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

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Abstract

Social exclusion represents a popular topic in the policy agendas of European governments, especially after the Great Recession. The existing literature highlights the presence of spatial patterns, although previous contributions consist of local or national level studies, lacking a broader continental perspective. This work resorts to regional data covering 22 EU countries and aims to characterise the nature of spatial patterns, controlling for socio-economic covariates. Using the Spatial Markov Chain Matrix, we find that the strong clusterisation process unfolded by previous studies tends to become less intense if socio-economic covariates are taken into account. Socio-economic factors represent in other words a containment cage that reduces the extent of neighbour influence.

Keywords: social exclusion; spatial spillovers; spatial markov chain matrix; European regions.

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 the inclusion of all citizens, including low-skilled, younger, older and disabled workers, ethnic minorities, migrants and women (EC, 2010). In particular, the Europe 2020 Strategy aims 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).

In spite of the political relevance of the problem, an unambiguous and universally accepted definition of the phenomenon is still missing at the academic level, clearing the path for an on-going debate on the precise meaning of the concept (Ward, 2009; Madanipour et al., 2015). In the recent literature, social exclusion has been 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). Some studies tackled social exclusion as a primarily economic problem (Mayes, 2002; Nolan and Marx, 2009), while others highlighted its multidimensionality (Davidsson and Petersson, 2017), focusing on how social exclusion encompasses several domains of human well-being, including lifestyles (Kabeer, 2005), socio-political participation (Silver 1994; Burchardt et al., 1999) and health (Santana, 2002; Wright and Stickley, 2013). This strand of the literature broadly defines social exclusion as a dynamic process that prevents individuals from joining social, economic and cultural networks at full (Barnes et al., 2002), reinforcing itself across generations. In this perspective, social exclusion may be viewed as an *absorbing state* (or '*trap*'), i.e. a status from which it is very difficult to transition over time without appropriate policy instruments (Bradley et al., 2003; Thomas and Gaspart, 2015).

Based on the Eurostat definition[1] (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 2007-2008 Great Recession 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 Great Recession has increasingly drawn the European Commission's attention towards the problem of social exclusion, whose persistent nature makes it especially concerning.

Besides being persistent in time, social exclusion has been shown to feature spatial patterns (Câmara et al., 2002; Baum and Gleeson, 2010). Neighbouring regions in other words influence each other in terms of social outcomes. The empirical literature explains this phenomenon with an imitation process that takes place either on part of policymakers or on part of citizens (Vettoretto, 2009; Shipan and Volden, 2012; Obinger et al., 2013). Although a number of studies on the spatial dimension of social exclusion have been carried out both nationally and at the local level in many EU Member States (Burgers and Kloosterman, 1996; Ceccato and Oberwittler, 2008; Martori and Apparicio, 2011; Marcińczak, 2012; Danson and Mooney, 2013), most contributions consist in localised case studies. The current literature is overall deficient in two regards: 1) no work has considered multiple EU countries, allowing for cross-border spatial patterns and 2) the effect of socio-economic covariates in the determination of spatial patterns has been to our knowledge overlooked.

[1] 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).

This article aims to address these two problems, resorting to official data covering NUTS-2 regions in 22 EU countries and controlling for a number of socio-economic covariates that may be responsible for the spatial patterns observed. In other words, we focus on detecting a spatial diffusion process in social exclusion across European regions, purified of the effect of underlying determinants of social exclusion.

The rest of this work is organised as follows: Section 2 introduces some stylised facts on social exclusion in the EU. Section 3 outlines the methodological instruments we employ in this analysis. Section 4 sums up the main features of the dataset we build, based on Eurostat observations. Section 5 presents and discusses the results of the empirical investigation. Section 6 provides our final considerations and concluding remarks.

2. Literature Background

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, when French officials constituted the backbone of the EU administration (Abrahamson, 1997; Atkinson, 2000). The conceptual distinction between poverty and social exclusion dates back to this period: poverty is defined as a distributional outcome (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).

The theoretical literature highlights the multidimensionality of the problem, that involves economic, social, political and cultural aspects of disadvantage and deprivation, resulting into limited access to employment, social services and community life (Bradshaw, 2004). Social exclusion deprives individuals of various rights and opportunities that are normally available to all citizens, like access to housing, health care, civic commitment, political participation and cultural integration (Chakravarty & D’Ambrosio, 2006; von Jacobi et al., 2017). A multidimensional approach is thus required in order to measure and evaluate social exclusion (Fisher, 2011; Giambona and Vassallo, 2014; Ciommi et al., 2017). To tackle this problem, 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.

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, 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 (Eurostat, 2010). While until 2008, in part due to the generosity of the EU initiatives, social exclusion decreased in Europe, after the financial crisis, 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.

3. Methods

In this section, we present the methods we employ to investigate the presence of spatial patterns in social exclusion across European regions. Before laying down the foundations of this work, one key concept must be introduced, i.e. variable purification: in order to detect the presence of the spatial persistence in social exclusion, we regress social exclusion on socio-economic variables, then we extract the resulting residuals. The residuals represent an estimate of the *purified variable* (see for example Fazio and Lavecchia, 2013; Ferraro et al., 2019), i.e. of what remains of the variable once the relevant covariates are controlled for. Subsequently, we proceed with the spatial analysis, computing the Moran Index and the Local Indicators of Spatial Association (LISA) and comparing the results obtained using the raw variables with those obtained using the purified variables.

3.1 Preliminary Analysis

As a first step, we wonder whether neighbours play a role in reducing social exclusion. To address this question, we introduce a measure of spatial autocorrelation, i.e. the Moran Index (MI), which is defined as follows (for further details, see Anselin, 1988; Agovino et al., 2016):

$$MI = \frac{x_k' W x_k}{x_k' x_k} \tag{1}$$

where x_k indicates the variable under investigation observed in region k, while W is the non-stochastic (NxN) spatial weights matrix[2]. So Wx_k is the spatial lag of x_k, i.e. the effect of regions k's neighbours. The MI allows to establish the relationship between a phenomenon observed in a given region and the same phenomenon observed in nearby regions. The index takes on values ranging between -1 and 1. A null value of the index indicates the absence of a spatial pattern. Spatially unrelated variables however may in some cases feature a significant MI, due to spatial autocorrelation in underlying factors. For this reason, it is important to purify variables. The most straightforward way to do so consists in regressing the variables on their spatially autocorrelated covariates and then computing the residuals, which are by construction orthogonal to the covariates.

3.2 SMC Analysis

Another major tool in spatial econometrics is the Local Moran Index (Anselin, 1995), which allows to identify the presence of spatial clusters (i.e. groups of regions sharing similar values) or spatial outliers (regions that stand out as very different from their neighbours). It decomposes the MI into contributions for each region, and may formally be defined as:

$$I_i = x_i \sum_{j \in J_i} w_{ij} x_j \tag{2}$$

where, analogous to the MI, x_i and x_j represent the phenomenon observed in region i and region j, and the summation over j is such that only neighbouring units $j \in J_i$ are included. The Local Moran Index may be viewed from two different perspectives: on the one hand, it allows to detect the presence of local spatial clusters; on the other hand, it represents a diagnostic tool that spots spatial outliers within the global spatial pattern.

After investigating the presence of spatial autocorrelation, we resort to Spatial Markov Chains (SMCs), in order to study the spatio-temporal dynamics of social exclusion (see Rey, 2001; Le Gallo, 2004; Agovino, 2014). The main output of a 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

[2] Here we use a binary spatial weights matrix. It is defined so that, when region i and region j are neighbours, i.e. they share a common border, the corresponding entry in the matrix is one; otherwise, the entry is set to zero. The elements on the main diagonal are set to zero, since a region cannot be contiguous to itself (see Agovino et al., 2016). The spatial weights matrix is row-standardised, so that spatial lags are computed as weighted averages of the values in neighbouring regions (Anselin, 1988).

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, conditional on the social exclusion levels of 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 tend to improve social outcomes even beyond administrative borders. Both effects are evaluated in a dynamic framework.

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 $t + 1$, 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 $k = 1, 2, \dots, K$ indicates the category to which unit i belongs. The unconditional transition matrix is then decomposed into K square submatrices of size (KxK) each, so as to condition on the K values of the variable observed in neighbouring units. We distinguish five categories of social exclusion (Low, Medium-Low, Medium, Medium-High, High), so $K = 5$. Each of the K blocks of the conditional transition matrix is a (KxK) square submatrix.

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 in period $t + 1$, knowing that the average social exclusion rate of its neighbouring regions belonged to class k at time t. The estimator of $p_{ij}\ (k)$ is defined as follows:

$$\hat{p}_{ij}\ (k) = \frac{n_{ij}(k)}{n_i(k)} \tag{3}$$

where $n_{ij}(k)$ is the number of units located in class i at time t and in class j in time $t + 1$, 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. We consider $t = 1, 2, \dots T$ periods, with $T = 11$, thus taking into account ten annual transitions. **Table 1** sketches the structure of the conditional matrix.

