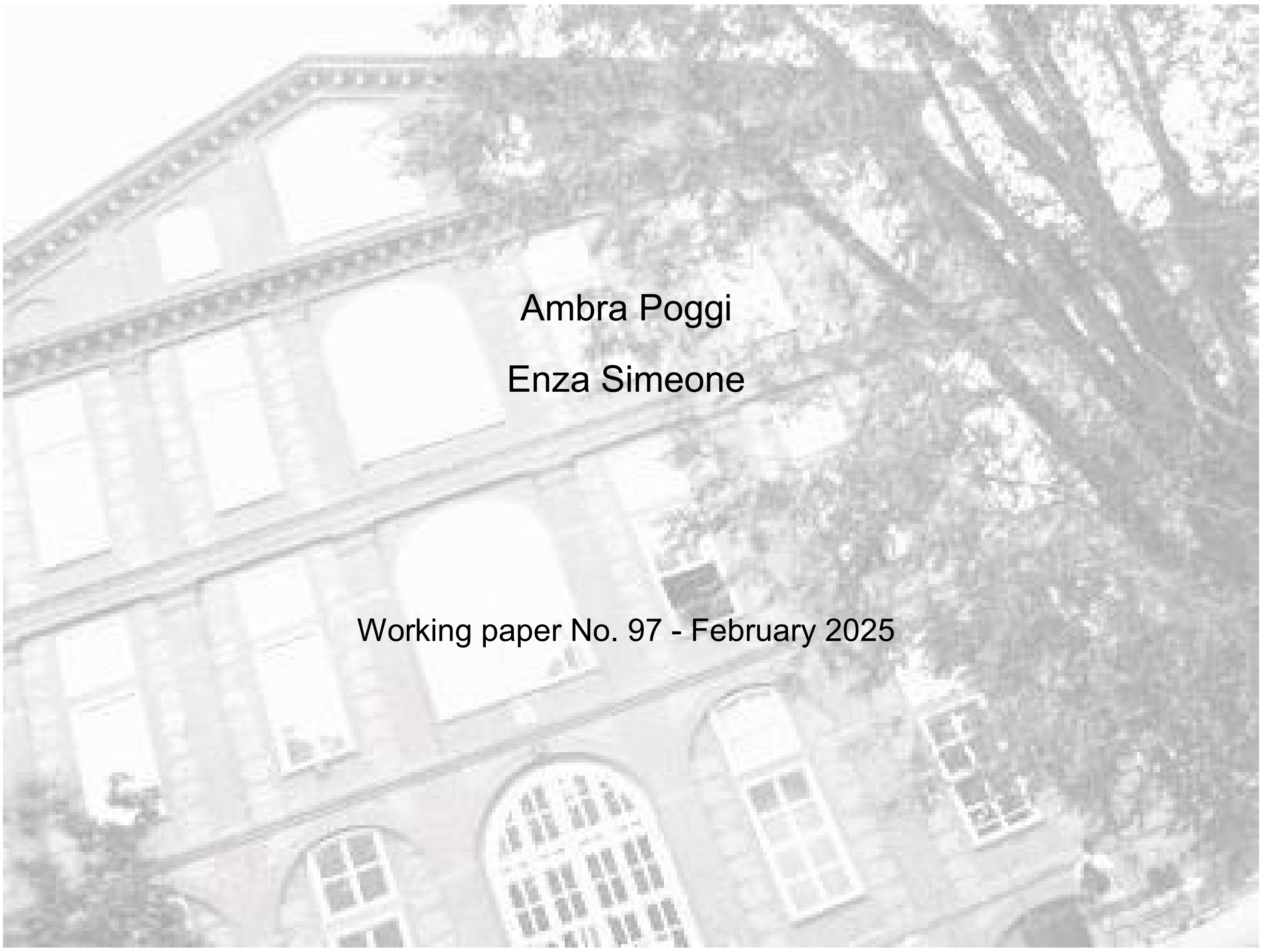
UNIVERSITÀ DEGLI STUDI DI TORINO
ALMA UNIVERSITAS TAURINENSIS
Founded in 1404

DEPARTMENT OF
ECONOMICS AND STATISTICS
WORKING PAPER SERIES

Quaderni del Dipartimento di Scienze
Economico-Sociali e Matematico-Statistiche

ISSN 2279-7114

SOCIAL CAPITAL FOR HEALTHY AGING IN THE EU: A REGIONAL INEQUALITY ANALYSIS



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Working paper No. 97 - February 2025

Social Capital for Healthy Aging in the EU: a regional inequality analysis

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Abstract

Social capital is a key factor in creating a supportive environment to healthy aging in the EU. Social capital is an individual resource embedded in one's social networks. Collective-owed regional level resources (e.g. sharing norms, institutional settings, etc.) can be mobilised by the individuals to build up their own social capital. Our aim is to investigate regional differences in the level of social capital held on average by older adults as well as the complexity of the relationship between individual social capital and regional level resources. Our analysis is twofold. First, using graphical methods and logistic nonlinear models, we investigate changes in social capital levels in specific groups of regions after the Covid-19 pandemic, changes that we interpret as the consequences of the different Covid-management strategies implemented in the EU regions. Second, using econometric methods, we investigate the determinants of social capital. We find that disparities in (unobserved) regional level resources explain a significant share of social capital inequality among the elderly.

This Version: 31 January 2025

Keywords: social capital, regional resources, inequality, mixed-effects model

JEL Code: I14, C23, D30, R10, O57

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1. Introduction

The World Health Organization declared 2020–2030 as the "Decade of Healthy Aging" emphasising the need to create a supportive environment to maintain older adults' functional ability and enable them to remain a resource to communities (WHO, 2015). Social capital is a key factor to create such supportive environment and meet emerging long-term care needs resulting from population aging and continuous workforce shrinkage. Social capital can be defined as resources embedded in one's social networks, resources that can be accessed or mobilised through ties in the networks (Lin, 2001). Social networks in general help meet members' basic social needs by providing socioemotional aid (acceptance, affection, emotional understanding, empathy, and esteem), instrumental aid (advice, information, help with family or work responsibilities, financial aid), or both (Christen, 1986; Putnam, 2017). From an economic point of view, an individual can invest in social capital since social resources generate an expected return for the individual. In the case of older adults, the expected return can be in terms of healthy aging and/or supportive environment for long-term care.

Social capital is, therefore, an individual resource. However, social capital requires the propensity and willingness of others to be realised. This means that social capital resides in the relationships among individuals (Claridge, 2018). It is possible to distinguish different dimensions of social capital depending on the network characteristics and the resources embedded in the network. In our analysis, we make the distinction between bonding social capital (that refers to resources accessible from one's inner circle), bridging social capital (that refers to resources accessible from one's outer circle), and connectedness (that refers to the proximity and richness of the resources that one can access). A mix of bonding, bridging and connectedness social capital is desirable as too much of one without the other can distort the benefits of social connections (Eurofound, 2005). However, the average mix of social capital hold by individuals differs across the EU regions and these differences are presumably correlated with differences in collective-owed regional level resources (e.g. sharing norms, beliefs, culture, history and institutional settings) that can be mobilised by the individuals to build up their own social capital. Regional differences in the level of social capital held on average by individuals as well as the complexity of the relationship between individual social capital and regional level resources have been insufficiently covered by the economic literature despite the economic importance of social capital in the lives of individuals. Our main focus is on narrowing this gap.

