Location matters for pro-environmental behavior: a spatial Markov Chains approach to proximity effects in differentiated waste collection

Massimiliano Agovino, Alessandro Crociata & Pier Luigi Sacco

The Annals of Regional Science
An International Journal of Urban, Regional and Environmental Research and Policy

ISSN 0570-1864
Volume 56
Number 1

Ann Reg Sci (2016) 56:295-315
DOI 10.1007/s00168-015-0740-7


Volume 56 • Number 1 • January 2016

The Annals of Regional Science

An International Journal of Urban, Regional and Environmental Research and Policy

Editors
Martin Andersson
Euijune Kim
Janet E. Kohlhase

ORIGINAL PAPERS

Evaluating multiple spatial dimensions of economic growth in Brazil using spatial panel data models
G.M. Resende · A.X.Y. de Carvalho · P.A.M. Sakowski · T.A. Cravo 1

The effect of new business creation on employment growth in regions facing population decline
H. Delfmann · S. Koster 33

Ripple effect and contagious effect in the US regional housing markets
M.-C. Chiang · I.-C. Tsai 55

Strategic input outsourcing and equilibrium location choice
Y.-J. Lin · Y.-S. Lin · K.-I. Tu 83

Riverboat casino gambling impacts on employment and income in host and surrounding counties
K.R. Geisler · M.W. Nichols 101

Commuting and timing of retirement
P. Bäckström · E. Sandow · O. Westerlund 125

Economic impact assessment of alternative European Neighborhood Policy (ENP) options with the application of the GMR-Turkey model
A. Varga · M.B. Baypinar 153

Dirty spatial econometrics
G. Arbia · G. Espa · D. Giuliani 177

(Contents continued on back cover)

Springer

Springer

Ann Reg Sci (2016) 56:295–315
DOI 10.1007/s00168-015-0740-7

ORIGINAL PAPER

Location matters for pro-environmental behavior: a spatial Markov Chains approach to proximity effects in differentiated waste collection

Massimiliano Agovino[1] · **Alessandro Crociata**[2] · **Pier Luigi Sacco**[3]

Received: 21 August 2015 / Accepted: 23 December 2015 / Published online: 9 January 2016

Abstract We analyze data on differentiated waste collection (as a proxy of pro-environmental behaviors) in Italian provinces in the years 1999–2012. We make use of a Markov Spatial Transition approach to model the dynamic of local transitions among different levels of environmental pro-sociality, and we find that behaviors, and in particular differentiated waste collecting habits, tend to be strongly influenced by proximity effects, so that provinces with good levels of environmental pro-sociality may positively influence nearby ones, and vice versa for provinces with poor levels of environmental pro-sociality. We also show that in the long term separate clusters with markedly different levels of differentiated waste collection rates emerge.

JEL Classification Q53 · R15 · C23 · C61

✉ Pier Luigi Sacco
pierluigi.sacco@iulm.it

Massimiliano Agovino
agovino.massimo@gmail.com

Alessandro Crociata
crociata@gmail.com

1 Department of Economic and Legal Studies, University of Naples “Parthenope”, Via Ammiraglio Ferdinando Acton, 38, 80133 Naples, Italy

2 Department of Philosophical, Pedagogical and Economic-Quantitative Sciences, University “G. D’Annunzio” of Chieti-Pescara, Viale Pindaro, 42, 65127 Pescara, Italy

3 Department of Comparative Literature and Linguistics, IULM University, Via Carlo Bo, 1, 20143 Milan, Italy

1 Introduction

Pro-environmental behaviors associated with waste management issues have taken increasing prominence in public management and policy, in terms of development and design of waste recycling schemes and practices, of definition and monitoring of appropriate targets, of deployment and testing of policy strategies, and so on. A rich array of interdisciplinary research on how to enable and foster socially sustainable pro-environmental behaviors has correspondingly developed.

An extensive review of such research would take a full paper in itself, but it can be useful to draw attention toward some classical approaches and references. Economists have explored to what extent responsible environmental behaviors can be fostered by designing suitable incentive mechanisms, including monetary rewards (e.g., Curlee 1986). Law studies have considered the effects of legal measures such as mandatory recycling laws (e.g., Lanza 1983). Engineering research has compared the relative effects of alternative technologies and systems of recycling (e.g., Noll 1985). Environmental psychologists have focused upon harnessing altruistic motivations (e.g., De Young 1986), while sociologists have highlighted the role of social pressures and environmental constraints (e.g., Burn and Oskamp 1986). Public pedagogues call for participation and learning processes within the context of a complex array of education for sustainable development (ESD) approaches and settings (e.g., Læssøe 2010; Van Poeck and Vandenabeele 2012). This multifaceted body of evidence clearly illustrates the complexity and elusiveness of the nature and dynamics of pro-environmental behaviors. A more recent approach (Crociata et al. 2015) has explored the effect of a new factor, substantially overlooked in the previous body of literature: cultural participation. The relationship between citizen participation and civic virtue has been in turn largely explored in the literature (e.g., Putnam 2000), but only in recent times the distinctive contribution of cultural participation to the emergence of pro-sociality has been properly highlighted, with all its local, contextual complexity (e.g., Clark et al. 2014). Despite that often cultural participation presents a strong, distinctive social component, the preliminary evidence by Crociata et al. (2015) shows that also more individualized forms of participation, like reading a book or listening to music at home, may have a distinctive effect on pro-sociality and on an environmentally related one in particular.

Most of the literature takes households as the main unit of analysis. According to Miafodzyeva and Brandt (2013), variables affecting recycling behaviors can be classified into four groups: sociopsychological, technical-organizational, individual-socio-demographic and study specific. The strongest predictors of households' recycling behaviors were identified as: convenience, moral norms, information and environmental concerns—each of which, we note, has some degree of cultural connotation. In this scenario, even though households are generally aware of the social benefits of recycling, such awareness does not necessarily reflect into actual recycling practice.

To really appreciate how pro-environmental behaviors evolve in a society, we think one should go beyond the individual perspective of the household and consider social transmission effects, and in particular socio-spatial ones. The literature shows, for instance, that phenomena such as happiness, which clearly can be read and understood in individual terms, are characterized by “contagion” patterns whereby happiness levels tend to be strongly influenced by proximity effects (Fowler and Christakis 2008); similar effects are found in the establishment of the trust and social cooperation conditions for effective co-inventive performance (Cassi and Plunket 2014). We ask whether a similar dynamics take place for pro-environmental behaviors, and in particular for attitudes toward waste recycling, as a spatial dependence phenomenon rather than as a mere reflection of spatial heterogeneity (Espa et al. 2013). We therefore postulate that, as a working hypothesis, proximity to socio-spatial contexts characterized by virtuous recycling behavior could positively influence those living in less virtuous contexts, thereby bringing about pro-social behavioral change. If this should be the case, we can conclude that conceptualizing an activity with a relevant social and cultural characterization such as waste recycling as not entirely traceable to the domain of individual analysis, and in particular as highly sensitive to the domain of socio-spatial analysis, can considerably improve the understanding of waste recycling habits, and possibly, on a more general note, of pro-environmental behaviors (Bliz and Nadler 2014). Some traces of this approach can already be found in the work of Oskamp et al. (1991), in their study of residents of a city that had just began a curbside recycling program, and where 95 % of those who recycled reported that their friends and neighbors recycled too. Therefore, if people become aware that their neighbors are recycling, it is more likely that they will recycle too. To capture such factors, in this paper we consider socio-spatial effects at the province levels, that is, an intermediate level of spatial aggregation between single households and whole regions.