Table 1. The Spatial Markov Chain Matrix

Time t	Neighbours	Time $t+1$				
Class	Class	L	Ml	M	Mh	H
L	L	$p_{LL\|L}$	$p_{LMl\|L}$	$p_{LM\|L}$	$p_{LMh\|L}$	$p_{LH\|L}$
M_l		$p_{MlL\|L}$	$p_{MlMl\|L}$	$p_{MlM\|L}$	$p_{MlMh\|L}$	$p_{MlH\|L}$
M		$p_{ML\|L}$	$p_{MMl\|L}$	$p_{MM\|L}$	$p_{MMh\|L}$	$p_{MH\|L}$
M_h		$p_{MhL\|L}$	$p_{MhMl\|L}$	$p_{MhM\|L}$	$p_{MhMh\|L}$	$p_{MhH\|L}$
H		$p_{HL\|L}$	$p_{HMl\|L}$	$p_{HM\|L}$	$p_{HMh\|L}$	$p_{HH\|L}$
L	Ml	$p_{LL\|Ml}$	$p_{LMl\|Ml}$	$p_{LM\|Ml}$	$p_{LMh\|Ml}$	$p_{LH\|Ml}$
M_l		$p_{MlL\|Ml}$	$p_{MlMl\|Ml}$	$p_{MlM\|Ml}$	$p_{MlMh\|Ml}$	$p_{MlH\|Ml}$
M		$p_{ML\|Ml}$	$p_{MMl\|Ml}$	$p_{MM\|Ml}$	$p_{MMh\|Ml}$	$p_{MH\|Ml}$
M_h		$p_{MhL\|Ml}$	$p_{MhMl\|Ml}$	$p_{MhM\|Ml}$	$p_{MhMh\|Ml}$	$p_{MhH\|Ml}$
H		$p_{HL\|Ml}$	$p_{HMl\|Ml}$	$p_{HM\|Ml}$	$p_{HMh\|Ml}$	$p_{HH\|Ml}$
L	M	$p_{LL\|M}$	$p_{LMl\|M}$	$p_{LM\|M}$	$p_{LMh\|M}$	$p_{LH\|M}$
M_l		$p_{MlL\|M}$	$p_{MlMl\|M}$	$p_{MlM\|M}$	$p_{MlMh\|M}$	$p_{MlH\|M}$
M		$p_{ML\|M}$	$p_{MMl\|M}$	$p_{MM\|M}$	$p_{MMh\|M}$	$p_{MH\|M}$
M_h		$p_{MhL\|M}$	$p_{MhMl\|M}$	$p_{MhM\|M}$	$p_{MhMh\|M}$	$p_{MhH\|M}$
H		$p_{HL\|M}$	$p_{HMl\|M}$	$p_{HM\|M}$	$p_{HMh\|M}$	$p_{HH\|M}$
L	Mh	$p_{LL\|Mh}$	$p_{LMl\|Mh}$	$p_{LM\|Mh}$	$p_{LMh\|Mh}$	$p_{LH\|Mh}$
M_l		$p_{MlL\|Mh}$	$p_{MlMl\|Mh}$	$p_{MlM\|Mh}$	$p_{MlMh\|Mh}$	$p_{MlH\|Mh}$
M		$p_{ML\|Mh}$	$p_{MMl\|Mh}$	$p_{MM\|Mh}$	$p_{MMh\|Mh}$	$p_{MH\|Mh}$
M_h		$p_{MhL\|Mh}$	$p_{MhMl\|Mh}$	$p_{MhM\|Mh}$	$p_{MhMh\|Mh}$	$p_{MhH\|Mh}$
H		$p_{HL\|Mh}$	$p_{HMl\|Mh}$	$p_{HM\|Mh}$	$p_{HMh\|Mh}$	$p_{HH\|Mh}$
L	H	$p_{LL\|H}$	$p_{LMl\|H}$	$p_{LM\|H}$	$p_{LMh\|H}$	$p_{LH\|H}$
M_l		$p_{MlL\|H}$	$p_{MlMl\|H}$	$p_{MlM\|H}$	$p_{MlMh\|H}$	$p_{MlH\|H}$
M		$p_{ML\|H}$	$p_{MMl\|H}$	$p_{MM\|H}$	$p_{MMh\|H}$	$p_{MH\|H}$
M_h		$p_{MhL\|H}$	$p_{MhMl\|H}$	$p_{MhM\|H}$	$p_{MhMh\|H}$	$p_{MhH\|H}$
H		$p_{HL\|H}$	$p_{HMl\|H}$	$p_{HM\|H}$	$p_{HMh\|H}$	$p_{HH\|H}$

Note: L, Ml, M, Mh and H represents respectively Low, Medium-Low, Medium, Medium-High and High levels.

The conditional matrix sheds some 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

[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.

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:

$$p_{ab|a} = p_{ab|b} = \cdots = p_{ab|K}, \qquad \forall\, a = 1, \dots, K \qquad b = 1, \dots, K \tag{4}$$

Equation (4) may be tested empirically. 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).

4. Data

The dataset we build up is largely based on Eurostat observation, available for 111 NUTS-2 regions, within 22 EU Member States[4] and encompassing the 2004-2016 time period. We complement the Eurostat information with the European Quality of Government Index (Charron et al., 2014).

Our dataset contains four dependent variables and four regressors. The dependent variables are Social Exclusion its three components, namely Poverty, Material Deprivation and Low Intensity of Work, while the regressors are Education, Unemployment, Life Expectation and Institutional Quality (EQI). All the variables are available at the regional level (NUTS-2). **Table 2** sums up the main features of our dataset.

Table 2. Dataset

Variable	Observation	Mean	St. Deviation	min	Max	Source
Social Exclusion	1,164	25.14	11.42	4.4	59.5	Eurostat
Poverty	1,164	16.97	7.86	0	44.6	Eurostat
Material Deprivation	1,164	10.40	11.03	0	55.2	Eurostat
Low Intensity of Work	1,164	9.73	4.97	0	32.11	Eurostat
Education	1,164	70.32	15.50	25.2	97.3	Eurostat
Unemployment	1,164	10.30	5.87	1.9	36.2	Eurostat
Life Expectation	1,164	79.68	3.30	70.6	85.2	Eurostat
EQI	1,164	-0.24	1.08	-2.655	1.76	Charron et al. (2014)

More on the regressors:

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

- *Education* is defined as the share of people who completed higher education (i.e. passing 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).
- *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)
- *Life Expectation* represents the average years that an individual born today would be expected to live. This variable is a demographic and 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).
- *Institutional Quality,* measured by the European Quality of Government Index (Charron et al., 2014) provides information on the provision of public services. Better institutions are expected to counter social exclusion (Easterly et al, 2006; Bosco, 2016).

5. 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 the dependent variables, in order is to understand whether the socio-economic covariates affect cluster size and stability and whether a spatial diffusion process is taking place. We mainly focus on social exclusion, but we also consider its three components separately (poverty, material deprivation and low intensity of work), so as to provide guidelines for policy interventions. For the sake of conciseness, from now on when referring to social exclusion and each of its components, we simply use 'X'.

5.1 Preliminary results: spatial autocorrelation

First, we regress X on the socio-economic covariates, in order to obtain the purified variables of interest. Since endogeneity may affect our estimates, we resort to instrumental variable estimation. In particular, unemployment and education may be in a two-way relation with social exclusion, so we instrument them with their time lags. In order to avoid losing periods, we replace the missing values in the instruments with zeros (see Holtz-Eakin et al., 1988; Arellano and Bond, 1991; Baltagi 2013; 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 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, robust for heteroscedasticity[5]. The results of both tests are displayed in **Table A1** (see Appendix).

The Sargan test for overidentification confirms the validity of the instrument set. The Hausman test instead ascertains the consistency of the random effects estimator, implying that it must be preferred. As a result, we regress X on the covariate set and we extract the residuals, which may be considered as purified variables, meaning they capture what is left after controlling for the covariates. First of all, we are interested in the degree of spatial autocorrelation featured by X, both raw and purified. To this end, **Figure 1** shows the Moran Index over time (the left side), and the unconditional correlations between X and the covariates (right side).

The Moran Index displays positive and significant values for the raw version of X over the whole 2004-2016 timespan. In other words, spatial autocorrelation is strong and persistent for all the variables considered. The picture however changes substantially when considering purified X. In particular, spatial autocorrelation drops for social exclusion, material deprivation and poverty, while it increases for low intensity of work. The Moran index remains positive and significant for all variables. This large difference in the extent of spatial autocorrelation depends on the fact that the underlying socio-economic variables are partly responsible for both the cross-border similarities and the differences 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).

To understand which covariates produce the greatest impact on spatial autocorrelation, we show the correlations between X and the covariates.

- Starting with *Social Exclusion*, both the raw and the purified variable follow the same trend, displaying a positive and significant MI, which decreases after 2013. The purification process decreases the MI, implying that the socio-economic covariates partly explain the spatial autocorrelation process. A possible explanation for this phenomenon is provided by the time