In the first part of our analysis, using graphical methods, we illustrate regional differences in the levels of bonding, bridging and connectedness social capital held on average by individuals. Estimating a logistic nonlinear model, we highlight changes in these levels in specific groups of regions after the Covid-19 pandemic, changes that can be interpreted as the consequences of the different Covid-management strategies implemented in the EU regions. In the second part of our analysis, using a linear mixed-effects model, we investigate the determinants of bonding, bridging and connectedness social capital. In particular, we assess the importance of (unobserved) regional level resources in explaining individual social capital. To achieve our goals, we use data from the Survey of Health, Ageing and Retirement in Europe (SHARE) and we focus on older adults (aged 50+) living in 154 European regions. Indicators of bonding, bridging and connectedness social capital are constructed using factor analysis as dimensions reducing strategy.

Our findings report changes in the social capital distribution between the EU regions and groups of regions (Southern, Eastern and Northen-Western European regions). Bridging social capital inequality reduces after the outbreak of the pandemic, while connectedness social capital inequality increases. The median values of bridging and connectedness social capital for Northern/Western European regions are higher throughout the study period than those for Southern or Eastern European regions. Instead, the median values of bonding social capital for Northern/Western European regions are slightly lower throughout the study period than those for Southern or Eastern European regions. Processes of convergence and divergence are underway during the period of analysis.

Evaluating the contribution of observed and unobserved factors to social capital inequality among older adults, we find that unobservable regional heterogeneity explains a significant share of social capital inequality. Therefore, regional differences in sharing norms, beliefs, culture, history and institutional settings help explain inequality between regions and groups of regions.

Our findings point to the need for the EU's commitment and targeted regional policies to pursue a more equitable geographical distribution of social capital.

The remainder of the paper is organised as follows. In Section 2, we introduce the dataset and variables of interest. In Section 3, the empirical strategy is presented. Section 4 reports and discusses the results, and Section 5 concludes.

2. Data and main variables

We use data from the Survey of Health, Ageing and Retirement in Europe (SHARE) that is a multidisciplinary and cross-national panel database of micro data on social (and family) networks, socio-economic status and health of individuals aged 50 and over from 28 European countries and Israel. SHARE is conducted every two years from 2004. Refreshment samples are included to account for sample size reduction due to panel attrition (natural mortality as well as longitudinal unit non-response). Longitudinal weights are provided, and we use them as appropriate. The core questionnaire of SHARE is stable over time, but its design allows for the inclusion of new modules and innovative research questions according to the circumstances of each wave. Of interest for our analysis is the social network (SN) module, initially included in wave 4 and repeated in waves 6, 8 and 9.

In our analysis, we focus on the countries of the European Union (EU) only[2]. We use data immediately before and after the Covid-19 pandemic to test changes in social capital accumulation due to the outbreak of the pandemic and the implementation of policies to prevent the spread of Covid-19. Thus, we use wave 8 (data collection started in October 2019 and was interrupted by the outbreak of the pandemic)[3] and wave 9 (data collection started in October 2021 and ended later than expected in October 2022). Our final sample is a balanced panel composed by 26,887 individuals aged 50+ living in 154 regions of the EU. The latter are defined by major socio-economic differences (NUTS 1) and the degree of urbanization (rural or urban).

To perform our analysis, we need to measure social capital at individual level. The SHARE survey provides the SN module as an innovative approach to collect data on the personal social environment. It asks respondents up to seven individuals who they consider confidants. For each individual named, the module collects detailed information on gender, the year of birth, occupational status, partner status, residential proximity to the respondent, frequency of contact, and emotional closeness. We used these questions to construct aggregate indicators of social capital.[4] To be useful in our analysis, the information contained in these questions are aggregated to form a small number of indicators and we use exploratory factor analysis as a dimension reducing strategy. Factor analysis is a statistical data reduction technique widely used to explain variability among observed random variables in terms of fewer unobserved random variables called factors. In general, factor analysis models the observed variables as linear combinations of the factors, plus normally distributed error terms. The algorithm produces a factor structure matrix representing the correlations between the variables and the factors and is called the factor loading matrix. The interpretation of each factor is marked by high loadings on a certain sub-sample of attributes that give information on a specific kind of unobservable. As consecutive factors are extracted, they account for less and less variability and the decision to stop extracting factors depends on when there is only very little ‘‘random” variability left. We retain only

[2] Ireland and Portugal are not included since information about social capital is incomplete.

[3] In wave 8, the collected longitudinal and refreshment interviews until the stopping of fieldwork were respectively 50545 and 6901 (Bergmanne et al, 2004). In Spain, Finland and Portugal, the drawn refreshment samples could not be fielded due to the outbreak of the COVID-19 pandemic.

[4] We construct our indicators adding on the approach used by Arezzo and Giudici (2017). In particular, we merge the latter approach with the approach used to construct the connectedness scale defined by SHARE (Gruber et al., 2024).

factors which account for sufficient variance: meaning that unless a factor extracts at least as much as the equivalent of one original variable, we do not consider it (Kaiser criterion). Since factor analysis is based on a correlation matrix, it assumes that the observed variables are measured continuously, are distributed normally, and that the association among indicators is linear. Many of our observed variables are discrete, so we assume that they are indicators of underlying continuous unobserved variables and use the appropriate correlations in the factor analysis. Finally, we perform an oblique rotation allowing factors to be correlated. This enhances the ability to interpret the factors.

Table 1 reports the results of the factor analysis run to construct the indicators of social capital[5] that will be our dependent variables. We identify three factors (in order of proportion of explained variance):

(i) "connectedness social capital", that refers to the proximity and richness of the resources that the individual can access through network size, e.g. members in the SN within 25 km, frequent contacts, individuals with close emotional ties, relationships diversity and family members in SN;

(ii) "bridging social capital", that refers to resources accessible from the individual's outer circle through voluntary work, educational or training courses, and political/community-related organizations;

(iii) "bonding social capital", that refers to resources accessible from the individual's inner circle through other household members and frequent contacts with family members in the SN.

