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RESEARCH PAPER

A Regional Perspective on Social Exclusion in European Regions: Context, Trends and Policy Implications

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Abstract

Social exclusion has become a popular topic in the policy agendas of European governments, especially after the global financial crisis of 2007–2009 hit the continent as hard as it could. The existing literature highlights the presence of spatial patterns in social exclusion, although previous contributions consist of local or national level studies, lacking a broader continental perspective. This work resorts to regional data covering 20 EU countries and aims to characterise the nature of spatial patterns, distinguishing between spatial heterogeneity and pure spatial autocorrelation. Using the Spatial Markov Chain Matrix, we find that the strong clusterisation process unfolded by previous studies tends to become less intense if the role of socio-economic covariates is taken into account. Socio-economic factors represent in other words a containment cage that reduces the extent of neighbour influence. Net of the covariates, we identify clusters of regions in Southern Europe where high levels of social exclusion constitute a structural problem, calling for long-term public intervention. The policy implications of our findings are then outlined.

Keywords Social exclusion · Spatial spillovers · Spatial Markov chain matrix · European regions

JEL Classification C31 · I32

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1 Introduction

In recent years, addressing social exclusion has become one of the top priorities in the policy agenda of the European Commission, as well as a central issue for the national governments of many EU Member States. The European Union fights social exclusion, promoting inclusion for all citizens, including low-skilled, younger, older and disabled workers, ethnic minorities, migrants and women (EC 2010). In particular, the Europe 2020 Strategy aimed to lift at least 20 million people out of social exclusion, recognising the problem as a dynamic process as well as a product of public policy, and not strictly as a function of individual characteristics (Eurostat 2018).

The notion of social exclusion originated in France at the end of the 1970s (Silver 1994; Martin and Leaper 1996; Spicker 1997; Atkinson and Da Voudi 2000) and grew increasingly popular in the EU policy discourse in the early 1990s (Abrahamson 1997; Atkinson 2000). The conceptual distinction between poverty and social exclusion dates back to this period: poverty is defined as a distributional outcome that refers to low income (Silver and Miller 2003; Bhalla and Lapeyre 2004), while social exclusion is a dynamic and persistent relational process, consisting in the breakdown of the societal ties that keep individuals, communities and institutions together (Ferraro et al. 2019). In this view, social exclusion materialises into a barrier preventing social participation persistently over time.

The dynamic dimension of social exclusion has paved the way for studies focusing on the historical perspective of the problem. Over the last century, technological change and globalisation have altered the labour market substantially, creating a disadvantage for some sections of the population and producing waves of unemployment (Cole et al. 1983). Gough et al. (2006) associate social exclusion precisely with joblessness, which generates poverty and in turn marginalisation. Beyond the purely economic variables however, factors like gender, race, disability and age represent additional social constructs that may create social exclusion by inhibiting the social participation of certain strata of the population regardless of income. It is interesting to notice that poverty and social exclusion are common phenomena even in wealthy 'developed' countries (Gough et al. 2006). In these areas, social exclusion is produced by the internal relations and mutual constructions of economy, state, social life and culture. In particular, the fundamental forms of social power that create exclusion—namely class, gender and race—are constructed across the categories of economy, politics, sociality and culture across spatial scales (Gough 1991).

Core and peripheral areas create poverty and social exclusion in distinct ways. In peripheral areas, the majority of jobs are poorly remunerated and require low skills, while high levels of unemployment are chronic. Even relatively privileged sections of the labour market are threatened by the flightiness of production, while turnover is around the corner. Under these circumstances, unions are hardly active and find it difficult even to recruit, while the informal/illegal economy often covers a large share of the economic activities. Over the decades, this situation may shape work culture and ethic. Expectations on wages, conditions, skills and careers are low, while the self-confidence of individuals as economic agents is minimal. Economic exclusion thus affects the majority of the population in these areas.

In core areas instead, where the cost of living is high, consumer service jobs are primarily responsible for social exclusion. Driven by high income, the demand for consumer services is widespread, and jobs in this sector tend to form a higher proportion than in poorer regions. However, wages are very low, especially in relative terms. Workers in low-wage jobs are likely to lack the bargaining power necessary to obtain raises and may thus be even worse off in core regions than in the periphery (Fainstein et al. 1992; Sassen 1991; Hamnett 2002). Furthermore, the social and spatial segmentation of labour tends to represent a more significant problem than elsewhere. Relatively low aggregate unemployment rates at the regional level may disguise high rates of unemployment and underemployment for the low-skilled, ethnic minorities, and people living in stigmatised neighbourhoods.

The geographical differences in employment have widened over the last 30 years, both between and within countries. In the 1970s and 1980s, the countries that struggled during the post-war boom were most hit by a slowdown growth and by spikes in unemployment. These countries included Britain, most of southern Europe and in certain ways the USA. During the 1990s however, these economies strengthened their competitive position, while the countries that soared during the boom—namely (West) Germany, France and Japan—experienced stagnation and rising unemployment. Differences also increased between the regions of most countries (Green and Owen 1998; Hudson 1989; Hudson and Williams 1995). Old industrial regions suffered major contractions in manufacturing and mining employment, whereas many agricultural regions experienced a drop in employment in agriculture and fishing. Job creation tended to be concentrated in cities and regions specialised specific sectors, such as finance, media, complex manufactures and tourism. Divergences between localities in both quantity and quality of jobs thus increased sharply.

Based on the above, social exclusion may be described as a downward spiral, where labour market marginality leads to poverty and social isolation, which in turn reinforce poor labour market outcomes (Gallie et al. 2003), generating persistent intergenerational pockets of marginality (Heckman and Raut 2016). In this perspective, social exclusion may be viewed as an *absorbing state* (or '*trap*'), i.e. a state from which it is very difficult to transition over time without appropriate policy instruments (Bradley et al. 2003; Thomas and Gaspart 2015). Besides being time-persistent, social exclusion has been shown to feature spatial patterns (Câmara et al. 2002; Baum and Gleeson 2010). In particular, spatial clusters characterised by either high or low levels of social exclusion are commonly identified in empirical studies. Usually, this phenomenon is either dismissed as a coincidence related to structural similarities between neighbours or justified as the result of an imitation process that takes place on part of policymakers or on part of citizens across the borders of neighbouring areas (Vettoretto 2009; Shipan and Volden 2012; Obinger et al. 2013).

A strand of the literature has tried to explain spatio-temporal persistence by looking at disaggregated geographical levels, including regions, cities, neighbourhoods, etc. (Burgers and Kloosterman 1996; Ceccato and Oberwittler 2008; Martori and Apparicio 2011; Marcińczak 2012; Danson and Mooney 2013). Most of these contributions however consist in localised case studies that fail to investigate the phenomenon in a broad perspective. Overall, spatio-temporal persistency patterns in social exclusion in the EU remain largely underinvestigated. In particular, it is not clear whether time-persistent spatial clusters arise as a result of historical events and specific socio-economic factors or whether they simply depend on neighbour influence. Under the former hypothesis, spatial heterogeneity is responsible for the formation of clusters and its driving factors may be identified. Under the latter hypothesis instead, pure spatial correlation is at the root of the phenomenon.