In this regard, we find an interesting precedent in Brueckner (2003), who refers to “agents” (decision makers) as “jurisdictions” in the context of a public economics model. In particular, Brueckner (2003) develops two theoretical frameworks for strategic interaction that yield a reaction function as the equilibrium solution: one is referred to as a spillover model, and the other as the resource flow model. In our case, we consider the spillover model, where an agent i chooses the level of a decision variable, y_i, but the values of the y variable chosen by other agents (y_j, where the j subscript refers to all agents other than i) affect her objective function as well. For example, one can think of a strategic framework where an agent has to decide whether to bother to recycle waste taking into account the behavior of other neighboring agents (see Anselin 2002a, b).

In this paper, we use the differentiated waste collection rate as a proxy of pro-environmental behavior. In particular, we apply the spatial Markov Chains methodology to differentiated waste collection rates in order to obtain the probabilities of changes in pro-environmental attitudes, conditional on the level of pro-environmental attitudes of neighboring provinces (Schettini et al. 2011). This technique allows us to analyze how the level of pro-environmental behavior in a province can be explained by its geographical environment, and the extent to which such environment influences the relative position of provinces in the cross-section distribution of differentiated waste collection rates (Le Gallo 2004). In particular, in order to provide a more detailed view of the geographic dimension of the socio-spatial pattern of pro-environmental behaviors, the spatial Markov Chains approach allows us to pose a number of interesting questions concerning the spatial dimension of environmental pro-sociality. For example, is the probability of a province moving up or down the pro-sociality ranking related to the current, or past, dynamics of the ranking of its neighbors? And moreover, can we identify stable clusters as limit outcomes of the spatial Markov Chain?

The identification of stable spatial clusters of homogeneous pro-social attitudes is relevant from a policy viewpoint, in that it allows us to discriminate provinces characterized by poor pro-environmental attitudes from highly pro-social ones. In particular, provinces with poor environmental pro-sociality as to differentiated waste recycling will call for substantially different policies than the highly pro-social ones.

The paper proceeds as follows: Section 2 introduces and reviews the methodology. Section 3 presents the data. Section 4 illustrates the results of the spatial Markov Chains analysis. Section 5 concludes and offers some final remarks.

2 Method: The Spatial Markov Chains (SMCs) Approach

Spatial econometrics is becoming a rapidly expanding area of research (Griffith and Paelinck 2007; Anselin 2010) that allows to study the socio-spatial dynamics of relevant phenomena. Spatial Markov Chains (SMCs), in particular, allow us to simultaneously study the spatial and time dynamics of a phenomenon (Rey 2001). The main output of a SMCs model is the spatial transition matrix, that in the context of our analysis evaluates the positive or negative influence of neighbors on the transition of a province between different pro-environmental attitudes. In particular, the matrix provides, for a given province, the probability to move upwards or downwards in the distribution in the next period $(t+1)$, conditional to the state of its neighbors in the current period (t): The transition matrix can thus trace the history of the distribution over time. More specifically, this technique allows us to track whether a province with a poor (good) level of pro-environmental behavior tends to remain in that state if surrounded by other provinces with similarly poor (good) levels of pro-environmental behaviors, and in particular whether provinces with poor pro-sociality negatively affect their neighbors, by depressing their differentiated waste collection rates, or likewise provinces with good pro-sociality positively influence their neighbors, boosting their differentiated waste collection rates. In particular, we can build a dynamic model that shows the dynamic evolution of these proximity effects over time.

The building of the spatial transition matrix is based on the decomposition of the traditional Markov transition matrix, that gives the spatial transition probability. In particular, in this approach the traditional transition matrix is modified so that the transition probabilities of a province in the next period $(t+1)$ are conditional to the average level of pro-environmental behavior at the current period (t) of its neighboring provinces. In other words, the spatial transition matrix is a *K-by-K* traditional Markov transition matrix decomposed into K sub-matrices, where each sub-matrix is a *K-by-K* matrix. In our case, K is equal to 5, i.e., the number of possible states.

In formal terms, if we consider the kth matrix among the conditional matrices, the $p_{ij}(k)$ element of such matrix represents the probability that a province located in class i in the current period (t) ends up in class j in the next period $(t+1)$, knowing that the average level of pro-environmental behavior of its neighboring provinces corresponded to class k in period t. The estimator of a $p_{ij}(k)$ element of a conditional transition matrix is thus defined as follows:

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

where $n_{ij}(k)$ is the number of provinces located in class i in period t and in class j in period $(t+1)$, knowing that the average level of pro-environmental behavior of their neighboring provinces places them in class k in period t; $n_i(k)$ is the total number of provinces located in class i, knowing that the average level of pro-environmental behavior of their neighboring provinces places them in class k at time t, during $T = 13$[1] annual transitions, i.e., $n_i(k) = \sum_j n_{ij}(k)$.

The spatial Markov matrix allows us to appreciate the positive or negative influence of the neighbors on the transition of a province across levels of pro-(environmental)sociality. Indeed, the influence of spatial proximity effects is reflected in the differences between the unconditional[2] transition values and the conditional ones (Le Gallo 2004). For example, in our case with 5 states ($K = 5$), the first state groups provinces with the poorest pro-environmental attitude, the third state caters provinces with intermediate levels of pro-sociality and the fifth state corresponds to the provinces with the best pro-environmental attitude.[3] Consequently, if $p_{35} > p_{35|1}$, the transition probability of moving upwards for a province with an intermediate level of pro-sociality without proximity effects, i.e., not taking into account the effect of its neighbors' pro-sociality, is greater than the transition probabilities of moving upwards for a province with an intermediate level of pro-sociality conditional to neighbors with poor pro-environmental attitudes. Likewise, if we consider the probability of moving upwards for provinces starting from other levels of pro-sociality. Conversely, if $p_{13} > p_{13|5}$, the transition probability of moving upwards for a province with poor pro-sociality conditional to neighbors with high pro-sociality is greater than the transition probabilities of moving upwards for a province with low pro-sociality without proximity effects.

If proximity effects do not matter for transition probabilities, then the conditional probabilities should be equal to the unconditional initial transition values (Le Gallo 2004):

$$\begin{gathered} p_{ij|1} = p_{ij|2} = \cdots = p_{ij|5} \\ \forall i = 1, \ldots, 5 \\ \forall j = 1, \ldots, 5 \end{gathered}$$

The relevance of the socio-spatial dimension reflects, and therefore the importance of considering neighbors in determining transition probabilities corresponds to, the rejection of the null hypothesis of spatial stationarity tests (see Le Gallo 2004). In our case, we reject the null hypothesis at 5 % and, consequently, the transition probability of a province does depend on the spatial environment and proximity effects matter.

[1] Our period of analysis consists of 14 years, so we have $T = 13$ annual transitions.

[2] For reasons of space, we do not report the values of the unconditional transition matrix. Interested readers can request them to the authors.

[3] We describe more in detail the 5 states in Sect. 4.

