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Municipal Waste Policies and Spillover Effects*

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Abstract

Using a unique dataset combining administrative data from the municipalities of the Veneto region of Italy for the years 2010-2019, we develop a spatial econometric model to study the effect of two policies (Door-to-Door collection and Pay-As-You-Throw tariff) on waste sorting and waste accumulation. We are especially interested in the spatial spillover effect of the policies. Both policies are successful and with similar impact on the outcome variables. Interestingly, we also find evidence of a spatial spillover effect. The effect is mostly negative and limits the effectiveness of the policies (especially PAYT). Our results highlight the importance of coordinating decisions on the implementation of waste management policies.

JEL Classification: Q53; C23.
Keywords: Waste; Door-to-Door; Pay-As-You-Throw; Spatial effects.

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1. Introduction

Every year an individual living in the OECD countries produces more than 500 kilograms of municipal solid waste[1]. A large amount of waste is detrimental for the environment, contributes to air pollution and affects ecosystems as well as our health (e.g. EEA, 2014). For this reason, limiting waste production or finding proper ways to get rid of waste – in particular, by sorting and then recycling it – has been drawing the attention of worldwide policymakers and is included in the broader paradigm of "circular economy" that is part of the Sustainable Development Goals in the 2030 agenda of the United Nations[2].

In the past few years, two policies emerged to promote waste sorting and to limit waste accumulation: the Door-to-Door (DtD) collection and the Pay-As-You-Throw (PAYT) tariff. The two policies respectively endow households with private bags or bins for the separate collection of different types of waste, and charge a fee proportional to the unsorted waste presented for collection. According to the existing literature, both policies create a set of monetary and non-monetary incentives that are able to promote waste sorting and, to a lower extent, the reduction of unsorted waste accumulation; see, e.g. Bucciol et al. (2015). To the best of our knowledge, it is still unclear if these policies also show spillover effects, namely, if there are consequences in municipalities close to those where the policies were adopted.

In this paper we pay attention to the space dimension of the waste policies. Spatial spillovers concern the consequences on the surrounding municipalities of adopting a policy in a given municipality. Effects can be either positive, with nearby municipalities trying to emulate good practices, or negative, with nearby municipalities receiving unsolicited waste from outside their borders. In this respect, negative effects describe a form of tax and effort elusion commonly known as "waste tourism", i.e. the movement of waste from the municipality of origin to a neighboring municipality[3]. Our work contributes to the existing literature by looking at these aspects of the waste policies. In particular, we investigate the following research questions: i) Are the DtD and PAYT policies effective to reduce unsorted waste accumulation and promote waste sorting? ii) Do they generate any quantitatively relevant spillover effects? And in case, iii) Are the spillovers mainly positive or negative?

We study the impact of the DtD and PAYT policies on waste sorting and waste

[1] Source: OECD, https://data.oecd.org/waste/municipal-waste.htm.

[2] https://sdgs.un.org/goals.

[3] In principle, two further ways of hiding waste are also possible. One consists in illegal dumping of waste on public lands (e.g. parks or the countryside). Another way consists in burning waste in the backyards. In our environment we tend to exclude these options because of the intensive monitoring process.

accumulation using a unique dataset combining administrative data. We focus on the Veneto region of Italy, an area with a large number of relatively small municipalities close one from each other, many of which have been implementing the DtD and PAYT policies with success. The region is among the worldwide top performers with its 490 kgs per capita of municipal waste and 75% of separate waste collection in 2019 (ISPRA, 2020). For each municipality in the region, our unique dataset informs on the per capita amount and type of waste accumulated, as well as on the type of collection and tariff policy, on an annual basis from 2010 to 2019. We combine these data with spatial information on the geographical proximity across the municipalities in the region. The structure of our longitudinal dataset allows us to assess the effectiveness of the policies over space, controlling for time and other observable characteristics. On this regard, we run a set of linear and spatial econometric analyses.

We contribute to the literature in two main directions. First, we study the spillover effects of both DtD and PAYT. To the best of our knowledge, previous research on waste management only focused on the spillover effects of the PAYT policy and found mixed evidence: large waste tourism (e.g. Fullerton and Kinnaman, 1996; Linderhof et al., 2001) or no significant spillover effects (e.g. Dijkgraaf and Gradus, 2004; Allers and Hoeben, 2010; Carattini et al., 2018; Valente, 2023). Interestingly, evidence of waste tourism has been documented in the literature when the empirical analysis relies on individual level data on single towns, while studies which found no spillover effects are based on aggregated data on multiple towns. Furthermore, since related literature relies on econometrics techniques such as difference-in-difference, regression discontinuity design and random forest, which we believe might not be properly suited to explicitly account for spatial correlation, our second contribution to the literature is the application of spatial autoregressions to a unique, large panel dataset where the reference unit is a single municipality.

In general, spatial autoregressions present the advantage of preserving tractability and offering a suitable interpretation of results in terms of marginal effects. More specifically, in spatial autoregressions the response variable of each unit is potentially related not only to a set of exogenous characteristics, as in standard regression models, but also to a weighted average of the response variables of neighboring units and/or to the weighted average of neighbors' covariates. Such weights are postulated to be known and exogenous, such that the autoregressive component of the model is fully known up to a finite set of spatial parameter that needs to be estimated. The weights are generally determined ex ante and they are often based on the inverse of some geographic and/or economic distance across units. A sensible weighting matrix will thus assign larger weights to the "closer" neighbors, while smaller weights will be given to those further away from it, with the notion of "closeness" being not necessarily geographical, but more generally based on some suitable economic distance. Even though spatial autoregressions might embed more general concepts of economic distances, in our context, "space" is strongly related to the notion of geographical distance across municipalities. For an exhaustive review of spatial model we refer the reader to, e.g. Arbia (2016).

To the best of our knowledge, spatial econometric models have not been applied in the context of waste disposal, with a notable exception in the literature being Heijnen and Elhorst (2018), who also use spatial models but have a different purpose. The authors indeed study the probability of implementing PAYT and find a contagion effect, with the implementation of the policy being more likely when nearby municipalities already implement it. The authors argue that this evidence could be the consequence of trying to prevent illegal dumping.

The remainder of the paper is organized as follows. Section 2 provides a brief overview on the DtD and PAYT policies; Section 3 introduces our unique dataset; Section 4 presents the linear models and their results; Section 5 presents the spatial models and their results; Section 6 discusses the results and Section 7 draws our conclusions. An Appendix provides further results using alternative ways of measuring the spatial distance between two municipalities.

2. Policies on waste management

In this paper we look at the direct and indirect effects of several policies on solid waste management, regarding the collection of waste and the charge for the use of the service.

The two main collection mechanisms are "Drop-off" and "Door-to-Door" (DtD). Under Drop-off, collectors provide public bins on the streets. Users carry their waste to the public bins, as much as they want and whenever they want. Under DtD, collectors provide each household with private bins or bags. When households decide to throw their waste, they leave it in the bins/bags outside their home entrance. The waste management company collects bins and bags at scheduled dates (typically, twice a week for organic waste and every two weeks for all the other types of waste) disclosed at the beginning of the year. Drop-off and DtD are typically arranged in such a way to separate waste, in which case they provide dedicated storage for the separate collection of each main type of waste (i.e. glass, paper, plastic, organic and residual).

The two main charge tariffs are "Flat-Fee" and "Pay-As-You-Throw" (PAYT) and they are tailored to cover the service costs[4]. Under Flat-Fee, the tariff is made of a fixed part

[4] In Italy, the flat fee is called "Tassa sui Rifiuti (Ta.Ri)". The average per capita cost is around 100 euros per year (Valente, 2023). The PAYT variable cost of a single emptying for a bin of 120 liters is in the order of 18-20 euros. See, e.g., https://contarina.it/cittadino/raccolta-differenziata/tariffa.

proportional to the square meters of the house and the household size. Under PAYT, the tariff is made of a fixed part similar to the Flat-Fee, plus a variable part proportional to the amount of unsorted (i.e. residual) waste presented for collection by the single household. The amount is usually measured by weight or volume, with the latter prevailing for its simplicity. Legislative Decree 22 of 1997 (the so called "Decreto Ronchi") set a slow transition from Flat-Fee to PAYT in Italy. At the time of this writing about 16% of the Italian municipalities implement PAYT and about 73% implement DtD[5].

Both DtD and PAYT policies have been implementing to promote waste sorting and reduce waste production. In particular, DtD carries a set of non-monetary incentives as it i) reduces the effort to sort; ii) sets a physical limit to the amount of waste that can be accumulated; and iii) increases awareness of the sorting problem. In contrast, PAYT carries a set of monetary incentives as it i) penalizes the accumulation of unsorted waste; and ii) does not penalize all types of sorted waste. Effects of PAYT have been studied in several contexts, mostly in the US (Fullerton and Kinnaman, 2000; Huang et al., 2011), in the Netherlands (Allers and Hoeben, 2010; Dijkgraaf and Gradus, 2009; Linderhof et al., 2001) and in Italy (Bucciol et al., 2015; Bueno and Valente, 2019). The policy is typically found to reach good results in terms of waste production and sorting. Some works (e.g. Kinnaman and Fullerton, 2000) highlight that the endogeneity of the decision to implement the policy may alter the estimates. The most intuitive argument is that municipalities paying more attenton to the environment are more prone to implement policies that are expected to be environment-friendly. This would end up over-estimating the policy effects.