Thus, the aim of this work is to fill this gap, using official regional-level data for several EU countries. The originality of this work lies in the scope of the investigation, which combines a broad continental perspective with the usage of local level data. Our dataset indeed covers a large portion of the European Union and focuses on a fine-grained territorial level, consisting in NUTS-2 administrative units. We identify both positive and negative clusters of regions, and we propose an identification strategy that allows to disentangle pure spatial correlation from spatial heterogeneity. It is interesting to notice that when the effect of spatial heterogeneity is removed, positive clusters tend to break up, while negative clusters persist. These results point to the need for a long-lasting season of policy intervention tailored to fight social exclusion at the local level.

The rest of this work is organised as follows: Sect. 2 outlines the methodological instruments we employ in this analysis. Section 3 sums up the main features of the dataset we build. Section 4 presents and comments the results of the empirical investigation. Section 5 provides a discussion of the results obtained, contextualising our contribution with respect to the recent literature.

2 Methods

In this section, we present the methods employed to investigate spatio-temporal persistency patterns in social exclusion across European regions. First, in order to remove the influence of (potentially autocorrelated) underlying factors and avoid the risk of spurious autocorrelation, we regress social exclusion on its socio-economic determinants and then we extract the resulting residuals. This 'purification' process is described in detail in the Appendix. The residuals obtained from the model represent an estimate of *purified* social exclusion, i.e. of what remains of the variable once the influence of the covariates and of region-specific fixed effects is removed.

A key measure of spatial autocorrelation, is the Moran Index (MI), defined as follows (for further details, see Anselin 1988a; Agovino et al. 2016):

$$MI = \frac{X'WX}{X'X} \tag{1}$$

where X indicates the variable under investigation, while W is the non-stochastic $N \times N$ spatial weights matrix, which is assumed to be symmetric.[1] WX represents the spatial lag of X, i.e. the effect of the region's neighbours. The MI allows to

[1] Assume the spatial weights matrix is row-standardised, so that spatial lags are computed as weighted averages of the values in neighbouring regions (Anselin 1988a). Should the property of symmetry be violated, the appropriate formula for Eq. (1) would be $MI = \frac{X'\frac{1}{2}\left(W+W'\right)X}{X'X}$ (Maruyama 2015).

establish the relationship between a phenomenon observed in a given region and the same phenomenon observed in nearby regions. While the MI usually takes on values ranging in the $[-1;\ 1]$ interval, different ranges are possible in the presence of particular spatial weights matrices. In particular, the upper bound of the interval corresponds to the highest eigenvalue of the spatial weights matrix, while the lower bound of the interval corresponds to the lowest eigenvalue of the spatial weights matrix (Waller and Gotway 2004). A value of the MI equal to $-\frac{1}{N-1}$ indicates absence of spatial patterns.[2]

After investigating the presence of spatial autocorrelation, we resort to Spatial Markov Chain (SMC), in order to study the spatio-temporal dynamics of social exclusion (see Rey 2001; Le Gallo 2004; Agovino 2014). SMC allows to study contemporaneously the spatial and temporal dynamics of a phenomenon, disaggregating patterns based on the type of neighbours. This method requires fewer assumptions with respect to alternative approaches (such as dynamic panel regression) and represents a non-parametric estimation technique (Rey 2001; Agovino et al. 2016). The main output of SMC is the spatial transition matrix, that allows to examine the influence of neighbours on the probability that a region shifts from a certain class to another. In particular, it displays the probability that a region will experience upward or downward movements in the distribution, conditional on the state of its neighbours before the transition takes place. In other words, the transition matrix traces the history of the distribution over time.

We aim to obtain the probability that the level of social exclusion varies at the regional level, conditional on the extent of social exclusion in the neighbouring regions (Schettini et al. 2011). More specifically, we wonder whether a region featuring low (high) levels of social exclusion tends to keep low (high) levels of social exclusion when it is surrounded by other regions with high (low) social exclusion. The transition matrix highlights whether 'bad' neighbours may worsen the performance of nearby units and whether 'good' neighbours may improve social outcomes even beyond administrative borders. Both effects are evaluated in a dynamic framework, i.e. over time. The construction of the spatial transition matrix is based on the decomposition of the traditional transition matrix, that displays the spatial transition probabilities. In particular, the traditional (unconditional) transition matrix is modified so that, for each transition from period t to period $t+\tau$, the transition probabilities of each region are conditioned on the information set of available at period t, consisting in the characteristics of neighbouring regions. The unconditional transition matrix is a (KxK) traditional matrix, where $k = 1, 2, \ldots, K$ indicates the category to which unit i belongs. It may be decomposed into K square submatrices of size $(K\ x\ K)$ each, so as to condition on the K values of the variable observed in neighbouring units.

In each submatrix k, each element $p_{ij}(k)$ represents the probability that a unit belonging to class i at time t ends up in class j at time $t+\tau$, knowing that the average social exclusion rate of its neighbouring regions belonged to class k at time t. The

[2] For large N, this value is approximately zero. Spatially unrelated variables may however feature a significant MI, due to the characteristics of the underlying factors. In other words, a significant MI may derive from spurious autocorrelation. For this reason, it is important to purify variables.

estimator of $p_{ij}\ (k)$ is defined as follows:

$$\hat{p}_{ij}(k) = \frac{n_{ij}(k)}{n_i(k)} \tag{2}$$

where $n_{ij}(k)$ is the number of units located in class i at time t and in class j in time $t+\tau$ knowing that their neighbouring units belong to class k in period t. $n_i(k) = \sum_j n_{ij}(k)$ is the total number of units belonging to class i, knowing that their neighbours belong to class k at time t.

The conditional matrix sheds light on the influence exerted by neighbours, which is reflected by the transition probabilities, conditional on the *type* of neighbours (Agovino 2014): differences between the unconditional and the conditional transition probabilities reveal a significant influence on part of neighbours[3] (Le Gallo 2004). For generic states a and b, if $p_{ab} > p_{ab|a}$ (meaning that the conditional probability il lower than the unconditional probability), neighbour influence hinders the transition. Conversely, if $p_{ab} < p_{ab|a}$, neighbour influence eases the transition. If proximity effects do not matter for transition probabilities, then the conditional probabilities should be equal to the unconditional initial probabilities:

$$p_{ab|a} = p_{ab|b} = \ldots = p_{ab|K}, \forall a = 1, \ldots, K b = 1, \ldots, K \tag{3}$$

Equation (3) may be tested empirically.[4] The relevance of the spatial dimension of the analysis, and therefore the importance of considering neighbour influence in determining transition probabilities, emerges when the null hypothesis of spatial stationarity is rejected (see Le Gallo 2004).