3 Data and preliminary results

In this section, we present the differentiated waste recycling rate (DWR) that we use in our spatial Markov Chains approach-based analysis. In particular, we use ISTAT data for the 103 Italian provinces, corresponding to the European level NUTS-3, over the period from 1999 to 2012. The data come from the Environment section of the ISTAT database on Territorial Indicators for Development Policies, available online at http://www.istat.it/archivio/16777.

In many empirical studies (see Arbia 2005), provincial data are used to introduce the spatial element in empirical analysis, and it is well known that administrative data aggregate individuals on the basis of arbitrary geographical boundaries reflecting political and historical situations. The choice of the spatial aggregation unit is therefore essential as different choices may lead to different results in the estimates (Arbia 1988). Regional data cannot be considered "independently generated" (Anselin 1988; Anselin and Bera 1998) because of spatial similarities of neighboring regions; thus, standard estimation procedures[4] can provide biased estimators of the parameters. Aggregating data at the provincial level will allow spatial effects, such as spatial spillovers, to be properly modelled (Arbia et al. 2002; Arbia 2005).

In particular, the choice of the provinces is made on the basis of the following reasons: (1) non-availability of data at a finer administrative level (e.g., municipalities); (2) the legislative decree 22 of February 5, 1997, assigns to the provinces the administrative functions concerning the planning and organization of waste management. In particular, article 23 of legislative decree 22 of February 5, 1997, defines the province as the optimal management area (ATO) for the management of municipal waste. This makes the province the administrative unit best suited to carry out our empirical analysis.

The provinces are regulated by Title V (Part II) of the Italian Constitution. The criteria used for the review of the size of the provinces and the creation of new provinces are provided by art. 133 of the Italian Constitution. In particular, this article indicates that the size of the province is based on suitability territorial criteria. Such criteria are defined on a minimum threshold of population that in the case of the provinces is equal to 200,000 inhabitants.

Although the population size is comparable in each province, what changes is the population density, i.e., the number of people living per unit of an area (e.g., per square mile). This result is obvious because each province has a different spatial dimension. This is a limitation present in all empirical analysis conducted with spatial data. However, it is partially overcome by the use of separate waste collection divided by the amount of waste generated in the province by the resident population. The problem would amplify if we were to use an absolute variable (e.g., only the amount of separate waste collection (in tonnes) in each province).

Article 183 of Italy's Legislative Decree 152/06 (comma f) provides a definition of differentiated waste collection. Differentiated collection (DC) is defined as: "the collection which aims to: (1) group the urban waste into homogeneous categories; (2)

[4] That is, estimates that do not take into account spatial dependence.

group the packaging waste materials separately from other waste. Moreover, an important condition is that the waste should be collected for recycling purposes. Finally, the differentiated collection must be carried out according to criteria of cost-effectiveness, efficiency, transparency and effectiveness".

An indicator of differentiated waste collection is given by the urban waste separately collected as a percentage of total urban waste. In particular, the above cited Article 183 prescribes the differentiated collection of the following items:

- organic waste (wet waste and gardening waste);
- packaging waste (paper and cardboard, plastic, glass, wood, metal) and multi-material;
- bulky waste (plastic, glass, wood, metal);
- electrical waste;
- textile waste and secondhand clothing;
- environmentally dangerous waste (batteries and accumulators, expired medicines, paints and inks, vegetable and mineral oils, etc.);

Waste from construction sites is not included in the differentiated waste collection figures as it is classified as a special category waste.

The differentiated waste collection rate is calculated as follows:

$$DWR_{it} = \frac{\sum_i DW_{it}}{\sum_i DW_{it} + UUW + BW + SDC} * 100$$

where:

$\sum_i DW_i$ is the sum of the quantities (in tons) of the different categories of differentiated waste collection in the ith province, at time t;
UUW is the quantity (in tons) of unsorted urban waste;
BW is the quantity (in tons) of bulky waste;
SDC are scraps of differentiated collection (in tons).

During the sample period, Italy's nation-wide recycling rate has increased from 13 % in 1999 to 40 % in 2012; in particular, the gap between Northern and Southern Italy shrank by about 10 percentage points (from 11.5 % in 1999 to 1.98 % in 2012),[5] and the gap between Northern and Central Italy shrank by about 1 percentage point (from 2.56 % in 1999 to 1.60 % in 2012). Summarizing, Northern Italy has the best performance in waste collection (a good pro-environmental attitude). The South, during the sample period, has improved its position, reducing the gap with Northern Italy. Central Italy has shown a tendency to converge toward Northern Italy during the sample period (Fig. 1).

In addition, we can observe (Fig. 2) an uneven distribution of annual average differentiated waste collection rates. In particular, we find two clusters: a first one, characterized by a high annual average differentiated waste collection rate (or good

[5] In the Italian case, it is customary to distinguish between Southern regions, or Mezzogiorno (namely, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia and Sardegna), Northern regions (namely, Piemonte, Valle d'Aosta, Lombardia, Trentino Alto Adige, Veneto, Friuli Venezia Giulia, Liguria, Emilia Romagna), and Central regions (Toscana, Umbria, Marche and Lazio).

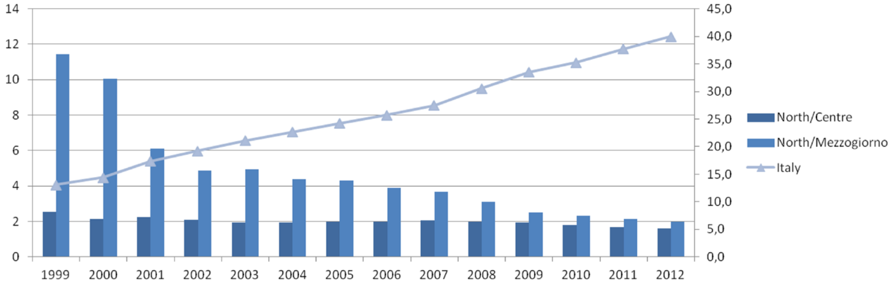


Fig. 1 National differentiated waste collection rate, North–South and North-Central divide, 1999–2012. *Source*: Our elaboration on ISTAT data

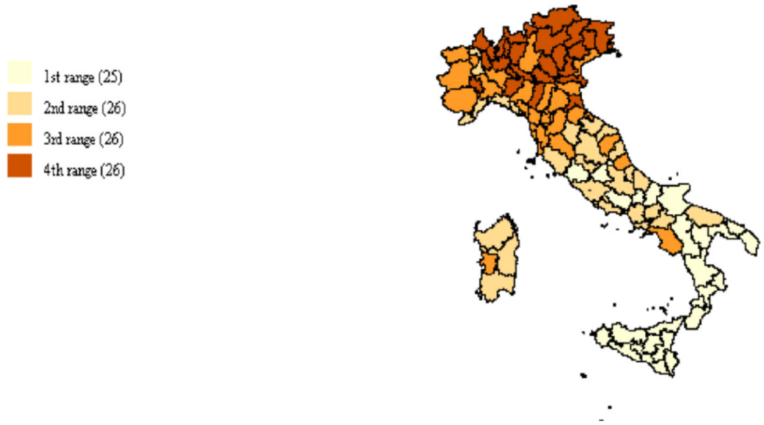


Fig. 2 Annual average differentiated waste collection rate. *Source*: Our elaboration on ISTAT data. *Note* we indicate in parenthesis the number of provinces included in each quartile

pro-environmental behavior), consisting of Northern Italy provinces, and a second one, characterized by a low differentiated waste collection rate (or poor pro-environmental behavior), consisting of Central and Southern Italy provinces.

