

Non-constant income elasticities of waste generation

Matteo Mazzarano^{a,*}, Simon De Jaeger^b, Sandra Rousseau^b

^a Università Cattolica Del Sacro Cuore, Brescia, Italy

^b CEDON, KU Leuven, Belgium

ARTICLE INFO

Article history:

Received 14 May 2020

Received in revised form

23 February 2021

Accepted 28 February 2021

Available online 11 March 2021

Handling editor: Dr. Govindan Kannan

Keywords:

Municipal waste management

Income levels

Spatial econometrics

ABSTRACT

The paper presents an alternative approach to analyzing decoupling between municipal solid waste and economic activity production. The methodology consists of generalizing the functional form of the statistical model of the environmental Kuznets curve. To avoid the limitation of one single alternative hypothesis, we developed a small set of alternatives based on the signs and statistical significance of estimates. We tested the model for all available categories of municipal solid waste in Italian provinces. The necessity of developing an alternative approach resulted from inconsistencies in past studies within the same policy context. Conclusions from similar statistical approaches and models provided contradictory findings for Europe and other regions. The results of our approach suggest that there is no linear correlation between economic activity and municipal solid waste, nor are they (yet) decoupled from economic activity: GDP per capita affects MSW production differently in each province, which is reflected through differences in spatial correlation.

© 2021 Elsevier Ltd. All rights reserved.

1. Introduction

Municipal Solid Waste (MSW) is an inevitable by-product of human activity (Periathamby, 2011). It amounts to approximately 10% of total waste generation (WG) in European countries (European Commission, 2020; Mourelatou, 2018). The Waste Framework Directive (WFD) of 2008 made MSW management a priority, due to the link with consumption and income levels. The issue is even more relevant in developing countries as stated in the World Bank report “What a waste” (Hoornweg and Perinaz, 2012): it highlighted that damages associated with the long-term production of urban waste are severely undervalued and should not be ignored. Moreover, increasing urbanization and densification of urban areas will have a significant impact on economic development and, therefore, on waste patterns.

Many events have fueled the interest in effective and efficient municipal waste strategies, such as the waste crisis of Naples, Rome and Milan (Italy) since 1994 (Di Nola, Escapa and Ansah, 2018). In recent decades, several aspects of municipal waste generation and

management have been studied by economists, such as illegal dumping (Chifari et al., 2018; Chifari et al., 2017; D'Amato et al., 2018; Sotamenou et al., 2019), driving factors of municipal waste generation (Jaligot and Chenal, 2018a; Mazzanti, 2008; Mazzanti et al., 2008; Mazzanti and Zoboli, 2008), and waste collection pricing (Fusco and Allegrini, 2019; Mazzanti et al., 2012).

Recycling is typically referred to as one of the strategies to move from a linear to a circular economy (Alaerts et al., 2019), yet the capacity to recycle MSW is not the only precondition needed to achieve a strictly circular economy. While waste is an acceptable category in a linear economy, its role is more ambiguous in a circular economy where actions range from waste prevention to allowing waste production as a source of material and resources. For example, Nelles et al. (2016) describe the transformation of waste management into resource management in Germany. Whilst waste becomes a valuable resource, it is still associated with several negative externalities and it is not clear whether MSW will be beneficial for welfare (Korhonen et al., 2018).

For the transition towards a circular economy, it is thus important to understand the interaction of economic activity and MSW. Previous studies focusing on this interaction have largely addressed the two following factors: heterogeneity and functional forms. In this paper, we aim to address both at the same time. When searching for tipping points, most authors estimate a model that ignores heterogeneity effects. We believe that results might be affected by both heterogeneity and tipping points, which we test

Abbreviations: EKC, Environmental Kuznets Curve; FF, Functional Form; GDP, Gross Domestic Product; MSW, Municipal Solid Waste; WEEE, Waste from Electronics and Electrical Equipment; WEEEP, WEEE package; WFD, Waste Framework Directive; WFP, Waste Framework Package; WG, Waste Generation.

* Corresponding author. Corso Magenta, 63, 20123, Milano, MI, Italy.

E-mail address: matteo.mazzarano@unicatt.it (M. Mazzarano).

for Italy. Italy provides an interesting case study due to the level of heterogeneity of the panel in such a small territory. Furthermore, we generate additional insight from a case that has produced some inconsistency using the Environmental Kuznets Curve (EKC) hypothesis by applying the spatial parametric approach. Besides economic activity and municipal waste production, other variables are also included, such as tourism, population density and occupation, in order to avoid selection bias. Policy breaks are added to control for EU intervention in waste management. The novelty of the study consists in the introduction of a different way of dealing with functional forms, spatial interaction and policy evaluation at a low level of aggregation. To check the robustness of this approach, a sensitivity analysis for the main parameters is carried out. The methodological clarification allows for an unbiased effect analysis of currently enforced waste. Without taking into account properly functional forms and heterogeneity, wait-and-see strategies would be negatively seen, as well as decentralization efforts in policy enforcement.

Current waste policies differ between countries and regions. In Italy, waste policies are developed at the regional and municipal levels. According to the ISPRA¹ classification, municipal waste generation (MWG) can be divided into four categories: 1) household waste (incl. bulky waste), 2) non-hazardous matter derived from urban economic activity, 3) street-cleaning derivatives, and 4) waste from cemeteries. These data represent the amounts of waste before any treatment occurs: incineration, landfill or recycling. Decision 2000/532/Ce² divided the four categories into 37 groups according to material composition. Focusing on the “sorted” fraction, we can find paper, glass, plastics, metal, wood, organic and textile as separate fractions; the other waste streams are mainly registered within the group “selective”. Our analysis will focus mainly on the above-mentioned categories.

Since waste and pollution usually are identified as a by-product of economic activity, national product-waste has been regarded as a topical research matter. Several papers link MSW with GDP. The importance of studying this relationship is highlighted by the idea that a region's economic development might reduce negative externalities while still increasing wellbeing. This phenomenon is called decoupling and it is frequently studied through the estimation of environmental Kuznets curves (UNEP, 2011). The Environmental Kuznets Curve (EKC) is a hypothesized relationship between various indicators of environmental degradation and income per capita. In the early stages of development, natural degradation and pollution increase, possibly at lower rates than economic growth. This is called relative decoupling. Above a certain level of income per capita, named a “tipping point”, the trend reverses. At this point, additional economic growth is expected to reduce pollution. This implies that the environmental impact indicator is an inverted U-shaped function of income per capita, as shown in Fig. 1. Typically, the logarithm of the indicator is modeled as a quadratic function of the logarithm of income (Stern, 2004). However, several critiques of the EKC have been formulated ranging from low-quality data sources, inadequate econometric modeling and failure to take feedback loops into account which would allow environmental quality levels to influence economic growth (Lieb, 2004; Perman and Stern, 2003; Seppälä, Haukioja, & Kaivo-oja, 2001; Uchiyama, 2016).

The paper is organized as follows. A reference review section follows this one. It conveys a synthesis related to the recent development of EKC and decoupling advances regarding MSW. A table collects the most relevant works, together with the geographical location of data and the results of the analysis. A

methodological section frames the theoretical premise of the estimation exercise, providing insights related to heterogeneity and multiple functional forms. These results lead to new insights to allow us to formulate some policy advice.

2. Literature

Past studies focusing on decoupling between economic growth and municipal waste reveal two aspects: first, decoupling in MSW is not always achieved (i.e. a tipping point does not always exist); second, for many regions, the results are at best inconclusive. These limitations emerge from an extensive literature review. Twenty articles on EKC (decoupling) and MSW were found by searching Science Direct and Scopus.⁴ The outcomes are summarized in Table 1. We found that studies for European countries do not produce homogeneous results. These studies mainly use the following approach: testing the validity of the environmental Kuznets Curve with two functional forms and some other proxy variables. These studies do not lead to the same conclusions concerning the applicability of EKC for MSW. Each study adapted the exact specification of the econometric model to reflect its specific context: e.g. tourism, policy enforcement. In most articles, the null hypothesis (H0) reflects the EKC hypothesis and thus the H0 is not rejected if all the estimated coefficients of the functional forms are statistically significant. The hypothesis is therefore rejected as soon as one estimated coefficient is found to be statistically insignificant. Table 1 summarizes the methodology, geographical scope and main result of each study in chronological order. We note that a similar model can have different outcomes for different locations.

Three main methods have been applied to the study of the interaction between municipal solid waste and economic activity. The first method is a more qualitative one. It is based on plotting and trend interpretations. The second one uses convergence; this methodology aims to capture trends among changes of rate. When trends are negative, then changes in waste production converge at zero. In other words, proving convergence is equal to finding relative decoupling. This is an alternative approach without strict tipping points. The third method implies the application of functional forms to test the EKC hypothesis. Such a test requires data from the economic and political variables together with the environmental ones. The interaction via regression is supposed to employ linear data, unchanged from non-linear transformation like logarithms. It is possible that with time passing, new entries are admitted to the datasets, changing the result of the test. For instance, Japan has several positive findings for decoupling. China started with negative decoupling (Liu, 2008), and, depending on the region, also had the opposite results (Chen, 2010; Wu et al., 2015b). Europe showed unclear patterns, probably due to heterogeneity between and within European nations. The Italian case was one of the most studied. Tipping points and therefore decoupling have been tested on total waste generation and waste shipped to landfills. Results suggest that the economic cycle might affect waste management, but not the production of waste. Still, these two aspects are necessarily interlinked due to the emergence of a circular economy as we aim to reduce non-recyclable waste and as recovering and recycling relate to the production of waste.

Testing for tipping points is the operational way to control for the EKC hypothesis, which allows for a standardized way to test a predetermined theoretical assumption (Campos et al., 2005). In other words, the test requires the use of models able to capture non-linear relationships between variables. Previous studies called

¹ <http://www.catasto-ri.uti.isprambiente.it/index.php?pg=ru>.

⁴ The searches were performed in January 2019 and later repeated in December 2019.

