Spatial Dependence in Disposable Waste Taxation; the Case of the Netherlands

Abstract:
This thesis investigates both spatial dependency in municipalities' choice of disposable waste taxing scheme and the levied tax itself. The panel dataset comprises data on 383 Dutch municipalities for the years 2014 to 2017. Minor indication for the notion of spatial dependence is found in both the choice of taxation scheme and households' marginal cost of disposing waste. Yet, the estimates produced by the followed methodological approaches are subject to simultaneity problems hence biased and inconsistent. Suggestions to improve the estimation strategy are offered.

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Table of Contents

1. Introduction

In the Netherlands the responsibility for collecting and processing disposable waste is entirely borne by the municipal governments. Municipalities are free to organise these as they prefer as well as to set their own taxations to cover the costs. This creates a plurality of organisational forms, which can broadly be classified into two organisational categories. On the one hand there are municipalities covering the costs based on a flat-fee which can be dependent upon the households' size. On the other hand there are those covering the cost with a unit-based pricing system, known under the acronym "DIFTAR" which stands for DIFferentiated TARiffs. Where the options for a flat-fee based system are limited, there is large variety of DIFTAR schemes. Most of these are based on either volume, frequency or weight but mixtures of two or more of these are observed too.

A paper by Heijnen and Elhorst (2018) has investigated the diffusion of DIFTAR and concluded its introduction to be dependent on the number of neighbouring municipalities that have already introduced such a system. This thesis will extend this work by exploring whether not only DIFTAR is clustered but whether the various unit-based pricing schemes DIFTAR comprises are spatially clustered too. This thesis will thus attempt to change Heijnen and Elhorst's binary approach in a categorical one as well as use more recent data and look at spatial dependence in the model's disturbance term. Moreover, the levied disposable waste tax will be investigated for spatial dependency too. This is something that to my awareness has never been done and will contribute to a larger literature that investigates spatial relations in municipal taxations.

The thesis is organised as follows. Section *2.* elaborates on DIFTAR and illustrates more thoroughly how this thesis connects to the previous literature. Section *3.* outlines the data sources and section *4.* the methods used to estimate the cost households face for disposing waste. Section *5.* illustrates how this thesis accounts for spatial relations and section *6.* offers background characteristics on municipalities with various disposable waste taxing schemes. Section *7.* and section *8.* respectively explain the methodologies used and interpret the estimation results. Section *9.* offers robustness checks and section *10.* concludes the research as well as outlines possibilities for further research.

2. Disposable waste taxation in the Netherlands

DIFTAR is most prevalent in less densely populated municipalities, because of the bureaucratic cost associated with operating such schemes and practical limitations for instance in the form of high-rise blocks. Yet, one of the main motivations to introduce DIFTAR is to reduce the amount of disposable waste presented at the curb. The literature consistently finds large effects of such unit-based pricing systems with weight-based and bag-based systems being most successful in reducing the amount of waste, not rarely by over 40%. [See for instance: Linderhof, Kooreman, Allers and Wiersma (2001), Dijkgraaf & Gradus (2004), Allers & Hoeben (2010), Fullerton & Kinnaman(1996), Pickin (2008) and Kinnaman &Fullerton (2000).]

It is also observed that ever more municipalities introduce DIFTAR. In 2003 just 27 percent of the municipalities operated such a scheme whereas this has risen to 50 percent in 2018 (Rijkswaterstaat, 2018). Research by Heijnen and Elhorst (2018) on the contingency of DIFTAR has shown the adoption of DIFTAR to be spatially interdependent. Heijnen and Elhorst concluded by means of a spatial probit approach and a panel dataset covering the years 1998 to 2005, that the probability of introducing a DIFTAR scheme is increasing in the number of neighbouring municipalities that have already introduced a DIFTAR scheme. Two spill-over effects were offered as potential drivers of this effect. First, neighbouring DIFTAR-municipalities may provide an opportunity to observe the effectiveness of DIFTAR on the amount of household waste produced and consequently inform about the potential benefit to be derived from introducing DIFTAR. Second, neighbouring DIFTAR-municipalities could impose an incentive to introduce DIFTAR due to increased levels of waste tourism. Waste tourism refers to the occurrence where citizens partly dispose their waste in neighbouring municipalities to circumvent their home municipality's unit-based taxation scheme. This could mean that for instance part of the waste is disposed in the containers of friends and family who do not face a unit-based pricing scheme.

The observed domino-effect has the potential to induce positive externalities as it may support the transition to a more sustainable world. The presence of the found spatial dependence may therefore trigger (national) government intervention in the form of facilitating and speeding up the diffusion of DIFTAR. However, a cautious note needs to be made. Heijnen and Elhorst (2018) lumped all DIFTAR schemes together and refrained from testing whether spatial dependence is present at each of every DIFTAR scheme which is interesting because not every unit-based pricing scheme has been found to be equally effective in reducing waste. The spatial effects are thus expected to differ over the various DIFTAR schemes.

Moreover, the level of the disposable waste tax, might be spatially interdependent too. A vast literature[1] focussing on spatial relations in municipal taxes, generally finds such effects going out from neighbouring municipalities' property tax rates. Allers and Elhorst (2005) for instance find that a 10 percent higher property tax rate in neighbouring municipalities leads to a 3.5 percent higher tax rate in the home municipality. Revelli (2001) looks at English districts and finds such a 10 percent increase to be associated with a somewhat larger effect of a 4 percent to 5 percent higher property tax rate in the respective district. Fiva and Rattsø (2007) as well as Sedmihradska and Bakos (2016) add to this that the observed dependence still is present in cases where municipalities are not legally obliged to levy the property tax, even when doing so is relatively scare. Researches as Solé Ollé (2003) and Delgado & Mayor (2011) have looked at other municipal taxes as the motor vehicle tax, business tax and building activities tax and are consistent in finding evidence for spatial dependencies in these types of taxes too.

To my awareness no research has been published that investigates spatial dependencies in the level of municipal disposable waste taxation. Doing this in the presence of unit-based pricing systems however is interesting. If it would turn out that DIFTAR municipalities are more susceptible to neighbouring municipalities' taxes than municipalities that levy a flat-fee, the increasing prevalence of DIFTAR

[1] See for instance; Fiva and Rattsø (2007), Sedmihradska and Bakos (2016), Solé Ollé (2003), Charlot and Paty (2010), Bosch and Solé-Ollé (2007) and Revelli (2002).

may worsen the arbitrariness with which taxations are set which in turn may lead to suboptimal levels of taxation and the consequential possibility of over-or-under provision of public goods and services.

This thesis is thus a contribution to a literature that test tax-mimicking hypotheses by investigating spatial interactions among municipal disposable waste taxation and is two-folded in its aims. First, it aims at extending Heijnen and Elhorst (2018) by establishing whether spatial relations go out from every class of DIFTAR-schemes and second it aims to test and compare the extent to which the levied disposal waste tax levels are spatially interrelated.

3. Data sources

To test the hypotheses of this thesis a panel dataset covering the years 2014 to 2017 was created containing as most important variables municipalities' disposable waste taxing scheme, the extent to which these schemes cover the cost of collecting and processing waste, and households' yearly average disposable waste tax payment. The decision to work with a rather limited number of years follows from the continuous merging of municipalities and the effect this will have on the spatial weights matrix [see also section 5.].

Rijkswaterstaat, a branch of the Dutch Ministry of Infrastructure and Water Management, provided the data on disposable waste taxing schemes municipalities had in place. Municipalities were free to determine and change their tax base and thus a large variety of taxing schemes is observed. Rijkswaterstaat grouped these schemes into eleven different classes based on their tax base, ranging from a flat-fee for every household in a municipality, to a scheme that taxes weight, frequency and household size all in the same municipality (table 3). These yearly reports on the state of municipal waste taxation also provided data on the extent to which the levied disposable waste tax covered the cost of collecting and processing waste as wells as data on the legal structure of the company in charge of collecting the waste at the curb (table 18 in the appendix). Some municipalities operate their own collection service whereas others outsourced this to a private firm or engaged in a joint-venture.
Data on average household disposable waste tax payments for a per municipality representative household, was obtained from a survey among the municipal governments conducted by the research institute *COELO* which is affiliated to the University of Groningen. "COELO" is an abbreviation of the "Centre for Research of the Economy of Lower Level Governments" and all the municipalities completed the survey for each of the years in the dataset[2].
Seat division of each municipal council is used to compare background characteristics of the various municipalities and is summarized as the percentage of seats held by every political party. The data was obtained from the *Kiesraad* and covers one election cycle. That is, in 2014 the councils were initiated and in March of 2017 elections were held for the in 2018 to be newly initiated councils.
Data on the amount of waste produced by a for that municipality representative average household was retrieved from" Afvalmonitor", Rijkswaterstaat's public database. Some observations were missing but have been estimated by linear interpolation if the gap was only one year. If no consecutive observation was available, the observation of the previous year has been replicated and if observations for all of the years were missing, these were filled by the average in the particular province, this happened four times.
Finally, data on the population size, unemployment rate and household sizes per municipality was obtained from the Netherlands' national statistical office "CBS".

[2] The observation for the municipality of Littenseradiel in 2017 was replaced by the one of 2016, because Littenseradiel decided for a one-off decrease of the tax to a 12 euro flat-fee per household, this to exhaust its accumulated government reserves.

4. Estimating households' marginal cost

In contrast to most of the literature on municipal tax-mimicking, the disposable waste tax is not expressed as a tax-rate nor defined over a common tax base. The most natural characterization to investigate the extent to which levied waste taxations are spatially interrelated is then to express the tax in terms of marginal cost. However, because data on the marginal cost of disposing waste is not available and because of the plurality of disposable waste taxing schemes, these marginal costs need to be estimated in a rather complicated manner.

Graph 1. illustrates the three general forms of budget constraints that can be encountered. As the third panel shows, some DIFTAR-municipalities do have a fixed-fee as starting point. Yet, variation is observed in the requirements as from when households are liable marginal cost payments. For instance, some municipalities offer to empty a household's container a pre-set number of times before charging the household for all additional times whereas others require a fixed-fee payment and charge the household's waste disposal from the very first unit presented at the curb. Panel three further illustrates that marginal costs would be severely overestimated would the households' tax payment be simply divided by the amount of waste disposed. This in combination with the fact that it is unknown to the researcher how many DIFTAR-municipalities operate a taxing scheme as illustrated in panels two and three of graph 1., has led to the expressions 1.1, 1.2 and 1.3 to estimate the marginal cost.

$$Flat\ fee\ ; \qquad \mathrm{CR} = \frac{\mathrm{FL}*\mathrm{NH}}{\mathrm{TC}*\mathrm{NH}} \qquad (1.1)$$

$$DIFTAR(Marginal\ cost); \qquad \mathrm{CR} = \frac{\mathrm{VC}*\mathrm{NH}}{\mathrm{TC}*\mathrm{NH}} \qquad (1.2)$$

$$DIFTAR(Combined); \qquad \mathrm{CR} = \frac{(\mathrm{FI}+\mathrm{VC})*\mathrm{NH}}{\mathrm{TC}*\mathrm{NH}} \qquad (1.3)$$

$$DIFTAR(Marginal\ cost); \qquad \mathrm{VC} = \mathrm{CR} * \mathrm{TC} \qquad (2.1)$$

$$DIFTAR(Combined)\ ; \qquad \mathrm{VC} = (\mathrm{CR} * \mathrm{TC}) - \mathrm{FI} \qquad (2.2)$$

$$DIFTAR; \qquad \mathrm{MC} = \frac{\mathrm{VC}}{\mathrm{KG}} \qquad (3.1)$$

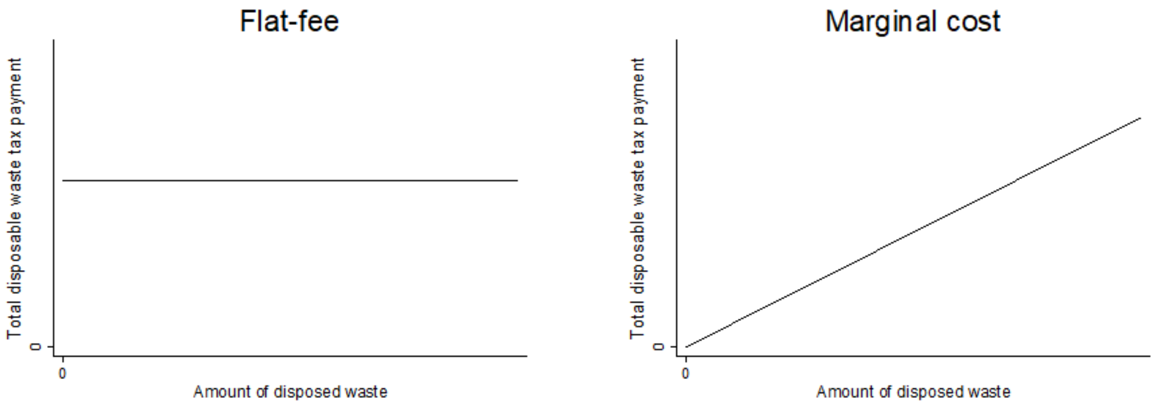
$$\mathrm{TC} = \frac{\mathrm{AV}}{\mathrm{CR}}$$

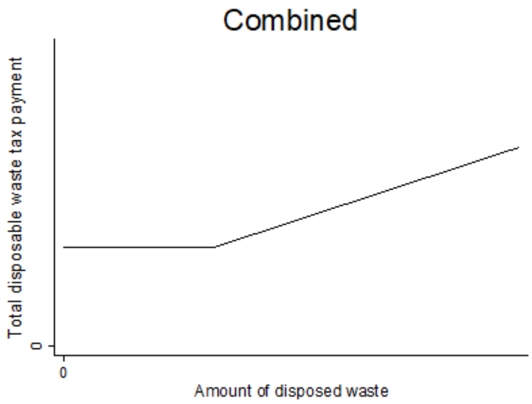
$$\mathrm{CF} = \frac{AV}{AVS}$$

$$\mathrm{FI} = \mathrm{FP} * \mathrm{CF}$$

The following abbreviations are used:

AV, *Average total disposable waste taxation payment by a for the municipality representative household*
AVS, *Average total disposable waste taxation payment by a for the municipality representative household in municipalities operating a similar DIFTAR scheme*
CF, *Correction factor*
CR, *Coverage ratio*
FL, *Flat-fee paid by a for the municipality representative household*
FP, *Preliminary fixed-fee*
FI, *Fixed-fee paid by the household*
KG, *Average amount of a representative household's waste in kilograms*
MC, *Marginal cost*
NH, *Number of households*
TC, *Total cost per household paid by the local government*
VC, *Variable cost paid by a for the municipality representative household*





Graph 1; The three general forms of budget constraints to which households are subject.