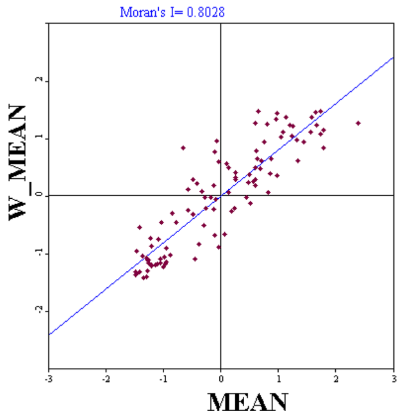
We conclude this section by drawing Moran's scatter plot[6] (Anselin 1993) for provincial annual average differentiated waste collection rates. Moran's I coefficient

[6] The Moran scatter plot provides a tool for visual exploration of spatial autocorrelation (Anselin 1996, 2002a, b). The four different quadrants of the scatterplot identify four types of local spatial association between a province and its neighbors:

- (HH) a province with a good pro-environmental behavior (high differentiated waste collection rate) surrounded by neighbors with good pro-environmental behavior (quadrant I);
- (LH) a province with a poor pro-environmental behavior (low differentiated waste collection rate) surrounded by neighbors with good pro-environmental behavior (quadrant II);
- (LL) a province with a poor pro-environmental behavior surrounded by neighbors with poor pro-environmental behavior (quadrant III);
- (HL) a province with a good pro-environmental behavior surrounded by neighbors with poor pro-environmental behavior (quadrant IV).

Quadrants I and III represent positive spatial dependence, while quadrants II and IV represent negative spatial dependence (Rey and Montouri 1999).

Fig. 3 Moran's scatter plot of annual average differentiated waste collection rate of provinces. *Source*: Our elaboration on ISTAT data. *Note* MEAN is the annual average differentiated waste collection rate of provinces; W_MEAN is the spatial lag of the annual average differentiated waste collection rate of provinces



of spatial autocorrelation is strongly linked to spatial Markov Chains analysis, and the Moran's scatter plot is an intermediate step of our analysis before carrying out the SMCs analysis proper. In particular, Moran's I coefficient is defined as follows:

$$I = \frac{\sum_i \sum_j W_{ij} (X_i - \mu) \left(X_j - \mu\right)}{\sum_j \left(X_j - \mu\right)^2}$$

where X_i and X_j indicate the variable describing the phenomenon under analysis, respectively, in province i and in province j, μ is the average value in the sample and W_{ij} is the standardized matrix of spatial contiguity, which specifies the criteria for defining contiguity. In this analysis, the neighboring relationships are based on the sharing of a common border (Anselin 1988).

This index allows us to determine the relationship between a phenomenon observed in a given province j, and the same phenomenon observed in contiguous provinces. Moran scatterplot (Fig. 3) shows Moran's I coefficient as the slope of the regression line in the scatter plot, where the spatial lag of the annual average differentiated waste collection rate is on the vertical axis and the annual average differentiated waste collection rate is on the horizontal axis (both standardized variables). Figure 3 indicates a high positive value of the Moran's I coefficient (0.8028),[7] that stands for positive spatial correlation for the annual average differentiated waste collection rate.[8] This result highlights a spatial proximity effect at work among Italian provinces in terms of pro-environmental attitudes. In particular, Fig. 3 shows spatial spillovers between contiguous provinces. According to these results, it will be interesting to verify whether the provinces with better (worse) pro-environmental attitudes are able to

[7] The null hypothesis of the Moran's I test is spatial independence. According to the results, we reject the null hypothesis at the 1 % level, and we conclude that the annual average of provinces' differentiated waste collection rate presents spatial autocorrelation.

[8] The Moran's I test, carried out on differentiated waste collection rates for each year analyzed, always rejects the null hypothesis of spatial independence. For reasons of space, we do not report these results, but interested readers can request them to the authors.

influence the ones with worse (better) pro-environmental attitudes, thus determining an improvement (deterioration) of their performance in the differentiated waste collection process.

This hypothesis will be tested in the next section by means of the SMCs analysis.

4 Spatial Markov Chains analysis

The transition spatial Markov matrix is calculated by using the differentiated waste collection rate as a proxy of pro-environmental behavior. According to this methodology, the transition of pro-environmental behavior states is considered between two subsequent time periods; in our analysis, we have thirteen possible transitions in the period 1999–2012 (e.g., 1999–2001, 2001–2002, …, 2011–2012), and for each couple of years we calculate the number of cases for each state. As we have 103 provinces (n), 13 years ($t-1$) from 1999 to 2012 and 5 (K) states,[9] it is possible to obtain, at most, $(103 \times 5 \times 13) = 6695$ cases of transitions.[10]

We report the SMCs results as in Rey (2001). In particular, we define five feasible states ($K = 5$) based on the state variable values (differentiated waste collection rate) with respect to the mean (M) (Schettini et al. 2011). In this case, we have states denoting:

- poor pro-environmental behavior (P), with a characteristic value of differentiated waste collection rate lower than the mean to 3/4 of a standard deviation (0.125);
- lacking pro-environmental behavior (L), with a characteristic value of differentiated waste collection rate lower than the mean to 1/4 of a standard deviation (0.430);
- average pro-environmental behavior (M), with a characteristic value of differentiated waste collection rate equal to 1.156 (the average sample value);
- fair pro-environmental behavior (U), with a characteristic value of differentiated waste collection rate higher than the mean to one standard deviation (1.742);
- good pro-environmental behavior (H), with a characteristic value of differentiated waste collection rate higher than the mean to 11/2 standard deviation (3.713).

In summary, the five states are set in the following order: P $<$ L $<$ M $<$ U $<$ H.

The results of conditioning the transition probabilities on the spatial lag[11] of a given province are reported in Table 1, where column 4 lists the number of cases in each situation. For example, line 8 indicates the transition probability of a province that starts in t with a M level of pro-environmental behavior to move to other pro-environmental behavior classes in the following year ($t+1$), given that it is surrounded by L neighbors. If we consider pairs of consecutive years, there are 62 cases (line 8 column 4) of provinces in that situation.

---

[9] The number of states (=5) is given by default by the software Space–Time Analysis of Regional Systems (STARS) and it is not editable.

[10] With n provinces, K states and t years, there are $(t-1) \times K \times n$ possible cases of transitions.

[11] The spatial lag is the average differentiated waste collection rate of neighboring provinces. The spatial lag is a weighted average, where the weights are represented by the elements of the contiguity matrix.