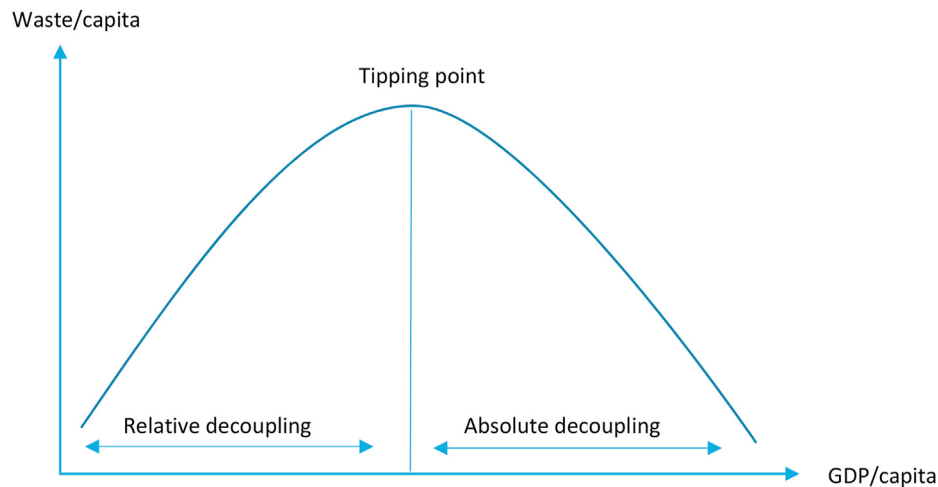


Fig. 1. The inverted U functional form and definition of tipping point.

Table 1

Overview of studies regarding the link between MSW and income levels.

Reference	Framework, Location	Outcome
Seppälä et al. (2001)	EKC, OECD	No tipping point
(Liu, 2008)	EKC, China	No tipping point
(Mazzanti and Zoboli, 2008)	EKC and convergence, EU28	Tipping point found for landfill
Zoboli et al., 2009	EKC, Italy	Partially rejected ³
Mazzanti and Zoboli, 2009	EKC, EU28	Tipping point (landfill), linear relation (Total)
(Chen, 2010)	EKC-N, China	Two tipping points found
(Yamamoto et al., 2011)	EKC, Japan	Tipping point found
(Hossain and Miyata, 2012)	Data analysis, Japan	Relative decoupling
(Mazzanti et al., 2012)	Convergence, Italy	Convergence found
Khajuria et al. (2012)	EKC, Japan	Tipping point found
Trujillo Lora, Carrillo Bermudez, Charris Vizcaino, & Iglesias Pinedo (2013)	EKC, Colombia	Tipping point, landfill
(X. Chen, Pang, Zhang and Li, 2014)	Data analysis, China	Absolute decoupling
Arbulú et al. (2015)	EKC, EU28	Tipping point found
Ichinose et al. (2015)	EKC, Japan	Tipping point found
Wu, Zhang, Xu, & Che (2015a)	EKC, China	Tipping point found
(Montevecchi, 2016)	Policy analysis, North Italy	Tipping point found for property tax levels and waste production
Gnonlonfin et al. (2017)	EKC, Mediterranean panel	No tipping point
(Ercolano et al., 2018)	EKC, Lombardy (Italy)	Tipping point (Referring to taxes as ex.)
Jaligot & Chenal (2018b)	EKC-N, Switzerland	No tipping point found
Gui et al. (2019)	EKC, China	Tipping point not found

these models functional forms (FF). These are mathematical formulas that plot shapes like a bell “U”, an “S”, an “N” etc. The choice of the model is related to the type of tipping point the researcher intends to test. Each FF contains one or more local optima (also called tipping points). The U bell functional form has one tipping point and can be reversed, as shown in Fig. 1. This is the preferred FF for EKC. The “S” curve is commonly known as a logistic, geometric or sigmoid curve. In economics, it is typically used for predicting trends (Cramer, 2005). The “N” functional form extrapolates two tipping points from data; it resembles one “U” and one inverted “U” (Jaligot and Chenal, 2018b). This form has been used to detect potential decoupling patterns in (panel) data (Gnonlonfin et al., 2017; Gui et al., 2019; Mazzanti et al., 2012; Mazzanti & Zoboli, 2008, 2009; Seppälä et al., 2001). However, some of these articles rejected the H0 based on statistical tests concerning the functional form (Gui et al., 2019; Mazzanti and Zoboli, 2009; Seppälä et al., 2001). The state of the art can be summarized in one question: does the EKC-hypothesis apply to the link between MSW and income? As it appears from Table 1, two possible answers have been provided. One is yes it does, but not for all regions. When this hypothesis seems to hold, income per capita appears to be statistically significant as a driver to promote decoupling. However, acceptance of

EKC is questioned by environmental economists (Seppälä et al., 2001). The second answer is no, when only a linear form is allowed for (Jaligot and Chenal, 2018; Liu, 2008; Mazzanti and Zoboli, 2009).

To summarize: the main features of MSW/income literature highlight the limitation of separating the analysis of heterogeneity from the functional forms approach. When assessing heterogeneity, the functional form might seem to be a secondary issue, but we can state the same for functional forms. Spatial regression can deal with both problems. This methodology might cover an important gap in the literature. The spatial approach and EKC have not often been studied together. The next section provides the theoretical framework for the analysis, while the heterogeneity component is presented in the data section.

3. Methodology

When considered in its totality, literature around MSW and income has produced inconclusive results. We believe one of its weak points is the use of functional form and the binary hypothesis approach of EKC literature. The approach used in reported articles is to find support for either the null hypothesis (EKC) or an alternative

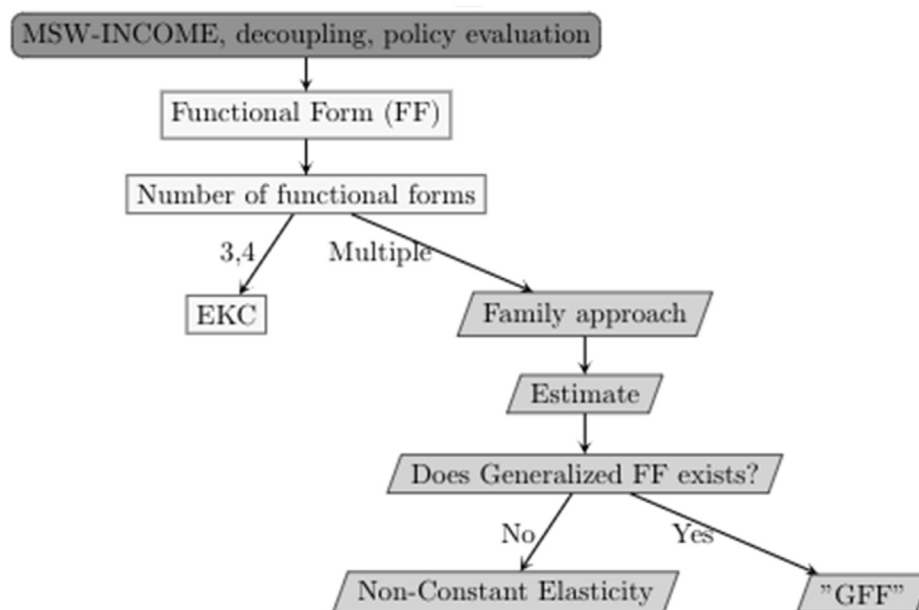


Fig. 2. Methodology map.

hypothesis, based on statistical significance. This first point can be tackled by a multi-functional form approach: considering many functional forms at a time. A second limitation is the rigidity of the alternative hypothesis. Mainstream analysis bases its functional form on the significance of the estimates of a polynomial equation. For example, the bell shape is a second-order polynomial such $a + bx + cx^2$. The insignificance of the estimate “c” means the rejection of the bell shape and supports a linear FF. Similarly, an “N” shape is a trinomial such $a + bx + cx^2 + dx^3$: insignificance of d would underpin the “U” form; the insignificance of both “c” and “d” means linear relation between the exogenous variable and the endogenous one. When the third-grade estimates fail, the second-order FF is accepted. When the second-order element is statistically insignificant, a linear relation is assumed, at least for the panel-data under observation. Our approach is designed to deal with the two limitations considered above. The first weakness is dealt with by using a family approach, while the second one is dealt with by a decision tree of alternatives. With a family approach, we imply that we use a “family”, a set of functional forms (FF), i.e. a group of functional forms at the same time (see Fig. 2). This approach allows us to consider multiple FF. The heterogeneous component of the analysis might consider different FF according to spatial unities such as provinces or regions. Such generalization is influenced by the study of the circular economy and the separation of waste and externalities. Specific approaches regarding the variability of functional forms have been studied before. For instance, Şentürk et al. (2020) suggested that the relationship between economic activity and greenhouse gas emissions presents non-linear FF, outside the general prescription of the EKC. Their study estimated threshold values for decoupling. Zapata and Paudel (2009) synthesized the semi-parametric approach towards EKC. Thus, while the variability or parametric structure of FF has already been considered, we present a new application. Besides the particular selection of family, the approach stems from the same theoretical background as the EKC approach. Moreover, the decoupling of environmental damages and economic growth has been explored by the green Solow model of Brock and Taylor (2010).

To account for heterogeneity and different functional forms, we use the following approach. To address heterogeneity, we use a generalization of the exponential components and we account for provincial heterogeneity of FF by using fixed effects. The generalization to a family of FFs is the next step in testing the applicability of the EKC. Fig. 2 provides a step-by-step outline of the alternative path. The lighter shapes are the current state of the art covered by the articles mentioned above. The darker ones highlight the contribution of this paper. The generalization represents a family of FF. Since there exists a difference between estimates and FF, a condition of existence of a tipping point is derived mathematically. This step is crucial as it can produce two outcomes. The “family” that is described here covers limited cases and ignores possible interactions between variables. Thus, it is still fair to assume that other FFs exists. When the estimates are outside the domain of possible solutions, the FF is not inside this family. Even if our estimates are significant, it may still be possible to interpret the results in another way.

The generalization of FFs can be resumed in the following manner: functional forms vary across countries. Our family of FF starts with a non-specified exponent in the EKC framework. For instance, the classical “U” can be generalized as:

$$y = ax + bx^c \quad (1)$$

Literature has applied the “N” functional form, based on a polynomial of order three (2). In this case, the generalization is:

$$y = ax + bx^c + dx^f \quad (2)$$

These equations can represent the FFs so far analyzed in the existing literature. By generalizing “c” and “f”, other functional forms can be represented. We call this a “family” FF, representing a specific limited number of shapes. The “Y” represents the dependent variable, which is usually MSW per capita in the context of the income-waste relation. The “X” represents the main independent variable, which is income per capita in this setting. The third group of exogenous variables, denoted as Z, is used to reflect control variables such as tourism, policy measures or temporal effects. For simplicity, we now focus on the economic covariate X and add the control variables Z later.