Together the three factors explain the 66.11% of the total variance. The Kaiser–Meyer–Olkin measure of sampling adequacy (KMO) reports a value of about 0.878 thus confirming that the variables have enough in common to run a factor analysis. Each factor has zero mean and standard deviation equal one by construction. We rescale our factors to have positive values and report descriptive statistics in Table 2a. Figure 1 displays heterogeneity in social capital across the EU regions. Southern Europe is characterised by high levels of bonding social capital, particularly in rural areas where family and close community ties are dominant. This pattern contrasts with Northern and Western Europe, which exhibit lower bonding scores, reflecting social networks that are less family-centred. In contrast, Southern (and Eastern) European rural areas report weaker levels of bridging social capital, while Northern European regions stand out for their stronger bridging social capital in rural areas. Urban areas reinforce these distinctions: bridging capital is most pronounced in Northern and Western

[5] We assume our indicators to be cardinal variables.

Europe. Southern and Eastern European regions also exhibit relatively low levels of connectedness compared to Northern and Western Europe, where higher scores prevail.

Finally, Table 2b reports descriptive statistics about the explanatory variables used in our analysis (e.g. gender, age groups, education, living with the partner, labour market participation, limitations with activities, internet use and difficulty in ends meet as income proxy). These variables are considered as time-constant variables: we refer to their pre-covid values as reported in wave 8. Among the explanatory variables, in Table 2a we also include indicators of time-constant personal traits. Physiological studies suggest that virtually all personality measures can be reduced or categorised under the umbrella of a 5-dimension model of personality, which has subsequently been labelled the "Big Five" (Goldberg, 1990). The dimensionality of the "Big Five" has been found to generalise across virtually all cultures (McCrae and Costa, 1997; Pulver et al, 1995; Salgado, 1997) and remains fairly stable over time (Costa and McCrae, 1988, 1992a). The dimensions composing the 5-dimension model are emotional stability, extraversion, conscientiousness, openness experiences and agreeableness. The literature suggests a link between personality traits and social capital. In particular, extraversion is related with the amount of available social capital (Brown, 1996; Kanfer and Tanaka, 1993; Pollet et al., 2011; Russell et al., 1997 and Swickert et al., 2002). Emotionally stable individuals are likely to have more extensive networks because they are better capable of adapting to interpersonal differences (Klein et al., 2004 and Wu et al., 2008). Individuals open to experience, given their communication with a wider variety of people, are likely to end up with more social capital (Wu et al., 2008). Thus, there are good reasons to include the "Big Five" indicators as explanatory variables in our analysis.

3. Empirical Strategy

We employ a two-fold strategy to investigate our research questions. First, we propose to use graphical methods and a logistic non-linear model, to illustrate regional changes in (bonding, bridging and connectedness) social capital held on average by individuals after the pandemic. Second, using a linear mixed-effects model with multiple random effects, we investigate the determinants of bonding, bridging and connectedness social capital.

3.1 Regional differences in the social capital

Our analysis focuses on average (bonding, bridging and connectedness) social capital held by individuals living in region k at time t. Therefore, the unit of analysis is the region. First, we compare the empirical frequency distributions of the regional social capital (that is the social capital held on average by individuals in a certain region) before and after the pandemic. To do so, we use kernel density estimation, a non-parametric way to obtain a graphical illustration of the shape of a distribution (Rosenblatt, 1956; Whittle, 1958 and Parzen, 1962). Second, we define three groups of regions: Southern, Eastern and Northen-Western European regions. We calculate the empirical cumulative densities and plot the distributions of corresponding groups of regions arranged in ascending order. This approach proposed by Kashnitsky et al. (2020) has several advantages. It permits us to identify different causes of convergence: convergence can be due to smaller differences between groups of regions (convergence between) or smaller differences within groups clusters of regions (convergence within), and cumulative distributions show both at the same time. In particular, changes in the distance between separate distributions point out whether there is convergence or divergence between groups, while changes in the slope of the distributions show whether there is convergence or divergence within a cluster of regions (e.g. a stepper slope suggests convergence within the cluster of regions). Moreover, the approach helps to identify the effects of changes that occur in the upper and lower parts of the distribution.

Finally, to assess the magnitude of changes pointed out in the visual comparison of the cumulative densities, we compute metrics based on the distributions. As in Kashnitsky et al. (2020), we use the following logistic non-linear model in which the slope parameter varies between the lower and upper parts of the distribution:

$$f(x) = \vartheta(x \geq m)\frac{e^{a(x-m)}}{1+e^{a(x-m)}} + \vartheta(x < m)\frac{e^{b(x-m)}}{1+e^{b(x-m)}}$$

where *f(x)* is the cumulative density function; x is the share of the estimated regional level social capital; m is the median value; $\vartheta\ (x)$ is the indicator function; and a, b, and m are the parameters to be estimated by non-linear least squares. The parameters a and b give information on the slope of cumulative density curve: higher values indicate more steeper curve. Hence, an increase in these parameter values over time means convergence, while a decrease means divergence. Furthermore, if a increases there is convergence above the median; if b increases there is convergence below the median. A change in the median value (parameter m) implies a shift of the whole distribution.

3.2 Determinants of individual social capital

To investigate the determinants of social capital, the starting point is the estimation of a linear mixed-effects model with multiple random effects. Our specification is the following:

$$(1) \qquad ln(y_{ikt}) = \beta_0 + \textstyle\sum_{h=1}^{p} \beta_h x_{hik} + \delta_{kt} + \mu_i + \varepsilon_{ikt}$$

with t=0, 1 (respectively, pre-pandemic and post-pandemic periods); y_{ikt} is an indicator of social capital (bonding, bridging or connectedness) of individual i in area k at time t; X_{hi} is the value of the ith individual for the hth of fixed-effects predictors (e.g. gender, age, education, living with a partner, limitation with daily activities, labour market participation, internet use, ability to make ends meet, personality traits, post-covid dummy), β_0 is the intercept, β_h is the regressor coefficient for the hth predictor, and μ_i is the individual-specific effect, assumed to be normally distributed in the population with mean and variance of 0 and σ_{μ}^2. At area level, the random effect (δ_{kt}) is composed by two crossed effects: each observation at area level is nested in the combination of an area random factor and a time factor. This is for testing if the pandemic had an impact on the area component of individual social capital. The area-specific effect is assumed to be normally distributed in the population with mean a variance of 0 and σ_{δ}^2. Finally, ε_{ikt} is an observation-specific residual, assumed to be normally distributed in the population with mean a variance of 0 and σ_{ε}^2.

Following Nakagawa et al. (2017), we can define the marginal R^2, which is the proportion of the total variance explained by the fixed effects:

$$(2) \qquad R_m^2 = \frac{\sigma_f^2}{\sigma_f^2+\sigma_\mu^2+\sigma_\delta^2+\sigma_\varepsilon^2}$$

where σ_f^2 is the variance explained by fixed effects, that is $\sigma_f^2 = var(\sum \beta_h x_{hikt})$.