Table 1 SMCs matrix

Line	*T*		No. of cases	(*t* + 1)				
	Neighborhood condition			**P**	**L**	**M**	**U**	**H**
1	P	P	27	***0.815***	0.185	0	0	0
2	L		7	0	***1***	0	0	0
3	M		0	0	0	*0*	0	0
4	U		0	0	0	0	*0*	0
5	H		0	0	0	0	0	*0*
6	P	L	32	*0.375*	**0.625**	0	0	0
7	L		259	0.023	***0.861***	0.116	0	0
8	M		62	0	0.226	***0.774***	0	0
9	U		0	0	0	0	*0*	0
10	H		0	0	0	0	0	*0*
11	P	M	1	*0*	**1**	0	0	0
12	L		65	0	***0.831***	0.169	0	0
13	M		220	0	0.005	***0.927***	0.068	0
14	U		83	0	0	0.096	***0.892***	0.012
15	H		2	0	0	0	**0.5**	***0.5***
16	P	U	0	*0*	0	0	0	0
17	L		0	0	*0*	0	0	0
18	M		88	0	0	***0.932***	0.068	0
19	U		243	0	0	0.041	***0.934***	0.025
20	H		79	0	0	0	0.241	***0.759***
21	P	H	0	*0*	0	0	0	0
22	L		0	0	*0*	0	0	0
23	M		8	0	0	***0.75***	0.25	0
24	U		64	0	0	0.016	***0.875***	0.109
25	H		99	0	0	0	0.121	***0.879***

Note: the largest value in each row is presented in boldface. Italicized values indicate permanence in the same situation between years

Lines 1–5 represent provinces sitting in neighborhoods with a poor pro-environmental behavior (P); lines 6–10 represent provinces sitting in neighborhoods with a lacking pro-environmental behavior (L); lines 11–15 represent provinces sitting in neighborhoods with an average pro-environmental behavior (M); lines 16–20 represent provinces sitting in neighborhoods with a fair pro-environmental behavior; finally, lines 21–25 represent provinces sitting in neighborhoods with a good pro-environmental behavior. It is interesting to note that the shaded cells generally deploy the highest values for each line, and as such cells denote the main diagonal, this reveals the presence of inertia: The probability of a province to remain in the same pro-environmental behavior class is relatively high, and in some cases this probability is over 0.90.

If we focus on provinces with a under-average pro-environmental behavior (P and L), we observe that the probability of remaining below the mean is:

– high for L provinces sitting in neighborhoods with a poor pro-environmental behavior (P); in particular, it is equal to one (sum of the cells up to L, line 2). The same probability is equal to one for the P provinces (sum of the cells up to L, line 1);
– high for both P and L provinces sitting in neighborhoods with a lacking pro-environmental behavior (L): one for P provinces (sum of the cells up to L, line 6) and almost 0.90 for L provinces (sum of the cells up to L, line 7);
– high for both P and L provinces sitting in neighborhoods with an average pro-environmental behavior (M): one for P provinces (sum of the cells up to L, line 11) and 0.83 for L provinces (sum of the cells up to L, line 12). In particular, L provinces have a probability of 0.169 of improving if they are surrounded by M provinces (the cell in correspondence of M, line 12);
– finally, it is interesting to note that, in the case of neighborhoods with fair and good pro-environmental behavior (U and H), both P and L provinces have a probability equal to zero because they are never surrounded by U and H neighbors (lines 16 (21) and 17(22)).

We now consider provinces starting off with fair or good pro-environmental behavior (in the year *t*), that is provinces with above the mean pro-sociality (U and H), but sitting in neighborhoods with poor or lacking pro-environmental behavior (P and L) (lines 4, 5, 9, 10). In this case, we can determine the probability of remaining above average or falling below in the subsequent period. In particular, we note that P provinces have no effect on U and H provinces, as the latter are never surrounded by P neighbors (lines 4 and 5), and this result is also found in the case of neighboring provinces with a lacking pro-environmental behavior (lines 9 and 10).

When provinces starting with good or fair pro-environmental attitudes are surrounded by provinces with a good pro-environmental attitude (U and H provinces) (lines 19, 20, 24 and 25), we observe that:

– U provinces, if surrounded by other U provinces, have a higher probability to worsen their pro-environmental (0.041) attitude than to improve it (0.025) (line 19). H provinces surrounded by U provinces have a probability of 0.24 to worsen their pro-environmental attitude (line 20).
– U provinces, if surrounded by H provinces, have a probability of about 0.11 to improve their pro-environmental attitude (line 24); on the contrary, H provinces surrounded by other H provinces have a 0.12 probability to worsen their pro-environmental attitude (line 25).

Finally, if U and H provinces are surrounded by M provinces, we observe that: U provinces have a probability of about 0.10 (0.012) to worsen (improve) their pro-environmental attitude (line 14), whereas H provinces have a probability of 0.5 to worsen their pro-environmental attitude (line 15).

In summary, we observe that provinces with an under-average pro-environmental behavior (poor or lacking) are closely linked in terms of proximity effects: P provinces affect L provinces and vice versa, but this influence is negative because it worsens pro-environmental attitudes; in other words, such provinces experience a perverse

Table 2 Ergodic separate collection rate distributions

Lag	P	L	M	U	H
P	0	1	0	0	0
L	0.024	0.645	0.331	0	0
M	0	0.015	0.571	0.404	0.01
U	0	0	0.354	0.586	0.06
H	0	0	0.032	0.509	0.459

spatial lock-in from mutual lack of positive pro-social behavioral cues. On the contrary, provinces with under-average pro-environmental behavior, if surrounded by M provinces, improve their attitudes in the differentiated waste collection process. Moreover, provinces with under-average pro-environmental attitudes are never influenced by provinces with good or fair differentiated waste collection rates, due to mutual geographical segregation. Accordingly, provinces with a under-average pro-environmental attitude do not affect provinces with good or fair pro-environmental attitudes. Finally, U provinces negatively affect H provinces, but not vice versa, while provinces with good pro-environmental attitudes positively affect themselves.

In addition, we consider the ergodic distribution[12] that can be interpreted as the long-run distribution of pro-environmental attitudes at the provincial level. Additional insights about the relationship between a province's transition probabilities and the pro-environmental behavior class of its spatial lag can be gained by considering the ergodic distributions implied by each of the estimated conditional transition matrices from Table 1. Five different ergodic state vectors are reported in Table 2.[13]

Similar to the initial distributions, the long-run distributions are strongly biased. Indeed, when provinces are surrounded by neighbors with above-average pro-environmental attitudes, the final distribution is more and more skewed upwards: The probability to maintain a good pro-environmental behavior on the long run is strong (Table 2, columns 5 and 6). Alternatively, when provinces are surrounded by neighbors with under-average pro-environmental behavior, the ergodic distribution is more and more negatively skewed: The probability to maintain a poor pro-environmental attitude is very strong (Table 2, column 3).

In Tables 3 and 4, we report the information extracted from the results presented in Table 1. In particular, Table 3 shows the probability of a province to stay in the same class of pro-environmental behavior, independently of its neighborhood (Schettini et al. 2011); in this case, we observe that this probability is high for L, M and U classes, respectively, 0.54, 0.68 and 0.54; less high for H class (0.43), while the lowest probability is registered for P class (0.24).

[12] "The ergodic distribution should be viewed as a "thought experiment" that illustrates how space may influence transition dynamics, rather than as a guide to what would transpire in reality" (Rey 2001). The ergodic distribution returned by the software is computed for each of the five transition matrices. For more details on the ergodic distribution concept, see Rey (2001) and Le Gallo (2004).

[13] Some conditional transition probabilities are computed on a small number of observations (in two cases there are only 1 and 2 observations, e.g., lines 11 and 15) and hence may be over- or underestimated. This problem occurs in all the empirical studies conducted with this method (Le Gallo 2004; Schettini et al. 2011).