We believe our setting should limit such potential endogeneity problems. Our analysis refers to the Veneto region of Italy. In this region, decisions to introduce DtD and PAYT policies are not directly made by the single municipality. Indeed, as a result of Regional Law 52 of 31 December 2012, strategic decisions regarding the collection and charging methods move from the jurisdiction of individual municipalities to independent supra-municipal entities called "councils". Councils, managed by technicians hired by the region, determine the matter on behalf of the municipalities they represent (a variable number of municipalities, pre-allocated by the region based on geographical proximity)[6]. Councils make multi-year plans and select which municipalities first implement new policies in a (almost) random way. Implementation is not totally random as it may take into account geographical characteristics (e.g. altitude, population density) that can make adoption more complicate.

[5]Source: ISTAT Statistiche Report 11 Novembre 2022, https://www.istat.it/it/files//2022/11/raccolata-differenziata-rifiuti.pdf.

[6]In Regional Decree DPCR 13/2014, Veneto identifies twelve geographical areas, each served by one council.

DtD and PAYT policies may induce two contrasting types of behavior. On the one hand, they may increase environmental awareness and this way favor pro-environmental behavior. On the other hand, they may crowd-out intrinsic motivation for adopting pro-environmental behavior and this way favor socially unethical actions. For this reason, they are typically combined with a monitoring system (e.g. CCTV, bin locks, random checks of the content of the bin or bag).

3. Data

For the purpose of our empirical analysis, we gathered administrative waste-management related data for all 563 municipalities within the Veneto region of Italy over a ten-year time span, covering the period from 2010 to 2019. We thus work with a balanced panel dataset whose size is 5,630 observations (563 municipalities over 10 years)[7]. We believe that focusing on one single region is a good compromise between having heterogeneity of policy implementation and, at the same time, having homogeneity on the rules and the policy characteristics.

Specifically, our panel dataset consists of the following building blocks: i) figures on annual waste generation (source: ISPRA, the national agency for environmental protection and research); ii) confidential annual data on the policies adopted in terms of both collection and charging systems (source: ARPAV, the agency for environmental prevention and protection of the Veneto Region); iii) annual figures on demographic characteristics (source: ISTAT, the national institute of statistics); iv) spatial data reporting the drive time between any two municipalities (source: ISTAT). Table 1 describes the variables in i)-iii) that we include in our analyses. We use data in iv) to explore the spatial correlation across municipalities.

Municipalities in the region implemented a combination of different policies for the collection (Drop-off or Door-to-Door) and the charge (Flat-Fee or Pay-As-You-Throw) of household solid waste. We collapse the policies in three categories: i) *Drop-off and Flat-Fee*; ii) *Door-to-Door (DtD) and Flat-Fee*; iii) *Door-to-Door (DtD) and Pay-as-You-Throw (PAYT) tariff*. We never observe the combination between Drop-off and PAYT. In our analyses, we account for these policies by including two dummy variables informing on the presence of DtD and PAYT policies, respectively. Given the structure of the data,

[7] A complication is due to the fact that some municipalities merged during the sample period. During the analysis period (2010-2019), 29 municipalities merged into 12 new municipalities. For sake of simplicity we assume that all mergers took place before the beginning of our sample period, as in Heijnen and Elhorst (2018), since there exists a certain degree of synchronization between the merging municipalities in the years prior to the merger. Our findings remain qualitatively unchanged if we exclude these municipalities from the analysis. Results are available upon request.

Table 1: Variables used in the analysis

Variable	Description
Outcome variables	
Sorted waste	Annual production of sorted waste (kg per capita)
Unsorted waste	Annual production of unsorted waste (kg per capita)
Total waste	Annual production of total (sorted + unsorted) waste (kg per capita)
Separated Waste Collection	Sorted waste/Total waste (%)
Policy variables	
PAYT	= 1 if a PAYT program is in place; = 0 otherwise
DtD	= 1 if a DtD program is implemented; = 0 otherwise
Control variables	
Population density	Residents per square km
Income	Income (per capita)
Under 14	Residents aged 14 or younger (%)
Over 65	Residents aged 65 or older (%)
Non-natives	Non-natives residents (%)
Year X	= 1 if the data refer to year X (2010-2019); = 0 otherwise

observing PAYT implies that DtD is also present. Figure 1 shows how the frequency of the three categories varies over time. We observe a clear pattern going toward an increase in the adoption of PAYT (as required by the "Decreto Ronchi"; see Section 2).

Table 2 shows the average values of the variables included in the analysis, taken together and separately by policy category. Our key dimensions are the amount of unsorted waste produced (kilograms per capita per year) and the percentage of Separated Waste Collection (SWC). It is noteworthy that the unsorted production of waste is much lower under the DtD-PAYT regime, which also generates an average higher SWC. The pattern is persistent over time as shown in Figure 2. This raw comparison, however, does not allow to distinguish the net effects of DtD and PAYT for several reasons: i) Municipalities move from one policy category to another in different years; ii) Municipalities may have intrinsically different characteristics that are not controlled for; iii) The policies and behavior of the surrounding municipalities are not taken into account. Our empirical exercise aims to fill in this gap.

Our dataset is unique as it combines data from several sources. Moreover, the area we analyze (the Veneto region of Italy) provides an ideal framework for several reasons. First

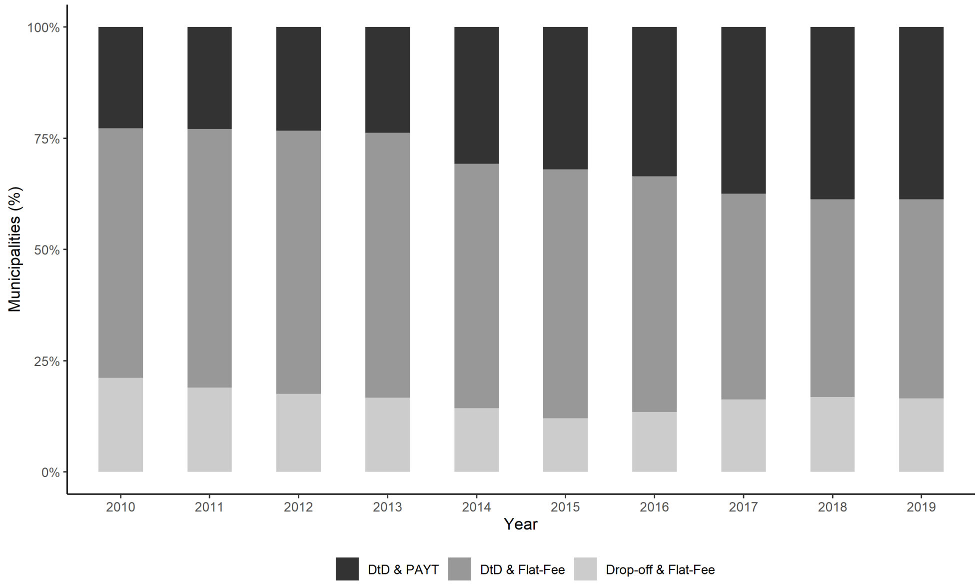
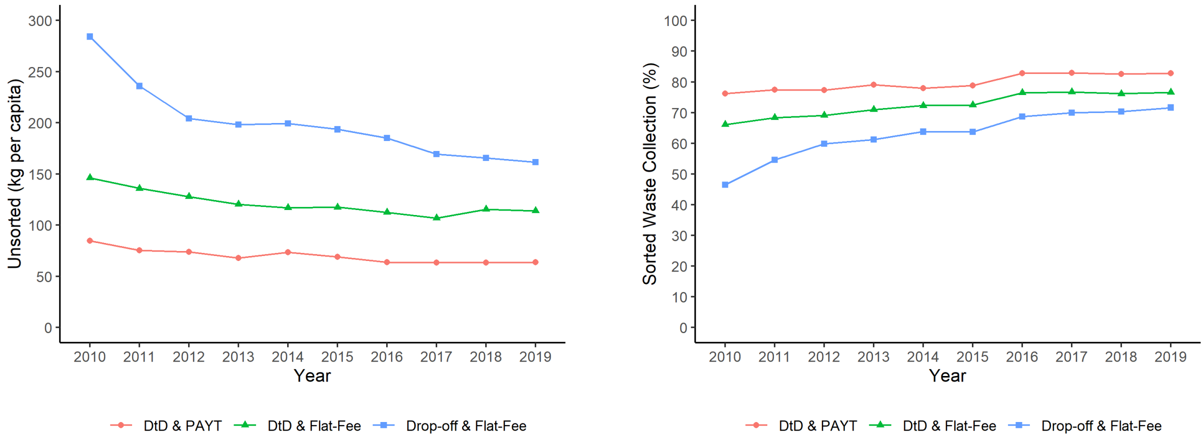


Figure 1: Dynamics of the waste policies in the Veneto Region, 2010-2019

Table 2: Descriptive statistics: average values by category

Variable	All	Drop-off & Flat-Fee	DtD & Flat-Fee	DtD & PAYT
Unsorted waste	119.2	202.8	122.2	68.78
Separated Waste Collection	73.04	62.35	72.22	80.28
DtD	0.836	0	1	1
PAYT	0.304	0	0	1
Under 14	13.06	12.11	12.94	13.78
Over 65	19.88	21.93	19.84	18.84
Non-natives	8.291	6.374	8.253	9.393
Population density	299.62	254.8	285.1	349.4
Income	18,849	18,431	18,681	19,371
Observations	5,630	924	2,995	1,711



(a) Unsorted production

(b) Sorted Waste Collection (SWC) Ratio

Figure 2: Trend on the key variables, 2010-2019

of all, the area is made of many small municipalities[8], all intertwined[9], each one endowed with its own policies for the collection and charge of the waste service. Second, the area mitigates potential endogeneity problems in the adoption of the policies. Indeed, decisions on the implementation of waste policies are not taken by the municipalities themselves but delegated to independent consortia (see Section 2)[10]. Third, the area shows large heterogeneity in terms of policies across both space and time, which helps to isolate space and time effects. Figure 3 shows the distribution of DtD and PAYT policies within the region at the beginning (2010) and at the end (2019) of our sample period. This reflects into large differences in terms of the outcome dimensions; see Figure 4 for a graphical representation again involving years 2010 and 2019.