3 Data

The theoretical literature highlights the multidimensionality of social exclusion, that involves economic, social, political and cultural aspects of disadvantage and deprivation (Bradshaw 2004). A multidimensional approach is thus required in order to measure it (Chakravarty and D'Ambrosio 2006; Fischer 2011; Giambona and Vassallo 2014; Ciommi et al. 2017; von Jacobi et al. 2017). The European Commission uses a composite indicator within the Europe 2020 strategy. The indicator is based on three dimensions, i.e. monetary poverty, severe material deprivation and low intensity of work. Since these three dimensions tend to overlap, they cannot simply be added up to obtain the total number of people at risk of poverty or social exclusion (EC 2014). Therefore, people are counted only once, even in case they fall into more than one category.

[3] Due to space constraints, we refrain from providing a detailed description of the unconditional transition probability matrix, and we focus on the conditional version of the matrix.

[4] The test statistic is $Q = -2\log\left\{\prod_{t=1}^{T}\prod_{i=1}^{K}\prod_{j=1}^{K}\left[\frac{\widehat{p}_{ij}}{\widehat{p}_{ij}(t)}\right]^{n_{ij}(t)}\right\}$, which is asymptotically distributed as a χ^2, with $K \times (K-1)$ degrees of freedom. See Kullback et al. (1962) for further details.

Table 1 Dataset

Variable	Observations	Mean	St. deviation	Min	Max	Source
Social exclusion	1500	25.14	11.42	4.4	59.5	Eurostat
Education	1500	70.32	15.50	25.2	97.3	Eurostat
Unemployment	1500	10.30	5.87	1.9	36.2	Eurostat
Life expectation	1500	79.68	3.30	70.6	85.2	Eurostat

Based on the Eurostat definition[5] (Eurostat 2018), more than one fifth of the EU population (22.4%) is counted among the socially excluded in 2017, of which almost one fourth of the European children (24.9%) and women (23.3%), as well as about one fifth of the older people (18.2%). These outstandingly high figures are related to the current economic situation: the aftermath of the financial crisis of 2007–2009 was not characterised by a quick recovery—as was the case in the US—, but instead featured high unemployment rates and long-lasting unemployment spells, coupled with fiscal austerity and budget cuts, especially in the so-called peripheral countries (Pavolini et al. 2016; Barth et al. 2017). In the face of growing levels of inequality, the different national welfare systems have not proved to be equally effective across member states, failing in some cases to reduce unemployment spells and to counter multiple spikes in poverty rates (EC 2014). The economic and social strain caused by the financial crisis has increasingly drawn the European Commission's attention towards the problem of social exclusion, whose persistent nature makes it especially concerning.

The dataset we use is based on Eurostat observations, available for 125 NUTS-2 regions, within 20 EU Member States[6] over the 2005–2016 period. The dependent variable in the dataset is Social Exclusion, while the regressors are Education, Unemployment and Life Expectation. All the variables are available at the regional level (NUTS-2). Table 1 sums up the main features of our dataset.

The rest of this section describes in detail the covariates and summarises the reasons why they are relevant determinants of social exclusion.

– *Education* is defined as the share of people who completed higher education (i.e. concluded between 12 and 13 years of formal education, depending on the country) over the total population. Education is a major instrument in the fight against social exclusion, as well as one of the policy instruments most often advocated by scholars (Selwyn et al. 2001; Alexiadou 2002; Thompson 2011). According to the current literature, investments on education play a key role within the broader framework

[5] To measure social exclusion, Eurostat uses the rate of people At Risk Of Poverty or social Exclusion (abbreviated as AROPE). This definition counts the sum of EU residents who are either at risk of poverty, or severely materially deprived or living in a household with a very low work intensity over the overall population. Individuals are only counted once, even in case they fall within multiple categories. The AROPE rate is the headline indicator to monitor the EU 2020 Strategy poverty target (Eurostat 2019).

[6] We use the EU countries for which the data were available, namely Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Ireland, Greece, Spain, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Romania, Slovenia, Slovakia, Finland and Sweden.

of social policy (Whitty 2001). In the fight against social exclusion, schooling institutions need to share the responsibility of inclusiveness from the earliest stages of formal education (O'Shea et al. 2016). Not only educated people are more likely to participate to the activities of their communities, but they are also more likely to be open to the inclusion of several minorities, including for example immigrants (Jenssen and Engesbak 1994; Cote and Erickson 2009; Ruiz-Román et al. 2017) and LGBT+ people (Ayoub 2014; Agovino et al. 2021).

– *Unemployment* is defined as the share of residents aged 15–64 who are not employed, are actively looking for a job and are willing to work immediately. Unemployed people, who experience labour market marginality are more likely to face social exclusion, especially when unemployment spells are lengthy (Gallie et al. 2003; Kieselbach 2003; Béland 2007). Labour market policies tackling unemployment represent one of the main lines of intervention that may reduce the problem of low intensity of work (Clasen et al. 2016). The targeting of these policies however is a very delicate matter: on the one hand passive policies, such as generous income support schemes and unemployment benefits, may discourage labour market participation (Van Ours and Vodopivec 2006). On the other hand, active policies, such as human capital accumulation programmes may generate the so-called *locking-in effect* (Van Ours 2004; Lechner et al. 2007; Crépon et al. 2009), consisting in repeated (and paid) attendance to vocational training programmes on part of unemployed workers, who typically become long-run unemployed by spending most of their time in training rather than searching for jobs. To avoid these failures, labour market policies must be designed so as to provide unemployed workers with the right set of incentives, target marginalised individuals and constitute a vehicle of inclusion into the labour market and the broader community life (Guth 2005).
– *Life Expectation* represents the average years that an individual born today would be expected to live. This variable is a demographic control that proxies the general health status of the population. On average, people featuring better health levels are less likely to incur social exclusion (Santana 2002; Morgan et al. 2007; Spandler 2007). The literature highlights that investments on health may help fight social exclusion (Klein 2004; Horton and Lo 2013), especially when they target some critical groups, such as marginalised elderly people (Craig 2004), people with disabilities (O'Grady et al. 2004) and individuals affected by mental illnesses (Morgan et al. 2007), for which the negative loop between poor health and social exclusion needs to be broken from the outside by public policy programmes. These social groups, if provided with the health assistance they need, may turn from a burden for public budgets into an active and productive resource for the community.