² <https://eur-lex.europa.eu/legal-content/IT/TXT/?uri=celex%3A32000D0532>.

From equation (1) we learn that “a” and “b” must be estimated jointly. In the same way, in equation (2), all variables must be estimated altogether. In a large part of the literature, researchers simply assume that c is equal to two, implying a quadratic form. However, there is insufficient evidence to justify this assumption. Thus, we look at the first and second derivatives of the tipping point, which is what most of the studies focus on. The tipping point is defined by equating the first derivative of the y-function with respect to x to zero. Based on equation (1), this leads to the following expression of the tipping point

$$\hat{x} = \left(-\frac{a}{bc} \right)^{\frac{1}{c-1}} \quad (3)$$

This tipping point is linear in “a”, while it is convex in “b”. This is interesting because the sign of “b” determines the convexity of the “U” shape in the classical EKC. We cannot say the same for the parameter “c”. For instance, when c is less than 1, both moments are positive in terms of sign. When c is more than one, it means that the tipping point is concave with c. Thus the sign of “c” is important as it gives the dimension of the tipping point, together with “a”.

The possible determination of the statistical model can be derived from the logarithmic transformation of the first generalization (equation (1)). For simplicity, we do not retain Z from the original model.

$$\ln(y - ax) = \ln(b) + c \ln(x)$$

$$\frac{\ln(y)}{\ln(a) + \ln(x)} = \ln(b) + c \ln(x)$$

$$\ln(y) = \ln(a + b) + \ln(a^c + b) \ln(x) + c \ln^2(x) \quad (4)$$

The second generalization has a similar process of determination. We start from equation (2) and follow a similar procedure. From (5) we learn that the changes are trivially similar. The main difference is that here we find the third grade x^3 translated to $\ln^3(x)$.

$$\ln(y - ax) = \ln(bx^c + dx^f)$$

$$\frac{\ln(y)}{\ln(a) + \ln(x)} = [\ln(b) + c \ln(x)] [\ln(d) + f \ln(x)]$$

$$\begin{aligned} \ln(y) &= \ln(a + b + d) + [\ln(a + b + f) + \ln(a + b + d) \\ &+ \ln(b + d)] \ln(x) + [\ln(c + d) + \ln(a + c + f) + \ln(b + f)] \ln^2(x) \\ &+ \ln(c + f) \ln^3(x) \end{aligned} \quad (5)$$

Next, the generalization of FF must be translated into a statistical model. This step allows hypothesis testing for the existence of a FF. The framework requires the establishment of vectors and matrices for variables and regressors. For instance, the matrix $X = \{\ln(x), \ln^2(x), \ln^3(x)\}$ collects the independent variable of economic activity. Vector β comprises the regressor of independent to dependent variables. This has a length equal to the number of grades we are referring to in a mathematical model. For instance, the maximum number of functional forms is taken by the FF resembling the N form. This has a third degrees polynomial, therefore β has a length of three. Its members are the following: $\beta_1 = \{\ln(a + b + f) + \ln(a + b + d) + \ln(b + d)\}$, $\beta_2 = \{\ln(c + d) + \ln(a + c + f) + \ln(b + f)\}$, and $\beta_3 = \{\ln(c + f)\}$.

The empirical model aggregates the economic variables in X and the socio-economic ones in Z, while the dependent variable Y is the logarithm of waste flow per capita. Such a model links GDP per capita with MSW per capita, while controlling for other socio-economic drivers. We employ the datasets provided by ISPRA for municipal waste generation and the EUROSTAT⁵ database for GDP. Socio-economic drivers have been extracted from ISTAT.⁶ This study focuses on the level of Italian provinces, which corresponds to Nuts 3 in the EUROSTAT classification. A province is an institutional level that comes between regions and municipal districts of cities in terms of hierarchy. They do not have relevant policy powers but are indeed useful for data analysis as they aggregate several municipal zones.

$$Y_{it} = \alpha_i + X_{it}\beta + Z_{it}\gamma + \varepsilon_{it} \quad (6)$$

This framework is specific for any case under study. For instance, when no functional form is captured but estimates are significant, we believe another explanation may exist. When estimating EKC, the researcher is interested in finding a tipping point. This happens when at least the order two polynomial of the mainstream model is significant and the marginal effects are linearly dependent on economic activity:

$$\frac{\partial y}{\partial x} = a + 2bx + 3cx^2 \quad (7)$$

The tipping point reflects the point where the marginal effect is equal to zero. In other words when marginal utility generated by economic activity is equal to its marginal disutility. When interpreting them in percentage terms we refer to elasticity, which in this case, is calculated as follows:

$$\eta_{EKC} = \frac{\partial \ln y}{\partial \ln x} = \frac{\partial y}{\partial x} \frac{x}{y} = \frac{1}{y} (ax + 2bx^2 + 3cx^3) \quad (8)$$

This percentage varies between each level of both income and MSW. In our model this quantity is strictly dependent on economic activity:

$$\eta_{FF} = \frac{\partial \ln y}{\partial \ln x} = \beta_1 + \beta_2 \ln(x) + \beta_3 \ln^2(x) \quad (9)$$

In this case, the elasticity is strictly endogenous to economic activity. Elasticity is an intuitive measure of the responsiveness of one variable to the change in another. For instance, MSW is elastic to economic activity when η_{FF} lies outside the interval $[-1, 1]$. Within it, MSW would be rigid to economic activity. When adding spatial heterogeneity, the statistical model must comprise weight matrices. Here we assume a spatial lag of the dependent matrix:

$$Y_{it} = \lambda W_i Y_{it} + \alpha_i + X_{it}\beta + Z_{it}\gamma + \varepsilon_{it} \quad (10)$$

The lag $\lambda W_i Y_{it}$ indicates the effect that surrounding areas have on the current province. The assumption that spatial dependence affects the elasticity highlights variability due to the spatial context. Thus, the elasticity would vary according to socio-economic factors and spatial interactions. In this case, the model might explain different spatial heterogeneity as an interaction between spatial framework and socio-economic dynamics. Thus, the elasticity has a different definition:

$$\eta_t^{mul} = \sum_{\forall i} (I_i - \lambda W_i) \frac{\partial Y_{it}}{\partial X_{it}} \quad (11)$$

³ Valid for landfill, linear for total on EU.

⁵ <https://ec.europa.eu/eurostat>.

⁶ <https://www.istat.it/en/>.

Table 2
Summary statistics.

Variables	N	Mean	SD	Min	Q1	Median	Q3	Max
MSW.CAPITA	1648	520.30	101.19	289.42	454.18	499.18	580.35	864.90
GDP.CAPITA	1648	24304.37	6379.05	11800.00	18600.00	24500.00	28900.00	52400.00
OCCUPATION	1648	0.45	0.33	0.01	0.32	0.40	0.47	0.51
DENSITY	1648	251.91	335.14	31.04	107.65	176.31	275.86	2687.40
PAPER	1648	45.53	34.39	0.00	22.15	44.64	61.52	400.40
ORGANIC	1648	61.75	50.84	0.00	14.78	54.28	100.94	245.50
WOOD	1648	10.47	10.42	0.00	1.69	8.60	16.51	72.37
METAL	1648	5.82	5.20	0.00	1.71	4.81	8.26	37.88
PLASTIC	1648	11.24	9.23	0.00	4.04	8.68	16.51	50.57
RAEE	1648	2.95	2.25	0.00	1.30	2.52	4.43	25.00
SELECTIVE	1648	0.58	1.03	0.00	0.06	0.41	0.83	22.48
TEXTILE	1648	1.45	1.76	0.00	0.43	1.32	1.98	30.21
GLASS	1648	24.09	15.47	0.00	10.44	23.40	36.23	113.20
TOURISM	1648	1381447	2458764	41505	290029	586640	1247583	17383151

According to the spatial analysis, the elasticity estimated within one province might be affected by both inner and outer economic activity. The measure used to account for both is called the vulnerability effect. We calculated the elasticity as a vulnerability in equation (11). The existence of such a measure accounts for the complexity that can arise from a spatial econometric problem. When estimates are “vulnerable”, policymaking should anticipate the effect on surrounding areas. In this case, the elasticity would be sensitive not only to inner economic activity, but also to surrounding socio-economic performances. When the estimate of lambda is high (the bounds are $[-1,1]$), the surrounding area effects are predominant and there exists a high chance of contagion, irrespective of the inner activity. When the estimate is restricted to a value far from the upper bound but not near zero, surrounding effects are added to the inner ones. When it is near zero or even insignificant, surrounding effects are negligible. Estimates found in this way might be similar in approach to the EKC but are irreducible to the same hypothesis (Campos et al., 2005).

4. Data

Before testing the presence of any FF, we need to describe and assess the data structure we use in the analysis. Since we expect spatial dependence, the Moran's I test is provided for each time and variable. We also test for autocorrelation and model selection and check for robustness. To start with, a general summary of the variables is reported in Table 2. For our analysis, we used a panel dataset with 103 Italian provinces. The dataset covers fifteen years (2001–2016). Note that during this time frame several institutional reforms had an impact on the exact division of the Italian provinces. Due to the reforms of 2007 and 2010, the number of provinces increased from 103 to 107 and 110 respectively. For this paper, we keep the initial territorial division of 2000. The dataset is generated by combining three open-access datasets: Eurostat, ISPRA and ISTAT databases. From the beginning, we collected the socio-economic variables such as density, occupation, GDP per capita expressed in 2010 euro. The data comprise the total flow of MSW and all collected sub-flows⁷ from the ISPRA dataset. The last database provided shapefiles for spatial analysis and tourist data.