Table 3 Probability of staying in the same pro-environmental behavior class

Probability	P	L	M	U	H
	0.238	0.5384	0.6766	0.5402	0.4276

Table 4 Summary of SMCs analysis

	Cases of provinces with better neighbors	Cases of provinces with better neighbors and that got better	Probability of getting better with better neighbors
Getting better	***A***	***B***	***B/A***
	249	**47**	**0.1887**
	Cases of provinces with worse neighbors	Cases of provinces with worse neighbors and that got worse	Probability of getting worse with worse neighbors
Getting worse	***A***	***B***	***B/A***
	233	**42**	**0.1802**

Following Schettini et al. (2011), we count in Table 4 all the cases of provinces whose neighbors are classified in better pro-environmental behavior classes (Table 4, column A) and, among these, count the cases of provinces that improve their situation (Table 4, column B). At this point, we calculate the probability of moving to better pro-environmental behavior classes, given that the province is surrounded by neighbors with a better pro-environmental behavior (column B/A in Table 4); the same method is applied to the cases of pro-environmental behavior class worsening (see Table 4, rows 5 and 6).

The calculations reported in Table 4 show that: (1) if a province is surrounded by neighbors with better (worse) pro-environmental behavior, it has a probability of about 0.18 to improve its performance; (2) the probabilities of improving vs. worsening the pro-environmental behavior class are the same. We can thus conclude that the *pull effect* (i.e., the impact of neighbors with a good pro-environmental behavior in the improvement of a province's pro-environmental attitude) is identical to the *drag effect* (i.e., the effect of neighbors with a bad pro-environmental behavior in the worsening of a province's pro-environmental attitude) (see Schettini et al. 2011).

The results of this analysis have shown the importance of neighbors with a good pro-environmental attitude in promoting an improvement in the differentiated waste collection process in a given province. In addition, the adverse proximity effects produced by bad neighbors should also not be underestimated, especially when under-average pro-environmental attitudes are concentrated in one specific quadrant of the country and show a time-space persistence. If not mitigated by policy makers, this persistence would result in a widening of the dualism in terms of pro-sociality—in our case, of the dualism between Northern and Southern Italy in terms of differentiated waste collection rates. This effect is evident from the results of the local Moran test (Anselin 1995) which allows to identify the presence of spatial clusters (see Table 5).

The local Moran test (Anselin 1995) can be used to identify local clusters (provinces where adjacent areas have similar values) or spatial outliers (areas distinct from their neighbors). In particular, the local Moran statistic decomposes the Moran's I into contributions for each location, I_i. The sum of I_i for all observations is proportional to Moran's I, an indicator of a global pattern. Thus, there are two interpretations of Local Moran statistics, i.e., one considering them as indicators of local spatial clusters and the other one considering them as a diagnostic tool for outliers in global spatial patterns. In Table 5, we report the results from the application of the local Moran statistics to the differentiated waste collection rate (a proxy of pro-environmental behavior) in each of the years considered; in the fourth column, we report the number of years for which the local Moran statistic provides indications of clustering using a pseudo-significance level of $p = 0.05$; we also report the number of years for which the statistic is significant in each of the four quadrants of the Moran's scatter plot (columns 5–8). These results show that:

- 100 % of significant local indicators fall in either quadrants I and III of the Moran's scatter plot, reflecting HH and LL clustering, respectively;
- two strong provincial clusters emerge and seem to be persistent in the 14 years under analysis. The first cluster, i.e., the Northern one, is characterized by good pro-environmental behavior and includes two provinces of Liguria (Genova and La Spezia), the whole of Lombardy and Trentino Alto Adige regions, and some provinces of Veneto (Verona, Vicenza, Belluno and Treviso), each of which appears in quadrant I when its local Moran is significant. The second one, i.e., the Southern Italy one, is characterized by poor pro-environmental behavior and includes some provinces of Abruzzo (Pescara and Chieti), and the whole of Molise, Campania, Puglia, Basilicata and Calabria regions, each of which appears in quadrant III when its local Moran is significant.

The effect of a persistent dualism in pro-environmental behavior in the differentiated waste collection process is a problem that must be seriously considered by policy makers, especially when provinces with poor pro-environmental behavior are surrounded by neighbors with similar attitudes, as it is the case in the Southern Italy cluster, where the probability of worsening of a province's pro-social attitude is equal to 0.18.

5 Conclusions and final remarks

In this paper, we have studied proximity effects at the provincial (NUTS-3) level in the Italian case in the socio-spatial dynamics of pro-environmental behaviors, in particular in terms of differentiated waste collection habits. We have found in particular that proximity matters, both in reinforcing positive pro-social dynamics among neighbors and in worsening negative ones, and that inertia plays a large role in making transition processes sticky.

Our results suggest in particular that not only the level of pro-sociality of neighbors can influence a province's pro-social attitude, but also that, due to the cumulative effect over time, the gap between areas with good pro-social attitudes and those with poor ones can widen in time, giving rise to structured clusters where good pro-sociality is self-reinforced and bad pro-sociality perversely locks-in. These phenomena could be

Table 5 Summary of local measures of spatial association: differentiated waste collection rate, 1999–2012

Macro area	Regions	Provinces	$p < 0.05$	$Q1$	$Q2$	$Q3$	$Q4$
N–W	Piemonte	Torino	1	1	0	0	0
N–W	Piemonte	Vercelli	0	0	0	0	0
N–W	Piemonte	Novara	12	12	0	0	0
N–W	Piemonte	Cuneo	0	0	0	0	0
N–W	Piemonte	Asti	0	0	0	0	0
N–W	Piemonte	Alessandria	0	0	0	0	0
N–W	Piemonte	Biella	0	0	0	0	0
N–W	Piemonte	Verbano–Cusio–Ossola	0	0	0	0	0
N–W	Valle d'Aosta	Aosta	0	0	0	0	0
N–W	Liguria	Imperia	0	0	0	0	0
N–W	Liguria	Savona	0	0	0	0	0
N–W	Liguria	Genova	14	14	0	0	0
N–W	Liguria	La Spezia	10	10	0	0	0
N–W	Lombardia	Varese	10	10	0	0	0
N–W	Lombardia	Como	11	11	0	0	0
N–W	Lombardia	Sondrio	12	12	0	0	0
N–W	Lombardia	Milano	8	8	0	0	0
N–W	Lombardia	Bergamo	1	1	0	0	0
N–W	Lombardia	Brescia	14	14	0	0	0
N–W	Lombardia	Pavia	14	14	0	0	0
N–W	Lombardia	Cremona	9	9	0	0	0
N–W	Lombardia	Mantova	9	9	0	0	0
N–W	Lombardia	Lecco	13	13	0	0	0
N–W	Lombardia	Lodi	14	14	0	0	0
N–E	Trentino Alto Adige	Bolzano	10	10	0	0	0
N–E	Trentino Alto Adige	Trento	14	14	0	0	0
N–E	Veneto	Verona	11	11	0	0	0
N–E	Veneto	Vicenza	14	14	0	0	0
N–E	Veneto	Belluno	11	11	0	0	0
N–E	Veneto	Treviso	4	4	0	0	0
N–E	Veneto	Venezia	0	0	0	0	0
N–E	Veneto	Padova	0	0	0	0	0
N–E	Veneto	Rovigo	2	2	0	0	0
N–E	Friuli Venezia Giulia	Udine	0	0	0	0	0
N–E	Friuli Venezia Giulia	Gorizia	6	6	0	0	0
N–E	Friuli Venezia Giulia	Trieste	0	0	0	0	0
N–E	Friuli Venezia Giulia	Pordenone	0	0	0	0	0
N–E	Emilia Romagna	Piacenza	0	0	0	0	0
N–E	Emilia Romagna	Parma	0	0	0	0	0