4. Econometric analysis: Linear models

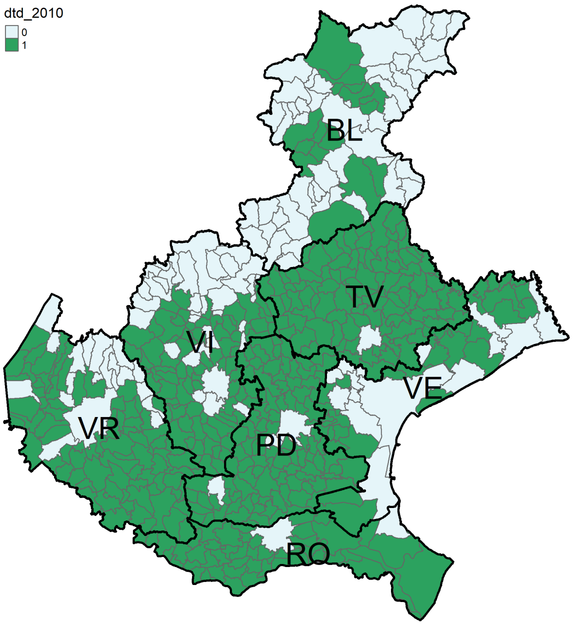
4.1. Strategy

We consider the baseline longitudinal model

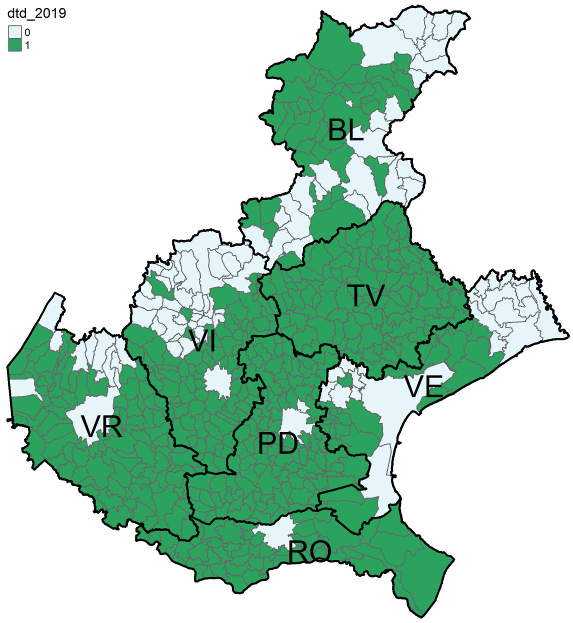
[8]The 563 municipalities display, on average, an area of 32.43 squared kilometers and a population of 8,665 inhabitants. Most municipalities are of small size: about 90% of them have up to 15,000 inhabitants, serving 53.5% of the population.

[9]The average daily commuting time is around 60 minutes in the sample period. Circulation across municipalities is frequent, also thanks to the large numbers of registered personal cars (649 cars per 1,000 persons in 2019). Source: Veneto Regional Statistical System, https://statistica.regione.veneto.it/ENG/index.jsp.

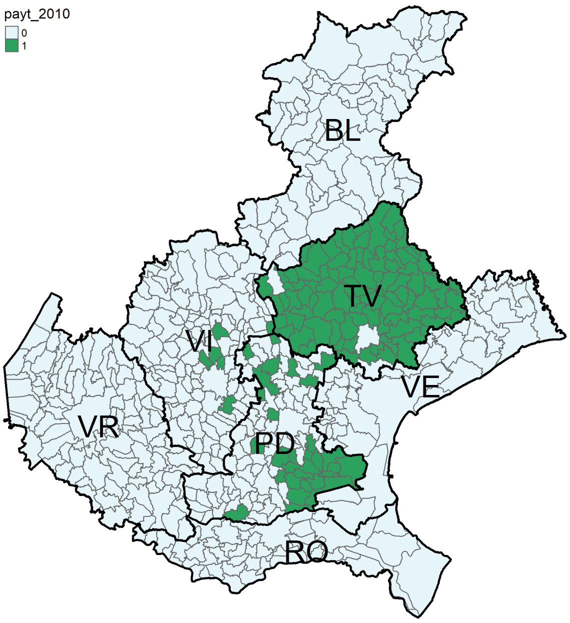
[10]We also control for further time-invariant characteristics of the municipality, not explicitly incorporated in the analysis, by means of municipality fixed effects.



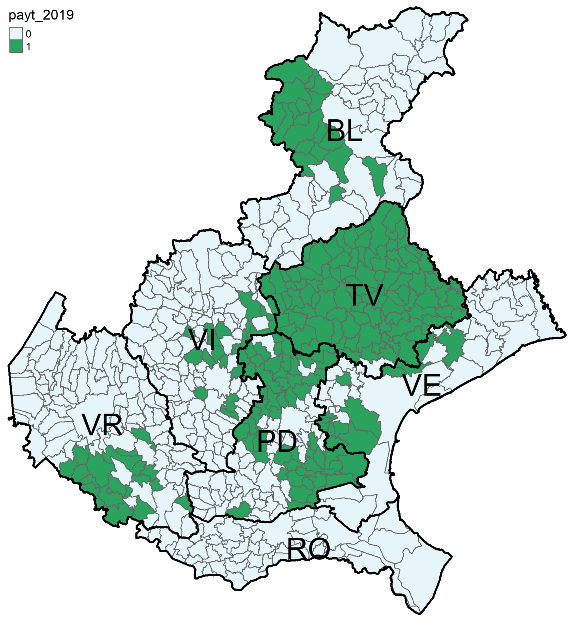
(a) DtD in 2010



(b) DtD in 2019

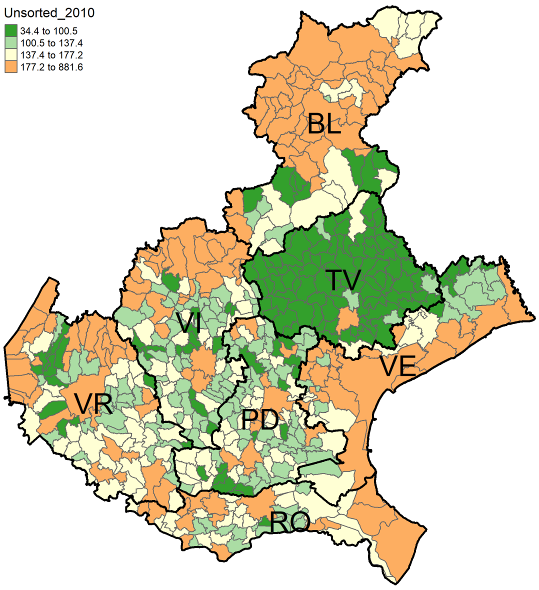


(c) PAYT in 2010

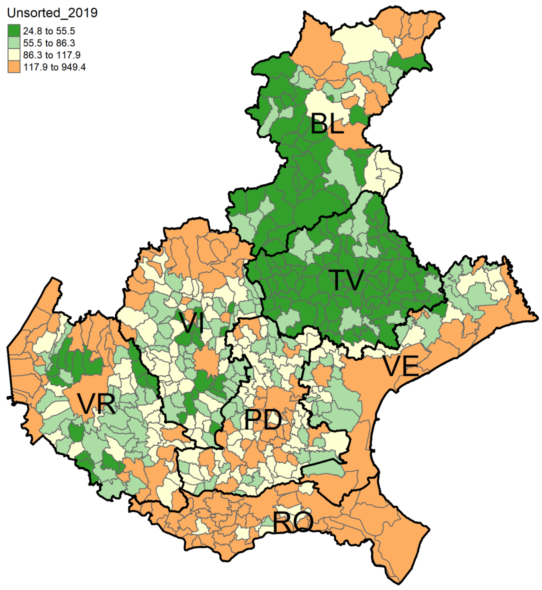


(d) PAYT in 2019

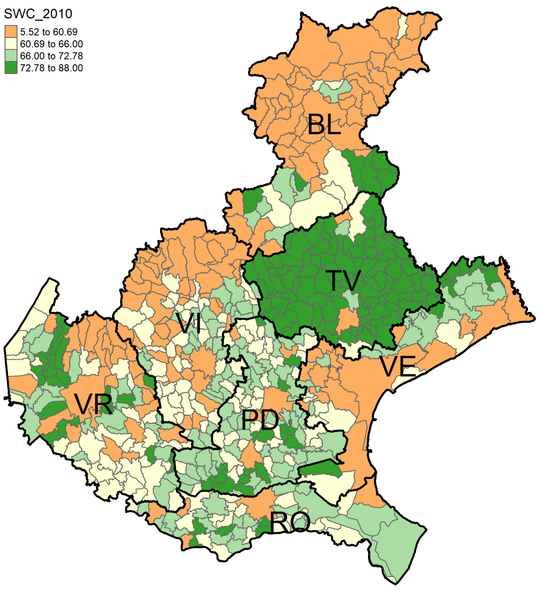
Figure 3: Spatial diffusion of the waste policies in the Veneto Region