For MSW generation related variables we used the ISPRA⁸ database, while control variables and spatial data were downloaded from ISTAT.⁹ All waste variables are measured in kilograms

(kg) per capita. MSW.CAPITA represents the sum of all separated and unseparated classes of waste. PAPER is the collection of paper-made objects, including paper packaging. ORGANIC accounts for discarded food, collected in separate bins. WOOD refers to the rest of the garden waste. METAL refers to all metal-made waste, such as cans or plugs. PLASTIC is the collection of all recyclable plastics: for instance, it contains plastic packaging. RAEE represents the collection of waste from household electrical equipment; commonly known as Waste from Electronics and Electrical Equipment (WEEE). SELECTIVE is the aggregate of different collections that require a unique class, such as exhausted batteries, medicines. Finally, GDP per capita was taken from Eurostat¹⁰. Missing data from ISPRA are converted into zeros. When a province did not have a collection system for a waste class, 0 was reported as collected quantity. We interpolated the quantity to 0.0001 to extend the time dimension of MSW.CAPITA to all other variables to avoid taking the logarithm of a null quantity¹¹ (Gnonlonfin et al., 2017). The definition of each waste flow conforms to the EU Commission decision of May 3, 2000. We represented the flow data within the appendix sections.

The exogenous variables can be divided into two main groups: GDP and its polynomial structure ($X_{1:3}$), and a set of socio-economic variables ($Z_{1:3}$). The second group is composed of the potential drivers of MSW typically accounted for in the literature (Ercolano et al., 2018; Mazzanti and Zoboli, 2009). Z_1 represents population density defined as the average number of residents per year (T) divided by the surface area of the province in km^2 (S). Z_2 equals tourism density, defined as the number of days tourists used hotels, Airbnb, hostels, etc. it is calculated by ISTAT using the accommodation tax system. We weighted to the area of a province to create tourist density. Finally, Z_3 is the occupation rate defined as the number of employed people resident within the region divided by the total number of residents.

Within the dataset, the average income per capita is 24,304 euros, while the total MSW per capita is 520 kg. The maximum values for income and MSW per capita were 52,400 euros and almost 865 kg respectively. The largest category recovered is organic waste, while the maximum registered is paper. The average population density is almost 252 habitants per km^2 . The average

⁷ A complete definition of nomenclatures used by ISPRA to define flows is provided in appendix.

⁸ www.isprambiente.gov.it/it.

⁹ <https://www.istat.it/en/>.

¹⁰ <https://ec.europa.eu/eurostat/home?>.

¹¹ We run the regression while dropping increasing numbers of lines from the dataset: apparently, most of the zeros were from start years, probably for implementation of policy. We dropped observations from 2001 to 2003 and from 2014 to 2016, reducing the convergence rate from $T/N = 0.145$ to 0.087. The results show minor loss of significance, but the signs remain the same and the values are close to those reported results.

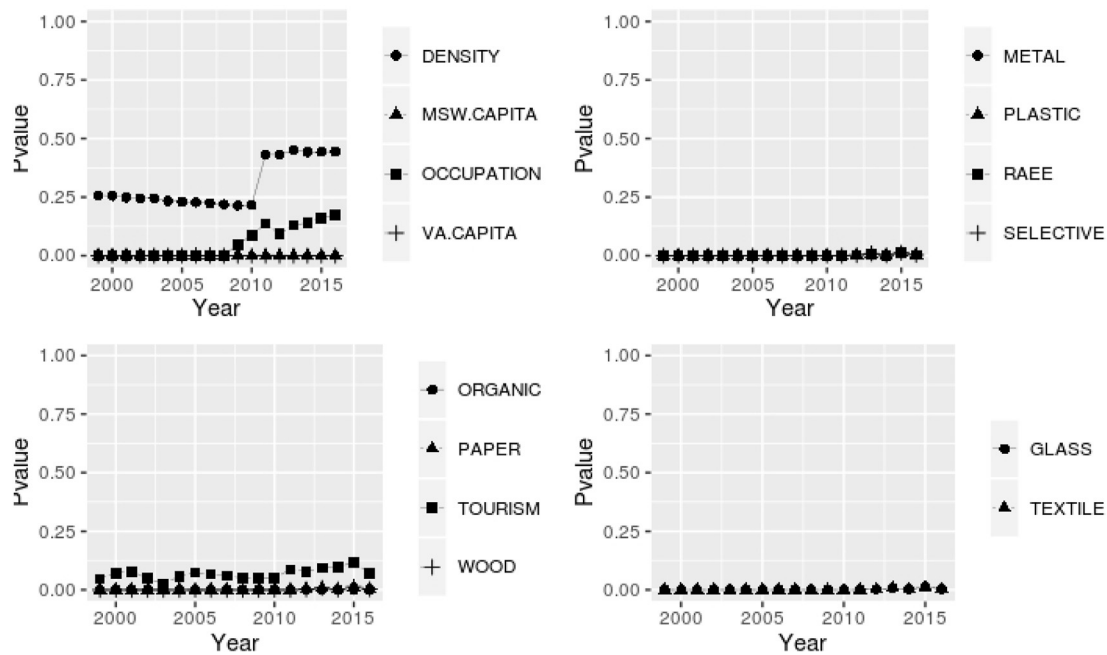


Fig. 3. Moran p-value according to year.

number of annual tourism visits is 1,381,448 for all provinces with a maximum of 17,383,151 visitors in 2005 within the province of Rome.

To integrate the spatial dimension into our regressions, we first generate a normalized spatial weight matrix (W) containing the relevant spatial information. The matrix is first set up as a binary matrix where each cell has a value of 1 or 0, with rows “ i ” and columns “ j ” as the number of provinces. The cell w_{ij} contains the value 1 when provinces “ i ” and “ j ” share a common border and 0 in the opposite case. Next, the matrix is row-normalized by dividing each w_{ij} by the number of cells equivalent to 1 in each row. Using this approach, neighboring provinces will receive $w_{ij} = 1/k$ where k is the number of neighboring provinces. Islands are isolated and thus their provinces can interact only with each other. Only one weight matrix is used.

We treated all variables with the Moran test to spot spatial dependence. The test includes the calculation of the Moran I and its p-value. The former can vary from -1 to 1 . When equal to zero, it represents a variable distributed randomly. We used the p-value obtained in Moran’s I test for values over 0.1 . We could not reject the null hypothesis of spatial interaction. We plotted the results of the test according to each year in Fig. 3. Every group variable relates differently to the spatial lag. Thus, each model requires a different pattern of autocorrelation. For instance, we cannot assume randomness in waste generation; in other words, areas tend to have similar waste patterns. Most of the waste patterns appear to follow this pattern along with tourism density. Interestingly, population density appeared more random after the reform of 2011. Furthermore, during the economic crisis, a “surge” in randomness affected density and occupation, probably due to increased population mobility. Thus, we need to add a second lag to the model for socioeconomic drivers.

After the selection of the spatial matrix and Moran test, we had to determine the models to estimate. Critical aspects under analysis were temporal, local cross-sectional control variables, errors and lags dependence as well as fixed effect selection. We reported the results of our tests in table 5 in the appendix. The general model of

equation (6) was treated for serial correlation in the idiosyncratic component “ ε ”. Thus, our model might efficiently use data while applying individual fixed effects and spatial lags. Results show that the tests for local cross-sectional dependence are positive. We tested for spatial dependence in errors; since the Moran test does not have a high p-value, we decided to use the error spatial model for all categories. The dummies for time and individuals have been tested. We chose to adopt the individual effect to avoid selection bias for redundancy. From this set of pre-selection tests, the spatial autoregressive model was identified. The model to be estimated is then the following:

$$Y_{it} = \alpha_i + \lambda WY_{it} + X_{it}\beta + Z_{it}\gamma + u_{it} \quad (12)$$

Vectors α, β, γ and the value of λ need to be estimated. We assumed that the noise u_{it} is independent and identically distributed in time and space. It is necessary to point out some complex aspects that arose during data analysis. According to the data set provided, most categories were registered as zero kg in the first years of recovery. This notation can produce some complication in data analysis: logarithm transformation required interpolation of data. Another option is to remove lines where such matter occurs. We preferred to choose the first to gain as much convergence as possible for the estimation of maximum likelihood (ML) and generalized moments (GM). From the model selection test, ML and GM displayed similar efficiency. Hence, we choose to use the first method for all except glass. This choice is supported by the outcomes of Hausman’s test. Glass is the only material not to support the ML (Table 5). The value of interaction between surrounding provinces is determined by the value of the estimate of λ (Anselin, 2003; Arbia, 2006). The interpretation of parameter β varies according to the sign of its estimate. When the estimates are all positive, a FF from Table 3 can explain income-waste dynamics. When the estimates violate these conditions but are still statistically significant, no known FF can be identified; hence, economic activity is variably elastic to MSW. More specifically, the elasticity of economic activity to MSW changes according to the level of the

former. As expressed in equation (9), the estimates of β_1 represent elasticity at very low values of GDP per capita. The other two determine the speed of change according to income, and the direction according to the estimated sign. For instance, a negative value of β_2 represents a negative impact of economic activity on elasticity. The third value β_3 in this case is a second derivative, so can be interpreted as a “speed of speed” or in other words acceleration of change.

This model is useful for understanding heterogeneity. Each estimate determines one aspect of variable elasticity. Firstly, the interaction between economic activity and waste production is not constant but changes across the spectrum, as is shown by the first two β . Secondly, we can infer how it varies across the GDP per capita spectrum. Second and third β show whether this variation is steep or rather flat. In the first case, heterogeneity is large. Thus, elasticity might vary greatly according to GDP per capita. When their value is near to zero or statistically insignificant, heterogeneity of elasticity is minimal across GDP per capita levels. To summarize, the significance of these three β signifies some level of variability of elasticity. To control for policy intervention, we refer to three major breaks. One was the WFD introduction in 2008. This was received as law in Italy the following year. It determines targets on recycling and preparing for reuse (more precisely, the target applies to specific types of household and similar waste) (European Environment Agency, 2016; Zoboli et al., 2014). Furthermore, since our work is related to several flows, we added breaks for the policy packages related to Plastics and Textile flows in 2015 and finally the WEEE directive of 2017 (Wilts et al., 2018). These policies aimed at increasing separation level and reducing the MSW per capita produced. The breaks are organized as dummy variables equal to 1 the year after the deliberation. We use a one-year lag as national law adaptation has to take place before experiencing some sort of effects. The value of the dummy is zero before the national law is passed.