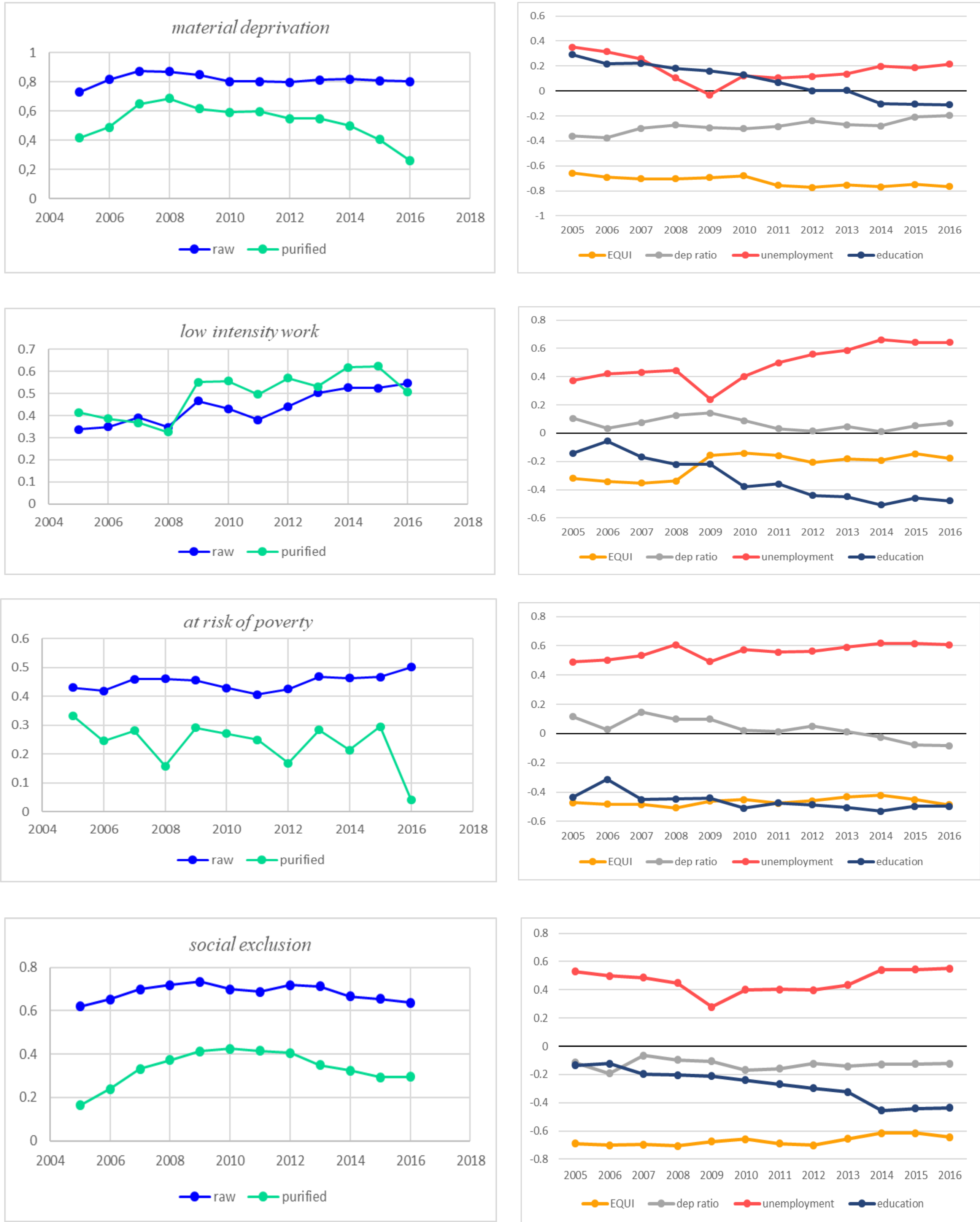
[5] The *hausman* command implemented in Stata assumes homoscedasticity and may not be used with clustered errors. To sort out this problem, we craft a procedure that replicates the Hausman test, using an auxiliary regression, obtained by quasi-demeaning the variables of the model. This procedure is based on Wooldridge (2002) and Cameron and Trivedi (2009).

series of the partial correlations. The variables exerting the greatest impact on the spatial diffusion process are the institutional quality and unemployment. The approximately parallel and constant trends featured by the raw and purified variables is due to the EQI and life expectancy variables, where the correlation is rather constant, while the reduction since 2013, of the MI index for the purified variable is due to the effect of education, whose effects only arise over time.

- A similar reasoning holds for *Material Deprivation*, that displays in both cases the highest MI (for both the raw and the purified variable), with respect to the other components of social exclusion. For both variables there is a parallel trend with a reduction, from 2012, of the MI for purified material deprivation. The variable that most affects material deprivation institutional quality, so the parallel trend is explained by the EQI and life expectancy, while education and unemployment feature a relatively low correlation and produce a smaller impact.
- *Poverty* displays a certain persistency in spatial autocorrelation for the raw variable, but when controlling for socio-economic factors, neighbour influence drops, indicating that the controls are mainly accountable for the spatial diffusion process observed. Unlike the other components, education plays a major role, as much as institutional quality.
- The *low intensity work variable* is the only case where the spatial autocorrelation process is hidden by socio-economic variables. The MI actually increases after purification, revealing an internal spatial process. The effect of education unfolds over time: at first correlation is very low, while it gradually becomes more stronger, reducing spatial persistence. Unemployment on the other hand features an opposite trend, since its effect is at first constant and later grows larger.

Based on these results, it is interesting to verify whether the regions with low (high) social exclusion manage to influence the regions high (low) social exclusion, thus determining an improvement (deterioration) in the process. This hypothesis may be verified by implementing the SMCs Analysis.

Figure 1. MI and Correlation Coefficient over time.



5.2 Spatial Marokv Chain Results

Transitions in X are considered across two consecutive time periods. In our analysis, eleven transitions occur over the 2005–2016 period (namely 2005–2006, 2006–2007, …, 2015– 2016). For each transition, five classes may be identified. Counting in total 122 regions, 11 years and five categories, it is possible to obtain at most 6,710 cases of transitions[6]. We report the SMC results as in Rey (2001). In particular, we define five feasible states ($K = 5$) based on the value of social exclusion rate and its components. Bearing in mind that $\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$ is the mean of X and $\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2}$ is the standard deviation of X, the states are defined as follows (see also Agovino, 2014):

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

In summary, the five states are set in the following order: $L < Ml < M < Mh < H$. The results of conditional transition probabilities are reported in **Table 3**, which lists the number of cases for each transition type. For example, line 8 indicates the probability that a region starting with level M at time t will move to other classes in the following year $(t + 1)$, given that it is surrounded by neighbours featuring an Ml level. If we consider the pairs of consecutive years, there are thirteen cases (line 9, column 4) of regions in that situation.

Lines 1–5 represent regions embedded in neighbourhoods with a low rate (L). Lines 6–10 represent regions embedded in neighbourhoods with a medium-low rate (Ml). lines 11–15 represent regions embedded in neighbourhoods with a medium rate (M). Lines 16–20 represent regions embedded in neighbourhoods with a medium-high rate (Ml). finally, lines 21–25 represent regions embedded in neighbourhoods with a high rate (H). This result reveals the presence of spatial persistent. In other

[6] With n regions, K states and t years, there are $(t - 1) * K * n$ possible cases of transitions. In our case, the total amounts to $11 * 5 * 122 = 6{,}710$.

words, the probability that a region will persist in the same class is relatively high, and in some cases, this probability is over 80%.

Table 3. SMC Matrix

Social exclusion

Raw

Line	Status at time t	Neighbors condition	Num. Cases	status at time (t+1) L	Ml	M	Mh	H
1	L		125	0.832	0.16	0.008	0	0
2	Ml		56	0.25	0.661	0.071	0.018	0
3	M	L	13	0	0.462	0.538	0	0
4	Mh		4	0	0	0.25	0.5	0.25
5	H		9	0	0	0	0.111	0.889
6	L		134	0.813	0.179	0.007	0	0
7	Ml		136	0.206	0.699	0.096	0	0
8	M	Ml	63	0.016	0.206	0.73	0.048	0
9	Mh		13	0	0	0.231	0.538	0.231
10	H		14	0	0	0	0.214	0.786
11	L		24	0.75	0.25	0	0	0
12	Ml		74	0.108	0.689	0.149	0.054	0
13	M	M	110	0.009	0.155	0.691	0.145	0
14	Mh		56	0	0	0.321	0.679	0
15	H		15	0	0	0	0.133	0.867
16	L		2	0	1	0	0	0
17	Ml		24	0.083	0.667	0.167	0.083	0
18	M	Mh	67	0	0.06	0.776	0.164	0
19	Mh		117	0	0	0.145	0.701	0.154
20	H		53	0	0	0	0.189	0.811
21	L		0	0	0	0	0	0
22	Ml		5	0	0.8	0.2	0	0
23	M	H	12	0	0.083	0.667	0.25	0
24	Mh		42	0	0	0.048	0.833	0.119
25	H		174	0	0	0	0.04	0.96

Purified

Line	Status at time t	Neighbors condition	Num. Cases	status at time (t+1) L	Ml	M	Mh	H
1	L		156	0.788	0.135	0.045	0.032	0
2	Ml		32	0.469	0.344	0.031	0.125	0.031
3	M	L	10	0.1	0.4	0.3	0.2	0
4	Mh		18	0.056	0.222	0.222	0.278	0.222
5	H		18	0.056	0	0	0.167	0.778
6	L		54	0.556	0.185	0.074	0.148	0.037
7	Ml		40	0.475	0.2	0.225	0.1	0
8	M	Ml	29	0.138	0.207	0.241	0.379	0.034
9	Mh		21	0.19	0.095	0.19	0.429	0.095
10	H		19	0	0	0.053	0.263	0.684
11	L		51	0.569	0.176	0.157	0.078	0.02
12	Ml		35	0.343	0.2	0.257	0.171	0.029
13	M	M	47	0.149	0.149	0.17	0.489	0.043
14	Mh		72	0.139	0.125	0.167	0.444	0.125
15	H		23	0.043	0.043	0	0.304	0.609
16	L		79	0.456	0.228	0.19	0.127	0
17	Ml		63	0.333	0.254	0.222	0.159	0.032
18	M	Mh	72	0.167	0.181	0.292	0.278	0.083
19	Mh		182	0.077	0.055	0.165	0.588	0.115
20	H		122	0.033	0.008	0.033	0.221	0.705
21	L		20	0.6	0.2	0.15	0	0.05
22	Ml		14	0.143	0.286	0.286	0.214	0.071
23	M	H	27	0.111	0.148	0.333	0.407	0
24	Mh		40	0.05	0	0.225	0.475	0.25
25	H		98	0.02	0	0.02	0.082	0.878