The flat-fee and variable costs are expressed in terms of the average payments by the for the specific municipality representative household. Data on the average fixed-fee payment per DIFTAR system was obtained from Rijkswaterstaat (table 17 in the appendix). The total cost per household are paid by the municipal government and represent the sum of all cost associated with collecting and processing household waste. A flat-fee scheme does not know any variable cost and thus by definition the marginal cost a household faces for disposing waste in these municipalities is equal to zero. The DIFTAR municipalities do know variable cost and expressing the equations 1.2 and 1.3 into variable costs yields equations 2.1 and 2.2. Because of a lack of data on the tax bases[3] and for the sake of comparability, the marginal costs are estimated by dividing the variable cost by the average weight of waste disposed by a for the municipality representative household. This implies that also for DIFTAR-municipalities that do not include weight into their tax base, the household's marginal cost of disposing waste is expressed in terms of variable cost per kilogram.

The by Rijkswatertstaat reported average fixed fees per DIFTAR system are subject to a large standard deviation. This is caused by the variation in service municipalities offer or alternatively phrased, the length of the horizontal part of the budget constraint in panel three of graph 1. For many municipalities this flat part is even omitted. A second point to take into account is the variation in which municipalities determine their total cost of waste collection and waste processing. Some municipalities for instance, include remissions to lower income households or the VAT into their calculations and consequently the calculation of the coverage ratio is affected. To address both these points municipality fixed-effect estimation techniques will be incorporated into the methodology.

[3] Except for DIFTAR-municipalities only taxing the weight of garbage, the tax base of DIFTAR-municipalities is unknown to the researcher. That is, no data is available on the average number of times the container of the for that municipality representative household is emptied nor her volume of waste.

Although in essence no claims can be made upon the relation between fixed cost and average taxes, it is assumed that a household's fixed cost are proportional to the household's average disposable waste tax payment. This proportionality assumptions allows to correct for the fact that the assigned fixed costs are solely based upon the average fixed cost in the respective DIFTAR-scheme [table 17 in the appendix]. A correction-factor (CF) was calculated as the household's average disposable waste tax payment over the average disposable waste tax payment of all municipalities operating a DIFTAR-scheme with a similar tax base. This correction-factor was multiplied by the fixed cost to come to a more representative fixed cost estimate to work with in the marginal cost computation.

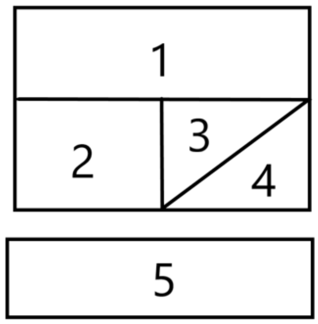
5. Spatial weights matrix

The spatial weights matrix has the function to account for possible spatial dependencies between municipalities and is based on municipalities sharing a border. Hereby is no account taken of the actual length of the border nor the intensity of the relation between both municipalities[4]. All relations with municipalities more than one municipality apart are thus neglected as well as any relations with foreign municipalities, this could create a bias in the estimates.

To illustrate the principle, assume a country consisting of only five municipalities. In the corresponding matrix each row represents a municipality and each column a possible neighbour. If the municipality in the column shares a border with the municipality in the row, this is indicated by a dummy. From this follows that the diagonal contains zeros by definition as a municipality cannot share a border with itself. Transforming the map of the figure below therefore yields the 5 by 5 binary indicator matrix "P", with elements $P_{ij} \in P$. To transform these indicators into weights, the rows need to be normalized, that is they need to sum to unity. This is done by summing the elements row-wise and dividing each element by the sum. This row-stochastic matrix "Z" is what this thesis refers to as a spatial weights matrix and will be denoted by "W". The product of "W"with a vector (or matrix) containing one observation for every municipality is what eventually is of interest for the analysis. [For a more detailed description on the creation of weights matrices, see LeSage (2008). Heijnen and Elhorst (2018) offer an example similar to the one presented in this thesis.]

[4] Rivers are accounted as regular borders but sea-borders, as for instance present in the provinces of Zeeland and Flevoland are not accounted as a border except when municipalities in these provinces share a bridge across sea. According to these definitions the Waddeneilanden do not share a border, however due to their relative similarity these five municipalities are assigned to share a border if they neighbour each other.

Figure 1: Mechanism spatial weights matrix



$$P = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad Z = \begin{bmatrix} 0 & 0.500 & 0.500 & 0 & 0 \\ 0.500 & 0 & 0.500 & 0 & 0 \\ 0.333 & 0.333 & 0 & 0.333 & 0 \\ 0 & 0 & 1.000 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Implementing the above strategy however is troubled by the inconsistencies in the number of border municipalities following the introduction and discontinuation of municipalities. To overcome this problem, all municipalities that did not exist in 2017 as well as all between 2014 and 2017 newly formed[5] municipalities are dropped from the dataset. These in the geographic map now artificially created gaps can be interpreted as lakes. This procedure was followed because of the inconsistency in the number of border municipalities, the introduction and discontinuation of new municipalities creates, in the weighting scheme of the neighbouring municipalities of the affected municipality. Particularly the incidence of municipalities being subject to multiple changes in different years in the set of their neighbours would require a complicated strategy for dealing with this, while yielding relatively little more information[6].

The chosen procedure thus guarantees that all elements of the matrix sum row-wise to unity. Moreover, none of the dropped observations is expected to be the sole driver of any spatial dependence as all of the 25 dropped municipalities are rather rural and at first-sight do not stand-out from remaining municipalities in the particular areas. A list of all dropped observations is included in table 19 of the appendix. Because dropping observations also omit one or more row-elements of the dropped municipality's neighbours, the number of indirectly affected municipalities is 46. However, given the average number of neighbours a municipality has, this is not expected to be a problem (table 2).

[5] The newly formed municipalities were dropped because otherwise the weights do not sum to unity in all years prior to the introduction of the newly formed municipality.

[6] Alternatively, shadow municipalities could be created that have the function of capturing a municipality as would it not have merged. Yet, incidences where municipalities are affected by multiple changes in the set of border-municipalities complicates this strategy, the more because the merging of municipalities was found to be often spatially clustered, meaning that municipalities are not only are subject to own changes in weighting schemes but also these of neighbours.

Table 1: Changes in the set of municipalities

Year	Number of municipalities	Introduced	Discontinued
2014	403	-	-
2015	393	2	12
2016	390	2	5
2017	388	1	3

Table 2: Properties of the border-matrix "*W*"

Years	Observations	Dimension	Mean	Min	Max
2014-2017	1,532	383 x 383	4.98	1	16

Note: The mean, minimum and maximum refer to the number of border municipalities.

One major weakness of the spatial econometric literature is that the weights cannot be estimated but need to be specified in advance. Therefore, these matrices are solely based on the expectations of the researcher. In this thesis it is assumed that municipalities are only affected by their direct neighbours, but this is thus not formally tested. Because, spatial dependency is expected to be most substantial at the border-level, the chosen weights matrix is expected to limit the size of the estimation error. Would one be interested in researching the reach of spatial dependence, weights matrices based on different radiuses would be required.

A second point to be aware of in analyses of spatial dependencies is the set of identification problems that arise as a result of merely observing the outcome variable. As Soetevent (2006) outlines, it is not straightforward what mechanism would drive any interdependency. Endogenous interactions in the form of feedback-loops may imply that municipality "B" not only influences municipality "A" but that in turn municipality "A" also influences municipality "B" and thus ultimately itself. Besides this simultaneity problem, exogenous interaction effects and correlated effects could play a role. This last problem arises when there is a group specific component in the error term that varies across groups and is correlated with exogenous characteristics of the individual municipalities. Finally, exogenous interactions could imply that spatial dependency is not driven by neighbouring values of the dependent variable but by its exogenous regressors. Sections seven and eight will explain how these three identification problems can be addressed and give relevant examples of these for both spatial dependency in municipalities' choice of taxation scheme and the level of their disposable waste tax.

Table 3: Distribution disposable waste taxing schemes as classified by Rijkswaterstaat

Taxation Scheme	Unit-based Pricing	Frequency	Share
Flat-fee	NO	100	6.53%
Flat-fee based on household size	NO	776	50.65%
Volume	YES	87	5.68%
Volume and frequency	YES	382	24.93%
Volume, frequency and household size	YES	34	2.22%
Expensive bag	YES	48	3.13%
Expensive bag and household size	YES	28	1.83%
Weight	YES	41	2.68%
Weight and frequency	YES	32	2.09%
Weight, frequency and household size	YES	4	0.26%
		1,532	100%

Table 4: Observations by group of taxation scheme

Group	Unit-based Pricing	Frequency	Share
Flat-fee based	NO	876	57.2%
Volume based	YES	503	32.8%
Bag based	YES	76	5.0%
Weight based	YES	77	5.0%
		1,532	100%

Note: The dataset comprises 383 municipalities and data for four years, hence 1,532 data points.

6. Descriptive Statistics

When dividing the dataset into DIFTAR and non-DIFTAR municipalities, it is observed that over the period 2014 to 2017 43% of the municipalities operated a DIFTAR scheme and that over that same period 49[7] times an adaptation of taxation scheme occurred. Following the grouping of Rijkswaterstaat, disposable waste taxing schemes can be grouped into eleven different classes (see table 3), these eleven classes can again be grouped into four different sub-samples based on their tax base. Namely; flat-fee, volume, expensive bag and weight. Table 4 makes clear that not all DIFTAR-schemes are equally prevalent. Even after grouping the schemes into the four different subsamples, the division remains strongly unbalanced: Most DIFTAR schemes are volume-based, bag and weight-based schemes are equally common but substantially less than volume-based ones. Finally, most flat-fee based systems are dependent upon the household's size.

Table 5 shows that the average costs of collecting and processing household waste is substantially lower in DIFTAR-municipalities. This could potentially be explained from a higher level of waste separation in DIFTAR-municipalities and consequently more revenue from selling off the sorted recyclable wastes and/or lower costs of processing. Yet, given the literature's findings on unit-based pricing schemes in relation to household waste, the cost difference may also result from DIFTAR-municipalities just generating less waste and thus having less associated costs. Regardless of what is causing this cost difference, the fact that DIFTAR-municipalities typically have lower taxes suggests that households directly share in the benefits of their efforts to reduce waste. Further it is interesting to observe that bag-based schemes on average have lower costs which is in line with the literature's finding of bag-based systems being most successful in reducing waste. A finding that is not necessarily in line with table 7. Note however the limited number of observations on which the figures for bag-based and weight-based schemes are based.
It is also important to note that table 5 cannot inform on the actual size of the gap between total cost per household and the average tax payment per household, this because for municipalities that cover their costs of waste entirely, no data on the size of any potentially realised surplus was available. Consequently, for municipalities of which the disposable waste tax revenue covers the costs entirely, it is assumed that the cost per household are equal to the average tax payment, that is the government surplus is none.

Regarding the background characteristics of municipalities with varying schemes, no difference in the coverage ratios is observed nor in political characteristics as measured by the share confessional[8], left-wing[9] and local political[10] parties take in the municipal councils. The Herfindahl-Hirschman[11] is added as a measure of political fragmentation, and the unemployment rate as a measure of socio-economic conditions, both are observed to differ neither. Population is added as a measure of scale and covers the number of inhabitants a municipality has. DIFTAR-municipalities indeed are observed to have far less inhabitants which is expected to result from the administrative burden associated with operating a DIFTAR-scheme as well as any practical limitations in more densely populated areas as for instance imposed in the form of high-rise blocks. Finally, table 6 does provide some indication that DIFTAR-municipalities generate less waste. It however needs to be noted that the "Waddeneilanden" form an important outlier in their levels of waste per capita while all operating a flat-fee system. For instance,

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[7] 20 incidences of municipalities switching to a DIFTAR system
2 incidences of municipalities switching to a flat-fee system
25 incidences of municipalities changing from DIFTAR system
2 incidences of municipalities changing from flat-fee system
Note: switches and changes also occur as a result of merging

[8] As measured by the share of seats the "Christen Democratisch Appel", "Christen Unie", and "Staats Gereforemeerde Partij" together have in the municipal councils.

[9] As measured by the share of seats "Groen-Link", "Partij van de Arbeid" and "Socialistische Partij" together have in the municipal councils.

[10] These capture all parties that do not compete in national politics. Therefore, the variable partly covers confessional and left-wing parties.

[11] All local political parties are lumped together in this calculation

“Schiermonnikoog”, the smallest member of the island group, reaches levels of over 1800 kilograms of waste per capita per year. A potential explanation for these high levels of waste could lay in the relatively high number of tourists the waddeneilanden host. A substantial part of the costs associated with collecting and processing waste is then expected to be covered by tourist-tax revenues instead of disposable waste tax revenues.

Table 5: Descriptive statistics on the cost of disposing waste for the various taxation schemes

	Total cost				**Average payment**				**Variable cost**				**Marginal cost**			
	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D	Mean	Min	Max	S.D.
Flat-fee based	246	128	350	50	241	40	397	47	-	-	-	-	-	-	-	-
DIFTAR based	197	70	356	42	196	21	356	43	90	4	318	61	0.08	0.01	0.27	0.05
Volume	200	103	356	42	199	103	356	41	99	21	318	64	0.09	0.02	0.27	0.05
Expensive bag	171	70	295	40	166	21	295	47	25	4	57	11	0.02	0.01	0.08	0.01
Weight	205	111	279	37	204	111	279	38	89	8	131	22	0.09	0.01	0.14	0.03
Flat-fee	251	165	419	48	249	165	375	46	-	-	-	-	-	-	-	-
Flat-fee based on household size	245	128	450	50	240	40	397	48	-	-	-	-	-	-	-	-
Volume	231	158	318	40	231	158	318	40	231	158	318	40	0.18	0.11	0.27	0.04
Volume and frequency	192	103	356	38	190	103	356	38	73	39	136	14	0.07	0.03	0.13	0.02
Volume, frequency and household size	215	117	263	39	214	117	254	39	57	21	81	18	0.05	0.02	0.09	0.02
Expensive bag	174	70	278	45	171	21	278	50	30	4	57	10	0.03	0.01	0.08	0.01
Expensive bag and household size	167	134	295	29	157	52	295	40	16	8	36	5	0.01	0.01	0.04	0.01
Weight	203	111	279	42	202	111	279	42	92	50	126	19	0.09	0.04	0.13	0.03
Weight and frequency	208	154	276	33	207	154	276	34	93	71	131	16	0.09	0.05	0.14	0.02
Weight, frequency and household size	197	169	224	25	195	169	224	24	35	8	60	22	0.03	0.01	0.04	0.02

***Note**:* Total cost are faced by the municipality whereas the average payment, variable cost payment and marginal cost payment are paid by households.

Table 6: Descriptive statistics on the background characteristics of municipalities with a flat-fee based scheme and DIFTAR scheme

	Flat-fee based				DIFTAR based			
	Mean	Min	Max	S.D	Mean	Min	Max	S.D.
Coverage ratio	0.98	0.12	1.00	0.07	0.99	0.15	1.00	0.05
KG of waste	1275	637	3621	300	1149	650	1720	205
Confessionalism	0.23	0.00	0.70	0.14	0.26	0.03	0.81	0.14
Left-wing	0.18	0.00	0.49	0.12	0.16	0.00	0.54	0.12
Local	0.36	0.00	1.00	0.16	0.39	0.00	0.95	0.19
HHI	0.26	0.12	1.00	0.12	0.30	0.13	0.90	0.13
Population in 1000s	52.46	0.92	844.95	85.61	31.58	6.60	173.56	26.45
Unemployment rate	0.06	0.03	0.13	0.01	0.05	0.03	0.10	0.01

Table 7: Descriptive statistics on the background characteristic of municipalities with various DIFTAR schemes.