To understand how different observable characteristics contribute to social capital inequality in Eq. 1, we initially estimate the null model (that is the model without covariates) and we gradually add the relevant covariates treating them as additional fixed effects. The inclusion of these additional fixed effects should absorb some of the residual variation in the outcome variable and produce higher estimates of the fixed effects variance (σ_f^{2*}) than what was found without their inclusion (σ_f^2). The increase in the fixed-effects variance ($\sigma_f^2 - \sigma_f^{2*}$) can be interpreted as an estimate of the amount of the overall variance that can be attributed to the additional specific factors that are included. In this way, we can decompose the proportion of the total variance explained by the fixed effects in the contribution of each fixed effect to total variability.

The amount of variation that remains not explained by any predictors in the model (1-R_m^2) can be attributed to the grouping variables as a proportion of the overall unexplained variance. We can use the intra-class correlation coefficients (ICC) to measure the proportion of variance in the outcome variable that is explained by the grouping structure of the hierarchical model. The ICC is calculated as the ratio of group level error variance over the total error variance. Since our data are grouped at area and individual levels, the ICCs can be written as

(3) $$ICC_{area} = \frac{\sigma_\delta^2}{\sigma_\mu^2+\sigma_\delta^2+\sigma_\varepsilon^2}$$

(4) $$ICC_{individual} = \frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_\delta^2+\sigma_\varepsilon^2}$$

where σ_δ^2 is the variance of the area level (between regions), σ_μ^2 is the variance of the individual level (between individuals), and σ_ε^2 is the variance of the residual level (within variance).

Finally, we focus on the variance between regions (σ_δ^2). In Section 3.1, we have defined three groups of regions: Southern (s), Eastern (e) and Northen-Western (nw) European regions. Now, we decompose σ_δ^2 in within and between elements:

(5) $$\sigma_\delta^2 = \underbrace{[w_s\sigma_{\delta_s}^2 + w_e\sigma_{\delta_e}^2 + w_nw\sigma_{\delta_{nw}}^2]}_{withi} + \underbrace{\sigma_{\bar{\delta}_s\bar{\delta}_e\bar{\delta}_{nw}}^2}_{between}$$

where $\sigma_{\delta_g}^2$ is the variance between regions in group g, and w_g is the share of regions on the total regions in group g. The last term is the variance of a fictitious distribution where we have replaced each actual specific effect with the mean specific effect of the group the region belongs to. The "within element" captures the inequality due to the variability of social capital between regions within each group, while the "between element" captures the inequality due to the variability of social capital between groups of regions.

4. Results

We discuss the results in several steps. First, we discuss changes in regional social capital after the outbreak of the pandemic. Second, we discuss the determinant of individual social capital. Finally, we discuss the importance of observed and unobservable attributes in explaining individual social capital.

4.1. Regional changes in social capital

In Figures 2-4, we compare the empirical frequency distributions of regional (bonding, bridging and connectedness) social capital held on average by individuals. We also compare empirical cumulative densities functions where regions are clustered in three groups: Southern, Eastern and Northern/Western Europe. The unit of analysis is the region. The density function shows the concentration of regions at each social capital level. The area under the curve between any pair of points at the social capital scale (horizontal axis) shows the proportion of the region with social capital between these two social capital levels. A rule of thump for assessing these curves is that the higher the concentration around the distribution mean is the lower the inequality between regions will be (Papatheodorou et al., 2004). We make use of the words “mountain”, and “hills” in order to describe curves’ shape and consequently the regions concentrations in various parts of the social capital scale (Jenkins, 1996). By “mountain” we refer to the highest regions concentration on the social capital scale while by “hills” we refer to other secondary concentrations and bumps on density function.

Bonding social capital

The density functions of bonding social capital present two poles of attraction, however the two poles are very close to each other (Figure 2a). The pre-covid frequency density curve shows a certain degree of symmetry: it presents a mountain with its peak below the mean and a similar high mountain with its peak above the mean. The post-covid curve also has two peaks, but the distance between the peaks slightly increases. We observe less dispersion around the peak below the mean (the post-covid mountain is higher) and more dispersion around the peak above the mean (the post-coved hill is lower).

Focusing on cumulative densities functions (Figure 2b), we observe that the median values of bonding social capital for Northern/Western European regions are slightly lower throughout the study period than those for Southern or Eastern European regions. The two mountains observed in pre-pandemic density function plotted in Figure 2a can, therefore, be interpreted as Northern/Western European regions and Southern/Eastern European regions. In particular, the post-covid cumulative function for Northern/Western Europe is dominated by the other two cumulative functions and, according to Figure 2a, we expect a decrease in dispersion within regions in Northern/Western Europe. The post-covid Northern/Western Europe line becomes steeper (higher a and b) confirming convergence within regions. According to Figure 2a, we also expect more dispersion in the remaining regions. Southern Europe shows a strong convergence within regions above the median (higher a) and a quite strong divergence within regions below the median (lower b). Eastern Europe shows a weak divergence within regions above the median (the parameter a is slightly lower) and a weak divergence within regions below the median (the parameter b is slightly higher).

The presence of two poles of attractions can be explained by differences in household size across the EU. In Northern/Western countries (e.g. Germany, Scandinavian countries and the Baltic states) the average household size is the lowest, while the average household size is larger than the EU average in the central-eastern region (e.g. Slovakia and Poland), the south-east (Croatia, Greece) or near (Romania) the Balkan peninsula and the Iberian Peninsula (Bellis et al, 2024). These differences depend on cultural, demographic, and economic reasons. Anti-contagious policies limited the number of interactions outside the inner circle but admitted with some degree of heterogeneity the interactions with family members. The latter heterogeneity can probably explain changes in distributions after the pandemic.

Bridging social capital

Focusing on bridging social capital, inequality reduces over time and the distribution moves to the left (lower levels of bridging social capital). The pre-covid density function shows a mountain with its peak lower than the distribution mean, and a hill with its peak higher than the distribution mean (Figure 3a). The post-covid curve presents the same shape but with less dispersion: both the mountain and the hill are higher. Therefore, we observe concentrations around two poles of attraction.

In figure 3b, the median values of bridging social capital for Northern/Western European regions are much higher throughout the study period than those for Southern or Eastern European regions. The cumulative functions for Northern/Western Europe clearly dominate the other cumulative functions in both periods. The two mountains observed in pre-pandemic density function plotted in Figure 3a can, therefore, be interpreted as Southern/Eastern European regions (regions clusters around the lower peak) and Northern/Western European regions (regions clusters around the higher peak). Coherently with Figure 3a, all cumulative distribution lines moved to the left and become steeper (the parameters *a* and *b* increase especially in Southern and Eastern Europe). Therefore, in all groups of regions, we observe lower median levels of bridging social capital and convergence within regions. The distance (in terms of median values) between Southern Europe and Eastern Europe slightly decreases suggesting a modest convergence between these groups. The latter result and within regions convergences explain the decrease in dispersion observed in the post-covid mountain shown in Figure 3a, while the within Northern/Western European regions convergence explains the decrease in dispersion observed in the post-covid hill also shown in Figure 3a.