Material deprivation

Raw

Line	Status at time t	Neighbors condition	Num. Cases	status at time (t+1) L	Ml	M	Mh	H
1	L		135	0.859	0.126	0.015	0	0
2	Ml		38	0.316	0.658	0.026	0	0
3	M	L	15	0.067	0.133	0.8	0	0
4	Mh		6	0	0	0.167	0.667	0.167
5	H		10	0	0	0	0.2	0.8
6	L		65	0.569	0.385	0.046	0	0
7	Ml		117	0.214	0.607	0.179	0	0
8	M	Ml	53	0.057	0.302	0.623	0.019	0
9	Mh		6	0	0	0.167	0.5	0.333
10	H		3	0	0	0	0.333	0.667
11	L		34	0.441	0.529	0.029	0	0
12	Ml		83	0.193	0.47	0.337	0	0
13	M	M	215	0.005	0.093	0.847	0.051	0.005
14	Mh		46	0	0	0.196	0.696	0.109
15	H		8	0	0	0	0.375	0.625
16	L		9	0.778	0.222	0	0	0
17	Ml		5	0.2	0.4	0.4	0	0
18	M	Mh	79	0.013	0.038	0.835	0.114	0
19	Mh		118	0	0	0.136	0.746	0.119
20	H		31	0	0	0	0.161	0.839
21	L		4	1	0	0	0	0
22	Ml		0	0	0	0	0	0
23	M	H	6	0	0	0.667	0.167	0.167
24	Mh		38	0	0	0.053	0.684	0.263
25	H		218	0	0	0	0.06	0.94

Purified

Line	Status at time t	Neighbors condition	Num. Cases	status at time (t+1) L	Ml	M	Mh	H
1	L		159	0.811	0.063	0.088	0.038	0
2	Ml		32	0.281	0.25	0.344	0.125	0
3	M	L	44	0.091	0.159	0.545	0.182	0.023
4	Mh		31	0.097	0.065	0.29	0.419	0.129
5	H		9	0	0.111	0.222	0.333	0.333
6	L		82	0.707	0.146	0.073	0.073	0
7	Ml		61	0.328	0.311	0.23	0.131	0
8	M	Ml	53	0.17	0.321	0.283	0.189	0.038
9	Mh		32	0.094	0.094	0.188	0.5	0.125
10	H		14	0.071	0.071	0	0.5	0.357
11	L		96	0.552	0.167	0.146	0.094	0.042
12	Ml		40	0.525	0.25	0.225	0	0
13	M	M	68	0.25	0.191	0.368	0.132	0.059
14	Mh		55	0.091	0.109	0.182	0.436	0.182
15	H		19	0	0.105	0	0.263	0.632
16	L		46	0.543	0.13	0.109	0.174	0.043
17	Ml		35	0.286	0.057	0.286	0.314	0.057
18	M	Mh	51	0.176	0.275	0.353	0.157	0.039
19	Mh		67	0.119	0.06	0.164	0.448	0.209
20	H		65	0.031	0.046	0.015	0.185	0.723
21	L		15	0.4	0.2	0.333	0	0.067
22	Ml		15	0.333	0.2	0.267	0.133	0.067
23	M	H	16	0.25	0.375	0.188	0.125	0.063
24	Mh		66	0.03	0.076	0.152	0.485	0.258
25	H		171	0.023	0	0.018	0.105	0.854

Low intensity of work

Raw

Line	Status at time t	Neighbors condition	Num. Cases	L	Ml	M	Mh	H
1	L	L	90	0.789	0.156	0.044	0	0.011
2	Ml		57	0.351	0.526	0.123	0	0
3	M		25	0.08	0.44	0.36	0.08	0.04
4	Mh		10	0	0	0.3	0.4	0.3
5	H		6	0	0	0	0.667	0.333
6	L	Ml	81	0.753	0.16	0.062	0.025	0
7	Ml		66	0.348	0.288	0.273	0.076	0.015
8	M		62	0.032	0.226	0.581	0.129	0.032
9	Mh		22	0	0.136	0.273	0.318	0.273
10	H		9	0	0	0	0.556	0.444
11	L	M	77	0.753	0.208	0.039	0	0
12	Ml		65	0.231	0.4	0.292	0.077	0
13	M		123	0.057	0.195	0.561	0.171	0.016
14	Mh		59	0	0.102	0.373	0.407	0.119
15	H		54	0	0	0	0.241	0.759
16	L	Mh	17	0.706	0.235	0.059	0	0
17	Ml		39	0.103	0.462	0.41	0.026	0
18	M		61	0.016	0.164	0.492	0.295	0.033
19	Mh		60	0	0.033	0.25	0.517	0.2
20	H		85	0	0.012	0.024	0.082	0.882
21	L	H	18	0.667	0.333	0	0	0
22	Ml		24	0.208	0.5	0.292	0	0
23	M		38	0	0.158	0.684	0.158	0
24	Mh		53	0	0.038	0.226	0.66	0.075
25	H		141	0	0	0	0.035	0.965

(Columns L–H: *status at time (t+1)*)

Purified

Line	Status at time t	Neighbors condition	Num. Cases	L	Ml	M	Mh	H
1	L	L	51	0.569	0.275	0.098	0	0.059
2	Ml		14	0.429	0.286	0.214	0	0.071
3	M		17	0.118	0.176	0.588	0.059	0.059
4	Mh		4	0.5	0	0.5	0	0
5	H		7	0	0.286	0.143	0.286	0.286
6	L	Ml	65	0.446	0.308	0.154	0.062	0.031
7	Ml		75	0.28	0.28	0.347	0.067	0.027
8	M		69	0.145	0.348	0.246	0.174	0.087
9	Mh		25	0.12	0.24	0.4	0.12	0.12
10	H		15	0	0.133	0.133	0.067	0.667
11	L	M	98	0.367	0.255	0.276	0.071	0.031
12	Ml		104	0.26	0.279	0.365	0.048	0.048
13	M		167	0.168	0.222	0.419	0.138	0.054
14	Mh		85	0.071	0.118	0.294	0.376	0.141
15	H		47	0.021	0.064	0.128	0.255	0.532
16	L	Mh	26	0.462	0.269	0.154	0.115	0
17	Ml		43	0.279	0.326	0.279	0.047	0.07
18	M		58	0.207	0.069	0.259	0.362	0.103
19	Mh		86	0.035	0.093	0.267	0.43	0.174
20	H		63	0	0.032	0.127	0.349	0.492
21	L	H	12	0.417	0.25	0.333	0	0
22	Ml		14	0.286	0.214	0.429	0	0.071
23	M		20	0.05	0.2	0.25	0.3	0.2
24	Mh		46	0.022	0.065	0.174	0.435	0.304
25	H		131	0.008	0.046	0.053	0.092	0.802

(Columns L–H: *status at time (t+1)*)

At risk of poverty

Raw

Line	Status at time t	Neighbors condition	Num. Cases	L	Ml	M	Mh	H
1	L		87	0.897	0.103	0	0	0
2	Ml		34	0.235	0.647	0.118	0	0
3	M	L	15	0	0.2	0.8	0	0
4	Mh		3	0	0	1	0	0
5	H		9	0	0	0	0.111	0.889
6	L		93	0.774	0.183	0.043	0	0
7	Ml		103	0.272	0.641	0.087	0	0
8	M	Ml	65	0	0.169	0.754	0.077	0
9	Mh		28	0	0	0.214	0.714	0.071
10	H		7	0	0	0	0.143	0.857
11	L		49	0.776	0.204	0.02	0	0
12	Ml		70	0.143	0.571	0.271	0.014	0
13	M	M	130	0.008	0.146	0.685	0.162	0
14	Mh		85	0	0	0.2	0.776	0.024
15	H		13	0	0	0	0.308	0.692
16	L		21	0.81	0.19	0	0	0
17	Ml		26	0.077	0.423	0.5	0	0
18	M	Mh	69	0.014	0.159	0.565	0.261	0
19	Mh		134	0	0	0.142	0.716	0.142
20	H		143	0	0	0	0.112	0.888
21	L		13	0.692	0.308	0	0	0
22	Ml		21	0.143	0.667	0.19	0	0
23	M	H	22	0	0.136	0.727	0.136	0
24	Mh		26	0	0	0.154	0.692	0.154
25	H		76	0	0	0	0.118	0.882

(Columns L–H: *status at time (t+1)*)

Purified

Line	Status at time t	Neighbors condition	Num. Cases	L	Ml	M	Mh	H
1	L		50	0.6	0.16	0.16	0.08	0
2	Ml		12	0.25	0.083	0.583	0.083	0
3	M	L	17	0.235	0.176	0.353	0.235	0
4	Mh		16	0	0.125	0.25	0.438	0.188
5	H		3	0	0	0	0	1
6	L		48	0.542	0.125	0.271	0.042	0.021
7	Ml		37	0.297	0.216	0.351	0.135	0
8	M	Ml	34	0.294	0.235	0.324	0.118	0.029
9	Mh		16	0	0.188	0.25	0.563	0
10	H		12	0	0	0.083	0.417	0.5
11	L		68	0.426	0.279	0.235	0.059	0
12	Ml		66	0.273	0.152	0.409	0.121	0.045
13	M	M	188	0.138	0.128	0.495	0.207	0.032
14	Mh		113	0.08	0.035	0.221	0.522	0.142
15	H		55	0.018	0.018	0.018	0.291	0.655
16	L		77	0.429	0.169	0.247	0.117	0.039
17	Ml		39	0.436	0.128	0.282	0.154	0
18	M	Mh	106	0.113	0.17	0.33	0.368	0.019
19	Mh		157	0.096	0.057	0.242	0.42	0.185
20	H		102	0.01	0	0.078	0.235	0.676
21	L		12	0.417	0.25	0.333	0	0
22	Ml		8	0.375	0.25	0.125	0.25	0
23	M	H	14	0.286	0.143	0.357	0.071	0.143
24	Mh		31	0.032	0.032	0.097	0.516	0.323
25	H		61	0.033	0	0.033	0.279	0.656

(Columns L–H: *status at time (t+1)*)

Note: Shaded cells indicate permanence in the same situation across the years

For all the four variables considered, the *raw* component features a strong degree of inertia, since the elements on the main diagonal are the largest in their row for every single case. It is very likely in other words that a region will persist in the same class over two consecutive periods. The extent of persistency is even stronger in the presence of neighbours belonging to the same class, unfolding a strong spatiotemporal autocorrelation process. When the purified component is considered instead, the probabilities associated to persistence decrease sensibly and the role of neighbours becomes weaker. Neighbours in other words exert little influence once the relevant socio-economic covariates are accounted for. This produces a twofold effect: one the one hand, starting from a low level (*L* or *Ml*), the probability of moving towards high levels (*Mh* or *H*) is low, even in case bordering regions belong to high classes. In this case the socio-economic factors prevent social exclusion from spreading out. On the other hand, when starting from a high level (*Mh* or *H*), the probability of persistence is high, 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.