	Volume based				Bag based				Weight based			
	Mean	Min	Max	S.D	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.
Coverage ratio	0.99	0.82	1.00	0.03	0.97	0.15	1.00	0.14	0.99	0.90	1.00	0.01
KG of waste	1157	650	1720	186	1202	693	1654	289	1046	776	1701	193
Confessionalism	0.27	0.03	0.81	0.15	0.25	0.03	0.70	0.15	0.27	0.11	0.48	0.11
Left-wing	0.16	0.00	0.54	0.12	0.12	0.00	0.48	0.15	0.18	0.00	0.34	0.11
Local	0.38	0.00	0.86	0.19	0.47	0.00	0.95	0.22	0.36	0.00	0.73	0.19
HHI	0.29	0.13	0.74	0.12	0.37	0.16	0.90	0.19	0.28	0.16	0.56	0.11
Population in 1000s	32.05	6.60	160.05	24.50	34.17	10.09	173.56	40.51	25.93	7.8	93.72	20.08
Unemployment rate	0.05	0.03	0.10	0.01	0.05	0.03	0.09	0.10	0.05	0.04	0.08	0.01

Note: “KG of waste” refers to the average number of kilograms of waste disposed be a for the municipality representative household.

7. Methodology

To examine whether both the decision to adopt DIFTAR 1) and the level of the disposable waste taxations 2) are spatially interdependent, standard estimation models cannot be used. Because, any spatial relation will violate Gauss-Markov's independence assumption hence produce biased and inconsistent estimates. To accommodate this dependence among observations, spatial econometric techniques extend the standard linear regression models by including the product of a spatial weights matrix and a vector (and/or matrix) of dependent (and/or independent) observations as a term in the regression model. The coefficients on the hereby produced variables are of particular interest because these reflect the average strength of the spatial dependence across the sample.

The nature of the research questions allows to reflect upon all the in section five mentioned remarks regarding disentangling the nature of any spatial relation [see also Soetevent (2006)]. As stated, endogenous interactions in the form of feedback-loops, spatial correlation due to unobserved but across municipalities correlated effects and exogenous interactions could potentially all play a role. Estimation techniques that determine the relative importance of each of these channels are thus needed. The following two subsections will outline these methods, consecutively for spatial dependence in the chosen taxation schemes and marginal costs of disposing waste. Section eight will interpret the results.

7.1 Spatial multinomial logistic regression

Heijnen and Elhorst (2018) focused on the spatial dependency of DIFTAR and proved municipalities with neighbours that adopted DIFTAR to be more likely to introduce DIFTAR than municipalities without such neighbours. However, the various DIFTAR schemes were not studied disjointly. One of the objectives of this thesis is therefore to formulate an estimation strategy that disaggregates Heijnen and Elhorst's spatial dependency measure into one that controls for the various unit-based pricing schemes. Such that can be establish whether the on by Heijnen and Elhorst concluded spill-over effect is present in each of these taxation schemes. This verification is important because not all DIFTAR-schemes are equally effective in reducing the amount of waste and thus in expectation not equally contagious. The by Heijnen and Elhorst reported effects therefore represent the average spatial dependency across DIFTAR-schemes with this estimated effect being heavily biased towards volume-based taxation schemes which are by far the most prevalent form of DIFTAR.

Because disaggregating Heijnen and Elhorst's lump of DIFTAR-schemes into multiple but unordered categories requires a multinomial logistic regression approach, such a model is formulated, including both spatial interaction terms that allow to test for spatial correlation in the dependent variable and in the error term[12]. Spatial correlation in the dependent variable would imply that a municipality's choice of taxation scheme partly is determined by the taxation schemes of its neighbours. Yet, the same principle will hold for its neighbours which in fact would make a municipality's choice of taxation scheme dependent upon itself. This endogeneity is difficult to account for and the in this thesis reported estimates are thus likely to be biased. Testing for spatial dependence in the error term is consistent with testing for unobserved but across municipalities correlated effects. Unobserved shocks following a spatial pattern or from the model omitted relevant determinants would cause such a spatial autoregressive process.

[12] For the purpose of simplification this thesis refrains from exploring spatial dependency in the exogenous regressors of the multinomial logit model.

Dependency in the choice of taxation scheme is measured by the extent to which the choice of taxation scheme correlates with that of neighbours. The therefore used shares (S) are obtained through altering the initial weights matrix W. If a border municipality (B_j) had the same class of taxation scheme in place as the respective municipality (i), the dummy in matrix "P" of section 5 remained, if the neighbour operated a taxation scheme of a different class, the one was recoded to zero. This procedure was repeated for each of the four classes of taxation schemes: flat-fee (f), volume (v), bag (b) and weight (w) -based and for each of the four years[13] ($t = (1, \dots, 4)$) the data set comprises such that 16 new weights matrices resulted, all of size 383 by 383. The number of entries in each of these matrices can be summed row-wise such that the number of border municipalities with a given taxation scheme in a given year is obtained. These summations are divided by the total number of neighbours (N_i) a municipality has such that the respective share results. The vectors created following this procedure can be grouped by class of taxation scheme and pasted after each other in chronological order such that four 1532 by 1 vectors result. These vectors can again be merged into a 1532 by 4 matrix of which's elements sum row-wise to unity. This matrix (M) captures the prevalence of each taxation scheme in the set of a municipality's neighbours and forms the measurement for spatial correlation in the dependent variable.

$$S(f)_{i,t} = \frac{\sum B_{f,t}}{N_i} \quad S(v)_{it} = \frac{\sum B_{v,t}}{N_i} \quad S(b)_{i,t} = \frac{\sum B_{b,t}}{N_i} \quad S(w)_{i,t} = \frac{\sum B_{w,t}}{N_i} \qquad 1 = \sum S_{i,t} \tag{4}$$

Spatial dependence in the disturbance terms "δ" is measured by predicting and spatially weighting the residuals obtained after running a baseline model without any spatial terms. A multinomial logit regression does not know a residual term as a standard linear model would. Residuals are therefore computed as one minus the by the model assigned probability of having the taxation scheme that a given municipality actually operates. Alternatively phrased, one minus the probability that the model's prediction is correct. The error margins are then spatially weighted by multiplying this vector of error margins with the spatial weights matrix W. The variable thus captures whether the model's error margins are spatially clustered.
The thesis refrains from testing spatially weighted exogenous interactions because this would computationally be very demanding while such relations are expected the least.

If Y_i denotes the choice of taxation scheme of municipality "i"and "G" the set of taxation schemes a municipality can choose from, that is volume, bag, weight- and flat-fee based, "V" the set of regressors belonging to the respective municipality and "β" the coefficients to be estimated on these regressors. Then the multinomial logistic model can then be written as expressed in the equation 5 and determines municipality i's probability of operating each of the four groups of taxation schemes. To identify the coefficients on the regressors "V", that is to come to a close form solution, the coefficients on flat-fee based taxation schemes "β_G" are set to zero. Consequently, the coefficients for all other "$G - 1$" taxation schemes will be estimated relative to the case where $e^{\beta_G * V_i} = 1$. This is expressed in equations 6 and 7[14].

The model presented does not account for the endogeneity problem that arises from the simultaneous spatial interactions between municipalities, hence its estimates are expected to be biased. To partly overcome this problem time-lags of the regressors will be introduced, but because the dataset contains only a limited number of years, this method is expected to be flawed. Nevertheless, statistically significant coefficients on the few lags that can be taken offer some indication for spatial interaction.

[13] The extracting had to be done for every year separately due to municipalities switching from taxation scheme.
[14] To reduce omitted variable biases fixed and random effects could be added. Pforr (2014) developed a *STATA* package "femlogit" that offers opportunities for modelling fixed effects but due to the lack of variation in G, such a model would be based on very few observations. Alternatively, random-effects could be estimated by manually creating these by means of generalized structural equation modelling. Yet, due to time-constraints when writing this thesis, the latter was not tried.

$$\Pr(Y_i = G) = \frac{e^{\beta_G * V_i}}{\sum_{g=1}^{G} e^{\beta_g * V_i}} \tag{5}$$

$$\Pr(Y_i = G - 1) = \frac{e^{\beta_{G-1} * V_i}}{1 + \sum_{g=1}^{G-1} e^{\beta_g * V_i}} \tag{6}$$

$$\frac{\Pr(Y_i = G-1)}{\Pr(Y_i = G)} = e^{\beta_{G-1} * V_i} \tag{7}$$

7.2 spatial analysis of the level of taxation

Endogenous interactions in the form of feedback-loops will also be in this subsection, the form of spatial interactions that are expected to impact the dependent variable most. That is, the marginal cost in municipality A can partly be based on the observed marginal cost in municipality B but in turn the marginal cost in municipality B can be partly based on the observed marginal cost in municipality A. In general, the level of marginal cost in a municipality can thus be endogenous. To test for this kind of relationship, the spatial lag model (equation 8) will be exploited which controls for the level of marginal cost in neighbouring municipalities.

To test whether marginal cost can be spatially correlated due to unobserved but across municipalities correlated effects, the spatial error model (equation 9) is used which interacts the spatial weights matrix with the disturbance term. In fact, it thus allows for a spatial autoregressive process in the disturbances. Such correlated effects would result from a situation where determinants of the marginal cost are omitted from the model and spatially autocorrelated or when unobserved shocks follow a spatial pattern.

Finally, it can be tested whether spatial dependency arises in the form of exogenous interactions. The exogenous regressors of another municipality are then directly linked to the marginal cost of the respective municipality. Such relations could for instance be tested by means of the spatial Durbin Model (equation 10).

An integrated model that controls for both a spatial-lag of the dependent variable and spatial correlation in the error term can also be estimated in the form of the spatial autocorrelation model (equation 11).

Following the recommendations for spatial panel analyses as outlined in Elhorst (2014), the above estimation models will be enhanced with either fixed or random-effects to control for unobserved variation over time and thus reduce omitted variable biases. The definitive choice for one or the other will rely upon the Hausman test. Both these techniques relate to the individual municipalities but the difference between these is that fixed-effects control for unobserved variations within the municipality that happen over time and random-effects control for unobserved variations that happen across municipalities over time and thus partly pool the municipalities. Examples of fixed effect are for instance whether a municipality is located at the coast, whether it shares a border with a foreign country but also its general attitude towards taxation. Examples of random effects are for instance regional influences due to provincial government legislation or culture.

Spatial Lag Model
The spatial lag model (SLM), also sometimes referred to as the spatial autoregressive model - SAR, is the most parsimonious of the three core models and posits that a municipality's marginal cost beside a set of observed local characteristics depends on the marginal cost in the through the spatial weights matrix assigned neighbouring municipalities.

$$Y_{i,t} = \alpha + \beta X_{i,t-n} + \rho W Y_{i,t-n} + \mu_{i,t} + \varepsilon_{i,t} \tag{8}$$

$$E(\varepsilon_{i,t}) = 0 \qquad E(\varepsilon_{i,t}\varepsilon_{j,s}) = 0 \; for\ all\ i \neq j\ and\ t \neq s$$

$Y_{i,t}$ denotes a N x 1 vector consisting of one observation for each municipality $i = (1, \dots, N)$ of the dependent variable Y for years $t = (1, \dots, T)$. The constant term parameter, α has to be estimated and $X_{i,t}$ denotes a N x K matrix of explanatory variables. The spatially weighted coefficient "ρ" is the variable of interest. Both $X_{i,t-n}$ and $Y_{i,t-n}$ will be time-lagged $n = (0,1,2)$. Fixed-or random effects are represented by μ_{it}. In case μ_{it} takes the form of fixed-effects, α drops out.
Finally, $\varepsilon_{it} = (\varepsilon_{1t}, \dots, \varepsilon_{Nt})$ denotes the error term. In expectation ε_{it} is independently and identically distributed and thus has a mean of zero and variance σ^2.

Spatial Error Model
The spatial error model (SEM) posits that a municipality's marginal cost is dependent on a set of observed local characteristics and that the error terms are correlated across space.

$$Y_{i,t} = \alpha + \beta X_{i,t-n} + \mu_{it} + \varphi_{i,t-n} \qquad \varphi_{it} = \lambda W \varphi_{i,t-n} + \varepsilon_{i,t} \tag{9}$$

$$E(\varepsilon_{i,t}) = 0 \qquad E(\varepsilon_{i,t}\varepsilon_{j,s}) = 0 \; for\ all\ i \neq j\ and\ t \neq s$$

In this model $\varphi_{it-n} = (\varphi_{1t-n}, \dots, \varphi_{Nt-n})$ represents a second and spatially weighted disturbance term and "λ" the spatial autoregressive coefficient of interest.

Spatial Durbin Model
The spatial Durbin model (SDM) augments the spatial lag model by also controlling for the matrix of spatially weighted explanatory variables, $\theta W X_{it-n}$.

$$Y_{i,t} = \alpha + \beta X_{i,t-n} + \rho W Y_{i,t-n} + \theta W X_{i,t-n} + \mu_{i,t} + \varepsilon_{i,t} \tag{10}$$

$$E(\varepsilon_{i,t}) = 0 \qquad E(\varepsilon_{i,t}\varepsilon_{j,s}) = 0 \; for\ all\ i \neq j\ and\ t \neq s$$

Spatial Autocorrelation Model
The spatial autocorrelation model (SAC), also sometimes referred to as the spatial autoregressive with spatially autocorrelated errors model – SARAR, forms the counterpart of the developed spatial multinomial logit model for continuous variables. It controls for both the marginal cost in neighbouring municipalities and correlation in the error terms across space which in expectation form the two main channels of spatial dependency.

$$Y_{i,t} = \alpha + \beta X_{i,t} + \rho W Y_{i,t} + \mu_{i,t} + \varphi_{i,t} \quad \varphi_{it} = \lambda W \varphi_{i,t} + \varepsilon_{i,t} \tag{11}$$

$$E(\varepsilon_{i,t}) = 0 \qquad E(\varepsilon_{i,t}\varepsilon_{j,s}) = 0 \; for\ all\ i \neq j\ and\ t \neq s$$

Statistical analysis software is in general only marginally equipped to estimate the above models. In particular overcoming the endogeneity problem due to the simultaneous interactions among municipalities has proven to be difficult when conducting this research. The $STATA$ package “xsmle” [see also Belotti, et al (2017)] is to my awareness the best tool to estimate spatial panel regression models. Yet, using this package I have been unable to overcome the endogeneity problem; hence the estimates are biased. To somewhat overcome the endogeneity problem, regressions are augmented with time-lagged versions of the spatial estimates (tables 11 and 12). However, the dataset contains only a limited number of years and thus $n(max) = 2$. In expectation the explanatory power of lagged variables decreases in n, but would coefficients remain statistically significant and substantial in magnitude than this offers some indication for the presence of spatial effects, although the number of time-lags that can be taken is likely to be insufficient.