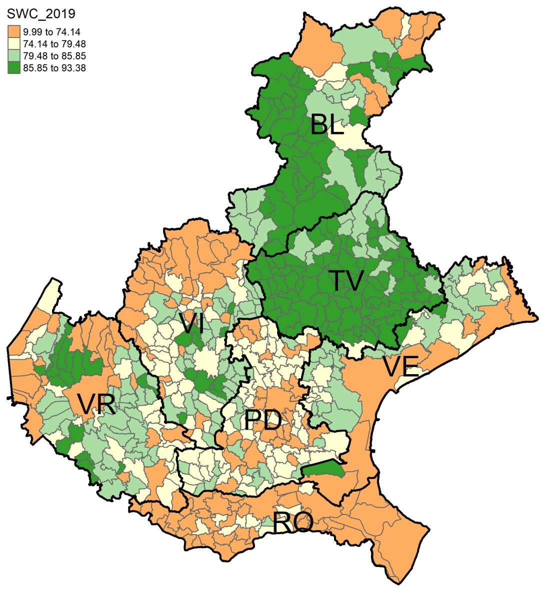
(a) Unsorted production in 2010



(b) Unsorted production in 2019



(c) SWC in 2010



(d) SWC in 2019

Figure 4: Spatial diffusion of the outcome variables in the Veneto Region

$$y_{it} = \beta_0 + \beta_1 DtD_{it} + \beta_2 PAYT_{it} + \phi' x_{it} + \theta_t + \mu_i + \epsilon_{it}, \tag{1}$$

where DtD_{it} is equal to one if Door-to-Door collection is in place in municipality $i = 1, ..., N$ at time $t = 1, ..., T$ and zero otherwise, $PAYT_{it}$ is equal to one if Pay-As-You-Throw policy is in place in municipality i at time t, and zero otherwise, x_{it} are $k \times 1$ vectors of time-varying characteristics, θ_t are parameters of year dummies, μ_i are municipality fixed-effects and ϵ_{it} is an idiosyncratic error term. We consider two different dependent variables: i) *Unsorted waste*, i.e. the annual amount of unsorted waste per capita (in kilograms), ii) *Separated Waste Collection, SWC*, namely the ratio between per capita sorted waste and per capita total waste (in percentage). Both dependent variables are taken in logarithms.

There are three possible combinations of policies (Drop-off and Flat-Fee; DtD and Flat-Fee; DtD and PAYT) and these vary across municipalities and years under investigation. We identify the effect of the policies by using a standard panel regression analysis, comparing municipalities over time and space.

We control for spatial correlation in two ways. First, in all our models we incorporate Driscoll-Kraay standard errors. This type of errors is meant to capture heteroskedasticity and possible correlation across errors arising over both time and space; for details see Driscoll and Kraay (1998). Second, we consider one further specification enriching Equation (1) with a set of new explanatory variables, denoted by $SDtD_{it}$ and $SPAYT_{it}$ in the following equation:

$$\begin{aligned} y_{it} = &\beta_0 + \beta_1 DtD_{it} + \beta_2 PAYT_{it} + \gamma_1 SDtD_{it} + \gamma_2 SPAYT_{it} \\ &+ \phi' x_{it} + \theta_t + \mu_i + \epsilon_{it}. \end{aligned} \tag{2}$$

The newly added variables inform on the presence of DtD/PAYT policies in nearby municipalities, using three alternative definitions of "nearby municipalities": i) *Most nearby municipalities*: a dummy variable equal to one if the majority of the bordering municipalities adopt a given policy; ii) *Fraction of nearby municipalities*: the fraction of bordering municipalities that adopt a given policy; iii) *At least one nearby municipality*: a dummy variable equal to one if at least one bordering municipality adopts a given policy. The sign of the coefficients on the $SDtD$ and $SPAYT$ variables should inform about the prevailing type of spillover effects. Positive (negative) effects should prevail in case the sign of the γ coefficients is the same as (the opposite to) the β coefficients. In what follows, we comment on coefficients that are significant at the 5% or lower level. Deviations from this rule will be mentioned explicitly.

4.2. Results

We first show in Table 3 the results from fixed-effect panel regressions using the specification in Equation (1), where the dependent variable takes the log-transformation of unsorted waste or SWC. Column (1) shows results on unsorted waste. We find that DtD collection is associated to a 24.3% decrease in unsorted waste. The PAYT tariff, whose charge is directly proportional to the unsorted waste produced per household, performs similarly, accounting for a 27.3% reduction in unsorted waste. The two effects are not statistically different (F-test of equality: 0.14; p-value: 0.719). The control variables are not significant, with the only exception of the percentages of over-65 and native residents that are negatively and positively associated to unsorted waste, respectively. During the period of analysis, we also note a clear downward trend in the production of unsorted waste, reflecting a commitment to the reduction of unsorted waste increasing over time.

Column (2) presents information on the impact of the two policies on SWC. Both the DtD system and the PAYT tariff have a positive effect, quantified in an increase of 11.4% (significant only at the 10% level) and 5.7%, respectively. The two effects are not statistically different in this case either (F-test of equality: 1.11; p-value: 0.319). We also observe an upward time trend in the SWC emerges, regardless of the waste management policy implemented. In summary, the two incentives seem to be effective in stimulating citizens' sorting habits, conditional on the environmental settings and the period of analysis.

The p-value of the Pesaran test reported at the end of Table 3 indicates a strong rejection of the null hypothesis of cross-independence, suggesting that our specification is not adequate to capture spatial correlation.

We then show in Table 4 the results from fixed-effect panel regressions using the specification in Equation (2) which, in contrast to Equation (1), adds to the model spatial variables on the policies adopted by neighboring municipalities. As anticipated, we consider three definitions of what can be considered a nearby municipality. For sake of brevity, we avoid reporting the full set of year coefficients (whose pattern is similar to that of Table 3).

First of all, we detect small differences in terms of the link between the policies and the outcome variables. The coefficients for both DtD and PAYT are slightly smaller than in the previous analysis without spatial controls, with the DtD (PAYT) effect on unsorted waste now ranging between -22.2 and -25% (between -23.5 and -24.9%), and the DtD (PAYT) effect on SWC now ranging between 9.8 and 11% (about 5.3% in all the specifications). The fact that these coefficients are smaller than in Table 3 suggests that the coefficients estimated in Equation (1) also absorb a small effect induced by the

Table 3: Baseline linear models

	(1) Unsorted	(2) SWC
DtD	-0.243**	0.114*
	(0.076)	(0.052)
PAYT	-0.273***	0.057***
	(0.046)	(0.011)
Log(population density)	-0.469	-0.559*
	(0.474)	(0.282)
Log(income per capita)	-0.054	0.076
	(0.154)	(0.050)
Under 14	0.008	0.003
	(0.006)	(0.004)
Over 65	-0.020**	-0.001
	(0.007)	(0.002)
Non-natives	0.011***	0.002
	(0.003)	(0.003)
Year 2011	-0.124***	0.062***
	(0.004)	(0.001)
Year 2012	-0.205***	0.088***
	(0.006)	(0.002)
Year 2013	-0.266***	0.113***
	(0.011)	(0.003)
Year 2014	-0.278***	0.138***
	(0.018)	(0.005)
Year 2015	-0.297***	0.136***
	(0.026)	(0.007)
Year 2016	-0.364***	0.193***
	(0.031)	(0.008)
Year 2017	-0.385***	0.198***
	(0.034)	(0.009)
Year 2018	-0.346***	0.195***
	(0.039)	(0.010)
Year 2019	-0.346***	0.201***
	(0.043)	(0.011)
Constant	8.336***	6.199***
	(1.979)	(1.514)
Municipality FE	YES	YES
Pesaran Test (p-value)	0.000	0.000
R-squared	0.510	0.398
Municipalities	563	563
Observations	5,630	5,630

Note: Fixed-effect panel regression with Driscoll-Kraay standard errors in parentheses. The dependent variable is log-transformed. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

omitted spatial variables.

We find mixed evidence of spillover effects in the Veneto region, all limited to unsorted waste rather than SWC. In particular, as shown in Column (1), the amount of unsorted waste in municipality i decreases significantly by 10.9% if most nearby municipalities adopt PAYT. We obtain a similar result in Column (3): unsorted waste decreases by 7.5% when at least one neighbor chooses to implement PAYT. These preliminary results would suggest a positive spatial effect of PAYT, i.e., an emulation behaviour of municipality i, regardless of whether it adopts such policies or not, toward the virtuous neighbors implementing them.

In contrast, the spatial effects of the DtD collection system are sparse and unclear, not suggesting a univocal direction. Specifically, the unsorted amount seems to decrease - as with PAYT - by 5.2% (albeit significant only at the 10% level) - when most nearby municipalities adopt it (Column 1). However, the unsorted amount increases by 2.1% in the case at least one nearby municipality implements the policy (Column 3). Hence, it may signal that a negative spatial effect exists.

For each column of Table 4, we report the p-value of the Pesaran test to assess lack of residual spatial correlation. The null hypothesis of cross-sectional independence is always strongly rejected, as it was in Table 3. In the following section we resort to a more sophisticated spatial specification to tackle this issue.

5. Econometric analysis: Spatial models

5.1. Strategy

The main condition underlying valid inference in the previous type of models is the so-called Stable Unit Treatment Value Assumption (SUTVA), which postulates that the treatment of a municipality (whether via the adoption of DtD or PAYT in our context) does not affect the outcome variable of other municipalities. Such assumption is likely violated here as long as people can communicate and move across different municipalities. Indeed, interactions induce knowledge of advantages/drawbacks of different policies and offer the opportunity to dispose of waste in other municipalities adopting less strict waste disposal policies (such as a municipality endowed with street bins as opposed to DtD).