5. Results

Nine ML and one GM models have been estimated. The coefficient associated with economic activity is high and statistically significant in eight of them. Socio-economic variables such as occupation, population density and tourism visits (q) were mostly consistent with expectations. According to R^2 the best fitting models are glass, total MSW and paper; the least was WEEE. The model estimating MSW generation had the smallest Akaike information criterion overall. To test the consistency of results in terms of the data manipulation described in section 3, we test the sensitivity by dropping data for some years. We removed 1999 until 2001, where data reported the zeros. Results show some overall loss in statistical significance from the original dataset, but no change in estimation signs. We reported the results in Table 3. We find that results vary greatly across the various sub-flows. This variability suggests that some flows are more dependent on economic activity than others. The high β values indicate that sensitivity of scale is lost at very low levels of income when β_2 is negative. This happens, for instance, for the total sum of flows and unsorted waste. The β_1 value is high in all estimations and indicates that the impact of economic activity is very elastic at a low level of income. When the β_1 sign is positive but β_2 is negative, this means that the elasticity reduces as economic activity rises. Furthermore, this change in elasticity is more sudden as β_3 rises.

We can classify recovered materials according to this estimate into three main categories. The first relates no statistically significant impact of economic activity on waste generation. Results suggest that Paper, Wood, Metal, Plastics, Selective, Glass and the sum of all sorted flows are not affected by the local economy. The

second comprises those flow with a positively elastic impact at low economic activity but that become rigid steadily or suddenly (according to β_3) inelastic with economic growth: plastics appear to fit into this category. The third category considers those flows with a negatively elastic impact at low economic activity, but which become rigid steadily or suddenly (according to β_3) inelastic with economic growth: Other flows, organic, WEEE and Textile waste represent this category.

Variability is very high in textiles and wood. This means that elasticity varies greatly between low-income provinces and high. In this case, low-income regions might have a significant reduction in waste as income rises. Since the change in the degree of variation has a similar tendency, we expect the change to come to a rapid halt. Therefore, variability ceases at a very low level of income. After that point, the percentage variation of economic activity affects textile and wood waste to a similar degree. Plastics and total MSW, on the other hand, act very differently. Elasticity varies slowly in terms of GDP levels. Heterogeneity across provinces and economic activity is, therefore, greater and does not behave in the same way as in the previous set of estimates. While per capita disposal of wood might be similar between average and high-income regions, this is not correct in the case of plastics. Total MSW represents the sum of the other flows. It has the variability of plastics and the signs of wood or textile. This means that the composition, but not the absolute level, of waste varies greatly according to income. As presented in the data, richer provinces produce relatively more waste than poorer ones. Policy breaks are statistically significant for most of the flows. The introduction of the Waste Framework Packages (WFPs) regarding the textile and plastic policy packages induced a reduction in total waste. This is probably related to the partial diversion of unsorted flows into sorted ones. In other words, sorted waste has replaced unsorted. Overall, this phenomenon occurred for the introduction of all three policies considered. The increased sorting generated more specific flows, in particular WEEE and plastics. Uncategorized sorted waste flows, under the heading ‘others’, were initially diverted due to the WFP and then increased due to new additions. The WEEEP has not only had a positive effect in terms of its original objective. All other sub-flows have registered positive increases, reducing the level of unsorted flows. A secondary effect of waste policies was the reduction in total flows.

The results do not underpin the hypothesis of weak or strong decoupling. If we take only total economic activity, MSW will probably not respond to changes in economic activity after a certain point of growth. As equation (9) points out, we could prove that the rigidity is strictly dependent on economic activity; there is no feedback effect from the scale of MSW as in (8) unless we consider vulnerability.

Other socioeconomic variables such as occupation appear to affect the generation of MSW per capita differently *ceteris paribus*. For instance, plastic waste generation is positively affected by tourism rates, indicating a vulnerability of the sector to waste intensity. This intensity is probably strictly endogenous in each province, as the spatial lag is statistically insignificant. The same could not be said for glass and paper generation, which are negatively impacted by the surrounding provinces’ tourism activity. Population density affects waste generation positively in almost all cases. Different signs in spatial lags may indicate spatial heterogeneity in their impact on MSW generation. Such a phenomenon falls within the scope of the previously defined vulnerability. This indicates that the total impact on MSW is affected by surrounding areas. This seems intuitive in the case of tourism, as it is rather common to find travelers that visit more than one city in a single region. When we embody the spatial effect, the results appear to be different, as shown in Fig. 4. When considered as endogenous to one province, elasticity is negative, but when all effects are added, it

Table 3
Regression results.

	<i>Dependent variable:</i>												
	Other	Paper	Organic	Wood	Metal	Plastics	WEEE	Selective	Textile	Glass	Sorted	Unsorted	Total
lambda	0.080*** (0.030)	0.199*** (0.027)	0.087*** (0.029)	0.100*** (0.029)	0.045 (0.030)	0.132*** (0.028)	0.141*** (0.029)	0.137*** (0.029)	−0.028 (0.030)	0.119*** (0.028)	0.090*** (0.029)	0.224*** (0.027)	0.586*** (0.063)
Ln (GDP_Capita)	−1679.056*** (551.002)	−10.829 (121.544)	−554.611* (321.472)	−359.032 (315.536)	191.450 (297.266)	−254.385 (176.009)	−907.747*** (223.023)	−468.551 (313.951)	−999.132*** (348.584)	167.043 (145.697)	−234.054 (239.349)	391.927*** (62.473)	60.497** (28.754)
Ln ² (GDP_Capita)	163.191*** (54.683)	3.640 (12.062)	58.325* (31.904)	37.488 (31.315)	−16.983 (29.502)	26.736 (17.468)	89.303*** (22.134)	47.194 (31.158)	99.381*** (34.595)	−13.514 (14.459)	26.767 (23.754)	−38.479*** (6.200)	−6.075** (2.859)
Ln ³ (GDP_Capita)	−5.281*** (1.808)	−0.200 (0.399)	−2.029* (1.055)	−1.292 (1.035)	0.498 (0.975)	−0.926 (0.578)	−2.921*** (0.732)	−1.579 (1.030)	−3.288*** (1.144)	0.350 (0.478)	−0.993 (0.785)	1.257*** (0.205)	0.203** (0.095)
Unemployment	0.015 (0.016)	0.026*** (0.004)	0.087*** (0.009)	0.034*** (0.009)	−0.026*** (0.009)	0.058*** (0.005)	0.0003 (0.006)	0.028*** (0.009)	0.064*** (0.010)	0.022*** (0.004)	0.043*** (0.007)	−0.011*** (0.002)	−0.004*** (0.001)
Density	3.172** (1.516)	−0.399 (0.336)	−4.480*** (0.885)	0.434 (0.869)	−0.408 (0.818)	0.161 (0.486)	2.298*** (0.614)	−2.243*** (0.864)	−2.996*** (0.959)	−0.605 (0.402)	0.169 (0.660)	0.473*** (0.172)	0.777*** (0.079)
Tourism	−0.405* (0.217)	−0.117** (0.048)	−0.256** (0.127)	−0.120 (0.124)	0.250** (0.117)	−0.187*** (0.069)	0.140 (0.088)	−0.372*** (0.124)	0.070 (0.138)	0.012 (0.057)	−0.119 (0.094)	0.252*** (0.025)	0.104*** (0.011)
WFD	−0.431*** (0.103)	0.189*** (0.024)	0.769*** (0.065)	0.334*** (0.060)	0.028 (0.055)	0.453*** (0.037)	0.661*** (0.048)	0.338*** (0.060)	0.266*** (0.065)	0.302*** (0.029)	0.310*** (0.046)	−0.193*** (0.014)	−0.023*** (0.006)
F&P packages	0.361*** (0.122)	−0.014 (0.027)	0.308*** (0.071)	0.013 (0.069)	0.059 (0.065)	0.215*** (0.040)	−0.046 (0.049)	0.024 (0.069)	0.373*** (0.077)	0.082** (0.032)	0.144*** (0.053)	−0.158*** (0.015)	−0.023*** (0.007)
WEEEP	1.131*** (0.146)	0.091*** (0.032)	0.181** (0.083)	0.224*** (0.082)	0.194** (0.077)	0.194*** (0.046)	0.126** (0.058)	0.168** (0.081)	0.097 (0.090)	0.171*** (0.038)	0.174*** (0.062)	−0.125*** (0.017)	0.008 (0.007)
AIC	6803.47	1216.90	4806.75	4738.42	4513.25	2577.50	3456.05	4724.53	5103.16	1875.38	3712.86	−1253.55	−2353.55

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

emerges as positive. Italy seems to have similar vulnerabilities for each province. Given spatial interaction, the peak from Rome transferred to the south in the province of Latina due to spatial proximity. Despite being both rich cities, Milano (Milan) and Torino (Turin) experience a different scenario. Surrounded by other rich provinces, Milan is the second-highest in Italy for vulnerability. Given the general growth of these areas, vulnerability tends to be higher on average. On the other hand, southern provinces do not suffer from the same vulnerability, but Bari, for instance, registers a high value. A second aspect arises from this figure. We have explained before that the composition of waste changes greatly according to GDP per capita level. Even by considering spatial interaction, heterogeneity is not fully accounted for as it also varies across time. This outcome is rather complex to interpret, as it assumes that elasticity varies according to the interaction of exogenous and endogenous factors.

6. Discussion

MSW management and its economic and environmental impacts have been extensively covered by academic journals as well as the mass media. Here we study the relationship between MSW and GDP per capita. We highlighted the main limitations in previous studies regarding the methodology for estimating the relationship between MSW and economic activities. One was the FF and the other was the heterogeneity of impacts. The generalization of FF and the findings of income-based heterogeneity in elasticity constitutes a novelty in the current debate on tipping points. We concluded from the results that instead of changing signs at a certain threshold or reaching a maximum point, MSW generation becomes more rigid as economic activity grows. The second novelty is the approach that underpins such a conclusion. The standard FF approach is modified to contain a set of alternative hypotheses instead of one. We were not able to find a FF that fits all. Still, we manage to interpret the results differently. From our preliminary results, it appears that MSW elasticity in relation to economic activity varies. Furthermore, it appears to tend to zero. We interpreted this rigidity to be directly induced by economic growth, while controlling for other socio-economic factors. The results show the

presence of spatial vulnerability: thus heterogeneity and spatial interactions affect the variation in elasticity across Italian provinces.