8. Discussion

8.1 Discussion spatial multinomial logit

Because in the presence of feed-back effects between municipalities the choice of taxation scheme would be endogenous, an estimation procedure is followed that first disregards this endogeneity and solely looks at correlation. Second, by means of introducing lagged versions of the dependent variable some exogeneity is introduced but estimates are likely to remain biased with the number of lags that can be taken. A more credible approach would be to instrument the endogenous variable but the thesis refrains from doing so. A second issue is the lack of variation in the dependent variable. Over the four years the dataset covers only 18 incidences of municipalities switching between class of taxation scheme are observed. Any test for these endogenous feedback-effects is thus troubled by little statistical power. Table 20 in the appendix provides estimation results when two time-lags are incorporated into the model. Yet, due to the thereby caused large loss in observations its estimates are deemed too unreliable to meaningfully interpret.

Table 8 displays the regression output of the spatial multinomial logit approach used to estimate the extent to which the various taxation schemes are spatially correlated. The estimates were constructed by means of the statistical analyses software $STATA$ and one of its core packages “mlogit”. All reported coefficients are relative to having a flat-fee based taxation scheme. Regression I establishes a baseline model that excluded any measure for spatial dependence and has a relatively poor model fit compared to the second regression that includes the measurement for spatial dependence in the taxation scheme. The coefficients on the spatial variables "$S(G)$" matching the class of taxation scheme “G”, enter significant at the one-percent level and have the largest coefficient among these three variables. Moreover, it is shown that the coefficients on the three unit-based pricing schemes are all positive. Together these two findings seem to imply that not only DIFTAR is clustered but that within DIFTAR the various unit-based pricing schemes are clustered too. Regression III further establishes this conclusion by showing the findings to be robust to including province and year dummies. Regression IV augments the latter model by introducing the measurement for spatial dependency in the model’s forecast error. The coefficients obtained on this spatial variable are less significant and are weaker in magnitude than the spatial variables capturing the interaction with neighbouring municipalities’ choices of taxation scheme. Spatial dependency thus seems to be weakly found in the choice of taxation scheme whereas even less in uncontrolled influences. This latter finding is also consistent with the very limited increase of the model fit following the introduction of the variable for spatial dependency in the disturbance term. Regression V shows the findings to reduce in significance when standard errors are clustered at the municipal level. This clustering corrects for the possible violation of the assumption that the error terms are independently and identically distributed. This is likely to be the case due to serial correlation in the dependent variable. Clustering solves the consequential understatement of the standard error. Compared to the other regression of table 8, model V thus contains the most conservative estimates.

Despite the result showing some consistency with the hypothesis that the various unit-based pricing schemes within DIFTAR are spatially clustered, it should not be forgotten that the bag-based and weight-based estimates are based on a relatively limited number of observations. A second point to consider is the non-intuitiveness of the magnitude of the estimated coefficients logit models yield. Regression VI therefore expresses the estimates of regression V in terms of relative risk ratios[15] which are interpreted as the factor with which the estimates differ from the base-line category, flat-fee[16]. Regression VI for instance shows that compared to municipalities operating a flat-fee-based scheme, municipalities operating a volume-based scheme are on average 1.1% more likely to operate such a scheme for every percentage-point increase in the share of neighbours operating a volume-based scheme. Similarly, are municipalities operating bag-based or weight-based schemes, respectively 11.8% and 7.4% more likely to operate such a system for every percentage-point increase in the share of neighbouring municipalities doing so too. Given that the average number of neighbours is five, one neighbour changing to DIFTAR may thus exert substantial influence.
Comparing these results to the ones reported in the spatial probit study of Heijnen and Elhorst (2018) is troubled not only by a difference in the manner the dependent variable is categorized but also by the fact that Heijnen and Elhorst reported separate spatial effects resulting from border municipalities that not yet adopted DIFTAR and those that already did. However, in terms of p-values the estimates of table 8 are substantially less significant than those reported in Heijnen and Elhorst (2018). Spatial dependency in the disturbance term was not investigated by Heijnen and Elhorst but this thesis finds these to be least pronounced and ranging from a factor 0.940 to 1.056. That is, if the average forecasting error in neighbouring municipalities increases by one-percentage point, the forecasting error of the municipality of interest increases by -6 to 5.6 percentage point relative to the forecasting error increase in municipalities operating a flat-fee based scheme.

Finally, all coefficients on population are negative which confirms the descriptive statistics of tables 6 and 7. An explanation for this could be that DIFTAR is more cumbersome to introduce in more densely populated areas due to associated bureaucratic cost and practical limitations for instance in the form of high-rise blocks. In light of this it is interesting to observe that household indeed seem to be slightly larger in DIFTAR municipalities which is consistent with DIFTAR being most prevalent in more rural areas where households are typically larger. The coefficient on the share of confessional parties in the council is also typically larger than the coefficient on the share of left-wing parties which is line with DIFTAR being more likely to be implemented at the countryside where confessionalism finds most of its voter base.
A positive coefficient on the Herfindahl-Hirschman Index is consistent with DIFTAR being more likely to be implemented in case of a less fragmentated government. This confirms the intuition as DIFTAR often is a politically sensitive subject on which political agreement can be hard to reach.

Table 9 presents the estimates corresponding to the model incorporating a one-year lag of the dependent variable. In these models the independent variables are one-year lagged too, this to better capture the fact that taxations are typically set at the end of the year (Allers and Elhorst, 2005). Lagging these however does not make much of a difference as all political variables are constant over the course of the dataset and relative changes in population and average household size are very limited on a yearly basis.
Although representing the coefficients in terms of relative risk ratios makes interpretation more intuitive, it was chosen not to do this for table 9 as the transformation possibly creates minor changes in the statistical significance of estimates.

[15] The RRR of each coefficient can be obtained through transforming that coefficient by exp(coefficient).
[16] A coefficient of 1.0 thus indicates that there is no difference compared to baseline.

When turning to the estimates, it is still observed that the share of border municipalities with the same class of taxation scheme most positively correlate with the class of taxation scheme a municipality has in place. However, this is a partly artificial result as the number of municipalities changing from class of taxation scheme is very limited. Both a municipality's values of the dependent and independent variables are thus rather static over time, implying that the regressions of table 9 are close to being only re-estimated forms of those in table 8 but based on less observations.
The coefficients on the spatially weighted error are now larger both in magnitude and statistical significance which hints at the importance of spatially clustered unobserved influences. These can for instance take the form of policy interactions between municipal governments or cultural attitudes towards DIFTAR and the importance of sustainability. One might wonder why the disturbance terms are not time-lagged. This is because these follow from obtaining the predicted probabilities according to model I (table 9) which already incorporated a time-lag. Lagging the spatially weighted disturbance term would then yet cost another year of observations while the values of the regressors are static.

Table 20 in the appendix contains the results when two-time lags are incorporated and shows no significant influences of the taxation scheme of neighbours. However, important to understand when interpreting these results (as well as the results from table 9), is that because there is little variation in both the dependent and independent variables, these lags do not add much explanatory power as soon the model controls for last period's value of the dependent variable. Of the three tables, the models presented in table 8 may therefore provide the most accurate estimation results.

Overall tables 8 and 9 provide some indication that the various classes of unit-based pricing schemes are clustered within the municipalities that adopted DIFTAR. However more research would be required to rightfully draw any conclusion regarding the strength of these (possible) spatial dependencies when controlled for the simultaneity. Yet, researching this is interesting, particularly identifying the driving factor behind these possible spatial dependencies as the literature has shown not all unit-based pricing schemes to be equally effective in reducing the amount of waste and to be equally cost-effective [See for instance: Linderhof, Kooreman, Allers and Wiersma (2001), Dijkgraaf & Gradus (2004), Allers & Hoeben (2010), Fullerton & Kinnaman(1996), Pickin (2008) and Kinnaman &Fullerton (2000).] From a social welfare point of view, it would thus be desired to introduce policy measures steering towards the socially optimal disposable waste taxation scheme, conditional on further research finding spatial dependency to be driven by arbitrariness. That is, municipalities contemplating to introduce DIFTAR just focus on the DIFTAR-schemes adopted by neighbours as opposed to focussing on the entire set of possible DIFTAR-schemes.

Table 8: Spatial dependence in municipalities' choice of taxation scheme

		I	II	III	IV	V	VI
	Reference class	Flat-fee based	Flat-fee based	Flat-fee based	Flat-fee based	Flat-fee based	Flat-fee based
	Omitted share		S(f)	S(f)	S(f)	S(f)	S(f)
Volume-based	Local	-0.013	-0.034***	-0.068***	-0.077***	-0.072***	0.931***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
(N=503)	Left wing	0.024***	-0.017	-0.053***	-0.059***	-0.055**	0.947**
		(0.01)	(0.01)	(0.013)	(0.01)	(0.02)	(0.02)
	Confessionalism	0.008	-0.002	-0.037***	-0.048***	-0.046**	0.955**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	HHI	0.051***	0.042***	0.037***	0.037***	0.033	1.033
		(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
	Pop in 1000s	-0.006***	-0.010***	-0.012***	-0.012***	-0.011*	0.989*
		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
	Unemploy.rate	0.081	0.081	0.215*	0.202	-0.012	0.988
		(0.05)	(0.06)	(0.13)	(0.13)	(0.07)	(0.07)
	Household size	1.907***	0.861	2.244***	2.787***	2.10*	8.169
		(0.49)	(0.60)	(0.819)	(0.85)	(1.39)	(11.26)
	Intercept	-6.711***	-4.045***	-3.811	-6.433***	-3.531	0.029
		(1.28)	(1.54)	(2.36)	(2.50)	(3.23)	(0.09)
	S(v)		0.045***	0.023***	0.010**	0.011	1.011
			(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
	S(b)		0.043***	0.017**	-0.011	-0.011	0.989
			(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	S(w)		0.020***	-0.003	-0.029***	-0.029	0.972
			(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	W δ				0.054***	0.055**	1.056**
					(0.01)	(0.2)	(0.02)
Bag-Based	Local	-0.007	-0.062**	-0.092***	-0.097***	-0.093**	0.911**
		(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
(N=76)	Left wing	0.016	-0.062**	-0.082***	-0.086***	-0.086	0.917
		(0.02)	(0.03)	(0.03)	(0.028)	(0.06)	(0.06)
	Confessionalism	0.031**	0.030	0.020	0.015	0.016	1.016
		(0.015)	(0.02)	(0.02)	(0.24)	(0.04)	(0.04)
	HHI	0.078***	0.098***	0.102***	0.104***	0.100*	1.105*
		(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	(0.06)
	Pop in 1000s	0.001	0.000	-0.007	-0.008	-0.009	0.991
		(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Unemploy.rate	-0.090	-0.093	-0.389	-0.350	-0.169	0.845
		(0.11)	(0.16)	(0.42)	(0.42)	(0.13)	(0.11)
	Household size	-0.345	-2.995**	-5.854***	-5.897***	-5.505	0.004
		(0.95)	(1.43)	(1.94)	(1.90)	(3.70)	(0.02)
	Intercept	-4.236*	0.416	-3.906	-1.672	-3.968	0.019
		(2.49)	(3.57)	(5126.30)	(1913.16)	(8.83)	(0.17)
	S(v)		0.060***	0.042***	0.042***	0.043**	1.044**
			(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	S(b)		0.128***	0.108***	0.111***	0.111***	1.118***
			(0.01)	(0.01)	(0.02)	(0.03)	(0.04)
	S(w)		0.025*	0.007	0.012	0.014	1.014
			(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
	W δ				-0.005	-0.008	0.992
					(0.03)	(0.04)	(0.04)

Table continued on the next page

Weight-based	Local	-0.009	-0.009	-0.067**	-0.053*	-0.053	0.949
(N=77)		(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.05)
	Left wing	0.047***	-0.020	-0.107***	-0.092***	-0.094	0.910
		(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.06)
	Confessionalism	0.027*	-0.000	-0.050**	-0.033	-0.033	0.968
		(0.01)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)
	HHI	0.051**	-0.032	-0.053	-0.057	-0.059	0.943
		(0.02)	(0.03)	(0.04)	(0.04)	(0.06)	(0.05)
	Pop in 1000s	-0.019***	-0.025***	-0.010	-0.014	-0.016	0.984
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	Unemploy.rate	-0.000	-0.102	-0.510	-0.386	-0.180*	0.835*
		(0.11)	(0.14)	(0.34)	(0.34)	(0.10)	(0.08)
	Household size	-0.093	0.333	3.768*	3.367*	3.386	47.26
		(0.99)	(1.26)	(1.93)	(1.92)	(3.48)	(164.50)
	Intercept	-4.127	-1.978	1.268	2.288	0.088	1.092
		(2.57)	(3.24)	(5.81)	(5.84)	(8.16)	(8.91)
	S(v)		0.017***	-0.018*	-0.006	-0.004	0.996
			(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
	S(b)		0.056***	0.020	0.050**	0.053	1.054
			(0.01)	(0.01)	(0.02)	(0.05)	(0.06)
	S(w)		0.088***	0.038***	0.068***	0.072	1.074
			(0.01)	(0.01)	(0.02)	(0.05)	(0.05)
	W δ				-0.055	-0.061	0.940
					(0.04)	(0.08)	(0.08)
	Province dummies			YES	YES	YES	YES
	Year dummies			YES	YES		
	Robust					YES	YES
	RRR						YES
	Observations	1,532	1,532	1,532	1,532	1,532	1,532
	R^2 (pseudo)	0.0546	0.3353	0.4236	0.4307	0.4284	0.4284
	AIC	2900.21	2071.236	1888.86	1873.547	1820.557	1852.557
	BIC	3028.234	2247.269	2288.935	2289.625	2076.604	2193.954

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The reported R^2(pseudo) is based on an approximation technique for non-linear models, because of its possible misspecification, also the Akaike's and Bayesian's information criteria are reported to evaluate the model fit. The predicted error margin on which δ is based was obtained after estimating model I. The "N" refers to the number of observations on which the estimates for each category of taxation scheme are based.