Even the specification in Equation (2), which incorporates spatial variables, may not be enough. In particular, the introduction of a DtD/PAYT policy in municipality i is likely to have consequences on the dependent variable of neighboring units, where "neighbors" are defined according to some notion of geographical proximity. Delgado and Florax (2015) discuss the advantages of modeling spatial interaction via a contiguity matrix in the framework of a spatial econometric model, as opposed to the definition of all treatment and control groups.

Table 4: Linear models with spatial controls

	(1) Unsorted Most	(2) Unsorted Frac	(3) Unsorted Least	(4) SWC Most	(5) SWC Frac	(6) SWC Least
DtD	-0.222**	-0.223***	-0.250***	0.110**	0.098**	0.109*
	(0.068)	(0.052)	(0.076)	(0.046)	(0.033)	(0.050)
PAYT	-0.249***	-0.235***	-0.242***	0.053***	0.053***	0.053***
	(0.041)	(0.036)	(0.038)	(0.009)	(0.007)	(0.008)
Most DtD	-0.052*			0.010		
	(0.023)			(0.019)		
Fraction DtD		-0.077			0.056	
		(0.087)			(0.072)	
At least one DtD			0.021***			0.025*
			(0.006)			(0.013)
Most PAYT	-0.109***			0.020*		
	(0.016)			(0.010)		
Fraction PAYT		-0.187			0.070	
		(0.110)			(0.075)	
At least one PAYT			-0.075**			0.024*
			(0.030)			(0.013)
Log(population density)	-0.493	-0.480	-0.444	-0.555*	-0.547*	-0.546*
	(0.459)	(0.455)	(0.479)	(0.275)	(0.265)	(0.276)
Log(income per capita)	-0.079	-0.072	-0.087	0.081	0.081	0.074
	(0.150)	(0.165)	(0.163)	(0.050)	(0.052)	(0.049)
Under 14	0.007	0.008	0.008	0.003	0.003	0.003
	(0.006)	(0.006)	(0.006)	(0.003)	(0.004)	(0.003)
Over 65	-0.020**	-0.020**	-0.020**	-0.001	-0.001	-0.001
	(0.007)	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)
Non-natives	0.011***	0.012***	0.013***	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	8.760***	8.631***	8.526***	6.122***	6.061***	6.123***
	(1.880)	(1.828)	(1.949)	(1.480)	(1.387)	(1.529)
Year FE	YES	YES	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES	YES	YES
Pesaran Test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.515	0.513	0.514	0.399	0.400	0.401
Municipalities	563	563	563	563	563	563
Observations	5,630	5,630	5,630	5,630	5,630	5,630

Note: Fixed effect panel regression with Driscoll-Kraay standard errors in parentheses. The dependent variable is log-transformed. *** $p < 0.01$, ** $p < 0.05$

In order to preserve the identification of the treatment effect we adopt a spatial weight matrix W so that spatial interactions are restricted to a subset of municipalities and do not extend to the whole spatial system. The spatial interactions are thus "local", as they only affect neighbors and we are not able to identify "global" spatial interactions.

In particular, we define our main weight matrix W based on driving times, with elements defined as $w_{ij} = (1/t_{ij})1(t_{ij} \leq 30)$, where t_{ij} is the travel time between the centers of municipalities i and j measured in minutes. Conventionally, $w_{ii} = 0$ for each i. Weights are then a decreasing function of the time distance between two municipalities, and are set to zero when the distance is above 30 minutes[11]. Each choice of W is then normalized by dividing each element by its maximum eigenvalue (i.e. by its spectral norm), so that the relative magnitude of spatial interactions are preserved after normalization.

Several types of spatial econometric models are available. We restrict our attention to three main specifications: i) a baseline regression model with a spatial lag on the dependent variable (spatial autoregressive model, SAR); ii) a regression with the spatial lag of both the dependent variable and the policy variables (spatial Durbin model, SDM); and iii) an *ad hoc* modification of the latter[12]. The baseline SAR specification for each i, t is then

$$y_{it} = \beta_0 + \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_1 DtD_{it} + \beta_2 PAYT_{it} + \phi' x_{it} + \theta_t + \mu_i + \epsilon_{it} \tag{3}$$

for a set of independent and identically distributed errors ϵ_{it}. The SDM model explicitly accounts for the spatial lag of policy variables and is given by

$$\begin{aligned} y_{it} = \beta_0 + \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_1 DtD_{it} + \beta_2 PAYT_{it} + \gamma_1 \sum_{j=1}^{N} w_{ij} DtD_{jt} + \gamma_2 \sum_{j=1}^{N} w_{ij} PAYT_{jt} \\ + \phi' x_{it} + \theta_t + \mu_i + \epsilon_{it}. \end{aligned} \tag{4}$$

Our third and final specification aims to explicitly account for the impact of neighbors' policy k, with k being either 1 (DtD) or 2 ($PAYT$), on municipality i when the latter does not adopt policy k. More specifically, we consider the following *ad hoc* modification

[11] We set the threshold at 30 minutes because statistics reveal that the average commuting time in Veneto is about 60 minutes per day (source: Veneto Regional Statistical System, https://statistica.regione.veneto.it/ENG/index.jsp). Considering a round trip, the distance between one place and another is in the order of 30 minutes. Findings remain qualitatively unchanged using alternative thresholds. Results are available upon request.

[12] The SDM model including spatially correlated errors (the so called general-nested-model) is not considered here as it poses identification issues.

of the SDM:

$$
\begin{aligned}
y_{it} = {} & \beta_0 + \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_1 DtD_{it} + \beta_2 PAYT_{it} + \gamma_1 \sum_{j=1}^{N} w_{ij} DtD_{jt} + \gamma_2 \sum_{j=1}^{N} w_{ij} PAYT_{jt} \\
& + \delta_1 \left(1 - DtD_{it}\right) \sum_{j=1}^{N} w_{ij} DtD_{jt} + \delta_2 \left(1 - PAYT_{it}\right) \sum_{j=1}^{N} w_{ij} PAYT_{jt} \\
& + \phi' x_{it} + \theta_t + \mu_i + \epsilon_{it}.
\end{aligned} \tag{5}
$$

In Equation (5) we thus split the impact of each policy variable k of neighboring municipalities into two components. The first component, with coefficient γ_k, depends on the policy status of the neighboring municipalities, disregarding the policy status of municipality i. The second component, with coefficient δ_k, depends on the policy status of the neighboring municipalities and the policy status of municipality i. In particular, the latter is non zero only when a policy is implemented by the neighbors but not by municipality i (or vice versa). Throughout the three models, the spatial lag on the dependent variable induces a feedback effect implied by the network structure.

5.2. Direct and indirect effects

SAR and SDM, the latter both in its traditional and *ad hoc* formulations given respectively in Equation (4) and Equation (5), allow to identify direct and indirect marginal effects. The *direct effect* measures the average impact on municipality i of introducing a policy in municipality i itself. The *indirect effect* measures the impact on municipality i of introducing a policy in neighboring municipalities.

We thus define the spatial multiplier as

$$V(W, \lambda) = (I_{NT} - \lambda W_{NT})^{-1},$$

where $W_{NT} = I_T \otimes W$ has size $NT \times NT$ and I_{NT} is the $NT \times NT$ identity matrix, with $\otimes$ indicating the Kronecker product. We also define the additional quantities

$$G(W, \lambda) = V(W, \lambda) \times W_{NT}$$

and

$$D^k(W, \lambda) = V(W, \lambda) \times \text{diag}(1 - \mathit{policy}^k) \times W_{NT},$$

where $\text{diag}(a)$ for a generic $NT \times 1$ vector a returns an $NT \times NT$ diagonal matrix with the vector a along the main diagonal and policy^k is an $NT \times 1$ vector with components policy^k_{it}, with $k = 1$ for DtD and $k = 2$ for PAYT. Moreover, we respectively indicate by

$v_{ii,tt}(W,\lambda)$, $g_{ii,tt}(W,\lambda)$ and $d^k_{ii,tt}(W,\lambda)$ the component of $V(W,\lambda)$, $G(W,\lambda)$ and $D^k(W,\lambda)$ on the diagonal for the observation involving municipality i at time t.

In line with standard spatial econometrics literature (e.g. LeSage and Pace, 2009), by standard algebra we define the average *direct effect* of policy k on each municipality i as

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\beta_k v_{ii,tt}(W,\lambda)$$

for the model in Equation (3) and as

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\beta_k v_{ii,tt}(W,\lambda)+\gamma_k g_{ii,tt}(W,\lambda))$$

for the model in Equation (4). From Equation (5), the average direct effect of policy k on each municipality is instead given by

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\beta_k v_{ii,tt}(W,\lambda)+\gamma_k g_{ii,tt}(W,\lambda)-\delta_k\sum_{j=1}^{N}w_{ij}policy^k_{jt}+\delta_k d^k_{ii,tt}(W,\lambda)\right) \tag{6}$$

and it represents the average effect of adopting policy k in municipality i on municipality i itself, while explicitly accounting for the policy status of all other municipalities.