Table 5 continued

Macro area	Regions	Provinces	$p < 0.05$	$Q1$	$Q2$	$Q3$	$Q4$
N–E	Emilia Romagna	Reggio Emilia	0	0	0	0	0
N–E	Emilia Romagna	Modena	0	0	0	0	0
N–E	Emilia Romagna	Bologna	0	0	0	0	0
N–E	Emilia Romagna	Ferrara	0	0	0	0	0
N–E	Emilia Romagna	Ravenna	0	0	0	0	0
N–E	Emilia Romagna	Forlì	0	0	0	0	0
N–E	Emilia Romagna	Rimini	3	3	0	0	0
C	Toscana	Massa	0	0	0	0	0
C	Toscana	Lucca	1	1	0	0	0
C	Toscana	Pistoia	0	0	0	0	0
C	Toscana	Firenze	0	0	0	0	0
C	Toscana	Livorno	0	0	0	0	0
C	Toscana	Pisa	0	0	0	0	0
C	Toscana	Arezzo	0	0	0	0	0
C	Toscana	Siena	0	0	0	0	0
C	Toscana	Grosseto	0	0	0	0	0
C	Toscana	Prato	1	0	0	1	0
C	Umbria	Perugia	12	0	0	12	0
C	Umbria	Terni	12	0	0	12	0
C	Marche	Pesaro	9	0	0	9	0
C	Marche	Ancona	14	0	0	14	0
C	Marche	Macerata	11	0	0	11	0
C	Marche	Ascoli Piceno	8	0	0	8	0
C	Lazio	Viterbo	3	0	0	3	0
C	Lazio	Rieti	1	0	0	1	0
C	Lazio	Roma	1	0	0	1	0
C	Lazio	Latina	12	0	0	12	0
C	Lazio	Frosinone	0	0	0	0	0
S	Abruzzo	L'Aquila	0	0	0	0	0
S	Abruzzo	Teramo	3	0	0	3	0
S	Abruzzo	Pescara	12	0	0	12	0
S	Abruzzo	Chieti	10	0	0	10	0
S	Molise	Campobasso	12	0	0	12	0
S	Molise	Isernia	14	0	0	14	0
S	Campania	Caserta	9	0	0	9	0
S	Campania	Benevento	7	0	0	7	0
S	Campania	Napoli	10	0	0	10	0
S	Campania	Avellino	14	0	0	14	0
S	Campania	Salerno	14	0	0	14	0
S	Puglia	Foggia	13	0	0	13	0

Table 5 continued

Macro area	Regions	Provinces	$p < 0.05$	$Q1$	$Q2$	$Q3$	$Q4$
S	Puglia	Bari	10	0	0	10	0
S	Puglia	Taranto	5	0	0	5	0
S	Puglia	Brindisi	13	0	0	13	0
S	Puglia	Lecce	13	0	0	13	0
S	Basilicata	Potenza	14	0	0	14	0
S	Basilicata	Matera	14	0	0	14	0
S	Calabria	Cosenza	14	0	0	14	0
S	Calabria	Catanzaro	14	0	0	14	0
S	Calabria	Reggio Calabria	14	0	0	14	0
S	Calabria	Crotone	14	0	0	14	0
S	Calabria	Vibo Valentia	3	0	0	3	0
I	Sicilia	Trapani	6	0	0	6	0
I	Sicilia	Palermo	6	0	0	6	0
I	Sicilia	Messina	10	10	0	0	0
I	Sicilia	Agrigento	14	0	0	14	0
I	Sicilia	Caltanissetta	6	0	0	6	0
I	Sicilia	Enna	0	0	0	0	0
I	Sicilia	Catania	11	11	0	0	0
I	Sicilia	Ragusa	10	10	0	0	0
I	Sicilia	Siracusa	0	0	0	0	0
I	Sardegna	Sassari	0	0	0	0	0
I	Sardegna	Nuoro	7	0	0	7	0
I	Sardegna	Cagliari	10	0	0	10	0
I	Sardegna	Oristano	12	12	0	0	0

We indicate with N–E, N–W, C, S and I, respectively: North–East Italy, North–West Italy, Central Italy, Southern Italy and the Islands.
$p < 0.05$: number of years the local statistic is significant at 0.05.
Q1: number of years for which the local statistic is in quadrant I of Moran's scatterplot
Q2: number of years l for which the local statistic is in quadrant II of Moran's scatterplot
Q3: number of years for which the local statistic is in quadrant III of Moran's scatterplot
Q4: number of years for which the local statistic is in quadrant IV of Moran's scatterplot

understood in terms of social learning processes. As Krasny et al. (2010) point out, environmental education efforts should not be seen as self-contained, sectoral initiative (e.g., in schools and for schools only), but rather as a complex and multifaceted component of a social strategy that addresses all citizens, local communities and organizations. Proximity effects contribute to social learning in many ways through a variety of relational, social and technological forms (Greunz 2003; Basile et al. 2012), as vehicles of information, ideas, practices, beliefs, traditions and values, with sensible impact on local patterns of pro-sociality, both in the short and the long term. This is an area of major relevance for policy research and design, and especially so in view of the huge challenges that large-scale waste collection and recycling issues pose in densely populated, fast growing areas of the world (Yan et al. 2014).

In the Italian case, both good and bad neighbors have an influence on a province's pro-social attitude, but due to geographical segregation provinces with good pro-sociality are seldom exposed to bad neighbor habits, and accordingly provinces with poor pro-sociality have little chance to learn from more virtuous neighbors. This inevitably leads to more territorial inequality in pro-sociality. Environmental education, however inclusive and comprehensive, cannot in itself suffice in breaking a perverse lock-in state in the absence of powerful social incentives that make pro-sociality more relevant at the local level. This condition is all the more critical if close neighbors are in a similar situation. On the other hand, once a positive transformational social dynamic is at work, proximity with relatively better neighbors can give a powerful push forward. The implication of these results is that in poorly pro-social geographical clusters, rather than single isolated action, a coordinated effort toward pro-sociality should be undertaken by neighboring regions to dismantle the negative influence of proximity effects.

The two main clusters that emerge from our analysis, the Northern and Southern Italy ones, not only reflect a gap in environmental pro-sociality, but are also in striking contrast in terms of many other forms of socioeconomic inequality: income, employment, quality of education, quality of welfare services, infrastructures, and so on. It is also interesting to notice that, in the Italian case, the Northern and Southern clusters are separated by a "buffer zone": Central Italy. Here, we have a somewhat intermediate situation where proximity effects are less definite and the resulting socio-spatial dynamics is not strong enough to generate a cluster, even if Central Italy tends to converge more toward the North than toward the South.