The ergodic distributions (see Rey, 2001; Le Gallo, 2004) displayed in **Table 4** may be interpreted as the long run distributions of the variables considered. Additional insights about the re transition probabilities may be obtained when considering the ergodic distributions implied by each of the estimated conditional transition matrices from. Five different ergodic state vectors for each variable (both raw and purified) are reported in **Table 4** and in **Table A3**.

Table 4. Ergodic Distributions

Social exclusion					
Lag	***L***	***Ml***	***M***	***Mh***	***H***
Lr	0	0	0	0	0
Lp	0	0	0	0	0
Mlr	0.407	0.356	0.167	0.034	0.037
Mlp	0.312	0.142	0.148	0.265	0.133
Mr	0.139	0.29	0.36	0.212	0
Mp	0.275	0.143	0.155	0.293	0.135
Mhr	0.006	0.067	0.281	0.356	0.29
Mhp	0.187	0.125	0.174	0.325	0.189
Hr	0	0.019	0.045	0.236	0.7
Hp	0.109	0.058	0.133	0.204	0.495

At risk of poverty					
Lag	***L***	***Ml***	***M***	***Mh***	***H***
Lr	0.589	0.259	0.152	0	0
Lp	0	0	0	0	0
Mlr	0.347	0.288	0.237	0.085	0.043
Mlp	0.228	0.278	0.252	0.098	0.144
Mr	0.13	0.184	0.359	0.303	0.023
Mp	0.192	0.204	0.326	0.158	0.119
Mhr	0.038	0.061	0.174	0.321	0.406
Mhp	0	0	0	0	0
Hr	0.081	0.175	0.245	0.217	0.282
Hp	0.081	0.111	0.172	0.167	0.469

Material deprivation					
Lag	***L***	***Ml***	***M***	***Mh***	***H***
Lr	0.646	0.27	0.083	0	0
Lp	0.393	0.114	0.287	0.164	0.042
Mlr	0.251	0.439	0.252	0.029	0.029
Mlp	0.385	0.19	0.157	0.217	0.051
Mr	0.059	0.159	0.566	0.162	0.054
Mp	0.332	0.166	0.184	0.168	0.15
Mhr	0.062	0.046	0.363	0.305	0.224
Mhp	0.211	0.104	0.154	0.26	0.272
Hr	1	0	0	0	0
Hp	0	0	0	0	0

Low income					
Lag	***L***	***Ml***	***M***	***Mh***	***H***
Lr	0.499	0.273	0.118	0.066	0.045
Lp	0	0	0	0	0
Mlr	0.29	0.181	0.266	0.163	0.1
Mlp	0.228	0.278	0.252	0.098	0.144
Mr	0.263	0.21	0.288	0.148	0.092
Mp	0.192	0.204	0.326	0.158	0.119
Mhr	0.05	0.11	0.216	0.209	0.415
Mhp	0	0	0	0	0
Hr	0.1	0.16	0.258	0.154	0.328
Hp	0.081	0.111	0.172	0.167	0.469

Note*: Lr, Mlr, Mr, Mhr, Hr stand for the raw variables, Lp, Mlp, Mp, Mhp, Hp stand for the purified variables.*

In the case of *L* and *Ml*, the long run probability of moving to high classes (*Mh, H*) is lower in the case of the *raw variable*, this means that the socio-economic covariates help to reduce and mitigate the phenomenon. In case the starting class is the middle one (*M*), for the raw variable it is very probable to stay still, for the purified variable the probabilities are distributed along the different lag. If the starting point is the class *Mh* and *H* there is a spatial persistence for the raw variable in moving to a better class, also in this case the socio-economic factors are the cause of spatial persistence. If on one hand they mitigate the transition to the worst classes on the other they prevent the improvement and the transition towards the better classes (i.e. *L, Ml*). These results are in line with the SMCs analysis. Graphical descriptions of the ergodic distribution, as well as some more comments, are provided in **Table A2** (see the Appendix).

These results have demonstrated the importance of socio-economic factors in reducing social exclusion and its components. 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).

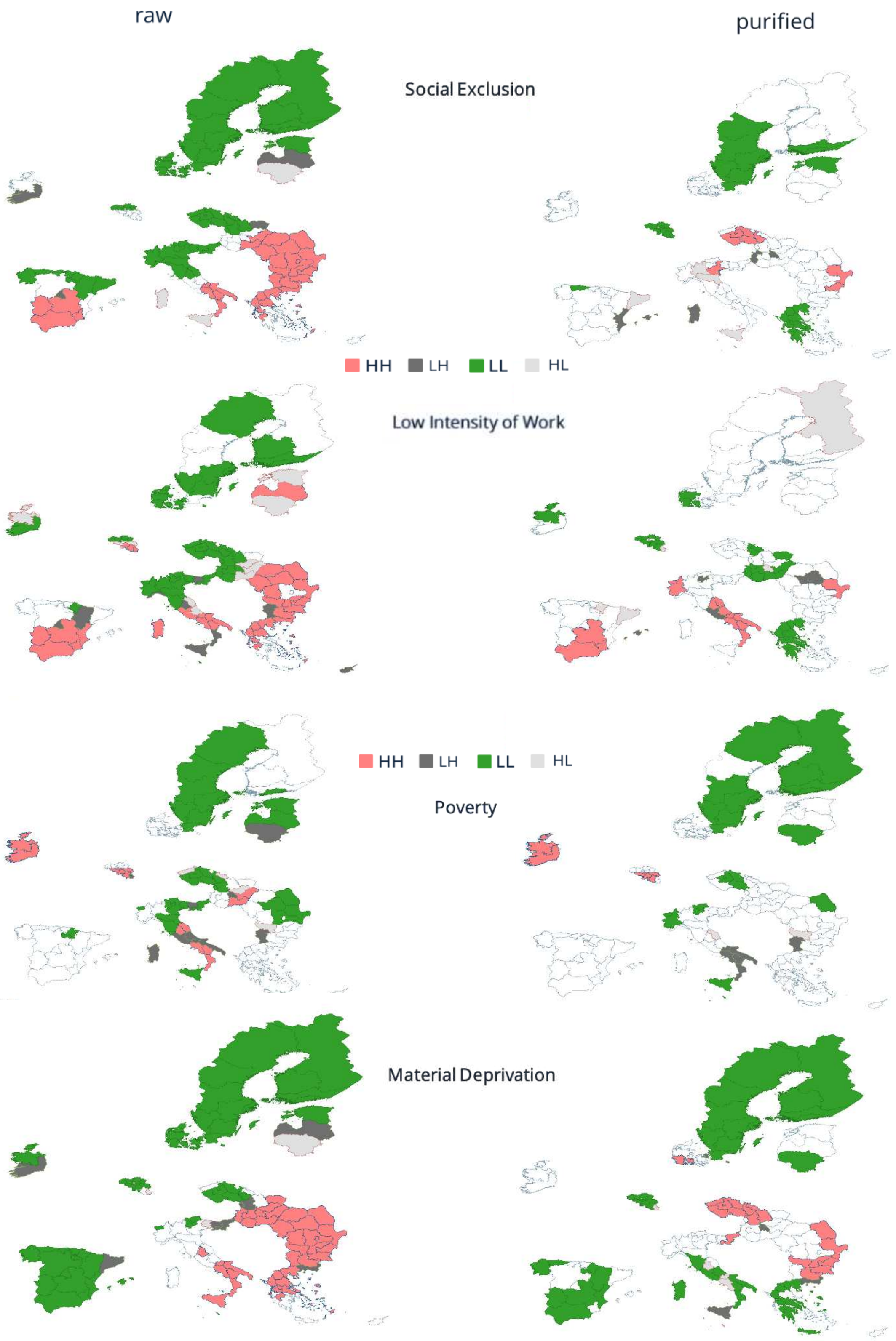
This effect is evident from the results of the local Moran test (Anselin, 1995) which allows to identify the presence of spatial clusters (see **Figure 2**). In other words, the allocation of regions to one of the four quadrants of the Moran scatterplot occurs according to the number of years in the 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, Figure 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, for the period analysed and for all the four variables, we observe that European regions mainly end up in either the first or the third of the Moran scatterplot, reflecting HH and LL clustering. A more thorough analysis for each variable follows:

- *Social Exclusion*: considering the raw variable, four HH and three LL clusters emerge. The LL clusters include Scandinavia, Northern Netherlands, Northern Spain, Northern Italy, Czech Republic and Slovakia. The HH clusters instead contain Greece, Southern Italy, Southern Spain and the Balkans. The duality between the regions of Northern and Southern Europe thus emerges once again (Bettio and Piantega, 2004; Gal, 2010). When considering the purified variable however, many clusters break. In particular, the LL cluster of Northern Europe is now limited to Scandinavia and the Netherlands. Northern Italy ends up in the HH class, while the negative cluster of Southern Italy breaks down, revealing that social exclusion in the Peninsula is driven by socio-economic differences. The cluster of Eastern Europe and Spain disappear, while Czech Republic turns from LL to HH. Overall, the picture looks completely different when controlling for the socio-economic drivers of social exclusion.