These estimates do not consider the policy performance developed by each zone. For instance, despite Milan being one of the most vulnerable provinces, its waste recovering performances are acceptable. It is not possible to say the same about Rome, where vulnerability is present too. In general, and irrespective of the level of expenditure per capita, provinces with high vulnerability may have lower circular performances. The results of vulnerability analysis provide a more systematic effect when perceived in terms of one area. Italy represents for instance the classical example of spatially heterogeneous economic performance. When both economic heterogeneity and non-linear elasticity hold, environmental and spatial policies such as decentralization should be considered together. Spill-over effects induce spatial vulnerability, indicating a spatial distribution of effects. In terms of the MSW-GDP dynamic, the inelastic impact of total economic activity on waste does not mean decoupling *per se*. Structural changes within an economic system can still affect MSW production. For instance, tourism exercises a significant and positive effect on production. Thus, tourism attraction policies could indirectly foster increases in MSW rates, *ceteris paribus*. In terms of policy effects, sorting policies have diverted unsorted and non-specific flows into more specific ones. Sorted materials are affected generally by all policies in place, and signs change only for non-specific flows.

The difference from previous studies is the interaction between spatial framework and EKC hypothesis discussion. This article proposes a novel approach by dealing with both matters. We highlighted the possibility that more than one FF arises. Enlarging the scope of approach, we tried to assess the question of why absolute decoupling does not appear in MSW. Given the differentiation of flows and spatial approach, we might have a possible explanation. Each economic level might have different cohorts of waste flows. While some waste flows have almost similar dynamics, others vary greatly. Here lies the importance of non-constant elasticity. A linear framework might have captured different tipping points, but not necessarily the differences of GDP per capita. Furthermore, other aspects intervene. The economic

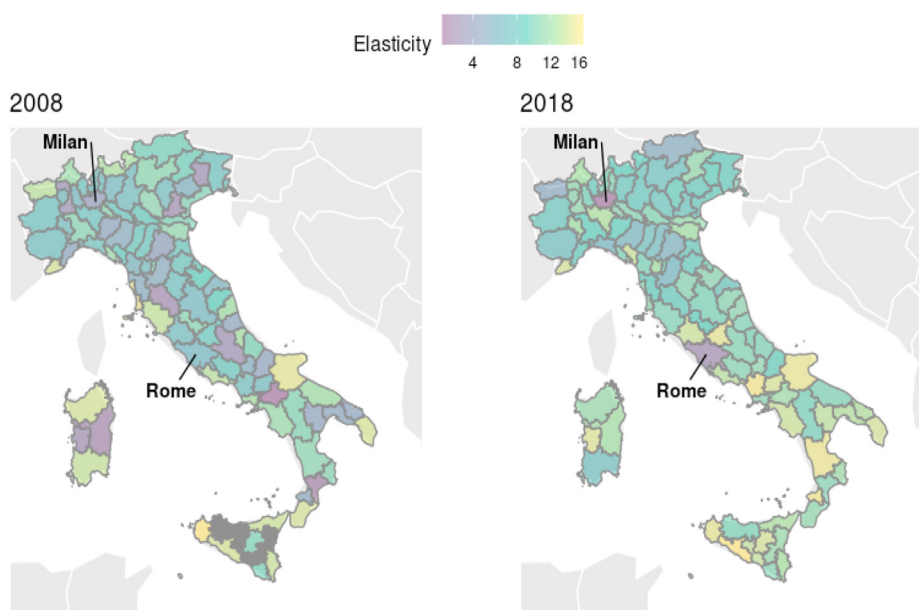


Fig. 4. Vulnerability effect of each province 2008–2015.

cycle is affected by location and endogenous variables. This is a reason for using spatial models for EKC. We then used this interaction to highlight the complex relationship between elasticity and income. Some regions have higher spatial interactions. Keeping all constant, provinces influenced by a complex network must consider secondary effects when planning for disposal. This is a crucial aspect for policymaking. Since each province has different GDP per capita levels, waste compositions vary. Since they vary, uses of incineration, landfill or recycling are strictly dependent on which waste composition emerges in a province. This heterogeneity of composition might be one of the drivers of circular policy. A high level of separation allows for better targeting for recycling. Meanwhile, it is impossible to recover materials or reuse some commodities without sorting them. Decentralization of policy might rule out heterogeneity of flows if waste separation fuels circular policies. Otherwise, materials are lost in the process. Furthermore, the interaction between areas is relevant for assessing possible changes in waste flows. In some cases, outside MSW policy, a semi-parametric approach to dealing with EKC and its heterogeneity problem has been considered (e.g. Wang, 2013; Zapata and Paudel, 2009). Compared to the spatial autoregressive model, this approach assumes that the distance between a true model and the observation cannot be fully captured. Therefore, estimates follow a non-normal distribution and could vary over time. The approach applied here does assume rigidity of spatial interaction over time. We preferred to use a spatial parametric approach to adapt the theory of decoupling to a wider number of FF while taking into account the Italian geographical system. Since provinces are embedded within a rigid scheme of interdependences with surrounding zones called regions, it is reasonable to assume that spatial interaction is fixed over time or varies within predictable intervals.

Another aspect we need to report is the time-varying spatial dependence registered in the Moran test. Such a matter would require an extension (Lee and Li, 2017), but should be covered by a separate study, given its complexity. Furthermore, since clustering on provinces clears out much information that is available at the regional level, we used variables that were available but still consistent with the literature. Given the heterogeneity of materials and utility that each good provides, extending the model by using other variables can add interesting knowledge to the field.

7. Conclusion

This work analyzed the relation of MSW-Income using a spatial panel data approach. We presented the relevant literature and highlighted the main gaps. Among these, we find the lack of a general approach for FF and limited use of a spatial framework, despite data evidence. We then approached the problem by dealing with both matters. Thus, we firstly classified FF and how they may arise in data estimation. We link this approach with an interest in tipping points. We used data for total MSW and its sub-flows to understand whether income affects each flow differently and focus on Italian provinces from 2001 to 2018. Socio-economic variables comprise tourism, density, and occupation levels. Since results from pre-selection tests and Moran tests underpinned spatial frameworks, we treated the model for spatial lags in the dependent and some independent variables. The model estimation suggested the absence of any general FF but the presence of varying elasticity. The main reasons for the observed changes are related to spatial interaction, economic activity, and the type of waste. Results suggest that GDP per capita affects the composition of waste flow.

Hence, elasticity varies according to waste type and economic variables. We found that economic activity might be relevant in some cases but only at a very low level. In other cases, elasticity varied greatly according to economic activity. Heterogeneity is evident when plotting vulnerability on a map. Elasticity changes over time according to this complex set of variables. Policy instruments in waste management should be applied, controlling for non-linearity in economic activity and other socio-economic dynamics in order to avoid undesirable regressive effects between zones. Decentralization might be effective in environmental adjustment as Italy is characterized by a high level of heterogeneity. However, differences in policy instruments to control waste production do not necessarily eliminate the possibility of heterogeneous performances.

We cannot explain whether waste separation positively affects circular policies. It is a *conditio sine qua non* without which material recovery and commodity reuse cannot arise. Nevertheless, some flows seem to reach very low levels of elasticity at low income. Those flows could easily be managed, as they will not change with economic growth. This is a relevant gap that further works might cover.

Our work has shed light on how socio-economic activity might have non-linear effects on waste generation. It offered new ideas in terms of methodology and policy comment. The se might be useful for other studies regarding waste sub-flows and effective policies. The necessary step after this work might be to investigate a similar approach to a wider context, such as the EU. We clarified the presence of heterogeneity both in terms of economic and spatial correlation and how these two interact. Nevertheless, this framework aims to close the gaps by widening the perspective on the income-waste relationship. It is especially important to specify the sub-flows in order to connect with different policy aspects such as climate change, environmental safety and food waste.

CRediT authorship contribution statement

Matteo Mazzarano: Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Simon De Jaeger:** Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Visualization. **Sandra Rousseau:** Conceptualization, Resources, Supervision, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

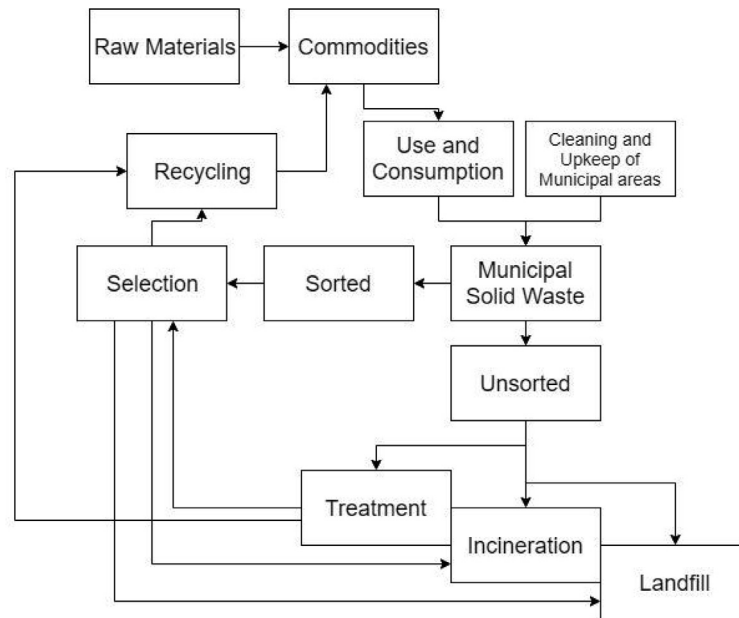
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We would like to thank three anonymous reviewers for the comments they made, professor Mark Corner for the language corrections and Juan Garcia PhD for the suggestions while writing the article.

Appendix

Material cycle in MSW and data

Fig. 5. Material Flow Chart¹²¹

The cited literature tends to apply various definitions of MSW without a debug of its composition or direction in a material chain. It represents the sum of sorted and unsorted flows. These are defined after collection from bins, door to door or by applying other policies. At this point, both can either be incinerated, landfilled, or processed for recycling. ISPRA does not identify the form of incineration at this point. Furthermore, the amount of recycling is unclear. Clothes are usually reused for secondary sales or donations after applying sanitary procedures. Other flows might be recycled in the sense of material recovery. Therefore, WEEE might be treated to extract precious materials and so on. Confusion between these two terms is evident in this case, and caution is needed when applying such data. In our case, we mainly focused on the total collection and sorted waste flows. We reported a summary of flows in Fig. 5.

as it represents the parameter of interaction between a linear independent variable and a dependent one. Hence, we have positive signs in the case of both moments of “x” for “a”. Parameter “b” is convex to its tipping point. This is where we can find two different FF: either U or its inverted shape. Its signs are different. The last parameter we considered is “c”. Here, the number of functional forms is the maximum reported in the literature. Non-linearities are evident as the value of “c” is influencing the sign of the first moment. The tipping point of X is strictly linear to “c” when its values are less than one. In other cases, it is concave, denoting other non-linearities. Outside “N” structural forms of $c < 1$, we cannot find examples in the literature where this has different values.