The environmental pro-sociality gap can be seen as a specific instance of the gap in social capital caused by the high-trust/low-trust divide in Italian regions that is a consequence of long-term historical processes, as argued in the classical analysis of Putnam (1993), and of resulting gaps in governance quality (e.g., Kyriacou et al. 2015). But on the other hand, environmental pro-social movements have recently been powerful drivers of social change (Jamison 2001), and therefore, one should not consider poor environmental pro-sociality as a permanent historical legacy, but rather as a stimulus for policy action that might positively reverberate also on other aspects of socioeconomic inequality, for instance, by leveraging upon innovative sustainable neighborhood development strategies (Valkering et al. 2013) calling for public–private partnerships and collaboration, and focusing upon extensive social cooperation to exchange and co-produce pro-socially useful knowledge and practices. It is also intriguing to consider innovative policy design options that exploit new opportunities from social innovation. For example, in light of the Crociata et al. (2015) result that differentiated waste recycling performance is positively influenced by the level of cultural participation, one could think of cultural policies as an as yet unexplored channel for eliciting large-scale behavioral change, also in view of the large resource availability for structural policies in the Southern Italian regions in the context of the EU cohesion policy. If cultural participation improves pro-social environmental attitudes, carefully designed interregional cultural could provide a big push to break the sociocultural lock-in. We look forward to more research and policy experimentation in this promising direction.

References

Anselin L (1988) Spatial econometrics: methods and models. Kluwer, Boston
Anselin L (1993) The Moran scatterplot as an ESDA tool to assess local instability in spatial association. Paper presented at the GISDATA specialist meeting on GIS and spatial analysis, Amsterdam, The Netherlands, 1–5 Dec (West Virginia University, Regional Research Institute, Research Paper 9330)
Anselin L (1995) Local indicators of spatial association—LISA. Geogr Anal 27:93–115
Anselin L (1996) The Moran scatterplot as an ESDA tool to assess local instability in spatial association. In: Fischer M, Scholten H, Unwin D (eds) Spatial analytical perspectives on GIS. Taylor and Francis, London, pp 111–125
Anselin L (2002a) Exploring spatial data with DynESDA2. CSISS and Spatial Analysis Laboratory University of Illinois, Urbana-Champaign, 12 Sept 2002
Anselin L (2002b) Under the hood: issues in the specification and interpretation of spatial regression models. Agric Econ 27:247–267
Anselin L (2010) Thirty years of spatial econometrics. Pap Reg Sci 89:3–25
Anselin L, Bera A (1998) Spatial dependence in linear regression models with an introduction to spatial econometrics. In: Ullah A, Giles DEA (eds) Handbook of applied economic statistics. Marcel Dekker, New York
Arbia G (1988) Spatial data configuration in statistical analysis of regional economics and related problems, advanced statistical theory and applied econometrics. Kluwer, Dordrecht
Arbia G (2005) Spatial econometrics, statistical foundations and applications to regional convergence. Springer, Berlin
Arbia G, Basile R, Mirella S (2002) Regional convergence in Italy 1951–199: a spatial econometric perspective. ISAE working papers 29, ISAE—Institute for Studies and Economic Analyses (Rome, ITALY)
Brueckner JK (2003) Strategic interaction among governments: an overview of empirical studies. Int Reg Sci Rev 26:175–188
Bliz K, Nadler J (2014) Law, moral attitudes, and behavioral change. In: Zamir E, Teichman D (eds) The Oxford Handbook of behavioral economics and the law. Oxford University Press, New York
Burn SM, Oskamp S (1986). Increasing community recycling with persuasive communication and public commitment. J Appl Soc Psych 26:29–41
Basile R, Capello R, Caragliu A (2012) Technological interdependence and regional growth in Europe: proximity and synergy in knowledge spillovers. Pap Reg Sci 91:697–722
Curlee RT (1986) The economic feasibility of recycling. Praeger, New York
Cassi L, Plunket A (2014) Proximity, network formation and inventive performance: in search of the proximity paradox. Ann Reg Sci 53:395–422
Clark TN et al (2014) Can Tocqueville karaoke? Global contrasts of citizen participation, the arts and development. Emerald, Bingley
Crociata A, Agovino M, Sacco PL (2015) Recycling waste: does culture matter? J Behav Exp Econ 55:40–47
De Young R (1986) Some psychological aspects of recycling: the structure of conservation-satisfactions. Environ Behav 18:435–449
Espa G, Arbia G, Giuliani D (2013) Conditional versus unconditional industrial agglomeration: disentangling spatial dependence and spatial heterogeneity in the analysis of ICT firms' distribution in Milan. J Geogr Syst 15:31–50
Fowler JH, Christakis NA (2008) Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham heart study. Br Med J 337:a2338
Greunz L (2003) Geographically and technologically mediated knowledge spillovers between European regions. Ann Reg Sci 37:657–680
Griffith DA, Paelinck JHP (2007) An equation by any other name is still the same: on spatial econometrics and spatial statistics. Ann Reg Sci 41:209–227
Jamison A (2001) The making of green knowledge: environmental politics and cultural transformation. Cambridge University Press, Cambridge
Krasny ME, Lundholm C, Plummer R (2010) Environmental education, resilience, and learning: reflection and moving forward. Environ Educ Res (Special Issue: Resilience in Social-Ecological Systems: The Roles of Learning and Education) 16:463–474
Kyriacou AP, Muinelo-Gallo L, Roca-Sagalés O (2015) Fiscal decentralization and regional disparities: the importance of good governance. Pap Reg Sci 94:89–107

Læssøe J (2010) Education for sustainable development, participation and socio-cultural change. Environ Educ Res 16:39–57
Lanza DR (1983) Municipal solid waste regulations: an ineffective solution to a national problem. Fordham Urban Law J 10:215–245
Le Gallo J (2004) Space-time analysis of GDP disparities among European regions: a Markov chains approach. Int Reg Sci Rev 27:138–163
Miafodzyeva S, Brandt N (2013) Recycling behaviour among householders: synthesizing determinants via a meta-analysis. Waste Biomass Valoriz 4:221–235
Noll K (1985) Recovery, recycle and reuse of industrial wastes. Lewis Publishers, Chelsea
Oskamp S, Harrington MJ, Edwards TC, Sherwood DL, Okuda SM, Swanson DC (1991) Factors influencing household recycling behavior. Environ Behav 23:494–519
Putnam RD (1993) Making democracy work: civic traditions in modern Italy. Princeton University Press, Princeton
Putnam RD (2000) Bowling alone: the collapse and revival of American community. Simon & Schuster, New York
Rey SJ (2001) Spatial empirics for economic growth and convergence. Geogr Anal 33:195–214
Rey SJ, Montouri BD (1999) US regional income convergence: a spatial econometric perspective. Reg Stud 33:143–156
Schettini D, Azzoni CR, Paez A (2011) Neighborhood and efficiency in manufacturing in Brazilian regions: a spatial Markov chain analysis. Int Reg Sci Rev 34:397–418
Valkering P, Beumer C, de Kraker J, Ruelle C (2013) An analysis of learning interactions in a cross-border network for sustainable urban neighbourhood development. J Clean Prod 49:85–94
Van Poeck K, Vandenabeele J (2012) Learning from sustainable development: education in the light of public issues. Environ Educ Res 18:541–552
Yan J, Sha J, Chu X, Xu F, Higano Y (2014) Endogenous derivation of optimal environmental policies for proper treatment of stockbreeding wastes in the upstream region of the Miyun Reservoir, Beijing. Pap Reg Sci 93:477–500