- *Material deprivation*: looking at the raw variable, three LL clusters and two HH clusters emerge Southern Italy and Eastern Europe. The LL clusters encompass Scandinavia, the Netherlands, Czech Republic and Spain, whereas the HH clusters cover Southern Italy, Greece and the Balkans. Once socio-economic covariates are taken into account, the LL clusters persist in parts of Scandinavia and the Netherlands, while the Spanish cluster becomes less extended and the Czech cluster turns to HH. Southern Italy and Greece shift from HH to LL, highlighting the decisive role of socio-economic factors in the spatial diffusion process.
- *People at risk of poverty*: similar to the case of social exclusion, when considering the raw variable, a clear North/South divide becomes evident. Three LL clusters appear in Scandinavia, Northern Italy, Czech Republic and Slovakia, while three HH cluster emerge in Southern Italy, Ireland and Hungary. After purification, the clusters break down, except Ireland and Scandinavia. The spatial patterns related to poverty depend in part on the effect of the socio-economic covariates.
- *Low intensity of* work: concerning the raw variable, two LL clusters may be identified, i.e. Northern Italy and Czech Republic-Slovakia-Hungary, as well as three HH, namely Southern Spain, Southern Italy and the Balkans, up to Greece. Considering the purified variable, the HH clusters of Southern Italy and Southern Spain persist, while new LL clusters emerge in Greece and the Netherlands.

Overall, the role of socio-economic covariates turns out to be primary within the spatial diffusion process. An interesting example is represented by Greece: although the country displays high rates of social exclusion at present, thus forming a negative HH cluster of social exclusion, this negative situation is mainly caused by the adverse socio-economic factors. Once these factors are controlled for, Greece stands out as an inherently virtuous area, where the Great Recession and the austerity policies that followed are the main responsible for the high levels of social exclusion.

Figure 2. Local Moran Distribution



Note: HH (red) and LL (green) denote the regions mainly ending up in either quadrants 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.

5.3 Policy Implications

The key role played by socio-economic variables in affecting the strength of the spatiotemporal diffusion process characterising social exclusion has emerged from the previous steps of the analysis. In particular, unemployment, education, life expectation and institutional quality are responsible for variations in the intensity of neighbour influence. While it is difficult to imagine significant changes in institutional quality in the short run (Acemoğlu and Robinson, 2006; 2008; Agovino et al., 2019), this result highlights the importance of active labour market policies, of investments in education and health in the fight against social exclusion.

In particular, labour market policies represent one of the main lines of intervention that may reduce the problem of low intensity of work (Clasen et al., 2016). Passive policies on the one hand – such as generous income support schemes and unemployment benefits – may discourage labour market participation (Van Ours and Vodopivec, 2006). Public programmes focusing on human capital accumulation may generate the so-called *locking-in effect* (Van Ours, 2004; Lechner et al., 2007; Crépon et al., 2009), consisting in the repeated paid attendance to vocational training programmes on part of unemployed workers, who typically become long-run unemployed by spending most of their time on training courses rather than searching for jobs. To avoid such policy failures, active labour market policies must be designed so as to provide unemployed workers with the right incentive set, target marginalised individuals constitute a vehicle of inclusion into the labour market and the broader community life (Guth, 2005).

Investments on education need to be positioned strategically within the broader framework of social policy (Whitty, 2001), whereas 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).

Along the same line of reasoning, investments on the health may help fight social exclusion (Klein, 2004), 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, possibly 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 recent literature highlights the fact that the composition of spending counts as much as the amount of spending, while the transfers in kind (e.g. dentures and wheelchairs) and transfers in cash may produce very different effects (see Crociata et al., 2019).

The Great Recession of 2007-2009 however reshaped the structure of public spending. As a consequence, the classical redistribution mechanisms that characterised the welfare state in the last decades of the XX and in the first decades of the XXI century appear to have lost part of their original effectiveness (Moulaert and Ailenei, 2005). 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). Formal social institutions, such as trade unions and local administrations played a limited role in contrasting this problem (Karakioulafis and Kanellopoulos, 2018), leading to the spontaneous establishment of semiformal and informal networks of mutual support in several EU countries and especially in the so-called EU periphery (Bosi and Zamponi, 2015; Camps-Calvet et al., 2015; Giudi 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).

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 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, 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.

While controlling for socio-economic covariates reduces the extent of spatial spillovers, persistent spatial patterns clearly emerge from the empirical analysis. 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.

6. Conclusion

This work investigates spatial patterns in social exclusion. Using cutting-edge spatial econometrics techniques and official data from Eurostat, we unfold the presence of a spatial diffusion process which affects social exclusion and its components in European regions. When controlling for the socio-economic determinants of social exclusion, the intensity of the process decreases, highlighting the role of the covariates, which act as a containment field, reducing neighbour influence.

The originality of this work lies in the scope of the investigation, which covers a large portion of the European Union – as opposed to previous contribution, typically focusing on local case studies, or at most national level overviews – and in the fine-grained detail of analysis, which focuses on NUTS-2 level observations.

The main limitation of this work consists in the lack of data for some large European countries, such as Germany and France. At present, information on social exclusion is available only at the national level for these relevant EU Member States. Future works may extend the analysis proposed, exploiting fresher data that will hopefully cover these big countries as well.

References

Abrahamson, P. (1997). Combating poverty and social exclusion in Europe. In Beck, W., Van der Maesen, L., Walker, A. (1997). *The social quality of Europe*, *1*, 127-155, Kluwer Law International.

Acemoğlu, D. Robinson, J. A. (2006). De facto political power and institutional persistence. *American Economic Review, 96*(2), 325-330

Acemoğlu, D. Robinson, J. A. (2008). Persistence of power, elites, and institutions. *American economic Review, 98(*1), 267-293

Adam, S., Papatheodorou, C. (2010). The involvement of social economy organizations in the fight against social exclusion: a critical perspective. *Studies*.

Agovino, M. (2014). Do "good neighbors" enhance regional performances in including disabled people in the labor market? A spatial Markov chain approach. *The Annals of Regional Science*, *53*(1), 93-121.

Agovino, M., Crociata, A., Sacco, P. L. (2016). Location matters for pro-environmental behavior: a spatial Markov Chains approach to proximity effects in differentiated waste collection. *The Annals of Regional Science*, *56*(1), 295-315.

Agovino, M., Garofalo, A., Cerciello, M. (2019). Do local institutions affect labour market participation? The Italian Case. *The BE Journal of Economic Analysis & Policy*, *19*(2).

Aiello, F., Pupo, V. (2012). Structural funds and the economic divide in Italy. *Journal of Policy Modeling*, *34*(3), 403-418.

Alexiadou, N. (2002). Social inclusion and social exclusion in England: tensions in education policy. *Journal of Education Policy*, *17*(1), 71-86.

Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical analysis*, *20*(1), 1-17.

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical analysis*, *27*(2), 93-115.

Anselin, L. (2002). Under the hood issues in the specification and interpretation of spatial regression models. *Agricultural economics*, *27*(3), 247-267.

Atkinson, R. (2000). Combating social exclusion in Europe: the new urban policy challenge. *Urban studies*, *37*(5-6), 1037-1055.

Atkinson, R., Da Voudi, S. (2000). The concept of social exclusion in the European Union: context, development and possibilities. *JCMS: Journal of Common Market Studies*, *38*(3), 427-448.

Barth, E., Davis, J., Freeman, R., Kerr, S. P. (2017). Weathering the Great Recession: Variation in Employment Responses, by Establishments and Countries. *The Russell Sage Foundation Journal of the Social Sciences*, *3*(3), 50-69.

Barnes, M., Heady, C., Middleton, S., Millar, J., Papadopoulos, F., Room, G., Tsakloglou, P. (2002). *Poverty and social exclusion in Europe*. Edward Elgar Publishing Ltd.

Baum, S., Gleeson, B. (2010). Space and place: social exclusion in Australia's suburban heartlands. *Urban Policy and Research*, *28*(2), 135-159.

Bhalla, A. S., Lapeyre, F. (2004). Towards an Analytical and Operational Framework. In *Poverty and Exclusion in a Global World*, 33-58. Palgrave Macmillan, London.

Bekker, S., & Klosse, S. (2013). EU governance of economic and social policies: chances and challenges for Social Europe. *European Journal of Social Law*, (2-2013), 103-120.

Béland, D. (2007). The social exclusion discourse: ideas and policy change. *Policy & Politics*, *35*(1), 123-139.

Bettio, F., Plantenga, J. (2004). Comparing care regimes in Europe. *Feminist economics*, *10*(1), 85-113.

Bosco, B. (2016). Corruption, Fatigued Democracy and Bad Governance: are They Co-Determinants of Poverty Risk and Social Exclusion in Europe? A Cross-Country Macro-Level Comparison. *University of Milan Bicocca Department of Economics, Management and Statistics Working Paper*, (323).

Bosi, L., Zamponi, L. (2015). Direct social actions and economic crises: The relationship between forms of action and socio-economic context in Italy. *Partecipazione e Conflitto*, *8*(2), 367-391.

Bradley, S., Crouchley, R., Oskrochi, R. (2003). Social exclusion and labour market transitions: a multi-state multi-spell analysis using the BHPS. *Labour Economics*, *10*(6), 659-679.

Bradshaw, J. (2004). How Has the Notion of Social Exclusion Developed in the European Discourse?. *The Economic and Labour Relations Review*, *14*(2), 168.

Burchardt, T., Le Grand, J., Piachaud, D. (1999). Social exclusion in Britain 1991—1995. *Social policy & administration*, *33*(3), 227-244.