We are furthermore interested in evaluating the average effect on each generic municipality i induced by a change in the weighted average of neighbors' policy k[13]. We thus define the average *indirect effect* of a change in neighboring municipalities' policy on each municipality as

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\gamma_k v_{ii,tt}(W,\lambda)$$

for the model in Equation (4) and by

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\gamma_k v_{ii,tt}(W,\lambda)+\delta_k v_{ii,tt}(W,\lambda)(1-policy_i)) \tag{7}$$

for the model in Equation (5). According to our definition of indirect effect, the latter is not defined for the model in Equation (3).

The model in Equation (5) allows to compare the magnitude of the direct and indirect effects with the corresponding counterfactual effects when *all* neighboring municipalities

[13]We stress that our definition of indirect effect is slightly different compared to, e.g., LeSage and Pace (2009), as the latter is computed as the average effect of a change in *all* other municipalities (apart from i) on unit i itself. Hence, technically, our indirect effect is calculated as the derivative of the reduced-form models in Equation (3), Equation (4) or Equation (5) with respect to $\sum_{j=1}^{N} w_{ij}DtD_{jt}$, averaged across i and t.

implement policy k and when *none* of the neighbors implement policy k.

Regarding direct effects, the (average) counterfactuals to Equation (6) when *no* neighbor and *all* neighbors implement the policy respectively amount to

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\beta_k v_{ii,tt}(W,\lambda)+\gamma_k g_{ii,tt}(W,\lambda)+\delta_k g_{ii,tt}(W,\lambda)\right) \tag{8}$$

and

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\beta_k v_{ii,tt}(W,\lambda)+\gamma_k g_{ii,tt}(W,\lambda)-\delta_k\sum_{j=1}^{N}w_{ij}\right). \tag{9}$$

Hence, the comparison of the magnitude of effects in Equation (6) with Equation (8) and Equation (9) in principle allows to assess the presence of "outward" waste tourism from municipality i introducing policy k to neighboring municipalities not implementing such policy, as well as previous existence of "inward" waste tourism from neighboring municipalities which adopt policy k to municipality i before it started adopting stricter policies. In the latter case, the introduction of policy k in municipality i removes the incentive of inward waste tourism.

Regarding indirect effects, the (average) counterfactual to Equation (7) when individual municipality i has already implemented policy k at time of the change in neighbors' policy status and when individual municipality i has not implemented policy k at time of the change in neighbors' policy status are respectively given by

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\gamma_k v_{ii,tt}(W,\lambda) \tag{10}$$

and

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\gamma_k v_{ii,tt}(W,\lambda)+\delta_k v_{ii,tt}(W,\lambda)\right). \tag{11}$$

Similarly to what discussed for the direct effect, the counterfactuals in Equation (10) and Equation (11) assist in determining the presence of waste tourism to and from the individual municipality i, according to its policy status, in response to neighbors adopting stricter waste disposal rules.

5.3. Results

The output is shown in Table 5. For sake of brevity we again avoid reporting the year coefficients. Columns (1)-(3) refer to results obtained using the logarithm of unsorted waste as dependent variable, while Columns (4)-(6) display corresponding results obtained with the logarithm of SWC as dependent variable. Columns (1) and (4) refer to the estimates of Equation (3), while Columns (2) and (5) refer to Equation (4) and finally Columns (3) and (6) display estimates from the specification in Equation (5). In all the specifications we adopt the aforementioned spatial structure W that reflects commuting times. Interpretation of the coefficients is not intuitive and, generally, less informative than the interpretation of marginal effects. For this reason, the table reports both the coefficients and, in its bottom part, the average direct and indirect effects resulting from the regressions. Effects are associated to standard errors and statistical significance computed by a residual-bootstrap routine[14]. We initially notice that the significance of the λ coefficients confirms the appropriateness of looking at models explicitly incorporating the spatial lag of the dependent variable. In what follows, we comment on the direct and indirect effects only.

Regarding unsorted waste, the pattern emerging from Column (1) is as expected and in line with results from Section 4. From Column (2), the direct effect of both DtD and PAYT is also as expected, but the statistically significant indirect effect of PAYT suggests that the unsorted waste production increases slightly in municipality i when the weighted average of its neighbors starts adopting either policies. The indirect effect is more pronounced for PAYT. Thus, the indirect effect associated to PAYT in Column (2) might suggest "inward" waste tourism from neighboring municipalities to municipality i. However, this has to be investigated further using the results in Column (3).

The size of direct and indirect effects from the model in Column (3) is similar to that of Column (2). The model, however, allows to shed light on waste tourism by comparing the effects with those emerging from counterfactual scenarios. The effects reported in Column (3) are those actually observed, in presence of a combination of units that might adopt the policy or not. To shed some light, results in Column (3) have to be compared with the magnitude of the equivalent expression when none or all of the neighbors adopts policy k, as given in Equation (8) and Equation (9) respectively. Table 6 shows the output resulting from this comparison.

Panel a) reports direct effects. In case no neighbor adopts DtD (counterfactual case "NO neigh."), the direct effect of adopting it in a municipality is significant and equal to -0.328, while the corresponding figure for PAYT is -0.416, also significant. By comparison with the direct effects actually observed and displayed in the first column of Table 6 (as well as in Column (3) of Table 5), we can attribute the further reduction of 11.3% for DtD and of 9.8% for PAYT to an average outward waste tourism from municipality i to neighborhoods without the policies. In case all neighbors adopt policy k (counterfactual

[14]Since statistical significance of marginal effects is computed by bootstrap, the usual ratio coefficient/standard error to assess statistical significance might be misleading in this context.

Table 5: Spatial models

	(1) Unsorted	(2) Unsorted	(3) Unsorted	(4) SWC	(5) SWC	(6) SWC
DtD	-0.241***	-0.239***	-0.322***	0.113***	0.114***	0.158***
	(0.013)	(0.014)	(0.023)	(0.007)	(0.008)	(0.013)
$PAYT$	-0.236***	-0.290***	-0.416***	0.044***	0.071***	0.110***
	(0.013)	(0.014)	(0.022)	(0.007)	(0.008)	(0.012)
$DtD * \overline{W}$		0.009	0.021*		-0.007	-0.014**
		(0.011)	(0.011)		(0.006)	(0.006)
$PAYT * \overline{W}$		0.067***	0.104***		-0.030***	-0.042***
		(0.008)	(0.009)		(0.004)	(0.005)
$(1 - DtD) * \overline{W}$			-0.025***			0.014***
			(0.006)			(0.003)
$(1 - PAYT) * \overline{W}$			-0.057***			0.018***
			(0.008)			(0.004)
Log(population density)	0.309***	0.182	0.035	-0.865***	-0.763***	-0.703***
	(0.120)	(0.120)	(0.120)	(0.065)	(0.067)	(0.067)
Log(income per capita)	-0.074	-0.064	-0.033	0.051	0.042	0.031
	(0.124)	(0.123)	(0.122)	(0.070)	(0.069)	(0.069)
Under 14	-0.005	-0.004	-0.002	0.010***	0.009***	0.008***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Over 65	-0.016***	-0.017***	-0.018***	-0.004	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Non-natives	-0.001	-0.003	0.000	0.007***	0.007***	0.006***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Year FE	YES	YES	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES	YES	YES
λ	0.093***	0.116***	0.117***	0.106***	0.120***	0.120***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Direct Effect DtD	-0.243***	-0.241***	-0.215***	0.114***	0.115***	0.100***
	(0.013)	(0.013)	(0.016)	(0.008)	(0.007)	(0.008)
Direct Effect $PAYT$	-0.237***	-0.285***	-0.318***	0.044***	0.067***	0.078***
	(0.013)	(0.016)	(0.013)	(0.007)	(0.008)	(0.009)
Indirect Effect DtD		0.009	0.017***		-0.007***	-0.012***
		(0.013)	(0.010)		(0.007)	(0.006)
Indirect Effect $PAYT$		0.068***	0.066***		-0.031***	-0.030***
		(0.008)	(0.007)		(0.004)	(0.004)
Municipalities	563	563	563	563	563	563
Observations	5,630	5,630	5,630	5,630	5,630	5,630

Note: Standard errors in parentheses. The dependent variable is log-transformed. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 6: Direct and indirect effects vs counterfactual

	Unsorted	Unsorted	Unsorted	SWC	SWC	SWC
			a) Direct effect			
Scenario	Observed	NO neigh.	ALL neigh.	Observed	NO neigh.	ALL neigh.
DtD	-0.215***	-0.328***	-0.299***	0.100***	0.161***	0.145***
	(0.016)	(0.023)	(0.019)	(0.008)	(0.014)	(0.011)
PAYT	-0.318***	-0.416***	-0.349***	0.078***	0.109***	0.088***
	(0.013)	(0.022)	(0.014)	(0.009)	(0.014)	(0.010)
			b) Indirect effect			
Scenario	Observed	NO mun.	YES mun.	Observed	NO mun.	YES mun.
DtD	0.017***	-0.004	0.021***	-0.012***	-0.000***	-0.014***
	(0.010)	(0.010)	(0.010)	(0.006)	(0.005)	(0.006)
PAYT	0.066***	0.048***	0.106***	-0.030***	-0.024***	-0.042***
	(0.007)	(0.007)	(0.009)	(0.004)	(0.004)	(0.005)

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

case "ALL neigh."), the average direct effect of its implementation in unit i amounts to -0.299 for DtD and to -0.349 for PAYT. The additional 8.4% and 3.1% reductions compared to what actually observed and displayed in Column (1) (as well as in Column (3) of Table 5) can be attributed to the presence of waste tourism from neighboring municipalities with stricter policies to municipality i, before the introduction of the policy in municipality i itself. Once also the individual municipality i adopts a stricter policy, the incentive of inward waste tourism is eliminated and thus the overall average effect of municipality i introducing the policy appears larger in absolute value than that displayed in the observed scenario. The latter counterfactual shows the importance of coordination among individual municipalities when establishing whether to implement stricter policies.