Table 9: Spatial dependence in municipalities' choice of taxation scheme, one time-lag

		I	II	III	IV
	Reference class	Flat-fee based	Flat-fee based	Flat-fee based	Flat-fee based
	Omitted share		S(f)		S(f)
Volume-based *(N=382)*	L.G	9.771***	9.710***	9.973***	9.848***
		(1.37)	(1.56)	(1.30)	(1.45)
	L.Local	0.014	0.013	0.012	0.009
		(0.03)	(0.03)	(0.04)	(0.04)
	L.Left wing	-0.043	-0.047*	-0.047	-0.059*
		(0.03)	(0.03)	(0.02)	(0.03)
	L.Confessionalism	0.008	0.006	0.004	0.000
		(0.02)	(0.02)	(0.02)	(0.02)
	L.HHI	-0.089*	-0.094	-0.080	-0.086
		(0.05)	(0.06)	(0.06)	(0.06)
	L.Pop in 1000s	-0.011	-0.013	-0.005	-0.007
		(0.01)	(0.01)	(0.01)	(0.01)
	L.Unemploy.rate	0.175	0.159	0.202	0.168
		(0.28)	(0.28)	(0.31)	(0.33)
	L.Household size	0.815	0.524	1.267	0.902
		(1.34)	(1.25)	(1.43)	(1.37)
	Intercept	-14.810***	-13.816***	-16.733***	-15.219***
		(4.01)	(3.75)	(4.48)	(4.47)
	L.S(v)		0.010		0.012
			(0.01)		(0.01)
	L.S(b)		-0.004		-0.010
			(0.02)		(0.02)
	L.S(w)		-0.032*		-0.013
			(0.02)		(0.02)
	W δ			0.077***	0.077***
				(0.01)	(0.01)
Bag-Based *N(=60)*	L.G	15.561***	14.592***	15.892***	14.948***
		(1.95)	(2.23)	(1.90)	(2.10)
	L.Local	-0.014	-0.028	-0.031	-0.048
		(0.04)	(0.04)	(0.05)	(0.05)
	L.Left wing	-0.083*	-0.088**	-0.089*	-0.106**
		(0.04	(0.04)	(0.05)	(0.05)
	L.Confessionalism	0.026	0.039	0.017	0.025
		(0.03)	(0.03)	(0.03)	(0.03)
	L.HHI	-0.068	-0.054	-0.040	-0.028
		(0.06)	(0.07)	(0.07)	(0.07)
	L.Pop in 1000s	-0.008	-0.008	-0.001	-0.000
		(0.01)	(0.01)	(0.01)	(0.01)
	L.Unemploy.rate	-0.210	-0.513	-0.556	-0.848
		(0.40)	(0.54)	(0.49)	(0.62)
	L.Household size	-1.668	-3.539	-2.500	-3.881*
		(1.86)	(2.17)	(1.99)	(2.30)
	Intercept	-21.391***	-15.357*	-18.464	-13.199
		(6.94)	(7.95)	(7.19)	(8.34)
	L.S(v)		0.034***		0.032***
			(0.01)		(0.01)
	L.S(b)		0.045*		0.039
			(0.02)		(0.03)
	L.S(w)		-0.038*		-0.018
			(0.02)		(0.02)
	W δ			0.137***	0.135***
				(0.02)	(0.02)

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Weight-based *(N=58)*	L.G	22.181***	19.913***	22.711***	20.701***
		(3.70)	(3.73)	(3.64)	(3.72)
	L.Local	0.027	0.091	0.009	0.065
		(0.06)	(0.07)	(0.06)	(0.08)
	L.Left wing	-0.020	0.036	-0.026	0.025
		(0.06)	(0.053)	(0.06)	(0.05)
	L.Confessionalism	0.042	0.065	0.032	0.047
		(0.04)	(0.05)	(0.04)	(0.05)
	L.HHI	-0.134**	-0.196**	-0.107	-0.159*
		(0.07)	(0.09)	(0.07)	(0.09)
	L.Pop in 1000s	-0.039**	-0.079***	-0.030*	-0.070***
		(0.02)	(0.03)	(0.02)	(0.02)
	L.Unemploy.rate	-1.306**	-1.522***	-1.769***	-2.052***
		(0.60)	(0.58)	(0.66)	(0.673)
	L.Household size	-7.352***	-11.138***	-8.285***	-12.348***
		(2.79)	(3.61)	(2.83)	(4.01)
	Intercept	-24.050	-5.127	-20.982	-1.501
		(14.70)	(9.61)	(14.42)	(9.52)
	L.S(v)		-0.049*		-0.053*
			(0.03)		(0.03)
	L.S(b)		-0.053		-0.067*
			(0.03)		(0.04)
	L.S(w)		-0.041		-0.026
			(0.03)		(0.03)
	W δ			0.177***	0.222***
				(0.05)	(0.05)
	Year dummies	YES	YES	YES	YES
	Robust	YES	YES	YES	YES
	Observations	1,149	1,149	1,149	1,149
	R^2 (pseudo)	0.8406	0.8498	0.8593	0.8681
	AIC	430.0205	426.9936	393.3621	391.0738
	BIC	596.5599	638.9528	575.0414	618.173

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The reported R^2(pseudo) is based on an approximation technique for non-linear models, because of its possible misspecification, also the Akaike's and Bayesian's information criteria are reported to evaluate the model fit. The predicted error margin on which δ is based was obtained after estimating model I. The "N" refers to the number of observations on which the estimates for each category of taxation scheme are based.

8.2 Discussion spatial analysis marginal cost

The procedure for estimating spatial dependence in households' marginal cost of disposing waste, is to introduce a benchmark that is estimated by *STATA's* statistical software package "xsmle" but does not incorporate any solution to the endogeneity (table 10). Second a set of models is introduced that to some extent account for this simultaneity problem of the dependent variable by introducing time-lags. These latter set of models are compared to the benchmark for consistency in the level of significance, magnitude and sign of the spatial coefficients (tables 11 and 12).

Table 10 constructs a benchmark by first introducing a model without any spatial dependence parameters and a set of control variables. From this baseline regression becomes clear that the political preferences of municipal councils, as well as their fragmentation seem to be unrelated to the level of marginal cost. Nor are the population size or unemployment rate of particular importance.
These findings contradict the expectations. Particularly left-wing oriented councils are expected to have relatively high levels of marginal cost, given their generally more positive stance towards increased levels of taxation[17]. The Herfindahl-Hirschman Index captures political fragmentation and an increase in the index would mean a decrease in the competition between parties. Which implies that councils with an HHI close to one are ruled by large majority governments. Based on work by Fiva & Rattsø (2007) and Sedmihradska & Bakos (2016), a negative coefficient on this variable is expected. Because, in a fragmentated political landscape individual parties can be hold less responsible for increases in taxation and thus it is politically more attractive to increase taxation under such regimes. Also note that the variables: on the share of political preferences, the HHI and the unemployment rate, are expressed in units of ten percentage-points. For instance, the coefficient "-0.007" on the variable local political parties make up in the council, means that would the share of these parties increase by ten percentage points, the average marginal cost decrease by 0.7 euro-cents. The minor magnitude of this effect can be explained from the observations in table 5 which shows the average marginal cost of disposing one kilogram of waste to be around 8 euro-cents. The -0.7 euro-cent change thus corresponds to a reduction in marginal cost of around 9%. Yet, the estimates on the repressors should be approached with caution, because none of these is randomly allocated. To interpret the "-0.007" as the true effect from the share local political parties have, the variable should for instance be instrumented with an instrumental variable. The "-0.007" thus present mere correlation.

Population size was added as a measure of economies of scale and the unemployment rate as a measure of socio-economic conditions. The null result on the number of inhabitants a municipality has is consistent with researches conducted by Charlot & Paty (2010) and Allers & Elhorst (2005). The result can possibly be explained by the existence of a national redistributive grant system. This system aims at equalizing tax bases across municipalities and thus compensates/charges municipalities in accordance to their revenues and costs. Hence little incentive might exist to exploit any possible economies of scale in collecting and processing waste.
In the Netherlands the responsibility to provide social welfare programs, for instance in the form of active labour market policies, is borne at the municipal level. Therefore, the socio-economic conditions to which a municipality is subject may correlate with municipal councils' demand for tax revenue. The baseline regression in table 10, however offers little evidence for such a relation. Again, potentially because of the existence of a redistributive national grant system that reduces municipalities' urge to increase taxation individually.

Regressions II and III enhance the baseline model by controlling for respectively the spatial lag and spatial correlation in the error term. Both these models yield coefficients statistically significant at the one-percent level. Regressions IV and V cluster the standard errors at municipal level for the same

[17] An explanation for the absence of a significant and positive coefficient on left-wing, might be the regressive character of DIFTAR-taxation. Research by Fullerton and Kinnaman (1996) for instance showed, the relation between income and waste generation to be weakly negative, implying that lower income households bear relatively much of the tax burden compared to other municipal taxes as the property tax. This might explain why left-wing politicians relatively disfavor increased disposable waste taxations.

reasons as discussed in section *7.1*. Compared to models II and III this does not change the importance of any of the spatial estimates. Models VI and VII included dummy variables for the by Rijkswaterstaat distinguished eleven taxation schemes, the legal structure of the firm collecting waste at the curb, province and year. R-squared, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) improved substantially implying a much better fit of this model. This is the consequence of xsmle requiring the panel to be strongly balanced and thus in regressions I-V all municipalities operating a flat-fee based scheme are coded as having zero marginal cost as opposed to none in the form of a missing observation. With the introduction of the eleven-scheme dummies, the models control for this inaccuracy and thus regression VI and VII substantially alter the earlier estimation results: The HHI now has the expected sign and the coefficient on the variable capturing neighbouring municipalities' marginal cost, lost much of its magnitude.

Regression VIII combines the spatial lag and spatial error model in the spatial autocorrelation model. This model yields the remarkable finding of a negative spatial-lag effect and a larger spatial-error effect, both these coefficients remain statistically significant. Compared to models VI and VII, R-squared is no lower but this partly results from having less regressors in the model. The information criteria also indicate model VIII to be a more preferred specification, hinting at the correctness of the negative coefficient on the spatial-lag.

Regression IX is the model closest to the estimates presented in table 11, because it controls both for a municipality's own marginal cost one-period lagged and the weighted marginal cost of its neighbours one-period lagged. Unfortunately, this is the only of the in table 10 presented models that can be estimated in such a manner (using xsmle) [Belotti, et al. (2017)]. The negative and almost significant coefficient on the spatially and time- lagged marginal cost of neighbours, is consistent with the negative coefficient on the non-time lagged version of this variable in regression VIII that also incorporates the spatial dependence in the disturbance term.

Table 21 in the appendix contains the estimation results following the Spatial Durbin Model specification and reports besides all insignificant exogenous interactions, a statistically significant spatial coefficient of 0.223 which is higher than the coefficient in regression VI of table 10 but likely inflated because the model did not control for spatial dependence in the error term. Nevertheless, because the Durbin model found the regressors of neighbouring municipalities to be of no statistically significant effect, spatial relations through exogenous interaction seem to be of relatively little importance. What is interesting to observe in the regression of table 21, is that coefficients on the values of neighbouring municipalities regressors have opposite signs compared to the coefficients on these regressors for the respective municipality.
A with a time-lagged dependent variable and time-and-spatially lagged dependent variable, augmented version of the above model is found in regression III of table 21. The coefficients on the spatially weighted regressors remain negative and again a negative coefficient on the spatially-time-lagged marginal cost is found. The robustness of this latter finding was further tested by means of lifting the proportionality assumption made in section four. This continued to yield negative coefficients of similar magnitude while the coefficients on the spatially weighted disturbance term did not change.

Because xsmle does naturally not allow users to take time-lags (except for the two model specifications presented in regression IX of table 10 and regression III of table 19), regressors in tables 10 and 19 are not time-lagged. Refraining from this might however bias the estimates because taxes are typically set at the end of each calendar-year (Allers and Elhorst, 2005). Implying for instance, that the taxes of 2017 are determined at the end of 2016 and thus influenced by the values of the regressors in 2016. The estimates for y_{it} of tables 11 and 12 are therefore based on all regressors being one-year lagged, $X_{i,t-1}$. Yet, a similar remark applies as to the discussion in section 8.1. That is, the values of the regressors are subject to very little variation over the course of the panel, meaning that the estimates of tables 10 and 19 are unlikely to be invalid because of this reason.

The models in table 11 are estimated by both generalized least squares (GLS) and xsmle. This approach was taken to test the robustness of findings obtained from this unnatural use of xsmle[18]. The spatially weighted disturbance terms are obtained from spatially weighting the residuals of the baseline model[19] (regressions I in table 11 and 12).
The fact that all baseline models are estimated by means of random-effects, allows the spatial estimates to be as conservative as possible. Namely, random-effects partly pool the data to control for between-subject variation. Hence part of any possible spatial dependency can already be captured by this variable and thus downward biases coefficients on spatial variables. Particularly the from the baseline models obtained residuals are expected to be affected by this.
No new Hausman tests were conducted for the regressions in tables 11 and 12, this for the matter of comparability with the models presented in table 10. Intuitively including fixed-effects in the final models' specification also makes most sense as this best captures the plurality in which municipalities administer their cost of collecting and processing waste (see bottom section four) and thus the non-randomness created in the calculation of the coverage ratios. Moreover, as Elhorst (2014) outlines, the choice of random-effects might be invalid if not all three of the following requirements are satisfied: First, the number of observations should potentially be able to go to infinity. Second, the observations should be representative of a larger sample and third the assumption of zero correlation between the random-effects and explanatory variables needs to be made. Model specifications incorporating fixed-effects are thus preferred over ones incorporating random-effects. Yet, random-effects are needed to keep track on the political control variables, whose values do not change over the course of the panel and to be as conservative as possible in estimating spatial dependence in the disturbance term.

Based on regressions IX and III of respectively tables 10 and 21, negative coefficients on the spatially-time lagged marginal cost are expected. The benchmark of models 10 and 19 could not test a time-lagged coefficient for the spatial error model but given the pattern observed in table 10, coefficients on the spatially weighted and time-lagged disturbance term are expected to be positive.
Table 11 is consistent with the earlier results in finding a positive, statistically significant and relatively large coefficient on this spatially weighted and time-lagged disturbance term. The coefficients on the spatially weighted and time-lagged marginal cost remain negative and all regressors have signs consistent with the expectations outlined at the beginning of this sub-section.

Because taking a time-lag in the disturbance term costs an additional year of observations, the estimates presented in table 12 are only based on 383 observations. Fixed-effects can therefore not be incorporated but to account for the fact that municipalities calculate the cost of collecting and processing waste differently, the dependent variable is first-differenced.
Because the model specification would require dropping three years of observations, the panel structure is lost and xsmle cannot be used anymore. Instead the maximum-likelihood random-effects estimator of STATA's xtreg command is used as a robustness check of the results obtained by the ordinary-least squares regressions III and IV (table 12).
First differencing changes the interpretation of the estimates. Consequently, the research question is slightly altered. All coefficients now inform about variables' influence on changes in households' marginal cost.

The results in table 12 are consistent with those presented in tables 10 and 11 in that the spatially and time-lagged marginal cost remain to have negative coefficients, and that the coefficients on the spatially and time-lagged disturbance term are positive. This latter also remains relatively large in magnitude as well as that the regressors remain of little influence but do carry the expected sign.

[18] Naturally xsmle does not allow to take time lags. Lagging variable is then only possible after doing this manually and dropping the lost years (such that a balanced panel- dataset results).
[19] Residuals need to be obtained at baseline otherwise the possible upward biases in the height of the spatial lag coefficient downward biases de residuals.

Although probably an insufficient number of lags is taken to overcome the endogeneity in marginal cost, and the estimates are not statistically significant, the obtained regression results are consistent in all ways.
The positive and relatively large coefficients on spatial dependency in the disturbance term, hint at the spill-over of unobserved effects. This finding is intuitively very plausible given the few and irrelevant control variables in the model. An example of an omitted variable could be the contracts municipalities have with waste-processing firms, thus the cost they face for either incinerating or recycling waste. These contracts are expected to be spatially correlated because waste is most likely be processed by the nearest waste-processing plant. Examples of unobserved shocks following a spatial pattern could for instance result from weather conditions. If certain parts of the country are subject to an outstanding number of rainy or snowy days, then people are expected to have been home more and thus to have generated and disposed more household waste[20]. Similar reasoning applies to the presence of public transport strikes and flue epidemics.