Burchardt, T., Huerta, M. C. (2009). Introduction: resilience and social exclusion. *Social Policy and Society*, *8*(1), 59-61.

Burgers, J., Kloosterman, R. (1996). Dutch comfort: postindustrial transition and social exclusion in Spangen, Rotterdam. *Area*, *28*(4), 433-445.

Câmara, G., Monteiro, A. M., Ramos, F., Sposati, A., Koga, D. (2002). Mapping Social Exclusion/Inclusion in Developing Countries: Social Dynamics of São Paulo in the 1990s. *Center for Spatially Integrated Social Science*.

Camps-Calvet, M., Langemeyer, J., Calvet-Mir, L., Gómez-Baggethun, E., March, H. (2015). Sowing Resilience and Contestation in Times of Crises: The case of urban gardening movements in Barcelona. *Partecipazione e Conflitto*, *8*(2), 417-442.

Colin, C. A., Trivedi, P. K. (2009). Microeconometrics using STATA. *Stata Press Books, Lakeway Drive, TX.*

Ceccato, V., Oberwittler, D. (2008). Comparing spatial patterns of robbery: Evidence from a Western and an Eastern European city. *Cities*, *25*(4), 185-196.

Chakravarty, S. R., D'Ambrosio, C. (2006). The measurement of social exclusion. *Review of Income and wealth*, *52*(3), 377-398.

Charron, N., Dijkstra, L., Lapuente, D. (2014). Regional Governance Matters: Quality of Government within European Union Member States. *Regional Studies, 48*(1), 68-90.

Ciommi, M., Gigliarano, C., Emili, A., Taralli, S., Chelli, F. M. (2017). A new class of composite indicators for measuring well-being at the local level: An application to the Equitable and Sustainable Well-being (BES) of the Italian Provinces. *Ecological indicators*, *76*, 281-296.

Clasen, J., Clegg, D., Goerne, A. (2016). Comparative social policy analysis and active labour market policy: Putting quality before quantity. *Journal of Social Policy*, *45*(1), 21-38.

Cote, R. R., Erickson, B. H. (2009). Untangling the roots of tolerance: How forms of social capital shape attitudes toward ethnic minorities and immigrants. *American Behavioral Scientist*, *52*(12), 1664-1689.

Craig, G. (2004). Citizenship, exclusion and older people. *Journal of social policy*, *33*(1), 95-114.

Crépon, B., Ferracci, M., Jolivet, G., Van den Berg, G. J. (2009). Active labor market policy effects in a dynamic setting. *Journal of the European Economic Association*, *7*(2-3), 595-605.

Crociata, A., Agovino, M., Furia, D., Osmi, G., Mattoscio, N., Cerciello, M. (2019). Impulse and time persistence of disaggregate welfare expenditure on growth in the EU. *Economia Politica*, 1-26.

Danson, M., Mooney, G. (2013). Glasgow: A tale of two cities? Disadvantage and exclusion on the European periphery. In *Unemployment and Social Exclusion* (pp. 217-234). Routledge.

Das, N. K. (2009). Identity politics and social exclusion in India's north-east: The case for redistributive justice. In *The Politics of Social Exclusion in India* (pp. 47-61). Routledge.

Davidsson, T., Petersson, F. J. (2018). Towards an actor-oriented approach to social exclusion: a critical review of contemporary exclusion research in a Swedish social work context. *European journal of social work*, *21*(2), 167-180.

Easterly, W., Ritzen, J., Woolcock, M. (2006). Social cohesion, institutions, and growth. *Economics & Politics*, *18*(2), 103-120.

EC, European Commission (2010). *Europe 2020: A strategy for smart, sustainable and inclusive growth*. Communication from the Commission, available at: https://ec.europa.eu/eu2020/pdf/COMPLET%20EN%20BARROSO%20%20%20007%20-%20Europe%202020%20-%20EN%20version.pdf.

EC, European Commission (2014). *Employment and Social Developments in Europe 2013*. European Commission Directorate-General for Employment, Social Affairs and Inclusion, available at: https://ec.europa.eu/social/main.jsp?catId=738&langId=en&pubId=7684.

EC, European Commission (2016). Review of the Social Protection Performance Monitor and Developments in Social Protection Policies. *Annual Report of the Social Protection Committee*.

Eurostat (2018). *Europe 2020 indicators: poverty and social exclusion.* Statistics Explained, available at: http://ec.europa.eu/eurostat/statisticsexplained.

Eurostat (2019). *Glossary: At risk of poverty or social exclusion (AROPE).* Statistics Explained. available at: https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:At_risk_of_poverty_or_social_exclusion_(AROPE).

Fazio, G., Lavecchia, L. (2013). Social capital formation across space: proximity and trust in European regions. *International Regional Science Review*, *36*(3), 296-321.

Ferraro, A., Cerciello, M., Agovino, M., Garofalo, A. (2019). The role of cultural consumption in reducing social exclusion: empirical evidence from Italy in a spatial framework. *Economia Politica*, *36*(1), 139-166.

Fischer, A. M. (2011). Reconceiving social exclusion. *Brooks World Poverty Institute Working Paper*, (146).

Gal, J. (2010). Is there an extended family of Mediterranean welfare states?. *Journal of European Social Policy*, *20*(4), 283-300.

Gallie, D., Paugam, S., Jacobs, S. (2003). Unemployment, poverty and social isolation: Is there a vicious circle of social exclusion? *European societies*, *5*(1), 1-32.

Giambona, F., Vassallo, E. (2014). Composite indicator of social inclusion for European countries. *Social Indicators Research*, *116*(1), 269-293.

González, S. (2011). The North/South divide in Italy and England: Discursive construction of regional inequality. *European Urban and Regional Studies*, *18*(1), 62-76.

Guth, M. (2005). Innovation, social inclusion and coherent regional development: A new diamond for a socially inclusive innovation policy in regions. *European planning studies*, *13*(2), 333-349.

Heckman, J. J., Raut, L. K. (2016). Intergenerational long-term effects of preschool-structural estimates from a discrete dynamic programming model. *Journal of econometrics*, *191*(1), 164-175.

Horton, R., Lo, S. (2013). Investing in health: why, what, and three reflections. *The Lancet*, *382*(9908), 1859-1861.

Jenssen, A. T., Engesbak, H. (1994). The Many Faces of Education: why are people with lower education more hostile towards immigrants than people with higher education?. *Scandinavian Journal of Educational Research*, *38*(1), 33-50.

Klein, H. (2004). Health inequality, social exclusion and neighbourhood renewal: Can place-based renewal improve the health of disadvantaged communities?. *Australian Journal of Primary Health*, *10*(3), 110-119.

Lechner, M., Miquel, R., Wunsch, C. (2007). The curse and blessing of training the unemployed in a changing economy: The case of East Germany after unification. *German Economic Review*, *8*(4), 468-509.

Kabeer, N. (2005). Social exclusion: concepts, findings and implications for the MDGs. *Paper commissioned as background for the Social Exclusion Policy Paper, Department for International Development (DFID), London*.

Karakioulafis, C., Kanellopoulos, K. (2018). Triggering Solidarity Actions towards Contingent Workers and the Unemployed. The Point of View of Grassroots Trade Unionists and Labour Activists. *Partecipazione e Conflitto*, *11*(1), 121-144.

Kieselbach, T. (2003). Long-term unemployment among young people: The risk of social exclusion. *American journal of community psychology*, *32*(1-2), 69-76.

Kousis, M., Paschou, M. (2017). Alternative forms of resilience. A typology of approaches for the study of citizen collective responses in hard economic times. *Partecipazione e Conflitto*, *10*(1), 136-168.

Le Gallo, J. (2004). Space-time analysis of GDP disparities among European regions: A Markov chains approach. *International Regional Science Review*, *27*(2), 138-163.

Madanipour, A., Shucksmith, M., Talbot, H. (2015). Concepts of poverty and social exclusion in Europe. *Local Economy*, *30*(7), 721-741.

Marcińczak, S. (2012). The evolution of spatial patterns of residential segregation in Central European Cities: The Łódź Functional Urban Region from mature socialism to mature post-socialism. *Cities*, *29*(5), 300-309.

Martin, C., Leaper, R. A. B. (1996). French review article: the debate in France over "social exclusion". *Social Policy & Administration*, *30*(4), 382-392.

Martori, J. C., Apparicio, P. (2011). Changes in spatial patterns of the immigrant population of a southern European metropolis: the case of the Barcelona metropolitan area (2001–2008). *Tijdschrift voor economische en sociale geografie*, *102*(5), 562-581.

Mayes, D. G. (2002). Social exclusion and macro-economic policy in Europe: a problem of dynamic and spatial change. *Journal of European Social Policy*, *12*(3), 195-209.

Mohaupt, S. (2009). Resilience and social exclusion. *Social Policy and Society*, *8*(1), 63-71.

Morgan, C., Burns, T., Fitzpatrick, R., Pinfold, V., Priebe, S. (2007). Social exclusion and mental health: conceptual and methodological review. *The British Journal of Psychiatry*, *191*(6), 477-483.

Moulaert, F., Ailenei, O. (2005). Social economy, third sector and solidarity relations: A conceptual synthesis from history to present. *Urban studies*, *42*(11), 2037-2053.

Nolan, B., Marx, I. (2009). Economic inequality, poverty, and social exclusion. *The Oxford handbook of economic inequality,* 315-341.

O'Grady, A., Pleasence, P., Balmer, N. J., Buck, A., Genn, H. (2004). Disability, social exclusion and the consequential experience of justiciable problems. *Disability & Society*, *19*(3), 259-272.

O'Shea, S., Lysaght, P., Roberts, J., Harwood, V. (2016). Shifting the blame in higher education–social inclusion and deficit discourses. *Higher Education Research & Development*, *35*(2), 322-336.