We can explain these results noting that anti-contagion policies reduced interactions and participation in voluntary organizations, educational/training courses, clubs and political/community organizations. Therefore, we expect for the majorities of the EU regions convergence to a level of bridging social capital lower than the mean, this because access to regional resources is restricted, especially during lockdown. For other EU regions with milder restrictions and stronger traditions of civic engagement (e.g. Sweden), we expect convergence versus a level of bridging social capital higher than the mean.

Connectedness social capital

Focusing on connectedness social capital, inequality increases over time. The pre-covid curve has a mountain with a bump at the left slope of the mountain (Figure 4a). The presence of bumps indicates a certain degree of dispersion toward low levels of connectedness that we do not observe in the post-covid curve. However, the mountain of the frequency density curve is lower after the pandemic, indicating more dispersion.

In Figure 4b, the median values of connectedness social capital for Northern/Western European regions are higher throughout the study period than those for Southern or Eastern European regions. In all groups of regions, we observe divergence above the median. Moreover, we observe convergence below the mean in Southern and Eastern Europe, a result that can explain the disappearance of the bump at the left slope of the mountain observed in Figure 4a.

The Southern Europe distribution line moves to the right with an increase of m, moving closer to the Northern/Western Europe line and moving apart from the Eastern Europe line. There is convergence between Northern/Western Europe and Southern Europe, while there is divergence between Eastern Europe and Southern Europe. There is also divergence between Northern/Western Europe and Eastern Europe. Therefore, the post-covid cumulative function for Eastern Europe is dominated by the other two cumulative functions. Differences between groups of countries are coherent with the two bumps of the post-covid mountain observed in Figure 4a and the observed rise in inequality. We can argue that these differences can be due to heterogeneous anti-contagion policies and different abilities to maintain social interactions using digital instruments. In fact, the digital divide exists in the EU: in Southern and Eastern countries there is a prevalence of basic internet users and non-users, while in Western and Northern countries there is a prevalence of instrumental and advanced users (Gomes, 2024).

4.2. Determinants of individual social capital

Estimates of the linear mixed-effects model are reported in Table 3. The specification assumes that individual social capital (in terms of bonding, bridging and connectedness social capital) is predicted by individual socio-demographic individual characteristics, personality traits, unobserved individual characteristics and unobserved regional level resources.

Individual socio-demographic characteristics are important predictors of individual social capital explaining more than ¾ of the social capital inequality among individuals. As expected, aging is negatively correlated with participation in social networks and community life, negatively impacting on the social capital. Coherently with this idea, we find that limitations in daily activities reduce bridging social capital. However, it enhances connectedness social capital, probably as a result of the support received in daily life. The younger older adults are more likely to participate in the labour market, participation that is positively correlated with bonding and bridging social capital, and negatively correlated with connectedness social capital.

Living with a partner has a large positive and significant impact on bonding and connectedness. Since the death of the partner is more likely among older individuals, the partner lost will reinforce the negative correlation between aging and social capital. However, we also find a negative correlation between living with a partner and bridging social capital; this suggests that, in absence of a partner, individuals participate more in voluntary work, educational courses, and/or political/community-related organizations.

We also find that women have higher amount of bonding and connectedness social capital, but they have lower level of bridging social capital. The latter results seem to suggest that women participate less in clubs, political organization, voluntary work and/or training courses accumulating less bridging social capital. Previous literature does not find any significant gender differences in volunteering among older individuals (Hank, 2011). Participation in social clubs, training courses and political organization might be perceived as a more "male-type" of activity.[6] Our result seems to confirm this view.

Education and the use of the internet for e-mailing, searching for information, making purchases, or for any other purpose (chatting, social networks, skyping etc.) are significantly positively correlated with bridging and connectedness social capital, while they are negatively correlated with bonding social capital. Thus, low educated individuals seem to rely more on the inner circle and have more

[6] For example, Solé-Auró and Arpino (2024) find that older adult women are less likely to participate in social clubs in the less gender-egalitarian countries.

difficulties to develop interactions outside the inner circle. In addition, individuals with a higher use of the internet tend to create higher connections outside the inner circle than within household.

Individuals with higher difficulty in making ends meet are those with less bridging and connectedness social capital. This is because these individuals experience economic constrains and could not afford to participate in external activities. Therefore, they could have difficulty in maintaining connections outside the inner circle. Thus, they rely more on bonding social capital.

Concerning the personality traits, we find the following results. Extraversion and agreeableness are strongly associated with higher bridging and connectedness social capital. Conscientiousness positively correlated to bonding and connectedness social capital. An individual open to experience seem to be more likely to access greater and richness resources from the outer circle, partially substituting interactions in the inner circle with interaction in the outer circle. In facts, we find positive correlation between openness to experience and bridging / connectedness social capital and negative correlation between openness to experience and bonding social capital. Finally, neuroticism has a significant negative impact on bridging and connectedness social capital. These findings highlight the critical role of personality traits in shaping different dimensions of social capital. The positive association of extraversion and agreeableness with bridging and connectedness social capital suggests that individuals with outgoing and collaborative behaviours are more likely to form diverse networks, facilitating trust and maintaining connections beyond their inner circles. The strong correlation between conscientiousness and bonding/connectedness social capital highlights the importance of reliability and responsibility in sustaining close-knit relationships and maintaining connections within larger social networks, ensuring stability and trust. Individuals with high openness prioritise diverse and enriching outer-circle interactions over close knit inner-circle ties, suggesting a substitution effect between those circles. Finally, the negative impact of neuroticism on bridging and connectedness social capital indicates that emotional instability and self-doubt hinder the ability to form and sustain broader social networks. Understanding these dynamics can help design targeted strategies, like building emotional resilience in people with high neuroticism or using the strengths of extroverts and open-minded individuals to improve social connections in communities.

About changes in the social capital due to the pandemic, we find that bridging social capital decreases, while connectedness social capital increases. Anti-contagious policies lead to restrictions in participation in voluntary work, social clubs, training courses and political organization. Resources from the outer circle are mobilized to overcome the pandemic leading probably to an increase in connectedness social capital. Instead, bonding social capital remains not affected by the pandemic.

In fact, interactions among household members and, more in general, with family members are mainly not affected by the anti-contagious policies.

4.3. Observed vs unobserved attributes: variance decomposition

In this section, we discuss how observable and unobservable factors contribute to social capital inequality. As explained in Section 4.2, we initially estimate the null model, and we gradually add the relevant covariates treating them as additional fixed effects (the final specification is the one presented in Table 3). The increase in the explained fixed-effects variance can be interpreted as the contribution of the additional fixed effects.[7] The result of our analysis is a decomposition of social capital variance that gives information on how much social capital inequality is accounted for by each explanatory factor. See Table 4.

Observable attributes

Observable socio-demographic characteristics explain more than ¾ of the (bonding, bridging and connectedness) social capital inequality among older adults. Personality traits relevantly contribute to bridging and connectedness social capital inequality (10,4% and 19.1%, respectively) suggesting that personal attitudes, such as openness or extraversion, could influence how individuals form and maintain their social connections in the outer circle. The pandemic also contributes to bridging and connectedness social capital inequality (9.9% and 3% respectively).