The EU has produced a range of laws, policies, programmes and initiatives to combat social exclusion at the regional, national, European and international level (EC 2016). The key documents are in this regard the European Commission's Social Policy Agenda for 2006–2010 and the Renewed Social Agenda, presented in July 2008. Within the European System of Integrated Social Protection Statistics (ESSPROS), social protection schemes encompass all the actions of public or private actors that are meant to relieve households and individuals from a defined set of risks and needs. Social protection benefits cover the risks and needs that may arise from sickness,

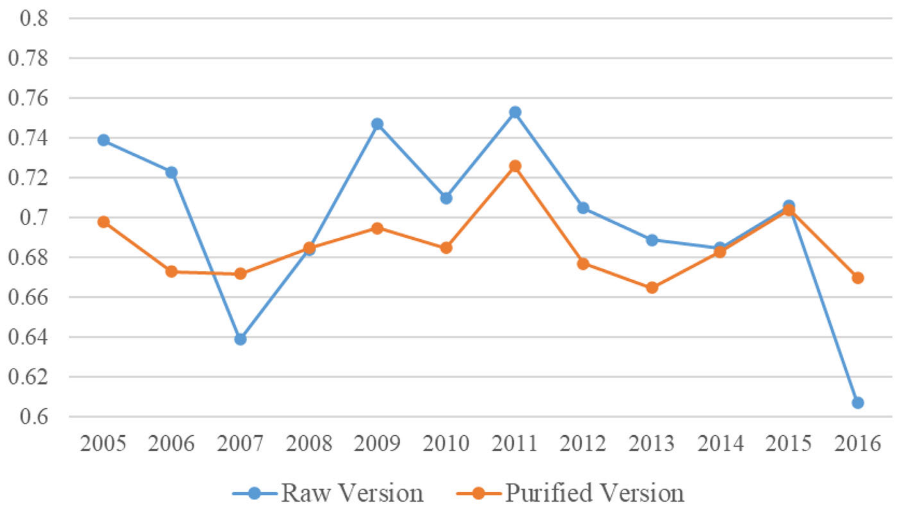

Fig. 1 Moran Index (2005–2016)

disability, old age, family losses, unemployment spells, housing issues and other forms of social exclusion of a different nature. The benefits granted under such measures can be distributed in cash or in kind—as when goods and services are provided directly to the protected persons. While until 2008, in part due to the generosity of the EU initiatives, social exclusion decreased in Europe, after the financial crisis,[7] it started growing again (Rogge 2017). One EU citizen out of four is currently considered at risk of poverty or social exclusion. The lack of resources in this perspective decreases not only the levels of consumption for individuals at risk of social exclusion, but also their chances to be active members of the society.

4 Results

This section shows our results in terms of spatial autocorrelation and displays the SMC transition probability matrix. The results are reported for both the raw and purified version of social exclusion, in order is to understand whether the socio-economic covariates affect cluster size and stability and whether a spatial diffusion process is taking place.

4.1 Preliminary Results: Spatial Autocorrelation

The MI for social exclusion displays positive and significant values over the whole 2005–2016 timespan, indicating spatial autocorrelation is strong and persistent. Figure 1 shows the MI over time, for both the raw and the purified version of the variable.

[7] The economic and social effects of the financial crisis materialised in Europe only in the second half of 2008 (Honkapohja 2014; Coveney et al. 2020).

Over most of the timespan, the MI is higher for the raw version than for the purified version. This difference in the extent of spatial autocorrelation suggests that the underlying socio-economic variables are partly responsible for the cross-border similarities featured by the regions in our sample. Overall, European regions seem to undergo a common trend, influencing each other and forming spatial clusters that persist over time (Anselin 2002). Based on these results, it is interesting to verify whether the regions with low (high) social exclusion influence their neighbours with high (low) social exclusion, thus determining an improvement (deterioration) in social exclusion. This hypothesis may be verified by implementing the SMCs Analysis.

4.2 Spatial Markov Chain Results

The SMC analysis allows to study jointly spatial patterns and time persistence conditional on neighbour characteristics. While other methods that allow to study both phenomena simultaneously—such as dynamic spatial panel regression—return coefficients based on the average effect of neighbours, SMC disaggregates neighbour influence based on the type of neighbours. Moreover, SMC is a non-parametric method that requires a minimal set of assumptions (Rey 2001; Agovino et al. 2016).

The test for spatial stationarity returns a chi-square statistic of 63.31, associated with a p-value equal to zero. This means that the null hypothesis is rejected, i.e. the conditional probabilities differ significantly from the unconditional probabilities. Thus, the type of neighbours does affect the probability of transitioning from a state to another. We consider $t = 1, 2, \ldots T$ periods, with $T = 11$, and $\tau = 3$, which means we focus on three-year transitions. In total, we have nine transition periods over the 2005–2016 period, namely 2005–2008, 2006–2009, …, 2013–2016. Counting in total 125 regions, nine transition periods and five categories, it is possible to obtain at most 5000 cases of transitions.[8]

We define $K = 5$ feasible states based on the value of the social exclusion rate. Bearing in mind that $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$ is the mean of X and $\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \overline{X})^2}$ is the standard deviation of X, the states are defined as follows (see also Agovino 2014):

- Low (L), if $X_i < \overline{X} - \frac{3}{4}\sigma$
- Medium–low (Ml), if $\overline{X} - \frac{3}{4}\sigma < X_i < \overline{X} - \frac{1}{4}\sigma$
- Medium (M), if $\overline{X} - \frac{1}{4}\sigma < X_i < \overline{X} + \sigma$
- Medium–high (Mh), $\overline{X} + \sigma < X_i < \overline{X} + \frac{3}{2}\sigma$
- High (H), if $X_i > \overline{X} + \frac{3}{2}\sigma$

These states are exactly equivalent to the quintiles of the distribution due to variable normalisation (see Appendix). In summary, the five states are set in the following order: L < Ml < M < Mh < H. We compute the conditional transition probabilities for the whole 2005–2016 timespan, the pre-crisis period (i.e. 2005–2008) and the post-crisis

8 With N regions, K states and T years, there are $(T-1) \times N \times K$ n possible cases of transitions. In our case, the total amounts to $9 * 5 * 125 = 5000$.

period (2009–2016). In order to highlight the differences between the pre- and post-crisis periods, we only show the difference matrix, whose elements are computed as the post-crisis probability minus the pre-crisis probability.[9]

We report the SMC results as in Rey (2001). For all the cases considered, the *raw* version of social exclusion features a rather strong degree of inertia, since the elements on the main diagonal tend to be the largest in each row. Time persistence in this view appears to be very likely. Neighbour influence reinforces this process, unfolding a strong spatiotemporal autocorrelation process (Table 2).

Dividing the sample between the pre- and post-crisis periods allows to obtain further information. First, when looking at the raw variable, after the crisis the share of regions belonging to the H class reaches 25%, while before the crisis it was as low as 20%. In this view, the effects of the financial crisis of 2007–2009 were not only economic, but also and pre-eminently social (Moffitt 2013). Second, the probabilities of persistence change substantially along the main diagonal, reporting an increase for extreme classes (L and H) and a generalised decrease for middling classes (Ml, M and Mh). In other words, the distribution of social exclusion was impacted by the crisis, which generated a polarisation process. The financial crisis of 2007–2009 indeed reshaped the structure of public spending, altering the classical redistribution mechanisms that had characterised the welfare state in the last decades of the XX and in the first decades of the XXI century. Social policies thus appear to have lost part of their original effectiveness (Moulaert and Ailenei 2005; Maks-Solomon and Stoker 2019). This phenomenon has led to a rise in inequality and social exclusion levels in both the US and Europe, worsening overall societal outcomes (Piketty 2015).