The analysis of indirect effects suggests a similar phenomenon. It is worth noting that from Equation (7), the effect of a change in neighbors's policy on the individual municipality i also depends on the policy status of municipality i itself. The figures reported in Table 5 have to be compared with the corresponding average spillovers when the individual municipality i does have policy k in place and when it does not, corresponding respectively to Equation (10) and Equation (11). When individual municipality i has already adopted policy k (counterfactual case "YES mun."), the indirect effects increase to 0.021 for DtD and 0.106 for PAYT, suggesting that the new adoption of a stricter policy in neighboring municipalities prevents citizens of municipality i (which already adopts such policy) to dispose of their waste in neighboring municipalities, resulting therefore in an increase of the overall waste production of municipality i. Such increase disappears for DtD and reduces to 0.048 for PAYT when municipality i did not have the corresponding policy in place at the moment of the neighbors' policy change (counterfactual case "NO mun.”). Indeed, when municipality i does not implement policy k, its citizens would not have the incentive to dispose of their waste elsewhere, regardless of the change in the status of neighboring policies. Thus, the indirect effect associated to DtD is not statistically significant when the municipality does not implement it, while positive marginal effect of PAYT, amounting to 0.048, can instead be attributed to inward tourism from neighboring municipalities that start adopting PAYT to unit i, which does not have it.

The pattern for SWC as dependent variable is similar. Again, the indirect effects of both policies reported in Column (5) of Table 5 suggest the presence of inward waste tourism to municipality i when its neighbors start to introduce the policy. We investigate this further by looking at the results in Column (6) of the same table. The overall direct effect of the adoption of DtD/PAYT in municipality i needs to be compared with the corresponding expression in Equation (8) and Equation (9), obtained when no and all neighbors, respectively, adopt DtD/PAYT. In case no neighbors adopt policy k, from Equation (8), the effect of a change in the policy status of municipality i amounts to 0.161 for DtD and to 0.109 for PAYT. Thus, SWC of municipality i, following the introduction of either policy in municipality i itself, increases more when the neighbors do not adopt such policy, and the difference of 6.1% for DtD and 3.8% for PAYT can be attributed to citizens in municipality i that choose to dispose of their waste in neighborhoods with looser policies. On the other hand, if all neighboring municipalities were to adopt policy k (referred to as the "ALL neigh." counterfactual case), the average direct effect of its implementation in unit i would be 0.145 for DtD and 0.088 for PAYT. The additional increases of 4.5% and 0.9% compared to the observed values in Column (4) (as well as in Column (3) of Table 5) can be attributed to the presence of inward waste tourism from neighboring municipalities to municipality i before the policy was introduced in municipality i itself. Furthermore, to shed some light on the indirect effects reported in Column (6) of Table 5, we compare such figures with the corresponding expressions in Equation (10) and Equation (11), i.e. with the average effect of a change in neighbors' policies on municipality i when the latter does have/does not have, respectively, such policy in place. In the former case (counterfactual case “YES mun.”), i.e. when individual municipality i has the policy in place at the time of the change of neighbors' policy status, the indirect effects of DtD/PAYT increase in absolute value and become -0.014 and -0.042, suggesting how the introduction of stricter policies in neighboring units prevents citizens on municipality i to dispose of their waste in neighboring municipalities and thus resulting in an average overall decrease of SWC in municipality i. Corresponding results when municipality i does not have DtD/PAYT in place at the time of the change of neighbors' policy status (“NO mun.”), instead, are negligible for DtD and reduce (in absolute value) to -0.024 for PAYT. Results are thus in line with what discussed for unsorted waste as dependent variable. Our results hold on a battery of robustness checks, reported in Appendix A, obtained by changing in the network structure.

6. Discussion

In this empirical paper we study the impact of Door-to-Door (DtD) and Pay-As-You-Throw (PAYT) policies on waste sorting and the accumulation of municipal waste. Our analysis is based on a unique dataset made of administrative data from the Veneto region of Italy over the period 2010-2019. Our analysis, run at the municipality-year level, informs that both policies are successful and with similar impact on the outcome dimensions: they reduce the amount of unsorted waste and increase the SWC ratio. However, the analysis also shows evidence of a significant spatial spillover effect. The direct effect typically shows larger size once we explicitly control for the indirect effect. This means that, on average, the indirect effect reduces the strength of the policies (especially PAYT). Indeed, the indirect effects we observe go in the opposite direction of the direct effects and suggest that, once the neighboring municipalities implement a policy, there is an increase of unsorted waste and a decrease of the SWC ratio (more pronounced for PAYT). Our results are then suggestive of an underlying specific behaviour. Citizens of the municipalities where DtD/PAYT is in place may opt to transport their waste to the neighboring municipalities. The motivation for this conduct could be to save on the time needed to separate waste and the costs to present unsorted waste for collection. Consequently, the neighboring municipalities would experience an inflow of external waste independent of the policy adopted. Comparisons based on counterfactual scenarios suggest that waste tourism is a relevant phenomenon that calls the policymakers' attention to the importance of coordinating decisions to avoid negative spillover effects.

7. Concluding remarks

On average, a couple living in OECD countries overall produces more than one tonne of municipal waste.[15] Effective policies concerning household waste can help to stimulate a proper behavior toward waste and, this way, contribute to reduce the ecological footprint.

About 73% of the Italian municipalities implemented DtD in 2021, and about 16% implemented PAYT in 2020,[16] with most of them located in the North-East of Italy

[15] Source: OECD. https://data.oecd.org/waste/municipal-waste.htm.

[16] Source: ISTAT Statistiche Report 11 Novembre 2022, https://www.istat.it/it/files//2022/11/raccolata-differenziata-rifiuti.pdf.

(Source: IFEL, 2019). In principle, the two policies can be implemented everywhere. However, they require some infrastructure (e.g. endowment of individual bins/bags and tools for the identification of the single user) that discourages many municipalities from approaching them. In the case of PAYT, often there is also ex-ante public opposition because citizens perceive the tariff as vexatious (e.g. Carattini et al., 2018). However, our analysis suggests that DtD and PAYT are rewarding and their implementation should be more effective when involving groups of municipalities.

We envisage several limitations to our study, that also offer avenues for future research. First, our study is able to study spillover effects only in the short run. It is an open question whether the evidence we find would persist in the long run. A richer dataset, covering a longer time span, would help to shed light on this issue. Second, we restrict our analysis to the municipalities of the Veneto region. Some of them, however, share borders with other municipalities from surrounding regions. Our models do not control for the policies of nearby municipalities in other regions. Their contribution should be absorbed, at least partly, in the municipality fixed effects. More properly, models should control for the policies of bordering municipalities in the surrounding regions. This extension is left for future research. Third, our results could be specific to the geographic area we analyze and differ from other areas. In particular, we may understate the size of the negative spillover effects since the area we analyze exhibits relatively high levels of SWC, monitoring and prosocial behavior. An interesting and ideal comparison would involve the Veneto region (our data) and a Southern region of Italy, i.e. two regions that are typically seen pretty different in terms of socio-economic and pro-social characteristics. However, at the time of this writing PAYT policies are rarely implemented in Southern regions. Moreover, unfortunately, waste data from the South are incline to mismeasurement (Valente, 2023).

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A. Appendix: Alternative weight matrix

We assess the robustness of our main results reported in Table 5 and Table 6 by using two alternative definitions of the spatial weight matrix denoted as W^{km} and W^{c}, with respective elements indicated as w_{ij}^{km} and w_{ij}^{c}. More specifically, w_{ij}^{km} for each (i, j) is constructed as the reciprocal of the distance (in kilometers) between municipalities i and j for distances up to 30 kilometers, and zero elsewhere, while w_{ij}^{c} is equal to one if municipalities i and j share a border and zero elsewhere. Both matrices, in line with the main weighting structure adopted in Section 5, are then normalized by the spectral norm.

Findings obtained using W^{km} as weighting structure are reported in Table A.1 and Table A.2. Results are in line with what reported in Table 5 and Table 6, in terms of magnitude, direction and significance with the exception of the significance of the indirect effect of DtD when unsorted waste is used as dependent variable in Equation (4). In order to avoid repetition, we omit here further comments on Table A.1 and Table A.2 as results are virtually overlapping with the main ones in Table 5 and Table 6. This confirms the robustness of our network specification when proximity is defined in terms of commuting times and distances.

Larger discrepancies are instead obtained when W^{c} is adopted in place of W defined in Section 5. The results corresponding to Table 5 and Table 6 obtained using W^{c} as the weighting structure are given in Table A.3 and Table A.4. Overall, the magnitude and direction of the coefficients reported in Table A.3 are consistent with the results in Table 5. However, significance of most spatial lag coefficients drops for model Equation (5), even though significance of direct and indirect effects remain in line with those reported in Table 5 (the only exception being the indirect effect DtD when unsorted waste is used as dependent variable).