Among the socio-demographic characteristics, we can identify the factors contributing the most in explaining social capital. Focusing on bonding social capital, the observable explanatory factors explain a total of 23.2% of inequality. The 88% of the latter is attributable to living with a partner. This is an expected result since bonding social capital is positively correlated with household size and frequency of family contacts. Focusing on bridging social capital, the observable explanatory factors explain a total of 12.5% of inequality. Of the latter, 35% is attributable to education, 19% to internet use, 15% to gender and age and 5.22% to difficulties in making ends meet. Focusing on connectedness social capital, the observable explanatory factors explain a total of 6.5% of the variance. Of the latter, 41.6% is attributable to living with a partner, the 16.7% to gender and age, the 8% to difficulties in making ends meet (8%), and the 7% to internet use.

[7] Estimates of the different specifications are available from the authors upon request.

Unobservable attributes

A significant portion of the social capital variance remains unexplained highlighting how unobservable factors (both at individual and regional level) may be relevant in shaping social capital inequality among older adults. In particular, we find that more than 40% of the unexplained variance is attributable to unobserved individual heterogeneity (see the ICCs in Table 4).

Of most interest for our analysis, the unobserved regional heterogeneity accounts for 12.75% of the bridging social capital inequality. Therefore, regional differences in sharing norms, beliefs, culture, history and institutional settings influence participation in voluntary work, educational/training courses, and political/community-related organizations. Clustering regions in three groups (Southern, Eastern and Northen-Western European regions), we can decompose the between regions variance in the within and between groups elements. The inequality due to the variability of bridging social capital between regions within each group is 3.4% (the 26% of the total between regions variance), while the inequality due to the variability of bridging social capital between groups is 9.4% (the 75% of the total between regions variance).

Focusing on connectedness social capital, the unobserved regional heterogeneity accounts for 7.66% of the inequality. Once again, we find that regional differences in sharing norms, beliefs, culture, history and institutional settings also model the size and the proximity of network size, the frequency of contacts and the diversity of relationships. The within groups element results more important than the between groups inequality: the former accounts for the 78% of the total between regions variance, while the latter account for the 22%.

Finally, the unobserved regional heterogeneity accounts only for 4% of the bonding social capital inequality. Therefore, regional differences seem to play a small but relevant role in determining inequalities among older adults. The inequality due to the variability of bonding social capital between regions within each group is 1.7% (the 41% of the total between regions variance), while the inequality due to the variability of bridging social capital between groups is 2.35% (the 59% of the total between regions variance).

From the above results, we observe an important role for the variance between groups (Southern, Eastern and Northen-Western European regions) confirming the findings of Section 4.1.

5. Conclusions

Using the 2019-2021 Survey of Health, Ageing and Retirement in Europe (SHARE) data, we empirically investigate regional differences in the level of social capital held on average by individuals as well as the complexity of the relationship between individual social capital and regional level resources. We find the following results. *First*, we observe changes in the social capital distribution between the EU regions. Bridging social capital inequality reduces after the outbreak of the pandemic, while connectedness social capital inequality increases. *Second*, we observe changes in the social capital distribution between groups of regions (Southern, Eastern and Northen-Western European regions). The median values of bridging and connectedness social capital for Northern/Western European regions are higher throughout the study period than those for Southern or Eastern European regions. Instead, the median values of bonding social capital for Northern/Western European regions are slightly lower throughout the study period than those for Southern or Eastern European regions. *Third*, processes of convergence and divergence are underway during the period of analysis. *Fourth*, unobservable regional heterogeneity explains a significant share of social capital inequality among the older adults. Therefore, regional differences in sharing norms, beliefs, culture, history and institutional settings help explain inequality between regions and groups of regions. A more balanced regional distribution of social capital could contribute to achieve social cohesion and supporting healthy aging across the EU.

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Figure 1. Social capital by NUTS1 region and degree of urbanization

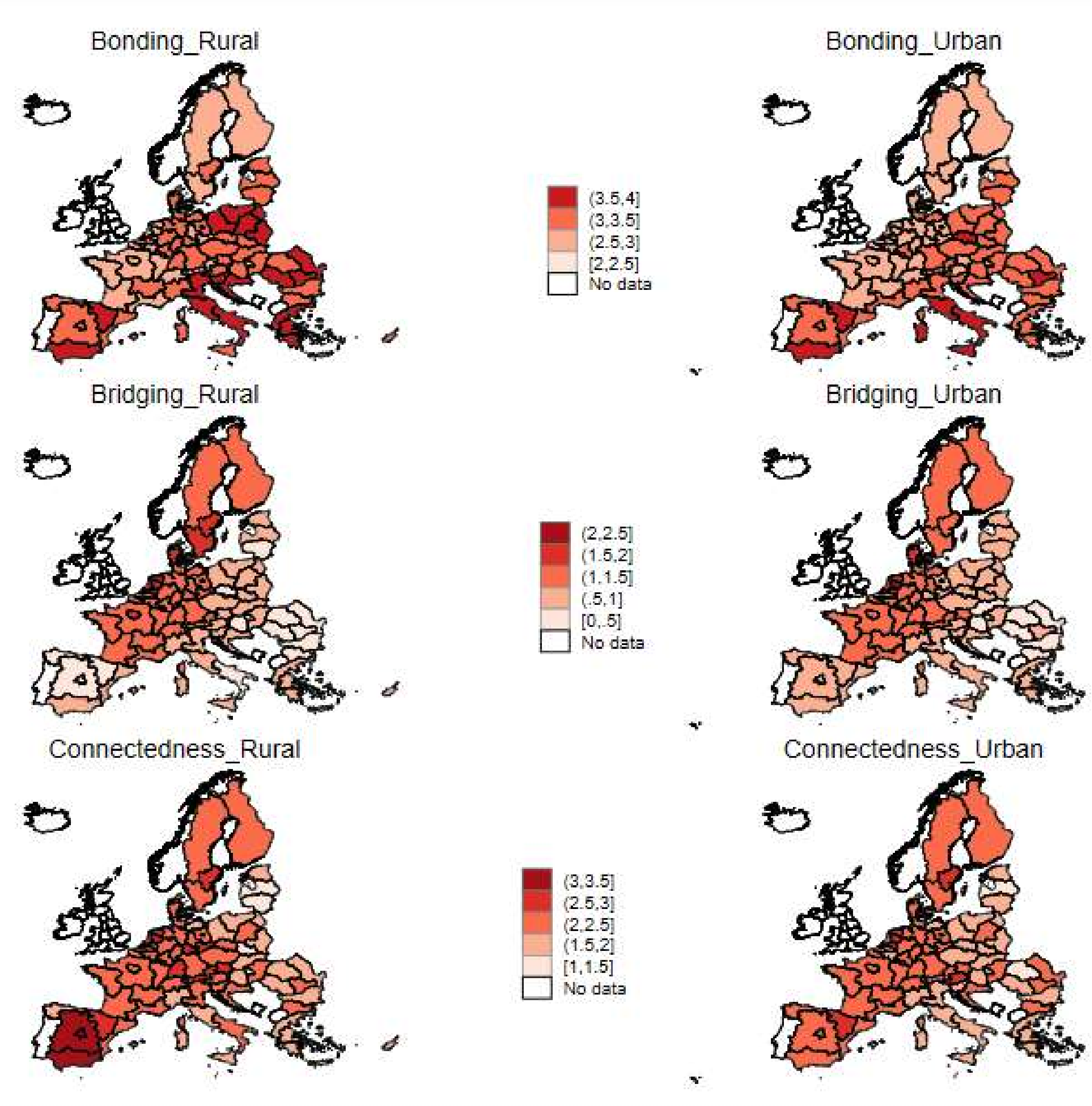
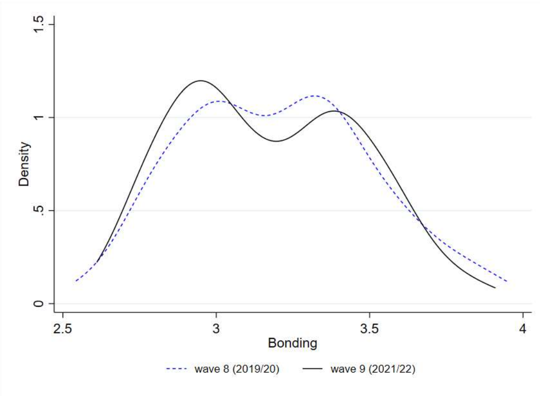
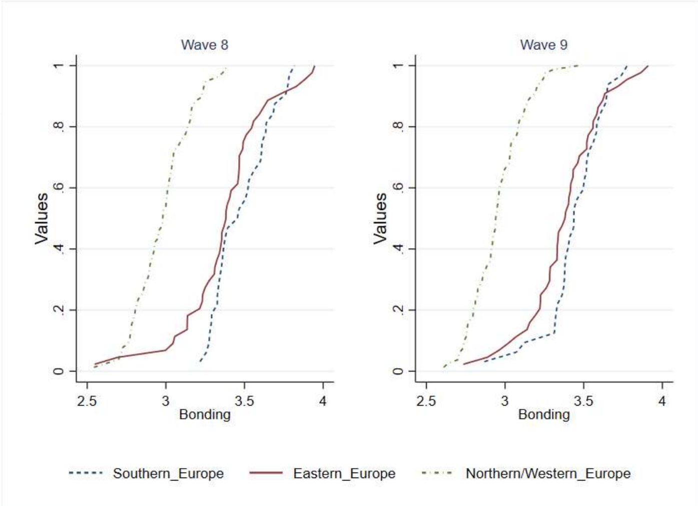