The negative relation with marginal costs in neighbouring municipalities could result from a strategic game between politicians luring for votes. If the electorate uses the level of taxation in neighbouring municipalities as a measure for the efficiency of their own municipal government, a situation might result where local politicians are incentivized to lower taxes to signal their quality as politician. A by the electorate easily understood and politically sensitive tax as unit-based waste pricing, is expected to be particularly fruitful for such a strategy because any change in this tax is expected to gain relatively much (media) attention while possibly being not too costly in terms of lost tax revenue.
Research as those conducted by Bosch and Solé-Ollé (2007) and Revelli (2002) have investigated the relation between municipal taxation and municipal election results. Bosch and Solé-Ollé (2007), find using data on three Spanish municipal election rounds in 1995, 1999 and 2003, that a one percentage-point increase in the property tax rate reduces the vote share of the government parties by 8.4% next election cycle. Revelli (2002) complements this finding by arguing that tax increases in neighbouring municipalities have a positive impact on the popularity of the incumbent government. Yet, despite illustrating the relation between taxation and vote share, the above researches both ascribe their results to yardstick competition. That is, the electorate uses neighbouring municipalities' taxes as a benchmark for what the level of taxation in their own municipality should be. This however implies a positive spatial relation in the level of taxation which is not observed in this thesis. A discrepancy possibly explained from neighbouring municipalities' taxes often being a bad comparison, as disposable waste taxing schemes differ across municipalities.
Tillman and Baekkwan (2009) examines electoral sanctions for changes in income tax rates and do find evidence that governing parties that lower taxes gain votes in subsequent elections, but conducted this analysis at the national government levels.

If indeed competition for votes is driving the spatial dependency, this might explain why the reported estimates on the spatially weighted marginal costs are insignificant. Namely, the spatial dependency is not expected to be equally strong each year but to experience spikes in magnitude in the years prior to an election. To test this, a panel dataset covering more election years would be required. It can then be tested whether indeed the estimated coefficients on the spatially weighted marginal cost of neighbouring municipalities follow such a pattern. Moreover, it could be tested whether small majority government are subject to more negative spatial dependence, which would be in line with their relative larger need to attract votes. Section 9 does an initial attempt to explore the above theory, but its empirical evidence is inconclusive.

[20] A practical example of this would be if due to the frequent showers or storms, people opt to have home-office more frequently and thus have lunch and coffee breaks at home, as such generating more disposable household waste.

Note:
A final note on the quasi-maximum likelihood estimation results produced by xsmle should be put in place. The package is devised for spatial panel data and as such its dynamic model specifications (regression IX in table 10 and regression III in table 21) are bias corrected by the quasi-maximum likelihood approach described by Yu, et al (2008). This correction is consistent when both $N \to \infty$ and $T \to \infty$. The command starts by constructing maximum-likelihood estimates treating the lagged dependent variable as exogenous. Then bias corrections are computed for each of the coefficients and used to adjust the initial estimates, see also Belotti, et al. (2017).

Table 10: Spatial dependence in households' marginal cost of disposing waste – no time-lag

Dependent variable: **Marginal cost**	I	II	III	IV	V	VI	VII	VIII	IX
Model	*GLS*	*SLM*	*SEM*	*SLM*	*SEM*	*SLM*	*SEM*	*SAC*	*SLM*
Local	-0.007*	-0.006*		-0.006		-0.000			
	(0.00)	(0.00)		(0.00)		(0.00)			
Left-wing	-0.002	-0.002		-0.002		0.001			
	(0.00)	(0.00)		(0.00)		(0.00)			
Confessionalism	0.000	0.000		0.003		-0.002*			
	(0.00)	(0.00)		(0.03)		(0.00)			
HHI	0.007	0.005		0.005		-0.001			
	(0.00)	(0.00)		(0.00)		(0.00)			
Coverage not 100%	0.004**	0.004**	0.005 ***	0.004	0.005*	0.000	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Population in 1000s	-0.000	-0.000	-0.000	-0.000**	-0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemploy.rate	0.006	0.004	-0.002	0.004	-0.002	0.006	0.006	0.005	0.001
	(0.00)	(0.00)	(0.01)	(0.00)	(0.12)	(0.01)	(0.01)	(0.01)	(0.01)
W. MC		0.334***		0.334***		0.052**		-0.093*	0.053**
		(0.03)		(0.05)		(0.02)		(0.12)	(0.03)
W. disturbance term			0.300***		0.300***		0.274***	0.350***	
			(0.03)		(0.06)		(0.04)	(0.06)	
L. MC									0.138***
									(0.03)
W L. MC									-0.062
									(0.04)
Taxation scheme dummies						YES	YES	YES	YES
Legal structure of waste collector dummies						YES	YES	YES	YES
Province dummies						YES			
Year dummies						YES			YES

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Intercept	0.044**	0.037*		0.037		0.011			
	(0.02)	(0.02)		(0.03)		(0.01)			
Mean FE			0.0359		0.0359		-0.0035	0.0013	-0.0108
RE	YES	YES		YES		YES			
FE			YES		YES		YES	YES	YES
Robust				YES	YES	YES	YES	YES	YES
Observations	1,532	1,532	1,532	1,532	1,532	1,532	1,532	1,532	1,149
R^2	0.0152	0.0210	0.0004	0.0210	0.0004	0.9185	0.7923	0.4796	0.8045
AIC		-7425.039	-9380.312	-9380.312	-6882.41	-9968.009	-7295.901	-11643.22	-8964.209
BIC		-7366.361	-9353.64	-5275.75	-9353.64	-9765.304	-7205.217	-11547.2	-8858.229

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: Fixed effects comprise both municipal and year fixed effects. "Local", "Left-wing", "Confessionalism", "HHI" and "unemployment rate" are expressed per ten percentage-points and all models, except I, are estimated by means of the "xsmle" command.

Table 11: Spatial dependence in households' marginal cost of disposing waste, one time-lag

Dependent variable: **Marginal cost**	I	II	III	IV	V	VI	VII
Model	*GLS*	*SLM*	*SEM*	*SAC*	*SLM*	*SEM*	*SAC*
Method	*GLS*	*GLS*	*GLS*	*GLS*	*XSMLE*	*XSMLE*	*XSMLE*
L. MC	0.250***	0.248***	-0.011	-0.009	0.163	-0.009	-0.006
	(0.05)	(0.05)	(0.03)	(0.03)	(0.04)	(0.03)	(0.3)
W. MC					0.081***		-0.006
					(0.26)		(0.05)
W Disturbance term						0.184**	0.192*
						(0.08)	(0.11)
W L. MC		0.019		-0.011	-0.044		-0.024
		(0.02)		(0.05)	(0.03)		(0.07)
W L. Disturbance term			0.249**	0.266*		0.246**	0.284
			(0.11)	(0.15)		(0.12)	(0.18)
L.Local	-0.000	-0.000			-0.000		
	(0.00)	(0.00)			(0.00)		
L.Left-wing	-0.001	-0.001			-0.001		
	(0.00)	(0.00)			(0.00)		
L. Confessionalism	-0.001	-0.001			-0.001		
	(0.00)	(0.00)			(0.00)		
L.HHI	-0.001	-0.001			-0.001		
	(0.00)	(0.00)			(0.00)		
L.Coverage not 100%	0.000	0.000	0.003**	0.003**	0.001	0.003**	0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	0.00	(0.00)	(0.00)
L.Population in 1000s	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Unemploy.rate	0.012*	0.011*	0.023**	0.023*	0.013**	0.020*	0.020
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.1)	(0.1)
Intercept	-0.001	-0.002	-0.013	-0.010	-0.001		
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		
Mean of FE						-0.0046	-0.0031
Taxation scheme dummies	YES	YES	YES	YES	YES	YES	YES
Legal structure of waste collector dummies	YES	YES	YES	YES	YES	YES	YES
Province dummies	YES	YES			YES		
Year dummies	YES	YES	YES	YES	YES	YES	YES
RE	YES	YES			YES		
FE			YES	YES		YES	YES
Robust	YES	YES	YES	YES	YES	YES	YES
Observations	1,149	1,149	766	766	1,149	766	766
R^2	0.9463	0.9464	0.7654	0.7667	0.9380	0.7685	0.7673
AIC					-7477.915	-6432.673	-6429.061
BIC					-7281.096	-6344.49	-6331.596

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The residuals to be spatially lagged are obtained after estimating model I. Fixed-effect comprise both municipality and year fixed effects and "Local", "Left-wing", "Confessionalism", "HHI" and "unemployment rate" are expressed per ten percentage-points.

Table 12: Spatial dependence in households' marginal cost of disposing waste, two time-lags

Dependent variable: **Δ Marginal cost**	I	II	III	IV	V	VI	VII
Method	*GLS*	*GLS*	*OLS*	*OLS*	*ML*	*ML*	*ML*
Model	*GLS*	*SLM*	*SEM*	*SAC*	*SLM*	*SEM*	*SAC*
L. Δ MC	-0.547***	-0.529***	-0.251	-0.250	-0.228***	-0.251***	-0.250***
	(0.15)	(0.14)	(0.17)	(0.17)	(0.04)	(0.05)	(0.05)
L2 ΔMC			-0.083	-0.079		-0.083	-0.079
			(0.10)	(0.11)		(0.08)	(0.10)
W L. Δ MC		-0.139		-0.507*	-0.066		-0.507*
		(0.15)		(0.30)	(0.09)		(0.28)
W L2. Δ MC				-0.315			-0.315
				(0.33)			(0.27)
W L. Disturbance term			0.141	0.651**		0.141	0.651**
			(0.12)	(0.31)		(0.10)	(0.29)
L2.Local	0.003***	0.003***	0.001	0.001	0.002**	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.Left-wing	0.001	0.001	-0.000	-0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.confessional	0.001	0.001	0.000	-0.000	0.001	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.HHI	-0.003**	-0.003**	-0.002	-0.002	-0.002**	-0.002	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.Coverage not 100%	0.001	0.001	-0.001	-0.001	0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.Population in 1000s	0.000**	0.000**	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.Unemploy.rate	-0.005	-0.004	0.002	0.002	-0.003	0.002	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Intercept	-0.006	-0.006	-0.003	-0.002	-0.003	-0.003	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Taxation scheme dummies	YES	YES	YES	YES	YES	YES	YES
Legal structure of waste collector dummies	YES	YES	YES	YES	YES	YES	YES
Province dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES			YES		
RE	YES	YES			YES	YES	YES
FE							
Robust	YES	YES	YES	YES			
Observations	766	766	383	383	766	383	383
R^2	0.0859	0.0867	0.1413	0.1488			
AIC					-4014.903	-2018.634	-2018.025
BIC					-3843.179	-1872.557	-1864.052

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The residuals to be spatially lagged are obtained after estimating model I. Fixed-effect comprise both municipality and year fixed effects and "Local", "Left-wing", "Confessional", "HHI" and "unemployment rate" are expressed per ten percentage-points.

9. Robustness checks

To test the robustness of the findings in section 8.2, the Spatial Lag, Spatial Error, Spatial Autocorrelation and Spatial Durbin -models are also run for municipalities' representative household's average disposable waste taxation payment per kilogram of waste, or alternatively phrased: households' average tax payment per kilogram of waste, as dependent variable.
The foremost benefit of this specification is that no longer municipalities operating a flat-fee based taxation scheme are coded as zero. Which is expected to have downward biased the earlier estimates, because these as zero-marginal cost coded municipalities are expected to exert relatively little spill-over effects as opposed to neighbour municipalities that operated a DIFTAR scheme.

Tables 13-15 present the estimation results. The coefficients capturing the spatial dependence largely exhibit the same pattern as observed in tables 10-12 but are weaker in magnitude. This last point intuitively makes sense as marginal cost are easier to adapt than average cost. The spatial Durbin model reported in table 21 of the appendix further illustrates the redundancy of controlling for exogenous interactions which is consistent with the earlier findings too. Finally when comparing the R-squared of the various models, it becomes apparent that the models explaining marginal cost have a substantially better fit.

In sum, it thus can be concluded that despite the numerous assumptions in the marginal cost computation, the findings of section 8.2 are confirmed when substituting the dependent variable for average cost. This strengthens the confidence in having estimated the marginal cost in a valid and meaningful manner.

To test whether the in section 8.2 observed negative spatial dependency can be ascribed to government parties trying to attract votes, table 16 splits the sample in the observations for 2015 & 2016 and 2017. 2014 is dropped because first differencing the dependent variable was required to account for the variation in which municipalities calculate their total cost of collecting and processing waste. If competition for votes is causing the spatial dependence, it would be expected that the coefficient on the spatial-lag is particularly large in 2017, the last year of the municipal-governments' term.

Table 16 indeed shows spatial coefficients that are statistically significantly different in 2017 than in 2015 and 2016[21] but from an opposing sign as compared to section 8.2. Yet, given the fact that the coefficient on the spatial disturbance term also switched sign and the models are a stripped-down version of the ones presented in section 8.2, this result should be interpreted carefully.
The choice to estimate the models in table 16 with OLS follows from the cross-sectional nature of the data when only one year, 2017, is used. Fixed-effects are omitted because these would complicate the comparison of coefficients based on 2015-2016 and 2017 data, as the latter cannot be estimated with fixed-effects. Finally, year dummies that capture any trend in the data and time-lagged versions of the dependent variable are excluded too. Time-lags were not incorporated because these would require dropping another year of observations and create overlap in the years to be compared.

[21] t-tests were conducted. All differences are significant at the one-percent level.