Obinger, H., Schmitt, C., Starke, P. (2013). Policy diffusion and policy transfer in comparative welfare state research. *Social Policy & Administration*, *47*(1), 111-129.

Papadaki, M., Kalogeraki, S. (2018). Exploring Social and Solidarity Economy (SSE) during the Greek Economic Crisis. *Partecipazione e Conflitto*, *11*(1), 38-69.

Pavolini, E., León, M., Guillén, A. M., Ascoli, U. (2016). From Austerity to Permanent Strain? The European Union and Welfare State Reform in Italy and Spain. In *The sovereign debt crisis, the EU and welfare state reform*, 131-157. Palgrave Macmillan, London.

Piketty, T. (2015). About capital in the twenty-first century. *American Economic Review*, *105*(5), 48-53.

Psycharis, Y., Kallioras, D., Pantazis, P. (2014). Economic crisis and regional resilience: detecting the 'geographical footprint'of economic crisis in Greece. *Regional Science Policy & Practice*, *6*(2), 121-141.

Rey, S. J. (2001). Spatial empirics for economic growth and convergence. *Geographical analysis*, *33*(3), 195-214.

Santana, P. (2002). Poverty, social exclusion and health in Portugal. *Social Science & Medicine*, *55*(1), 33-45.

Schettini, D., Azzoni, C. R., Paez, A. (2011). Neighborhood and efficiency in manufacturing in Brazilian regions: a spatial Markov chain analysis. *International Regional Science Review*, *34*(4), 397-418.

Selwyn, N., Gorard, S., Williams, S. (2001). Digital divide or digital opportunity? The role of technology in overcoming social exclusion in US education. *Educational Policy*, *15*(2), 258-277.

Shipan, C. R., Volden, C. (2012). Policy diffusion: Seven lessons for scholars and practitioners. *Public Administration Review*, *72*(6), 788-796.

Silver, H. (1994). Social exclusion and social solidarity: Three paradigms. *International Labour Review*, *133*(5, 6), 531.

Silver, H., Miller, S. M. (2003). Social exclusion. *Indicators*, *2*(2), 5-21.

Spandler, H. (2007). From social exclusion to inclusion? A critique of the inclusion imperative in mental health. *Medical Sociology Online*, *2*(2), 3-16.

Spicker, P. (1997). Exclusion. *Journal of Common Market Studies*, *35*(1), 133-143.

Thomas, A. C., Gaspart, F. (2015). Does poverty trap rural Malagasy households?. *World Development*, *67*, 490-505.

Thompson, R. (2011). Individualisation and social exclusion: the case of young people not in education, employment or training. *Oxford Review of Education*, *37*(6), 785-802.

Van Ours, J. C. (2004). The locking-in effect of subsidized jobs. *Journal of Comparative Economics*, *32*(1), 37-55.

Van Ours, J. C., Vodopivec, M. (2006). How shortening the potential duration of unemployment benefits affects the duration of unemployment: Evidence from a natural experiment. *Journal of Labor economics*, *24*(2), 351-378.

Van Vliet, O. (2010). Divergence within convergence: Europeanization of social and labour market policies. *European Integration*, *32*(3), 269-290.

Vettoretto, L. (2009). A preliminary critique of the best and good practices approach in European spatial planning and policy-making. *European Planning Studies*, *17*(7), 1067-1083.

von Jacobi, N., Nicholls, A., Chiappero-Martinetti, E. (2017). Theorizing social innovation to address marginalization. *Journal of Social Entrepreneurship*, *8*(3), 265-270.

Ward, N. (2009). Social exclusion, social identity and social work: Analysing social exclusion from a material discursive perspective. *Social Work Education*, *28*(3), 237-252.

Welsh, M. (2014). Resilience and responsibility: governing uncertainty in a complex world. *The Geographical Journal*, *180*(1), 15-26.

Whitty, G. (2001). Education, social class and social exclusion. *Journal of Education Policy*, *16*(4), 287-295.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT press, Cambridge.

Wright, N., Stickley, T. (2013). Concepts of social inclusion, exclusion and mental health: a review of the international literature. *Journal of Psychiatric and Mental Health Nursing*, *20*(1), 71-81.

Appendix

Table A1. Diagnostic Tests

Variable	Sargan Test	Hausman test
Social Exclusion	0.173	0.35
	(0.677)	(0.986)
Poverty	0.413	0.84
	(0.520)	(0.933)
Material deprivation	0.112	0.27
	(0.738)	(0.991)
Low Intensity of Work	0.234	0.40
	(0.629)	(0.982)

Note: p-values are shown in parentheses

The robust versions of the Sargan and Hausman tests fail to reject to null hypothesis, pointing to the validity of the first step of our analysis.

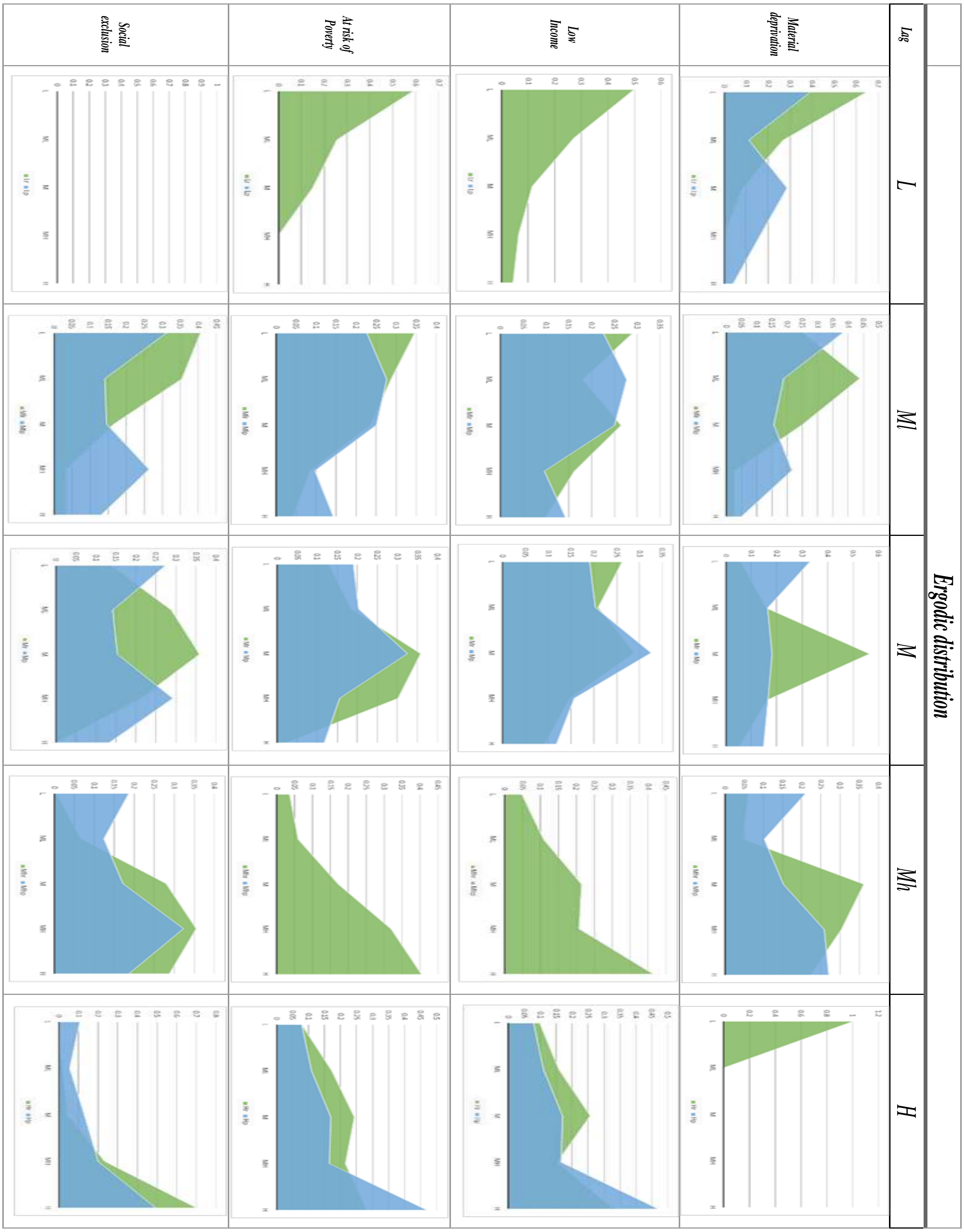
Table A2. Variable Purification

	Social Exclusion	Poverty	Material Deprivation	Low intensity of Work
Unemployment‡	0.493	0.148	0.418	0.593
	(0.053)***	(0.045)***	(0.055)***	(0.032)***
Education	-0.027	-0.107	0.135	0.018
	(0.047)	(0.041)***	(0.040)***	(0.031)
EQI	-5.945	-3.448	-5.886	-0.577
	(0.671)***	(0.570)***	(0.573)***	(0.340)*
Life Expectancy	-0.446	0.329	-1.042	0.152
	(0.166)***	(0.109)***	(0.184)***	(0.108)
_cons	56.072	-4.066	78.293	-9.914
	(13.418)***	(8.735)	(15.128)***	(9.174)
N	1,061	1,061	1,061	1,061

* p<0.1; ** p<0.05; *** p<0.01; ‡*endogenous variable, instrumented*

Not surprisingly, unemployment increases social exclusion, institutional quality reduces it and life expectancy – which proxies health – reduces it as well. The coefficient estimates associated to these variables are significant at the 1% level. Education instead, though reporting a negative impact on social exclusion, fails to produce a significant coefficient.

Table A3. Ergodic Distributions



Note: raw variables are shown in green and purified variables are shown in blue