The first submatrix in the table concerning the raw variable indicates a substantial increase in the probability of either persisting in the original state (regions originally in states L, Mh and H) or transitioning to lower states (regions originally in states Ml and M). The probability of transitioning to a higher state instead either decreases or remains largely unchanged after the crisis. The situation is very similar for the second submatrix, where only regions in the M state report a relevant increase in the probability of transitioning to a higher state in the post-crisis period (Mh, + 12.9%). Virtuous neighbours here clearly exert a positive influence. Things start to change in the third submatrix, that refers to regions whose neighbours belong to the M state. For these regions, while persistence remains likely and increases for all but the regions

[9] Due to space constraints, we refrain from showing the other matrices, which are however available upon request on part of interested readers. Concerning the full-sample matrix for the raw variable, the main points that may be highlighted regard the clear evidence of significant neighbour influence. In each of the five submatrices indeed the class to which the neighbours pertain attracts the regions of every groups. On the other hand, relevant time persistency patterns do emerge, confirming the complicated interplay between diachronic and territorial persistence. Concerning the full-sample matrix for the purified variable, the picture becomes less neat and more nuanced. A lower extent of time persistency emerges, suggesting the presence of a somewhat weaker spatial pattern. The probabilities associated to persistence decrease sensibly and the role of neighbours grows weaker. Neighbours in other words exert a smaller influence once the relevant socio-economic covariates are accounted for. This phenomenon materialises into a twofold effect: one the one hand, starting from a low level, the probability of moving towards higher levels decreases, even in spite of the influence produced by bordering regions. In this case the socio-economic factors prevent social exclusion from spreading out. On the other hand, when starting from a high level, the probability of persistence increases, even in spite of virtuous neighbours. In this case the socio-economic covariates create a negative inertia, blocking the positive effects that may derive form the proximity to virtuous regions.

Table 2 SMC Matrix

Line	Time t	Neighbours	Time t+3				
			L	Ml	M	Mh	H
1	L		20.20%	-22.40%	2.20%	0.00%	0.00%
2	Ml		52.40%	-33.30%	-19.00%	0.00%	0.00%
3	M	L	6.70%	33.30%	-40.00%	0.00%	0.00%
4	Mh		0.00%	33.30%	33.30%	33.30%	0.00%
5	H		0.00%	0.00%	0.00%	33.30%	66.70%
6	L		43.40%	-51.20%	7.80%	0.00%	0.00%
7	Ml		28.00%	-31.10%	0.70%	2.30%	0.00%
8	M	Ml	9.70%	21.20%	-43.70%	12.90%	0.00%
9	Mh		0.00%	10.00%	-30.00%	20.00%	0.00%
10	H		0.00%	0.00%	0.00%	-100.00%	100.00%
11	L		4.90%	-16.80%	11.80%	0.00%	0.00%
12	Ml		33.30%	2.40%	-42.90%	4.80%	2.40%
13	M	M	3.70%	-3.70%	-28.00%	22.50%	5.60%
14	Mh		6.30%	-7.70%	-21.20%	14.60%	7.90%
15	H		0.00%	0.00%	-20.00%	-51.40%	71.40%
16	L		0.00%	100.00%	0.00%	0.00%	0.00%
17	Ml		14.30%	57.10%	-71.40%	0.00%	0.00%
18	M	Mh	0.00%	0.00%	-35.70%	35.70%	0.00%
19	Mh		0.00%	2.00%	-12.00%	-26.00%	36.00%
20	H		0.00%	0.00%	4.20%	-30.80%	26.70%
21	L		0.00%	0.00%	0.00%	0.00%	0.00%
22	Ml		0.00%	0.00%	-100.00%	0.00%	100.00%
23	M	H	0.00%	13.30%	-26.70%	6.70%	6.70%
24	Mh		0.00%	0.00%	3.80%	-46.20%	42.30%
25	H		0.90%	0.00%	0.90%	-12.20%	10.50%

Line	Time t	Neighbours	Time t+3				
			L	Ml	M	Mh	H
1	L		23.2%	-23.2%	0.0%	0.0%	0.0%
2	Ml		23.2%	14.4%	-37.6%	0.0%	0.0%
3	M	L	0.0%	37.5%	-50.0%	12.5%	0.0%
4	Mh		0.0%	0.0%	25.0%	62.5%	12.5%
5	H		0.0%	0.0%	0.0%	0.0%	100.0%
6	L		12.8%	-15.1%	2.3%	0.0%	0.0%
7	Ml		7.3%	31.2%	-43.2%	4.5%	0.0%
8	M	Ml	6.5%	-4.7%	-5.5%	3.8%	0.0%
9	Mh		16.7%	0.0%	-33.3%	16.7%	0.0%
10	H		0.0%	0.0%	0.0%	-100.0%	100.0%
11	L		20.0%	-40.0%	5.0%	15.0%	0.0%
12	Ml		6.9%	12.7%	-35.6%	12.0%	4.0%
13	M	M	2.9%	5.6%	-44.7%	33.2%	2.9%
14	Mh		0.0%	2.0%	-12.6%	10.6%	0.0%
15	H		0.0%	0.0%	0.0%	-100.0%	100.0%
16	L		0.0%	60.0%	40.0%	0.0%	0.0%
17	Ml		18.2%	54.5%	-72.7%	0.0%	0.0%
18	M	Mh	2.8%	25.0%	-36.1%	5.6%	2.8%
19	Mh		0.0%	2.5%	-7.2%	-5.6%	10.4%
20	H		0.0%	0.0%	1.7%	-6.7%	5.0%
21	L		0.0%	0.0%	0.0%	0.0%	100.0%
22	Ml		0.0%	0.0%	0.0%	0.0%	0.0%
23	M	H	0.0%	14.3%	-100.0%	71.4%	14.3%
24	Mh		0.0%	2.8%	0.6%	-20.1%	16.7%
25	H		1.1%	0.0%	-2.9%	-14.5%	16.3%

Difference Between the Post-Crisis and Pre-Crisis Periods. Shaded cells indicate time persistence. Some ‘extreme’ transitions, i.e. that from L to H for regions surrounded by H neighbours for the purified variable in the post-crisis period are computed using very few observations and may thus be unreliable departing from state M, transitions to higher states become more likely after the crisis. At the same time, transitions to lower states also report a general probability increase, with the notable exceptions of regions originally in state H, whose probability of persistence skyrockets following the financial crisis, decreasing the probability of transitioning to lower states substantially. In this particular case, neighbours generate a centrifugal thrust, pushing regions to transition towards more extreme states. Finally, the regions in the last two submatrices are surrounded by bad neighbours, whose negative influence decreases the probability of persistence in states M and Mh and increases the probability of transitioning to higher sates. This influence is stronger for regions that already lie in the top half of the social exclusion distribution. Overall, both good neighbours and bad neighbours appear to drag the regions nearby towards their own states more decisively in the aftermath of the crisis.