Table 13: Spatial dependence in households' average cost of disposing waste, no time-lag

Dependent variable: **Average tax per kg**	I	II	III	IV	V	VI	VII	VIII	IX
Model	*GLS*	*SLM*	*SEM*	*SLM*	*SEM*	*SLM*	*SEM*	*SAC*	*SLM*
Local	-0.005	-0.003		-0.003		-0.001			
	(0.00)	(0.00)		(0.00)		(0.00)			
Left-wing	-0.002	0.002		0.002		0.002			
	(0.00)	(0.00)		(0.00)		(0.00)			
Confessionalism	-0.013***	-0.009***		-0.009***		-0.006**			
	(0.00)	(0.00)		(0.00)		(0.00)			
HHI	-0.007	-0.006		-0.006*		-0.007			
	(0.00)	(0.00)		(0.00)		(0.00)			
Coverage not 100%	0.004**	0.004**	0.004**	0.004**	0.004**	0.003*	0.003*	0.003*	0.004**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Population in 1000	0.000***	0.000***	-0.000	0.000***	-0.000	0.000***	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment rate	0.011**	0.010**	0.028**	0.010	0.028	0.054*	0.024	0.022	0.009
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)	(0.16)	(0.012)	(0.02)
W Av tax per kg		0.285***		0.285***		0.207***		-0.253	0.153***
		(0.03)		(0.03)		(0.03)		(0.18)	(0.04)
W Disturbance term			0.189***		0.189***		0.190***	0.409***	
			(0.04)		(0.04)		(0.04)	(0.15)	
L. Av tax per kg									0.494***
									(0.04)
W L Av tax per kg									-0.003
									(0.08)
Taxation scheme dummies						YES	YES	YES	YES
Legal structure of waste collector dummies						YES	YES	YES	YES
Province dummies						YES			
Year dummies						YES			
Intercept	0.244	0.161		0.161***		0.142***			
	(0.02)	(0.02)		(0.02)		(0.03)			
Mean FE			0.1784		0.1784		0.1781	0.2363	0.0875
RE	YES	YES		YES		YES			
FE			YES		YES		YES	YES	YES
Robust				YES	YES	YES	YES	YES	YES
Observations	1,532	1,532	1,532	1,532	1,532	1,532	1,532	1,532	1,532
R^2	0.3003	0.3362	0.1024	0.3362	0.1024	0.4384	0.1244	0.0470	0.6233
AIC		-6895.274	-8650.777	-6895.274	-8650.777	-7029.162	-8847.236	-8848.821	-6980.944
BIC		-6836.596	-8624.105	-6836.596	-8624.105	-6826.457	-8756.552	-8752.803	-6885.057

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The residuals to be spatially lagged are obtained after estimating model I. Fixed effects comprise both municipal and year fixed effects and "Local", "Left-wing", "Confessionalism", "HHI" and "unemployment rate" are expressed per ten percentage-points

Table 14: Spatial dependence in households' average cost of disposing waste, one time-lag

Dependent variable: **Average tax per kg**	I	II	III	IV	V	VI	VII
Model	*GLS*	*SLM*	*SEM*	*SAC*	*SLM*	*SEM*	*SAC*
Method	*GLS*	*GLS*	*GLS*	*GLS*	*XSMLE*	*XSMLE*	*XSMLE*
L. Av tax per kg	0.887*** (0.02)	0.882*** (0.02)	-0.090 (0.07)	-0.089 (0.07)	0.906*** (0.02)	-0.096 (0.08)	-0.089 (0.07)
W. Av tax per kg					0.128*** (0.04)		-0.475*** (0.15)
W Disturbance term						0.264*** (0.06)	0.638*** (0.09)
W L. Av tax per kg		0.026 (0.02)		-0.035 (0.18)	-0.100** (0.4)		-0.069 (0.16)
W L. Disturbance term			0.123* (0.07)	0.140 (0.10)		0.079 (0.07)	-0.001 (0.08)
L.Local	-0.001 (0.00)	-0.001 (0.00)			-0.001 (0.001)		
L.Left-wing	-0.001 (0.00)	-0.000 (0.01)			-0.000 (0.00)		
L. Confessionalism	-0.001 (0.00)	-0.001 (0.00)			-0.000 (0.00)		
L.HHI	0.001 (0.00)	0.001 (0.00)			0.001 (0.00)		
L.Coverage not 100%	-0.000 (0.00)	0.000 (0.00)	0.005* (0.00)	0.005* (0.00)	0.000 (0.00)	0.004** (0.00)	0.004* (0.00)
L.Population in 1000s	0.000 (0.00)	0.000 (0.00)	0.001 (0.00)	0.001 (0.00)	0.000 (0.00)	0.000 (0.00)	-0.001 (0.00)
L.Unemploy.rate	0.020** (0.01)	0.020** (0.009)	0.009 (0.03)	0.009 (0.03)	0.014* (0.01)	0.010 (0.03)	0.008 (0.2)
Intercept	0.012 (0.01)	0.007 (0.01)	0.199*** (0.04)	0.204*** (0.05)	0.006 (0.01)		
Mean of FE						0.2428	0.3407
Taxation scheme dummies	YES	YES	YES	YES	YES	YES	YES
Legal structure of waste collector dummies	YES	YES	YES	YES	YES	YES	YES
Province dummies	YES	YES			YES		
Year dummies	YES	YES	YES	YES	YES	YES	YES
RE	YES	YES			YES		
FE			YES	YES		YES	YES
Robust	YES	YES	YES	YES	YES	YES	YES
Observations	1,149	1,149	766	766	1,149	766	766
R^2	0.9107	0.9108	0.0760	0.0713	0.9110	0.1454	0.1656
AIC					-5897.295	-5079.957	-5084.521
BIC					-5700.475	-4987.133	-4982.415

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The residuals to be spatially lagged are obtained after estimating model I. Fixed effects comprise both municipal and year fixed effects and "Local", "Left-wing", "Confessionalism", "HHI" and "unemployment rate" are expressed per ten percentage-points.

Table 15: Spatial dependence in households' average cost of disposing waste, two time-lags

Dependent variable: **Δ Average tax per kg**	I	II	III	IV	V	VI	VII
Method	*GLS*	*GLS*	*OLS*	*OLS*	*ML*	*ML*	*ML*
Model	*GLS*	*SLM*	*SEM*	*SAC*	*SLM*	*SEM*	*SAC*
L. Δ Av tax	-0.093**	-0.094**	-0.100	-0.098	-0.094**	-0.100**	-0.098*
	(0.05)	(0.05)	(0.07)	(0.07)	(0.04)	(0.05)	(0.05)
L2. Δ Av tax			-0.099	-0.100		-0.099*	-0.100*
			(0.07)	(0.07)		(0.05)	(0.05)
W L. Δ Av tax		0.065		-0.087	0.065		-0.087
		(0.08)		(0.44)	(0.08)		(0.49)
W L2. Δ Av tax				-0.060			-0.060
				(0.10)			(0.11)
W L. Disturbance term			0.081	0.174		0.081	0.174
			(0.13)	(0.43)		(0.12)	(0.49)
L2.Local	-0.000	-0.000	-0.001	-0.001	-0.000	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.Left-wing	0.000	0.000	-0.000	-0.001	0.000	-0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.confessional	0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.HHI	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.Coverage not 100%	-0.001	-0.001	-0.003	-0.003	-0.001	-0.003	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.Population in 1000s	0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L2.Unemploy.rate	-0.002	-0.002	-0.006	-0.006	-0.002	-0.006	-0.006
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Intercept	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Taxation scheme dummies	YES	YES	YES	YES	YES	YES	YES
Legal structure of waste collector dummies	YES	YES	YES	YES	YES	YES	YES
Province dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES			YES		
RE	YES	YES			YES	YES	YES
FE							
Robust	YES	YES	YES	YES			
Observations	766	766	383	383	766	383	383
R^2	0.0822	0.0831	0.1843	0.1850			
AIC					-3864.496	-1915.798	-1912.108
BIC					-3688.131	-1769.72	-1758.135

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The residuals to be spatially lagged are obtained after estimating model I, Fixed effects comprise both municipal and year fixed effects and "Local", "Left-wing", "Confessionalism", "HHI" and "unemployment rate" are expressed per ten percentage-points.

Table 16: Competition for votes

	I	II	III	IV	V	VI
Dependent variable	Δ MC	Δ Av cost	Δ MC	Δ Av cost	Δ MC	Δ Av cost
Period	2015-2017	2015-2017	2015-2016	2015-2016	2017	2017
Spatial lag			0.575*	0.059	0.669	0.287
			(0.33)	(0.34)	(0.81)	(0.65)
Spatial error			-0.194	0.059	-0.328	-0.193
			(0.30)	(0.34)	(0.77)	(0.69)
L.Local	0.001*	-0.001	0.001*	-0.000	0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Left-wing	-0.000	-0.001	0.000	-0.000	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.confessional	0.001	-0.000	0.001*	-0.000	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.HHI	-0.001*	0.001	-0.002*	0.001	-0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Coverage not 100%	0.003***	0.001	0.003**	0.001	0.002	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Population in 1000s	0.000	-0.000	0.000**	-0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Unemploy.rate	0.008	0.007	-0.010	0.001	0.017	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Intercept	-0.008	-0.004	0.004	0.006	-0.011	-0.004
	(0.01)	(0.01)	(0.01)	(0.11)	(0.02)	(0.02)
Taxation scheme dummies	YES	YES	YES	YES	YES	YES
Legal structure of waste collector dummies	YES	YES	YES	YES	YES	YES
Province dummies	YES	YES	YES	YES	YES	YES
Robust	YES	YES	YES	YES	YES	YES
Observations	1,149	1,149	766	766	383	383
R^2	0.0498	0.0507	0.1381	0.0669	0.1219	0.1688

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The residuals to be spatially lagged are obtained after estimating the model in the first two columns and guarantee a ceteris paribus comparison. All the in this table presented models are SAC-models and “Local”, “Left-wing”, “Confessionalism”, “HHI” and “unemployment rate” are expressed per ten percentage-points.

10. Conclusion

This thesis has provided minor indication for the notion that not only DIFTAR is clustered but that within DIFTAR the various unit-based pricing schemes are clustered too. Some positive spatial dependency was hereby found in the interaction between municipalities' choices of taxation scheme. When examining spatial dependency in the cost of disposing waste, a negative relation with the cost in neighbouring municipalities was observed. None of the spatial relations was found to be statistically significant and the estimates are expected to suffer from endogeneity problems making the results biased and inconsistent.

The positive relation across municipalities' choice of taxation scheme is expected to result from municipalities contemplating to introduce DIFTAR, observing the effectiveness of DIFTAR on the amount of waste produced in neighbouring municipalities. Yet, this might create arbitrariness in the choice of taxation scheme as the set of neighbour municipalities is unlikely to comprise all possible DIFTAR schemes. The choice of taxation scheme may than be biased towards the ones neighbours already have in place as opposed to a more socially optimal one. However, more research is required to prove this theory, as well as to formally establish the observed positive spatial relation.

The negative relation across municipalities' level of disposable waste taxation is expected to result from incumbent governments trying to increase their vote share by trying to signal sound fiscal performance. This would explain the statistical insignificance of the spatial estimates as such strategies cannot be played each year and are expected to be most effective the year prior to election. Yet, the confidence intervals with which the magnitude of these spatial interactions are estimated are not strictly negative. To formally establish that "political signalling" is driving the negative spatial dependency, more research is needed that overcomes the endogeneity problem, for instance by means of an instrumental variable approach that instruments neighbouring municipalities marginal cost with their marginal cost previous election period, and that focusses on political factors as a driver of the effect. It can for instance be investigated whether small majority government coalitions are subject to a more negative spatial relation, which would be in line with their relatively larger need to attract votes. This strategy follows from a more established literature on "yardstick competition" that often introduces political regimes in its regression models to determine whether large majority governments are less prone to mimick neighbouring municipalities' taxes as they can be relatively confident of re-election [see for instance Allers & Elhorst (2005) and Solé Ollé (2003)]. Yet, yardstick competition implies a positive spatial relation and differs from the in this thesis theorised "political signalling" in that incumbent governments do not under-cut neighbouring municipalities taxes but increase taxation to stay put with neighbours. For more administratively costly taxes to change, or taxes in which small reduction can easily create large budget deficits, yardstick competition seems more plausible than "political signalling" but it is at least questionable whether this holds for the disposable waste tax which is more easily understood by the electorate and politically sensitive in the case of DIFTAR.

Besides researching the driver behind any possible spatial dependency, it might prove useful to test the robustness of the obtained results by instead of using a "quasi-maximum likelihood" approach a "generalized method of moments" (GMM) approach, as for instance is taken in Revelli (2001) and Revelli (2002). Finally, it would be interesting to investigate the reach of spatial relations by using weights matrices with various radiuses and to explore more unconventional weights matrices. That is, for instance looking at relative distances as opposed to absolute distances. An example in the context of this thesis would be a weights matrix based upon municipalities within the same organisational COROP-region. These are artificial regions created for statistical purposes and constructed such that each region has a centre with a corresponding servicing area, taking into account the existing commuter relations. A spatial weights matrix based on provincial road connectivity would be another example of such a matrix.

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References

Allers, M.A. and Elhorst, J.P. (2005). Tax Mimicking and Yardstick Competition Among Local Governments in the Netherlands. *International Tax and Public Finance*. Volume 12. Issue 4. Pages 493-513.

Allers M.A. and Hoeben C. (2010). Effects of Unit-Based Garbage Pricing: A Differences-in-Differences Approach. *Environmental and Resource Economics*. Volume 45. Issue 3. Pages 405-428.

Anselin, L. (1988). Spatial Econometrics: Methods and Models. Dordrecht: Kluwer.

Anselin, L., Bera, K., Florax, R. and Yoon, M. (1996). Simple Diagnostic Tests for Spatial Dependence. *RegionalScience and Urban Economics*. Volume 26. Issue 1. Pages 77–104.

Belotti, F, Hughes, G & Piano Mortari. (2017). Spatial panel data models using Stata. *The Stata Journal*. Volume 17. Issue 1. Pages 139-180.

Bosch, N and Solé-Ollé, A. (2007). Yardstick competition and the political costs of raising taxes: An empirical analysis of Spanish municipalities. *International Tax and Public Finance*. Volume 14. Issue 1. Pages 71-92.

Charlot, S and Paty, S. (2010). Do Agglomeration Forces Strengthen Tax Interactions? *Urban Studies*. Volume 47. Issue 5. Pages 1099–1116.

Delgado, J. Francisco and Mayor, Matías. (2011). Tax mimicking among local governments: some evidence from Spanish municipalities. *Portuguese Economic Journal*. Volume 10. Issue 2. Pages 149-164.

Dijkgraaf, E and Gradus, R.H.J.M. (2004). Cost savings in unit-based pricing of household waste: The case of The Netherlands. *Resource and Energy Economics*. Volume 26, Issue 4, Pages 353-371.

Elhorst, J. Paul. (2014). Spatial econometrics: From Cross-Sectional Data to Spatial Panels. SpringerBriefs in Regional Science. Springer Springer Heidelberg New York Dordrecht London. ISBN 978-3-642-40340-8.

Fiva, Jon H. and Rattsø, Jørn. (2007). Local choice of property taxation: evidence from Norway. *Public Choice*. Volume 132. Issue 3–4. Pages 457–470.

Fullerton, Don and Kinnaman, Thomas C. (1996). Household Responses for Pricing Garbage by the Bag. *American Economic Review*. Volume 86. Issue 4. Pages 971-984.

Heijnen, P. and Elhorst, J.P. (2018). The Diffusion of Local Differentiated Waste Disposal Taxes in the Netherlands. *De Economist*. Volume 166. Issue 2. Pages 239-258.

Kinnaman, Thomas C. and Fullerton, Don. (2000). Garbage and Recycling with Endogenous Local Policy. *Journal of Urban Economics*. Volume 48. Issue 3. Pages 419-442.

LeSage, James P. (2008). An Introduction to Spatial Econometrics. *Revue d'économie industrielle*. De Boeck Supérieur. ISSN: 1773-0198. Pages 19-44.

Linderhof, Vincent., Kooreman, Peter., Allers, Maarten and Wiersma, Doede. (2001). Weight-based pricing in the collection of household waste: the Oostzaan case. *Resource and Energy Economics*. Volume 23. Issue 4. Pages 359-371

Parys, van Stafan and Verberke, Tom. (2010). Tax competition among Belgian Municipalities: a multi-dimensional battle. *Regional Science and Urban Economics*. Volume 40. Issue 5. Pages 336-342.

Pforr, Klaus. (2014). femlogit -Implementation of the multinomial logit model with fixed effects. *The STATA Journal*. Volume 14. Issue 4. Pages 847-862.