Figure 2. Bonding social capital: changes over time



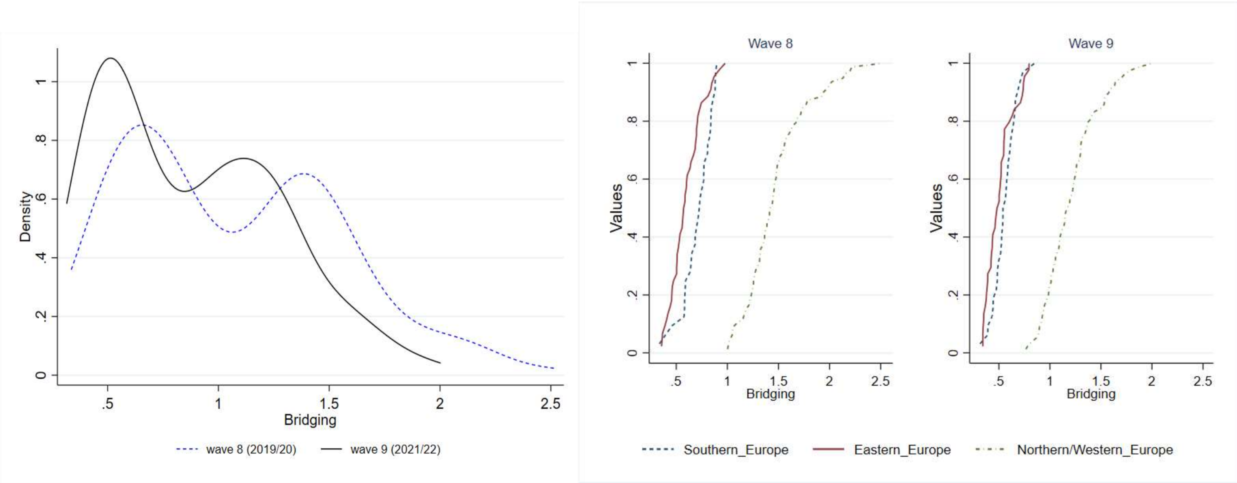


(a) Density function

(b) cumulative function

Bonding	Wave 8			Wave 9		
	South	East	West	South	East	West
a	5.567	8.375	9.232	9.826	8.227	10.034
b	14.771	7.409	9.279	12.811	7.822	10.480
m	3.404	3.384	2.971	3.438	3.376	2.940
N. Obs	32	44	78	32	44	78

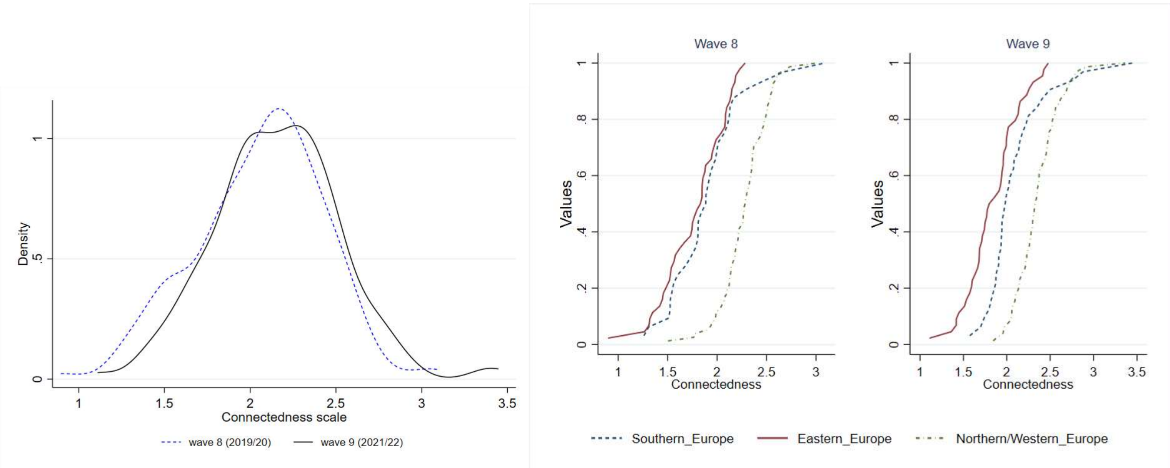
Figure 3. Bridging social capital: changes over time