Concerning the purified variable, the general picture is similar, with neighbours in the extreme states influencing all regions and eventually drawing them closer. The main difference pertains to time persistence, which becomes more marked. In particular, for the first three submatrices, only the regions in state M see a drop in their probability of persistence, while all the others become more likely to remain in their original state after the crisis. With respect to the raw variable, this result indicates more inertia, pointing to a lower extent of neighbour influence. For the last two submatrices instead, regions in states M and Mh feature a decrease in the probability of persistence and an increase in the probability of transitioning to both higher and lower states in the post crisis period. It is interesting to notice that in both submatrices, even the probability of transitioning from state L to higher states increases dramatically due to the influence of negative neighbours. Finally, evidence on the presence of a post-crisis polarisation process emerge when looking at the probabilities of transitioning to the L and H states, which are invariably higher across all submatrices after the crisis.

The ergodic distributions displayed in Table 3 may be interpreted as the long run distributions of the variables considered (see Rey 2001; Le Gallo 2004). Additional insights about the transition probabilities may be obtained when considering the ergodic distributions implied by each of the estimated conditional transition matrices.

Persistence appears to be overall stronger after the crisis. For the raw variable, this is true of all regions except those in state Ml, while for the purified variable this applies to all regions but those in state M. Transitions instead are heavily affected by socio-economic covariates. Departing from low classes (L and Ml), the long-run probability of moving to higher classes is lower in the case of the purified variable, implying that the socio-economic covariates reinforce time persistence. Conversely, departing from high classes (Mh and H), long-run transitions towards lower classes are more likely for the purified variable, indicating that socio-economic covariates contribute to mitigating the phenomenon. These results are in line with the SMCs analysis.

Overall, socio-economic covariates emerge as paramount factors of social exclusion. The effects produced by bad neighbours should not be underestimated, especially when they are concentrated in one area of the country and feature spatiotemporal persistence. If not mitigated by policymakers, this persistence would result into an enlargement of the dualism between Northern and Southern Europe (González 2011; Aiello and Pupo 2012; Agovino et al. 2019). This effect is evident from the results of the local Moran test (Anselin 1995) which allows to identify the presence of spatial

Table 3 Ergodic Distributions: Raw (left) and Purified (right) Social Exclusion

Raw:

Lag	*L*	*Ml*	*M*	*Mh*	*H*
L	64.40%	22.70%	-87.00%	0.00%	0.00%
Ml	-3.40%	-40.90%	44.30%	0.00%	0.00%
M	0.00%	-25.70%	30.40%	-4.30%	-0.30%
Mh	0.30%	2.40%	-76.30%	34.20%	39.40%
H	0.60%	0.70%	5.50%	-78.90%	72.10%

Purified:

Lag	*L*	*Ml*	*M*	*Mh*	*H*
L	0.0%	0.0%	-1.0%	0.0%	100.0%
Ml	25.5%	48.1%	13.5%	11.9%	0.0%
M	0.0%	-0.2%	-0.7%	-0.1%	100.0%
Mh	3.7%	17.4%	18.4%	39.5%	20.0%
H	0.6%	1.6%	2.4%	40.2%	54.1%

clusters (see Fig. 2). In other words, the allocation of regions to one of the four quadrants of the Moran scatterplot occurs according to the number of years in the region has spent in each class. To guarantee robust results, we assign to a certain quadrant only the regions that remained in a certain class for at least 90% of the periods in our sample. For example, if a region, in the 12 years of analysis (2005–2016), remains for 11 years in class HH (91.6% of the timespan of analysis) and two years in class LH, it will be allocated to class HH.

In particular, Fig. 2 may be used to identify local clusters (regions where adjacent areas have similar values) or spatial outliers (areas distinct from their neighbours). In brief, we observe that European regions mainly end up in either the first or the third of the Moran scatterplot, reflecting HH and LL clustering. Considering the raw variable over the full sample, four HH and three LL clusters emerge. The LL clusters include Scandinavia, most of Belgium, Northern Spain, Northern Italy, Czech Republic and Slovakia. The HH clusters instead cover Southern Italy, Southern Spain and a large area that departing from Greece stretches across Balkans and encompasses most of Eastern Europe. The duality between the regions of Northern and Southern Europe thus emerges once again (Bettio and Plantenga 2004; Gal 2010). When considering the purified variable however, many clusters break. In particular, the LL cluster of Northern Italy becomes considerable smaller, while the one in Northern Spain disappears. The HH Eastern cluster grows smaller, while the HH cluster of Southern Italy expands into the centre of the Peninsula. These results reveal even more decisively the role played by socio-economic differences in shaping social exclusion in Europe. Overall, the picture looks somewhat different when controlling for the socio-economic drivers of social exclusion.

In the post-crisis period, the differences between raw and purified social exclusion become even more evident. Most of the clusters collapse when removing the effect of the covariates, leaving only the HH clusters in Southern Spain, Southern Italy and Greece-Balkans. Overall, the role of socio-economic covariates turns out to be primary within the spatial diffusion process.

5 Looking at History to Frame the Problem: Discussions, Policy Implications and Conclusions

The analysis conducted allowed us to verify how European regions influence each other in terms of social exclusion. In particular, the SMC analysis showed that social exclusion is characterised by a tenacious space–time persistence, both before and after the financial crisis of 2007–2009. Furthermore, the purification process allowed to disentangle pure spatial dependence from spatial heterogeneity.

Social exclusion clearly features both phenomena, although pure spatial dependence plays a dominant role. In other words, although socio-economic factors are relevant in determining social exclusion, their influence is not strong enough to break the negative clusters, concentrated mostly in regions of Southern Europe. Removing the effect of the socio-economic covariates however weakens the positive clusters to a relevant extent. This points to two important remarks: (1) social exclusion is configured as a structural problem in the regions of Southern Europe and (2) social exclusion does not