Pickin, Joe. (2008). Unit pricing of household garbage in Melbourne: improving welfare, reducing garbage, or neither? *Waste management and research*. Volume 26. Issue 6. Pages 508-514.

Revelli, Federico. (2001) Spatial patterns in local taxation: tax mimicking or error mimicking? *Applied Economics*. Volume 33. Issue 9. Pages 1101-1107.

Revelli, Federico. (2002). Local taxes, national politics and spatial interactions in English district election results. *European Journal of Political Economy*. Volume 18. Issue 2. Pages 281-299.

Rijkswaterstaat (2018). Water, Verkeer en Leefomgeving. Afvalstoffenheffing 2018, version 1.0. Utrecht. ISBN 978-94-91750-22-9

Sedmihradska, Lucie and Bakos, Eduard. (2016). Municipal tax autonomy and tax mimicking in Czech municipalities. *Journal of Local Self-Government*. Volume 14. Issue 1. Pages 75-92.

Soetevent, Adriaan R. (2006). Emperics of the identification of social interactions; an evaluation of the approaches and their results. *Journal of Economics Surveys*. Volume 20. Issue 2. Pages 193-228.

Solé Ollé, Albert. (2003). Electoral accountability and tax mimicking: the effects of electoral margins, coalition government, and ideology. *European Journal of Political Economy*. Volume 19. Issue 4. Pages 685-713.

Tillman, Erik. R. and Park, Baekkwan (2009). Do Voters Reward and Punish Governments for Changes in Income Taxes? *Journal of Elections, Public Opinion and Parties*. Volume 19. Issue 3. Pages 313-331.

Yu, Jihai., de Jong, Robert and Lee, Lung-fei. (2008). Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large. *Journal of Econometrics*. Volume 146. Issue 1. Pages 118-134.

Appendix

Table 17: Available Fixed Fee Data

	2014	2015	2016	2017
Flat-fee	0	0	0	0
Flat-fee based on household size	0	0	0	0
Volume	0	0	0	0
Volume and frequency	114	117	118	120
Expensive bag	150	144	147	131
Expensive bag and household size	115 & 148	114 & 146	109 & 140	130 & 172
Expensive bag and emptying bin	115 & 148	114 & 146	109 & 140	130 & 172
Weight	108	110	110	111
Weight and frequency	117	120	116	101
Weight, frequency and household size	132 & 171	125 & 166	131 & 176	133 & 170
Volume, frequency and household size	132 & 171	125 & 166	131 & 176	133 & 170

Note: for “Expensive bag and household size”, “Expensive bag and emptying bin” and “Volume, frequency and household size”, only the average fixed costs for a one-person and three-person household are reported. To estimate the fixed cost in these municipalities, data on the number of one, two, three, four-person households and five-or-more person households per municipality is used[22]. The shares one-person and multiple-person households take in the total of a municipality’s households is calculated and multiplied with respectively the average-one-person-household fixed cost and the average-three-person-household fixed cost after which these are summed to come to the estimated fixed-cost payment for a representative household.
For “Weight, frequency and household size” no data is available. Yet, given that the average fixed-fees for “Weight and frequency” and “Volume and frequency” seem to be closely linked, it assumed that this also is the case for “Weight, frequency and household size” and “Volume, frequency and household size” and thus assign “Weight, frequency and household size” the calculations of “Volume, frequency and household size”.

Table 18: Distribution Various Legal Structures

	Flat-fee	DIFTAR	Volume	Expensive bag	Weight	Share
Municipal public service	206	67	44	12	11	17.8%
Public cooperation	116	119	105	6	8	15.3%
Public-private cooperation	20	27	27	0	0	3.1%
State limited liability undertaking	288	187	144	27	16	31.0%
Private company	232	217	155	31	31	29.3%
Neighbouring municipality	14	39	28	0	11	3.5%

[22] Data was obtained from Statistics Netherlands. Observations for the municipality “Friese Meren” was missing for 2014 and 2015, both these missing observations have been filled with the municipality’s household sizes of 2016.

Table 19: Alterations in the municipal government structure

Year	Municipality			
	Discontinued	*Remark*	*Introduced*	*Remark*
2015	Bergambacht	Became part of the newly formed municipality Krimpenerwaard	Krimpenerwaard	A newly formed municipality consisting of the former municipalities: Bergambacht, Nederlek, Ouderkerk, Schoonhoven and Vlist
	Bernisse	Became part of the newly formed municipality Nissewaard	Nissewaard	A newly formed municipality consisting of the former municipalities: Bernisse and Spijkenisse
	Graft-De Rijp	Merged with Alkmaar		
	Maasdonk	Was split and merged with the municipalities of 's-Hertogenbosch and Oss		
	Millingen aan de Rijn	Merged with Groesbeek		
	Nederlek	Became part of the newly formed municipality Krimpenerwaard		
	Ouderkerk	Became part of the newly formed municipality Krimpenerwaard		
	Schermer	Merged with Alkmaar		
	Schoonhoven	Became part of the newly formed municipality Krimpenerwaard		
	Spijkenisse	Became part of the newly formed municipality Nissewaard		
	Ubbergen	Merged with Groesbeek		
	Vlist	Became part of the newly formed municipality Krimpenerwaard		
2016	Bussum	Became part of the newly formed municipality Gooise Meren	Berg en Dal	The municipality Groesbeek changed name into Berg en Dal
	Groesbeek	The municipality Groesbeek changed name into Berg en Dal	Gooise Meren	A newly formed municipality consisting of the former municipalities: Bussum, Muiden and Naarden
	Muiden	Became part of the newly formed municipality Gooise Meren		
	Naarden	Became part of the newly formed municipality Gooise Meren		
	Zeevang	Merged with Edam-Volendam		
2017	Schijndel	Became part of the newly formed municipality Meierijstad	Meierijstad	A newly formed municipality consisting of the former municipalities: Schijndel, Sint-Oedenrode and Veghel
	Sint-Oedenrode	Became part of the newly formed municipality Meierijstad		
	Veghel	Became part of the newly formed municipality Meierijstad		

Table 20: Spatial dependence in municipalities' choice of taxation scheme, two time-lags

		I	II	III	IV
	Reference class	Flat-fee based	Flat-fee based	Flat-fee based	Flat-fee based
	Omitted share		S(f)		S(f)
Volume-based	L.G	5.062***	8.851***	5.400***	9.425***
		(0.85)	(1.24)	(0.92)	(1.19)
(N=261)	L2.G	21.249***		20.280***	
		(2.37)		(2.19)	
	L.Local	0.036	0.008	0.042	0.006
		(0.04)	(0.03)	(0.06)	(0.04)
	L.Left wing	-0.069*	-0.050*	-0.064	-0.063*
		(0.04)	(0.03)	(0.04)	(0.04)
	L.Confessionalism	0.008	0.004	-0.001	-0.006
		(0.02)	(0.02)	(0.02)	(0.02)
	L.HHI	-0.194**	-0.097*	-0.191**	-0.090
		(0.080)	(0.05)	(0.09)	(0.06)
	L.Pop in 1000s	-0.009	-0.010	-0.003	-0.006
		(0.01)	(0.01)	(0.01)	(0.01)
	L.Unemploy.rate	0.094	0.061	0.079	0.113
		(0.31)	(0.32)	(0.38)	(0.37)
	L.Household size	0.321	0.470	1.508	1.219
		(1.55)	(1.32)	(1.86)	(1.54)
	Intercept	-25.919***	-10.110***	-29.802***	-14.235***
		(4.39)	(4.06)	(5.90)	(5.26)
	L.S(v)		-0.036		-0.038*
			(0.04)		(0.02)
	L.S(b)		-0.053		-0.010
			(0.04)		(0.03)
	L.S(w)		-0.027		-0.021
			(0.03)		(0.03)
	L2.S(v)		0.046		0.054***
			(0.04)		(0.02)
	L2.S(b)		0.043		-0.006
			(0.04)		(0.03)
	L2.S(w)		-0.008		0.0159
			(0.03)		(0.03)
	δ			0.093***	0.094***
				(0.02)	(0.02)
Bag-Based	L.G	-9.092***	12.655***	-11.989***	13.490***
		(3.339)	(1.83)	(4.22)	(4.08)
(N=43)	L2.G	41.957***		44.296***	
		(3.911)		(3.30)	
	L.Local	0.027	-0.037	0.029	-0.054
		(0.06)	(0.05)	(0.07)	(0.06)
	L.Left wing	-0.109*	-0.094*	-0.090	-0.109**
		(0.059)	(0.05)	(0.06)	(0.06)
	L.Confessionalism	0.040	0.040	0.028	0.020
		(0.03)	(0.03)	(0.04)	(0.04)
	L.HHI	-0.211**	-0.048	-0.196*	-0.032
		(0.10)	(0.06)	(0.26)	(0.07)
	L.Pop in 1000s	-0.010	-0.003	-0.005	0.000
		(0.01)	(0.01)	(0.01)	(0.01)
	L.Unemploy.rate	-0.387	-0.822	-0.889	-1.145
		(0.516)	(0.63)	(0.66)	(0.72)
	L.Household size	-2.856	-3.840	-3.547	-4.600
		(2.39	(2.50)	(2.76)	(2.70)
	Intercept	-32.132***	-7.894	-29.781***	-6.900
		(8.76)	(8.48)	(9.70)	(9.03)

Table continued on the next page

	L.S(v)		-0.108		-0.128
			(0.530)		(0.26)
	L.S(b)		-0.199		-0.147
			(0.529)		(0.41)
	L.S(w)		-0.201		-0.194
			(0.52)		(0.40)
	L2.S(v)		0.136		0.161
			(0.535)		(0.42)
	L2.S(b)		0.243		0.187
			(0.54)		(0.42)
	L2.S(w)		0.163		0.186
			(0.52)		(0.41)
	δ			0.154***	0.162***
				(0.03)	(0.03)
Weight-based *(N=39)*	L.G	2.178	25.266***	2.763	47.710***
		(2.55)	(4.79)	(1.88)	(15.22)
	L2.G	37.237***		36.544***	
		(2.96)		(3.26)	
	L.Local	0.208**	0.072***	0.204**	2.043**
		(0.09)	(0.19)	(0.10)	(0.84)
	L.Left wing	0.039	0.329**	0.065	0.905**
		(0.09)	(0.13)	(0.90)	(0.41)
	L.Confessionalism	0.132**	0.092	0.114*	-0.068
		(0.06)	(0.10)	(0.06)	(0.07)
	L.HHI	-0.405***	-0.929***	-0.379***	-2.309**
		(0.11)	(0.27)	(0.12)	(0.94)
	L.Pop in 1000s	-0.069***	-0.106	-0.066***	-0.092
		(0.02)	(0.07)	(0.02)	(0.06)
	L.Unemploy.rate	-0.793	-0.661	-1.567**	-1.510
		(0.70)	(0.56)	(0.80)	(0.94)
	L.Household size	-10.536***	-14.149	-12.152***	-11.803
		(3.52)	(11.20)	(3.78)	(10.16)
	Intercept	-38.138***	-24.605	-34.166***	-171.948***
		(14.92)	(16.78)	(15.07)	(22.07)
	L.S(v)		-2.662***		-5.460***
			(0.54)		(1.56)
	L.S(b)		-2.777***		-5.158***
			(0.54)		(1.34)
	L.S(w)		-2.920***		-5.359***
			(0.56)		(1.34)
	L2.S(v)		2.613***		5.245***
			(0.53)		(1.47)
	L2.S(b)		2.843***		4.469***
			(0.55)		(1.08)
	L2.S(w)		2.581***		5.221***
			(0.53)		(1.29)
	δ			0.241***	0.491***
				(0.09)	(0.17)
	Year dummies	YES	YES	YES	YES
	Robust	YES	YES	YES	YES
	Observations	766	766	766	766
	R^2 (pseudo)	0.8234	0.8157	0.8499	0.8446
	AIC	324.8011	360.6661	295.8539	334.0176
	BIC	445.4718	537.031	444.3718	552.1531

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: The reported R^2(pseudo) is based on an approximation technique for non-linear models, because of its possible error margin, also the Akaike's and Bayesian's information criteria are reported to evaluate the model fit. The predicted error margin on which δ is based was obtained after estimating model I. The "N" refers to the number of observations on which the estimates for each category of taxation scheme are based.

Table 21: Spatial Durbin Model estimated with XSMLE for both the marginal and average cost

	I	II	III	IV
Dependent variable:	MC	AV	MC	AV
Local	-0.001	0.000		
	(0.00)	(0.00)		
Left-wing	0.001	0.006		
	(0.00)	(0.00)		
Confessionalism	-0.002**	-0.005**		
	(0.00)	(0.00)		
HHI	-0.001	-0.003		
	(0.00)	(0.00)		
Coverage not 100%	0.000	0.003	0.001	0.004**
	(0.00)	(0.00)	(0.00)	(0.00)
Population in 1000s	0.000	0.000***	0.000	0.000
	(0.00)	(0.00))	(0.00)	(0.00)
Unemploy.rate	0.006	0.061***	0.001	0.008
	(0.01)	(0.16)	(0.01)	(0.02)
W. MC	0.223***	0.197***	0.248***	0.157***
	(0.03)	(0.03)	(0.04)	(0.04)
L. MC			0.131***	0.493***
			(0.03)	(0.04)
W L. MC			-0.035	0.036
			(0.04)	(0.09)
Taxation scheme dummies	YES	YES	YES	YES
Legal structure of waste collector dummies	YES	YES	YES	YES
Province dummies	YES	YES		
Year dummies	YES	YES	YES	YES
W. Local	-0.003	-0.007		
	(0.00)	(0.01)		
W. Left-wing	-0.002	-0.006		
	(0.00)	(0.01)		
W. Confessionalism	0.001	0.004		
	(0.00)	(0.00)		
W. HHI	0.003	0.011		
	(0.00)	(0.01)		
W. Coverage not 100%	0.003	0.001	0.001	0.003
	(0.00)	(0.00)	(0.00)	(0.00)
W. Population in 1000s	0.000	0.000*	0.000	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
W. Unemploy.rate	-0.007	-0.037	-0.004	-0.019
	(0.01)	(0.02)	(0.01)	(0.03)
W. Taxation scheme dummies	YES	YES	YES	YES
W. Legal structure of waste collector dummies	YES	YES	YES	YES
W. Province dummies	YES	YES		
W. Year dummies	YES	YES	YES	YES
Intercept	0.014	0.094**		
	(0.02)	(0.05)		
Mean FE			-0.0394	-0.0050
RE	YES	YES		
FE			YES	YES
Robust	YES	YES	YES	YES
Observations	1,532	1,532	1,149	1,149
R^2	0.9222	0.5212	0.7252	0.4297
AIC	-9995.447	-7034.47	-9002.998	-6984.638
BIC	-9616.709	-6655.732	-8821.318	-6802.959

*** if p<0.01, ** if p<0.05 and * if p<0.10

Note: Fixed-effects comprise both municipal and year fixed effects, and “Local”, “Left-wing”, “Confessionalism”, “HHI” and “unemployment rate” are expressed per ten percentage-points.