(a) Density function (b) cumulative function

Bridging	Wave 8			Wave 9		
	South	East	West	South	East	West
a	14.885	9.404	5.387	16.201	10.160	5.630
b	9.248	12.433	7.728	15.090	16.284	7.955
m	0.734	0.571	1.408	0.553	0.471	1.159
N. Obs	32	44	78	32	44	78

Figure 4. Connectedness social capital: changes over time



(a) Density function (b) cumulative function

Connectedness	Wave 8			Wave 9		
	South	East	West	South	East	West
a	6.020	6.033	7.669	5.012	4.965	6.673
b	5.016	4.180	7.543	11.075	5.786	7.532
m	1.872	1.815	2.281	1.978	1.818	2.329
N. Obs	32	44	78	32	44	78

Table 1. Factor analysis of social capital

Social network variables	**Factor 1 Connectedness**	**Factor 2 Bridging**	**Factor 3 Bonding**
Household size			0.8019
Freq. of family contacts in SN (from “daily contact” to “never”)			-0.7398
Freq. of voluntary or charity work (from “no activity” to “almost every day”)		0.696	
Freq. attended an educational or training course (from “no activity” to “almost every day”)		0.5523	
Frequency gone to a sport, social or other kind of club (from “no activity” to “almost every day”)		0.5851	
Freq. of taken part in a political/community-related org. (from “no activity” to “almost every day”)		0.5945	
No. family members in SN (scale: 0-7)	0.8509		
Network size (scale: 0-7)	0.9631		
No. members in SN within 25 km (scale: 0-7)	0.8543		
Contact frequency (weekly or more)	0.92		
Support (Very or extremely close emotional ties)	0.9091		
Diversity in SN	0.8466		
Proportion explained	0.4073	0.1349	0.1189
Kaiser-Meyer-Olkin measure of sampling adequacy			0.878

Table 2a. Descriptive statistics: personality traits and social capital

	Mean	Std. Dev.	Min.	Max.
Personality traits:				
- Extraversion	3.404	0.895	1	5
- Agreeableness	3.614	0.808	1	5
- Openness	3.317	0.966	1	5
- Conscientiousness	4.144	0.753	1	5
- Neuroticism	2.688	0.968	1	5
Social capital:				
- Bonding	3.235	1.000	0.001	9.359
- Bridging	0.945	1.000	0.001	8.452
- Connectedness	2.082	1.000	0.001	5.526
N. Observations		*53774*		

Table 2b. Descriptive statistics: socio-economic and demographic characteristics

Socio-economic and demographic characteristics	**%**
Age groups:	
- Age 50-64	0.529
- Age 65-74	0.284
- Age 75+	0.187
Female	0.537
Education attainment (ISCED 1997):	
- Low	0.352
- Medium	0.423
- High	0.225
Labour market participation (yes/no)	0.373
Living with a partner (yes/no)	0.676
Limitation with daily activities (yes/no)	0.439
Internet use (yes/no)	0.633
Difficulty ends meet (yes/no)	0.376
Country group:	
- Southern Europe	0.301
- Eastern Europe	0.238
- Western/Northern Europe	0.46
Degree of urbanization (Rural/Urban)	0.638
Observations	53774

Table 3. Regression results

	ln(bonding)			ln(bridging)			ln(connectedness)		
	Coeff.		*Std.err.*	*Coeff.*		*Std.err.*	*Coeff.*		*Std.err.*
Socio-demog. attributes:									
Female	0.016	**	0.004	-0.020	**	0.008	0.141	**	0.006
Age 50_64	0.054	**	0.005	-0.004		0.011	-0.001		0.008
Age 75 plus	0.011	*	0.005	-0.106	**	0.010	-0.006		0.008
Living with partner	0.428	**	0.004	-0.022	**	0.009	0.205	**	0.007
Medium education	-0.029	**	0.005	0.071	**	0.010	0.012		0.007
High education	-0.032	**	0.006	0.325	**	0.012	0.042	**	0.009
Labour mkt participation	0.027	**	0.006	0.049	**	0.012	-0.020	*	0.009
Limitation in daily activities	0.006		0.004	-0.081	**	0.008	0.016	**	0.006
Difficulty ends meet	0.009	*	0.004	-0.080	**	0.009	-0.070	**	0.007
Internet use	-0.012	**	0.005	0.231	**	0.010	0.071	**	0.007
Personality traits									
Extraversion	0.002		0.002	0.063	**	0.004	0.033	**	0.003
Agreeableness	-0.002		0.002	0.018	**	0.005	0.041	**	0.004
Conscientiousness	0.013	**	0.003	-0.004		0.005	0.022	**	0.004
Openness to experience	-0.007	**	0.002	0.052	**	0.004	0.021	**	0.003
Neuroticism	-0.001		0.002	-0.015	**	0.004	-0.006	*	0.003
Post covid dummy	-0.001		0.009	-0.173	**	0.031	0.050	**	0.018
Constant	0.743	**	0.019	-0.907	**	0.043	-0.090	**	0.030
var(re_regions)	0.005	**	0.001	0.072	**	0.007	0.024	**	0.002
var(re_id)	0.061	**	0.001	0.263	**	0.003	0.126	**	0.002
Log-likelihood	-16194.0			-53468.4			-39993.5		
N. Observations	53774			53774			53774		
N. individual	26887			26887			26887		
N. areas	154			154			154		

Note: (**) significance level <=0.01; (*) significance level <0.05.

Table 4. Variance decomposition

	Total	Decomposition % of the total		Total	Decomposition % of the total		Total	Decomposition % of the total	
Explained variance (R^2_m)*100	**23.20%**			**12.47%**			**6.45%**		
Socio-demographic attributes:		99.53%			79.63%			77.82%	
Gender and age			9.93%			15.05%			16.66%
Living with partner			87.77%			0.11%			41.55%
Education			1.24%			35.10%			4.60%
Labour market participation			0.08%			1.66%			0.00%
Limitation in daily activities			0.00%			3.03%			0.02%
Difficulty in making ends meet			0.21%			5.22%			7.92%
Internet use			0.30%			19.46%			7.07%
Personality traits		0.47%			10.44%			19.14%	
Covid		0.00%			9.94%			3.05%	
Unexplained variance (1-R^2_m)*100	**76.80%**			**87.53%**			**93.55%**		
ICC_region		4.02%			12.75%			7.66%	
between groups (*)			2.36%			9.38%			1.69%
within groups (*)			1.66%			3.37%			5.97%
ICC_individual		47.84%			46.25%			40.86%	
Residual		48.14%			41.01%			51.48%	

(*) Groups are Southern, Eastern and Northern/Western European regions.