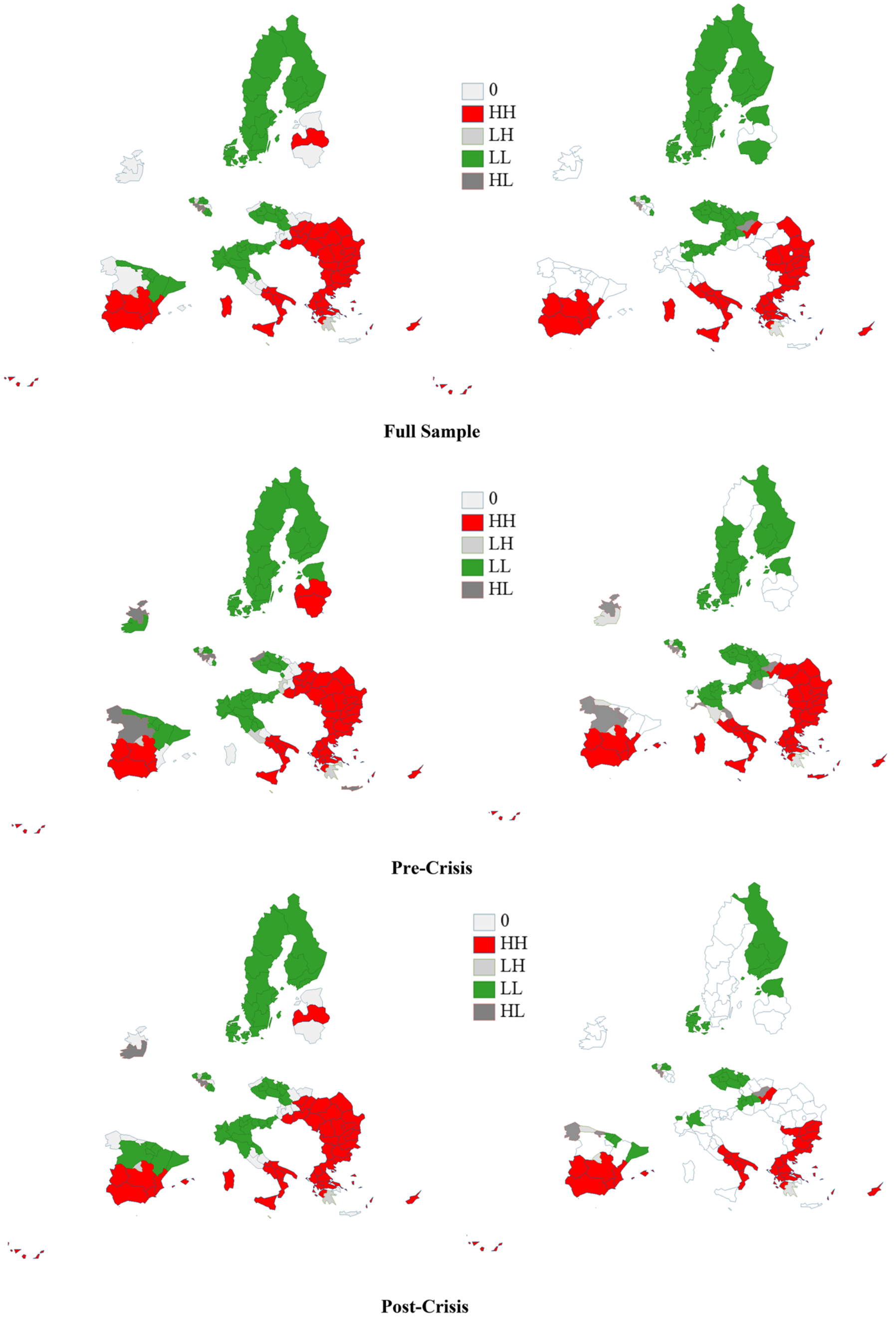

Fig. 2 Local Moran Distribution. Raw (Left) and Purified (Right) Social Exclusion. HH (red) and LL (green) denote the regions mainly ending up in either quadrant I (HH) and III (LL) of the Moran scatter-plot; LH (blue) and HL (orange) denote the regions mainly ending up in either quadrants II(HL) and IV (LH) of the Moran scatter-plot

take the form of a structural phenomenon in the regions of Northern Europe and the economic policy interventions concerning work, education and health may have an immediate and positive effect in these regions. While policy intervention is unlikely to produce a visible effect in the regions of Southern Europe in the short run, it still represents the main way to first shrink and then erase the negative clusters. Given the structural nature of the phenomenon however, policies need to be far-sighted and must take into account historical developments and the local socio-economic fabric.

Programmes targeting education, training and entrepreneurship are acclaimed as valid means to overcome social exclusion. In this view, institutionalised links between businesses and schools represent an asset, providing students with a feel of the actual labour market. Education and training programmes however suffer from the same problem that affects welfare-to-work schemes, i.e. the absence of broader job-creating strategies. Unless training provision attracts extensive investments, it may at best enhance the job prospects of its participants at the expense of others potential workers. In practice, even this zero-sum redistribution is seldom achieved, since the long-term unemployed tend to remain unattractive to employers despite training programmes, however intensive. In this view, for the economy as a whole, extending education and training without altering production processes simply raises the paper qualifications required to obtain a job. Unemployment-related poverty and low wages can only be countered by increasing both the supply and the quality of jobs. Moreover, the idea that education represents a way out of social exclusion has a corrosive effect on education itself, which tends to turn into job-training. Knowledge is thus reduced to information and IT skills (Robins and Webster 1988), while artistic, imaginative and critical thinking are side-lined. Similarly, the recent popularity of 'learning' and 'information' favours technical expertise at the expense of social understanding and of the quality of social relations (Moulaert and Nussbaumer 2005).

The failures of labour and education policies in Southern Europe over the years have been echoed by the social economy, also known as the Third Sector or community businesses (Destefanis and Musella 2009). The third sector's very broad political appeal lies in its distance from both private firms and the state, which leaves room for many variations and nuances. Supporters claim it provides the best of both worlds, combining the variety of options offered by the market and the social solidarity afforded by welfare. The social economy promises to play simultaneously three roles in overcoming social exclusion: the provision of 'soft' employment, the supply of services for the poor, and the construction of community ties and local democratic structures. In other words, its contribution is economic, social and political at the same time. The potential benefits to employment are several. First, social enterprises are generally labour intensive, thus tapping the only plentiful resource of poor regions. Second, they may provide both conventional employment contracts and softer professional opportunities for those who have little to no experience, in an environment without the pressures of conventional business. Third, these jobs may as well be designed to fit the needs of people engaged in care provision or people with disabilities. Finally, they allow workers to operate in a strongly individual autonomous fashion or in a communal fashion with a sense of solidarity, participation and collective decision-making (Oatley 1999). Moreover, the Third Sector may overcome the commodification of subsistence goods, which represents one of the main causes of deprivation. For instance, the Third Sector often provides important services at low prices, such as repairs to durables. It supervises the provision of common goods or service, such as environmental upgrades to common areas. It establishes direct relations between producers and consumers, as in the case of community gardens supplying fresh vegetables and fruit. Finally, it may as well dispense with (conventional) money in its activities, creating more opportunities for the poor. The quality of final products may as well exceed that achieved in the private sector, thanks to softer production relations and worker control. Cooperatively run retirement homes for instance may provide better care than privately owned structures.