The analysis of direct and indirect effects and, especially, of their counterfactuals, instead provides mixed results suggesting that the border matrix might fail to capture the complete picture of spatial interactions between the citizens of nearby municipalities. More in detail, we notice from Table A.3 and Table A.4 that evidence of outward and inward waste tourism associated with PAYT still exists. From the direct effects in Table A.4, the average outward waste tourism from municipality i to neighboring municipalities is quantified as an additional reduction in the unsorted waste of unit i of 1.7%, obtained from the difference between the counterfactual in which no neighbors adopt the policy (-0.272) and the observed case (-0.254). Also, the average effect of outward waste tourism for SWC consists of an additional increase of 0.2%. The analysis of indirect effects and their counterfactuals related to PAYT reveals that inward waste tourism from the municipalities that start adopting more restrictive policies toward the municipality i that does not adopt the policy ("NO mun.") is significant and amounts to 2.9% when unsorted waste is used as dependent variable and is not significant for SWC. Moreover, the introduction of the policy in neighboring municipalities, when unit i also implements the policy ("YES mun."), results in an increase in the unsorted amount of 5.2%, which is 1.6% greater than the actually observed case. Thus, it confirms that neighbors' adoption of the policy prevents citizens in unit i from disposing of their waste in neighboring municipalities, thereby leading to an increase in the unsorted amount of unit i itself. The same effect occurs when SWC is used as dependent variable and it is quantified in an additional reduction of 0.2%. Thus, the interpretation of the spatial effects of PAYT is largely unchanged when compared to the main specification in Section 5.

The discrepancies between Table A.4 and Table 6 arise when we focus on the effects of DtD, either in terms of significance and direction of the marginal effects compared to their respective counterfactuals. The discrepancies with results obtained by both W and W^{km} suggest that W^c is not fully adequate to capture proximity across municipalities and it represents only a first approximation of a suitable network structure. The border matrix is, in fact, imposing a binary relationship, and hence it rules out the possibility that citizens of one municipality may dispose of their waste in non-bordering municipalities. Considering the morphological composition of the Veneto Region (small cities and all connected) and the statistics on the daily per capita mobility of citizens[17], it is reasonable to believe that interactions may occur predominantly between non-bordering municipalities.

[17]On average 60 minutes per day in 2010-2019. Source: Veneto Regional Statistical System, https://statistica.regione.veneto.it/ENG/index.jsp.

Table A.1: Spatial models with weight matrix of distances measured in kilometers

	(1) Unsorted	(2) Unsorted	(3) Unsorted	(4) SWC	(5) SWC	(6) SWC
DtD	-0.239***	-0.241***	-0.295***	0.113***	0.117***	0.147***
	(0.013)	(0.014)	(0.023)	(0.007)	(0.008)	(0.013)
$PAYT$	-0.234***	-0.285***	-0.402***	0.045***	0.067***	0.099***
	(0.012)	(0.014)	(0.021)	(0.007)	(0.008)	(0.012)
$DtD * \overline{W}$		0.015	0.022*		-0.012*	-0.016**
		(0.011)	(0.012)		(0.006)	(0.007)
$PAYT * \overline{W}$		0.070***	0.101***		-0.028***	-0.038***
		(0.009)	(0.010)		(0.005)	(0.006)
$(1 - DtD) * \overline{W}$			-0.021***			0.012***
			(0.007)			(0.0040
$(1 - PAYT) * \overline{W}$			-0.067***			0.018***
			(0.009)			(0.005)
Log(population density)	0.382***	0.252**	0.130	-0.867***	-0.787***	-0.743***
	(0.118)	(0.118)	(0.118)	(0.064)	(0.066)	(0.066)
Log(income per capita)	-0.013	-0.016	0.008	0.018	0.017	0.011
	(0.123)	(0.122)	(0.122)	(0.069)	(0.069)	(0.069)
Under 14	-0.006	-0.005	-0.003	0.010***	0.009***	0.009***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Over 65	-0.017***	-0.018***	-0.018***	-0.003	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Non-natives	-0.004	-0.005*	-0.002	0.008***	0.008***	0.007***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Year FE	YES	YES	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES	YES	YES
λ	0.127***	0.146***	0.145***	0.136***	0.146***	0.145***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Direct Effect DtD	-0.242***	-0.244***	-0.224***	0.115***	0.118***	0.106***
	(0.013)	(0.012)	(0.015)	(0.008)	(0.008)	(0.010)
Direct Effect $PAYT$	-0.237***	-0.281***	-0.309***	0.045***	0.064***	0.072***
	(0.012)	(0.015)	(0.017)	(0.007)	(0.010)	(0.009)
Indirect Effect DtD		0.016***	0.019***		-0.012***	-0.015***
		(0.012)	(0.013)		(0.007)	(0.008)
Indirect Effect $PAYT$		0.071***	0.065***		-0.028***	-0.026***
		(0.009)	(0.010)		(0.005)	(0.005)
Municipalities	563	563	563	563	563	563
Observations	5,630	5,630	5,630	5,630	5,630	5,630

Note: Standard errors in parentheses. The dependent variable is log-transformed. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.2: Direct and indirect effects vs counterfactual

	Unsorted	Unsorted	Unsorted	SWC	SWC	SWC
	a) Direct effect					
Scenario	Observed	NO neigh.	ALL neigh.	Observed	NO neigh.	ALL neigh.
DtD	-0.224***	-0.301***	-0.277***	0.106***	0.150***	0.136***
	(0.015)	(0.024)	(0.019)	(0.010)	(0.012)	(0.010)
PAYT	-0.309***	-0.404***	-0.326***	0.072***	0.098***	0.076***
	(0.017)	(0.022)	(0.018)	(0.009)	(0.013)	(0.009)
	b) Indirect effect					
Scenario	Observed	NO mun.	YES mun.	Observed	NO mun.	YES mun.
DtD	0.019***	0.001*	0.023***	-0.015***	-0.004***	-0.017***
	(0.013)	(0.012)	(0.014)	(0.008)	(0.008)	(0.008)
PAYT	0.065***	0.044***	0.112***	-0.026***	-0.020***	-0.039***
	(0.010)	(0.011)	(0.010)	(0.005)	(0.005)	(0.006)

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.3: Spatial models with weight matrix of borders

	(1) Unsorted	(2) Unsorted	(3) Unsorted	(4) SWC	(5) SWC	(6) SWC
DtD	-0.204***	-0.210***	-0.184***	0.094***	0.096***	0.094***
	(0.012)	(0.013)	(0.022)	(0.007)	(0.007)	(0.012)
$PAYT$	-0.223***	-0.246***	-0.266***	0.044***	0.052***	0.054***
	(0.012)	(0.013)	(0.019)	(0.007)	(0.008)	(0.011)
$DtD * \overline{W}$		0.016	0.006		-0.007	-0.006
		(0.012)	(0.013)		(0.006)	(0.007)
$PAYT * \overline{W}$		0.036***	0.050***		-0.011**	-0.013*
		(0.010)	(0.013)		(0.005)	(0.007)
$(1 - DtD) * \overline{W}$			0.018			-0.002
			(0.013)			(0.007)
$(1 - PAYT) * \overline{W}$			-0.022			0.002
			(0.014)			(0.008)
Log(population density)	-0.367***	-0.368***	-0.362***	-0.463***	-0.461***	-0.461***
	(0.108)	(0.108)	(0.108)	(0.061)	(0.061)	(0.061)
Log(income per capita)	-0.209*	-0.197*	-0.201*	0.134**	0.129**	0.129**
	(0.117)	(0.116)	(0.116)	(0.066)	(0.066)	(0.066)
Under 14	-0.001	-0.001	-0.001	0.007***	0.006**	0.007**
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Over 65	-0.020***	-0.020***	-0.020***	-0.000	-0.000	-0.000
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Non-natives	0.006**	0.005**	0.006**	0.003**	0.003**	0.003**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Year FE	YES	YES	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES	YES	YES
λ	0.191***	0.201***	0.200***	0.201***	0.204***	0.204***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Direct Effect DtD	-0.213***	-0.216***	-0.226***	0.098***	0.099***	0.100***
	(0.012)	(0.012)	(0.014)	(0.007)	(0.006)	(0.008)
Direct Effect $PAYT$	-0.232***	-0.249***	-0.254***	0.046***	0.052***	0.052***
	(0.012)	(0.016)	(0.016)	(0.006)	(0.006)	(0.008)
Indirect Effect DtD		0.017	0.010		-0.007***	-0.006***
		(0.011)	(0.011)		(0.007)	(0.007)
Indirect Effect $PAYT$		0.038***	0.036***		-0.012**	-0.012**
		(0.010)	(0.011)		(0.004)	(0.005)
Municipalities	563	563	563	563	563	563
Observations	5,630	5,630	5,630	5,630	5,630	5,630

Note: Standard errors in parentheses. The dependent variable is log-transformed. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.4: Direct and indirect effects vs counterfactual

	Unsorted	Unsorted	Unsorted	SWC	SWC	SWC
			a) Direct effect			
Scenario	Observed	NO neigh.	ALL neigh.	Observed	NO neigh.	ALL neigh.
DtD	-0.226***	-0.187***	-0.210***	0.100***	0.097***	0.099***
	(0.014)	(0.021)	(0.019)	(0.008)	(0.012)	(0.008)
PAYT	-0.254***	-0.272***	-0.244***	0.052***	0.054***	0.051***
	(0.016)	(0.013)	(0.015)	(0.008)	(0.012)	(0.007)
			b) Indirect effect			
Scenario	Observed	NO mun.	YES mun.	Observed	NO mun.	YES mun.
DtD	0.010	0.026***	0.007	-0.006***	-0.008***	-0.006**
	(0.011)	(0.014)	(0.011)	(0.007)	(0.008)	(0.007)
PAYT	0.036***	0.029***	0.052***	-0.012**	-0.011	-0.013***
	(0.011)	(0.012)	(0.012)	(0.005)	(0.005)	(0.007)

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$