Table 4
First and second moments of the tipping point

	First derivative	Second derivative
a	$\hat{x}_a = \frac{1}{a(c-1)} > 0$	$\hat{x}_{aa} = -\frac{(c-2)\hat{x}}{a^2(c-1)^2} \quad c < 2, \hat{x}_{aa} < 0 \quad c \geq 2, \hat{x}_{aa} \geq 0$
b	$\hat{x}_b = -\frac{1}{b(c-1)} < 0$	$\hat{x}_{bb} = c\hat{x} \frac{1}{b^2(c-1)^2} > 0$
c	$\hat{x}_c = -\frac{\ln(\hat{x})\hat{x}}{c-1} = \begin{cases} c < 1, \hat{x}_c > 0 \\ c > 1, \hat{x}_c < 0 \end{cases}$	$\hat{x}_{cc} = \left[\hat{x} \ln(\hat{x}) \frac{2}{(c-1)^2} + \hat{x} \ln(\hat{x}) \frac{1}{(c-1)} + \frac{1}{c^2(c-1)^2} + \frac{1}{c^2(c-1)} + \frac{2}{c(c-1)^2} \right] > 0$

Tipping points and possible functional Forms

In this section, we briefly present how first- and second-moments change according to each parameter change. We refer to the equation for a family of FF where the first polynomial is used. It takes the form:

$$y = ax + bx^c$$

Results are reported in Table 4 as a theoretical examination. It must be noted that complexity arises when each parameter is presented. Tipping point “x” in FF is strictly positive on “a”. This is trivial

In table 5 we then synthesized how the composition of these three parameters might plot different functional forms. We refer to equation (1). This is the first generalization. It assumes that the exponent “c” might be different from 2, which is something that is different from what literature states. We can count more than ten theoretical functional forms. According to literature references, only three might represent waste income dynamics. We, therefore, plotted the main features. The most important changes are captured according to c variation. The assumption that the parameter c is strictly equal to two is probably limiting. According to this premise, we established our multiple FF or family approach.

Table 5
All possible shapes that generalized FF takes

	$c = 0$	$0 > c > 1$	$c < 0$	$c > 1$
$a < 0 \ b < 0$	Negative linear	Negative log	Negative linear	Exponential Negative
$a > 0 \ b > 0$	Positive linear	Positive log	Positive linear	Exponential Positive
$a > 0 \ b < 0$	Positive linear	"U" shape	Hyperbolic	Inverted "U"
		Fast turning	3rd, 4th with 1st quadrant	
$a < 0 \ b > 0$	Negative linear	Inverted "U"	Hyperbolic	"U"
		Fast turning	2nd, 4th with 1st quadrant	
$a = 0 \ b > 0$	No relation	Positive log	Hyperbolic 1st or 2nd quadrant	Exponential Positive
$a = 0 \ b < 0$	No relation	Negative log	Hyperbolic 3rd or 4th quadrant	Exponential Negative

Table of model tests

In this section, we briefly present [table 6](#) with a summary of pre-selection tests. We tested for serial correlation (Breusch-Godfrey/Wooldridge), local cross-sectional dependence (Pesaran CD), Lagrange multipliers and their robust counterparts, five different Hausman tests and finally Honda tests for panel balance. Hausman tests were divided into: ML individual (1), time (2) and two-ways (3) effect, then GM time (4) and individual (5). The tests have a null hypothesis of fixed effect inconsistency versus an alternative of random effects inconsistency. These tests are relevant as the convergence rate of our model is not high. Low convergence in estimation makes random effect regressors less efficient than fixed effect. In most articles we cited, both models are estimated. Local

cross-sectional dependence represents a different definition of spatial dependence. The main purpose of the CD is to test dependence between observations. It can test global dependence without a spatial matrix or any weight matrix and local dependency with one. We tested here for the second one with proof of presence. The difference from Moran I is the time frame. Pesaran CD can scope for local dependence across a timeline. The latter is strictly cross-sectional. To select the spatial lag, we used the Lagrange Multipliers. The robustness allows us to rule out possible individual effects. Despite a change in the magnitude of the p-value, we register no change in test results apart from Glass. Honda tests are used to rule out inefficient fixed effects. When the p-value is above 0.1, we will consider the treated effect as inefficient.

Table 6
Model Selection tests

Test	Others	Paper	Organic	Wood	Metal	Plastics	WEEE	Selective	Textile	Glass	Recovered	Unrecovered	Total_MSW
Breusch-Godfrey/Wooldridge test for serial correlation in panel models	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***
Pesaran CD test for local cross-sectional dependence in panels	0***	0.7	0***	0***	0.043	0.002***	0***	0***	0.001***	0.003***	0***	0***	0***
LM test for spatial error dependence	0.097*	0.681	0.599	0.781	0.863	0.74	0.081*	0.348	0.046**	0.35	0.019**	0.113	0.174
LM test for spatial lag dependence	0.062*	0.022**	0.021**	0.397	0.078*	0.005***	0***	0***	0.317	0***	0***	0.978	0.234
Locally robust LM test for spatial error dependence sub spatial lag	0.746	0.033**	0.005***	0.148	0.004***	0***	0***	0***	0.017**	0***	0.001***	0.004***	0***
Locally robust LM test for spatial lag dependence sub spatial error	0.365	0.002***	0***	0.098	0.001***	0***	0***	0***	0.098*	0***	0***	0.017**	0***
Hausman test for spatial models	0***	0***	0***	0***	0***	0***	0.111	0***	0***	0.259	0***	0.985	0.713
Hausman test for spatial models	0.038	0***	0***	0.003***	0.677	0***	0***	0***	0.003***	0***	0.001***	0***	0.041**
Hausman test for spatial models	0.019**	0***	0***	0.005***	0.403	0***	0***	0***	0.002***	0***	0***	0***	0.261
Hausman test for spatial models	0.012**	0***	0***	0***	0.21	0***	0***	0***	0***	0***	0***	0.223	0***
Hausman test for spatial models	0.032**	0***	0***	0.008***	0.665	0***	1	0***	0***	0.633	0***	0***	0***
Lagrange Multiplier Test - (Honda) for balanced panels	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***
Lagrange Multiplier Test - time effects (Honda) for balanced panels	0***	0.022**	0.05*	0.008***	0.037**	0***	0***	0.007***	0.053	0.303	0***	0***	0.896
Lagrange Multiplier Test - two-ways effects (Honda) for balanced panels	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***

¹² Translated by the authors from ISPRA Website.