The role of the Third Sector expanded gradually in the peripheral areas of Southern Europe during the aftermath of the financial crisis. When budget cuts decreased social spending, formal social institutions, such as trade unions and local administrations, generally failed to contrast social strain (Karakioulafis and Kanellopoulos 2018), leading to the spontaneous establishment of semiformal and informal networks of mutual support (Bosi and Zamponi 2015; Camps-Calvet et al. 2015; Guidi and Andretta 2015; Kousis and Paschou 2017). In other words, in response to the negative economic shock, many communities reorganised their activities, in a fashion that has been described by sociologists as resilient. Resilience is a notion based on network relations and community identity (Ruiz-Román et al. 2017), that has been growing more and more central in public policy discourse in recent years (Welsh 2014; Ferraro et al. 2021). In the European periphery (but also in the rest of continent), resilience may be viewed as a defensive mechanism that arises from hardship and aims to overcome social unrest and strain, producing bottom-up instances of social transformation (Adam and Papatheodorou 2010; Psycharis et al. 2014; Papadaki and Kalogeraki 2018). Modern and cutting-edge social policies need to build on resilience, complementing informal and semiformal networks with public policies in order to address the problem social exclusion (Burchardt and Huerta 2009; Mohaupt 2009). While the welfare state is being dismantled under the blows of recession and public debt in many peripheral European countries in other words, new community-based policy responses need to be devised if the fight against social exclusion is to be won. The recent literature however highlights the fact that the composition of social spending counts at least as much as the budget: transfers in kind, like dentures and wheelchairs, may produce very different effects from transfers in cash (see Crociata et al. 2020).

The spatial patterns identified by the empirical analysis proposed have resulted to persist even after the role of the covariates is accounted for. This calls for a stronger integration and coordination of national social policies, whose effectiveness may be hindered by ‘bad’ neighbours. Although the European Commission sets common targets and suggests some best practices, a significant lack of homogeneity may still be observed in national measures against social exclusion (Van Vilet 2010; Bekker and Klosse 2013). This is one of the main areas where EU governments will need to work together, under the leadership of the European Commission.

While this work proposes a sophisticated empirical approach, the lack of data certainly represents a limitation. At present, information on social exclusion is available only at the national level for some large European countries, such as Germany and France. It is up to future works to extend the analysis proposed here to the whole EU, exploiting newer data that will hopefully cover the whole continent.

Appendix

This methodological appendix describes in detail the variable purification process and the normalisation procedure applied before computing the transition probabilities. The results were obtained using the following software: (1) Stata 16 for the process, including spatial dependency tests, information criteria and normalisation; (2) and STARS (Space Time Analysis of Regional Systems, version 0.8.2, by Sergio Rey) for the Spatial Markov Chain Analysis. In order to purify Social Exclusion, we regress it on the socio-economic covariates identified by the literature, namely Unemployment, Education and Life Expectancy. More formally,

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \varepsilon_{it} \tag{4}$$

Three problems related to Eq. (4) need to be addressed, i.e. (1) Endogeneity, (2) Model Specification and (3) Spatial Patterns. Since both Unemployment and Education may be in a two-way relation with Social Exclusion, we resort to instrumental variable estimation. In particular, we instrument the potentially endogenous variables (namely Unemployment and Education) with their time lags. In order to avoid losing periods, we replace the missing values in the instruments with zeros, following an established practice (see Holtz-Eakin et al. 1988; Arellano and Bond 1991; Baltagi 2008; Ferraro et al. 2019). The validity of the instrument set selected may be tested through the Sargan test for overidentification. Moreover, since we are dealing with a panel dataset, either fixed or random individual effects may be assumed. The Hausman test indicates the appropriate specification. Since the error terms are likely to be clustered by state however, the classic formulation of the Hausman test, which assumes homoscedasticity, is not suitable. As a consequence, we run a more flexible version of the Hausman test, which is robust for heteroscedasticity.[10] Finally, one more relevant point to evaluate during the purification process pertains the presence of spatial effects, which might need to be included in the model estimated. To solve this problem, we estimate not only Eq. (4), but also the Spatial Autoregressive (SAR), the Spatial Lag of X (SLX), the Spatial Durbin Model (SDM) and the Spatial Error Model (SEM). Once the models are estimated, we compute the Information Criteria (AIC and BIC) and we run the LM test for spatial dependency to choose among these alternative specifications. The model that minimises AIC and BIC is to be preferred. Moreover, the LM tests evaluate the size and significance of the spatial lags based on regression residuals (Anselin 1988b; Anselin et al. 1996). Since our dataset contains some islands, standard contiguity matrices such as the Queen Binary Matrix are not suitable. Thus, we use an Inverse Distance Matrix.[11]

Turning to the results, the Sargan test fails to reject the null, thus confirming the validity of the instrument set. The Hausman test instead returns a significant test

[10] The *hausman* command implemented in Stata assumes homoscedasticity and may not be used with clustered errors. To sort out this problem, we use an auxiliary regression, obtained by quasi-demeaning the variables of the model. This procedure is based on Cameron and Trivedi (2010).

[11] We thank our anonymous referee for suggesting this solution. The SMC analysis shown in the results section was also obtained using this matrix. For the sake of robustness, we also run the SMC analysis using the Sphere of Influence Matrix and the Gabriel Proximity Matrix. The results hold.

Table 4 Variable Purification

	Social exclusion
Unemployment$^{\pm}$	0.474 (0.028)***
Education$^{\pm}$	− 0.048 (0.026)*
Life expectation	− 1.279 (0.107)***
_cons	126.631 (8.158)***
Sargan test _(p-value)	0.865 (0.352)
Hausman test _(p-value)	69.56 (0.000)***
N	1500

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; $^{\pm}$ *endogenous variable, suitably instrumented*

statistic, implying that the fixed effects estimator must be used. The information criteria both indicate that the OLS model (or more precisely in our case the fixed effects model) is to be preferred. This indication is confirmed by the LM tests for spatial dependence. The test results and the coefficient estimates obtained from Eq. (4) are displayed in Table 4.The information criteria are displayed in Table 5. The LM tests for spatial specification are shown in Table 6.

The estimates indicate that—unsurprisingly—unemployment increases social exclusion, while education and life expectancy reduce it. The coefficients are significant at the 1% level for Unemployment and Life Expectancy and at the 10% level for Education. After implementing the regression, we extract the residuals, which may be considered as the purified version of Social Exclusion. In other words, the residuals capture what the component of Social Exclusion that does not depend on the covariates (and on the region-specific fixed effects).

Table 5 Information Criteria for Model Selection

	AIC	BIC
OLS	7,906.329	7,927.581
SAR	7,911.145	7,932.735
SLX	7,909.198	7,918.16
SDM	7,909.747	7,913.835
SEM	7,925.547	7,928.881

Table 6 LM tests for Spatial Dependence

	Test statistic
LM test for omitted spatial lag	2.12 (0.145)
LM test for spatial residual autocorrelation	1.43 (0.231)

Once Eq. (4) is estimated, we extract the residuals. Subsequently, the residuals are normalised using the Box-Cox transformation (see Box and Cox 1964) for each year of the dataset. The Shapiro–Wilk and the Jarque–Bera tests for normality confirm that the distribution of the transformed residuals is actually normal in every year. The same transformation is applied to raw social exclusion before implementing the SMC analysis, in order to guarantee a one-to-one correspondence between the five classes identified and the quintiles of the distribution.

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