References

- Alaerts, L., Van Acker, K., Rousseau, S., De Jaeger, S., Moraga, G., Dewulf, J., Eyckmans, J., 2019. Towards a more direct policy feedback in circular economy monitoring via a societal needs perspective. *Resour. Conserv. Recycl.* 149, 363–371. <https://doi.org/10.1016/j.resconrec.2019.06.004>.
- Anselin, L., 2003. Spatial econometrics. In: *A Companion to Theoretical Econometrics*. Blackwell Publishing Ltd, Malden, MA, USA, pp. 310–330. <https://doi.org/10.1002/9780470996249.ch15>.
- Arbia, G., 2006. *Spatial Econometrics*. Springer-Verlag, Berlin/Heidelberg. <https://doi.org/10.1007/3-540-32305-8>.
- Arbulú, I., Lozano, J., Rey-Maqueieira, J., 2015. Tourism and solid waste generation in Europe: a panel data assessment of the Environmental Kuznets Curve. *Waste Manag.* 46, 628–636. <https://doi.org/10.1016/j.wasman.2015.04.014>.
- Brock, W.A., Taylor, M.S., 2010. The green Solow model. *J. Econ. Growth* 15 (2), 127–153. <https://doi.org/10.1007/s10887-010-9051-0>.
- Campos, J., Ericsson, N.R., Hendry, D.F., 2005. General-to-specific Modeling : an Overview and selected bibliography. *Int. Fin. Discuss. Pap.* (838), 1–94. <https://doi.org/10.17016/IFDP.2005.838>, 2005.
- Chen, C.C., 2010. Spatial inequality in municipal solid waste disposal across regions in developing countries. *Int. J. Environ. Sci. Technol.* 7 (3), 447–456. <https://doi.org/10.1007/BF03326154>.
- Chen, X., Pang, J., Zhang, Z., Li, H., 2014. Sustainability assessment of solid waste management in China: a decoupling and decomposition analysis. *Sustainability* 6 (12), 9268–9281. <https://doi.org/10.3390/su6129268>.
- Chifari, R., Lo Piano, S., Bukkens, S.G.F., Giampietro, M., 2018. A holistic framework for the integrated assessment of urban waste management systems. *Ecol. Indic.* 94, 24–36. <https://doi.org/10.1016/j.ecolind.2016.03.006>.
- Chifari, R., Renner, A., Lo Piano, S., Ripa, M., Bukkens, S.G.F., Giampietro, M., 2017. Development of a municipal solid waste management decision support tool for Naples, Italy. *J. Clean. Prod.* 161, 1032–1043. <https://doi.org/10.1016/J.JCLEPRO.2017.06.074>.
- Cramer, J.S., 2005. The origins of logistic regression. *SSRN Electr. J.* <https://doi.org/10.2139/ssrn.360300>.
- D'Amato, A., Mazzanti, M., Nicoli, F., Zoli, M., 2018. Illegal waste disposal: enforcement actions and decentralized environmental policy. *Soc. Econ. Plann. Sci.* 64 (December 2017), 56–65. <https://doi.org/10.1016/j.seps.2017.12.006>.
- Di Nola, M.F., Escapa, M., Ansah, J.P., 2018. Modelling solid waste management solutions: the case of Campania. *Italy Waste Manag.* 78, 717–729. <https://doi.org/10.1016/j.wasman.2018.06.006>.
- Ercolano, S., Lucio Gaeta, G.L., Ghinoi, S., Silvestri, F., 2018. Kuznets curve in municipal solid waste production: an empirical analysis based on municipal-level panel data from the Lombardy region (Italy). *Ecol. Indic.* 93, 397–403. <https://doi.org/10.1016/j.ecolind.2018.05.021>.
- European Commission, 2020. Municipal Waste Statistics. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Municipal_waste_statistics. (Accessed 14 December 2020).
- European Environment Agency, 2016. *Municipal Waste Management across European Countries*. European Environment Agency.
- Fusco, E., Allegrini, V., 2019. The role of spatial interdependence in local government cost efficiency: an application to waste Italian sector. *Socioecon. Plann. Sci.* 1–10. <https://doi.org/10.1016/j.seps.2019.01.003>, September 2018.
- Gnononfon, A., Kocoglu, Y., Peridy, N., 2017. Municipal solid waste and development: the environmental Kuznets curve evidence for mediterranean countries. *Reg. Develop.* 45, 113–130. <http://region-developpement.univ-tln.fr/en/pdf/R45>.
- Gui, S., Zhao, L., Zhang, Z., 2019. Does municipal solid waste generation in China support the Environmental Kuznets Curve? New evidence from spatial linkage analysis. *Waste Manag.* 84, 310–319. <https://doi.org/10.1016/j.wasman.2018.12.006>.
- Hoornweg, D., Perinaz, B.T., 2012. *What a Waste: a Global Review of Solid Waste Management* Washington DC, vol. 15. <https://openknowledge.worldbank.org/handle/10986/17388>.
- Hossain, N., Miyata, Y., 2012. Municipal solid waste management of Toyohashi city: an analysis by Environmental Kuznets Curve. *Reg. Sci. Inq.* 4 (2), 97–110. <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84873452477&partnerID=40&md5=c860f9afd809c39442d145caad6a6ede>.
- Ichinose, D., Yamamoto, M., Yoshida, Y., 2015. The decoupling of affluence and waste discharge under spatial correlation: do richer communities discharge more waste? *Environ. Dev. Econ.* 20 (2), 161–184. <https://doi.org/10.1017/S1355770X14000370>.
- Jaligot, R., Chenal, J., 2018a. Decoupling municipal solid waste generation and economic growth in the canton of Vaud, Switzerland. *Resour. Conserv. Recycl.* 130, 260–266. <https://doi.org/10.1016/j.resconrec.2017.12.014>.
- Jaligot, R., Chenal, J., 2018b. Decoupling municipal solid waste generation and economic growth in the canton of Vaud, Switzerland. *Resour. Conserv. Recycl.* 130 (December 2017), 260–266. <https://doi.org/10.1016/j.resconrec.2017.12.014>.
- Khajuria, A., Matsui, T., Machimura, T., Morioka, T., 2012. Decoupling and environmental Kuznets curve for municipal solid waste generation: evidence from India. *Agric. On-Line Pap. Econ. Informat.* 2 (3), 1670–1674. <https://doi.org/10.6088/jtes.002020300051>.
- Korhonen, J., Honkasalo, A., Seppälä, J., 2018. Circular economy: the concept and its limitations. *Ecol. Econ.* 143, 37–46. <https://doi.org/10.1016/j.ecolecon.2017.06.041>.
- Lee, J., Li, S., 2017. Extending Moran's index for measuring spatiotemporal clustering of geographic events. *Geogr. Anal.* 49 (1), 36–57. <https://doi.org/10.1111/gean.12106>.
- Lieb, C.M., 2004. The environmental Kuznets curve and flow versus stock pollution: the neglect of future damages. *Environ. Resour. Econ.* <https://doi.org/10.1007/s10640-004-1046-x>.
- Liu, L., 2008. Sustainability efforts in China: reflections on the environmental Kuznets curve through a locational evaluation of “eco-communities. *Ann. Assoc. Am. Geogr.* 98 (3), 604–629. <http://www.jstor.org/stable/25515145>.
- Mazzanti, M., 2008. Is waste generation de-linking from economic growth? Empirical evidence for Europe. *Appl. Econ. Lett.* 15 (4), 287–291. <https://doi.org/10.1080/13504850500407640>.
- Mazzanti, M., Montini, A., Nicoli, F., 2012. Waste dynamics in economic and policy transitions: decoupling, convergence and spatial effects. *J. Environ. Plann. Manag.* 55 (5), 563–581. <https://doi.org/10.1080/09640568.2011.616582>.
- Mazzanti, M., Montini, A., Zoboli, R., 2008. Municipal waste generation and socio-economic drivers. *J. Environ. Dev.* 17 (1), 51–69. <https://doi.org/10.1177/1070496507312575>.
- Mazzanti, M., Zoboli, R., 2008. Waste generation, waste disposal and policy effectiveness. Evidence on decoupling from the European Union. *Resour. Conserv. Recycl.* 52 (10), 1221–1234. <https://doi.org/10.1016/j.resconrec.2008.07.003>.
- Mazzanti, M., Massimiliano, Zoboli, Roberto, 2009. Municipal waste Kuznets curves: evidence on socioeconomic drivers and policy effectiveness from the EU. *Environ. Resour. Econ.* 44, 203–230. <https://doi.org/10.1007/s10640-009-9280-x>.
- Montevecchi, F., 2016. Policy mixes to achieve absolute decoupling: a case study of municipal waste management. *Sustainability* 8 (5).
- Mourelatou, A., 2018. *Environmental Indicator Report 2018*. Copenhagen. <https://doi.org/10.2800/180334>.
- Nelles, M., Grünes, J., Morscheck, G., 2016. Waste management in Germany – development to a sustainable circular economy? *Procedia Environ. Sci.* 35, 6–14. <https://doi.org/10.1016/j.proenv.2016.07.001>.
- Periathamby, A., 2011. Introduction. In: Letcher, T.M., Vallero, D.A. (Eds.), *Waste*, vol. 1. Academic Press, Boston. <https://doi.org/10.1016/B978-0-12-381475-3.10041-5>.
- Perman, R., Stern, D., 2003. Evidence from panel unit root and cointegration tests that the Environmental Kuznets Curve does not exist. *Aust. J. Agric. Resour. Econ.* 47 (3), 325–347. <https://doi.org/10.22004/ag.econ.116988>.
- Şentürk, H., Ömay, T., Yıldırım, J., Köse, N., 2020. Environmental Kuznets curve: non-linear panel regression analysis. *Environ. Model. Assess.* 25 (5), 633–651. <https://doi.org/10.1007/s10666-020-09702-0>.
- Seppälä, T., Haukioja, T., Kaivo-oja, J., 2001. The EKC hypothesis does not hold for direct material flows: environmental Kuznets curve hypothesis tests for direct material flows in five industrial countries. *Popul. Environ.* 23 (2), 217–238. <https://doi.org/10.1023/A:1012831804794>.
- Sotamenou, J., Jaeger, S. De, Rousseau, S., 2019. Drivers of legal and illegal solid waste disposal in the Global South - the case of households in Yaoundé (Cameroon). *J. Environ. Manag.* 240, 321–330. <https://doi.org/10.1016/j.jenvman.2019.03.098>.
- Stern, D.I., 2004. The rise and fall of the environmental Kuznets curve. *World Dev.* 32 (8), 1419–1439. <https://doi.org/10.1016/j.worlddev.2004.03.004>.
- Trujillo Lora, J.C., Carrillo Bermudez, B., Charris Vizcaino, C.A., Iglesias Pinedo, W.J., 2013. The environmental Kuznets curve (EKC): an analysis landfilled solid waste in Colombia. *Rev. Facultad Ciencias Econ.: Investig. Reflex.* 21 (2), 7–16. <http://www.umng.edu.co/web/revistas/revista-fac-ciencias-economicas%5Cnhttp://search.ebscohost.com/login.aspx?direct=true&db=ecn&AN=1486850&site=ehost-live>.
- Uchiyama, K., 2016. Empirical analysis of the environmental Kuznets curve. In: Uchiyama, K. (Ed.), *Environmental Kuznets Curve Hypothesis and Carbon Dioxide Emissions*. Springer Japan, Tokyo, pp. 31–45. https://doi.org/10.1007/978-4-431-55921-4_3.
- UNEP, 2011. *Natural Resource Use and Environmental Impacts from Economic Growth*. United Nations Environment Programme.
- Wang, Y.-C., 2013. Functional sensitivity of testing the environmental Kuznets curve hypothesis. *Resour. Energy Econ.* 35 (4), 451–466. <https://doi.org/10.1016/j.reseneeco.2013.01.003>.
- Wilts, H., Bahn-Walkowiak, B., Hoogeven, Y., 2018. *Waste Prevention in Europe — Policies, Status and Trends in Reuse in 2017*. Copenhagen. <https://doi.org/10.2800/15583>.
- Wu, J., Zhang, W., Xu, J., Che, Y., 2015a. A quantitative analysis of municipal solid waste disposal charges in China. *Environ. Monit. Assess.* 187 (3), 60. <https://doi.org/10.1007/s10661-015-4305-0>.
- Wu, J., Zhang, W., Xu, J., Che, Y., 2015b. A quantitative analysis of municipal solid waste disposal charges in China. *Environ. Monit. Assess.* 187 (3), 60. <https://doi.org/10.1007/s10661-015-4305-0>.
- Yamamoto, M., Yoshida, Y., Ichinose, D., Yamamoto, M., Yoshida, Y., 2011. *Reexamining the Waste-Income Relationship*.
- Zapata, H.O., Paudel, K.P., 2009. Functional form of the environmental Kuznets curve. *Adv. Econom.* 25 (2009), 471–493. [https://doi.org/10.1108/S0731-9053\(2009\)0000025017](https://doi.org/10.1108/S0731-9053(2009)0000025017).
- Zoboli, Roberto, Mazzanti, Massimiliano, Montini, Anna, 2009. Municipal waste generation and the EKC hypothesis new evidence exploiting province-based panel data. *Appl. Econ. Lett.* 16, 719–725. <https://doi.org/10.1080/13504850701221824>.
- Zoboli, R., Paleari, S., Marin, G., Mazzanti, M., Nicoli, F., Montini, A., et al., 2014. Resource-efficient Green Economy and EU Policies. Copenhagen. <https://doi.org/10.2800/18514>.