Erasmus
School of
Economics

# ERASMUS UNIVERSITY ROTTERDAM

## Erasmus School of Economics

# Effects of municipal waste management practices on household waste: The case of The Netherlands

Master Thesis Strategy Economics

Abstract: This paper explores the relationship between municipal waste management and household waste. This study is in particular interested in the potential impact of unit-based pricing (UBP), the waste collection method, and the frequency of collection on residual waste quantities and the separation rate. Using a unique 17-year dataset of all 342 Dutch municipalities, which contains information on household waste, municipal waste management, and demographic and socio-economic characteristics all at the municipality level, I employ a fixed effects regression and utilize the synthetic control method to perform empirical analyses. Results suggest that there is a negative relationship between the use of UBP and household residual waste quantities, yet a positive relationship with the separation rate. In addition, drop-off points are found to decrease waste quantities and increase the separation rate, compared to curbside collection. Furthermore, collecting household residual waste every three or four weeks rather than (bi-)weekly can lead to lower amounts of household residual waste and to a higher separation rate. Finally, I find preliminary results which suggest that the effects of implementing a UBP system may not persist over time. The results shed new light on the effects of municipal waste management practices and household waste and can be of importance to policymakers, local governments, and the waste management industry.

Keywords: Municipal waste management, Household waste, Separation rate, Unit-based pricing, Curbside collection, Drop-off points, Collection frequency, Fixed effects, Synthetic control method

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# Preface

In front of you lies my thesis written for the Master of Science "Strategy Economics". With this thesis, I hope to contribute to the body of knowledge on Environmental Economics and provide insights to policy makers.

Me living in Rotterdam, my mother in Maastricht and my father in Ede, I noticed how our trash is collected in different ways. Where I need to bring my trash bag to an underground waste container, my mother simply puts hers on the sidewalk every other week on Tuesday to be collected. At my father's house in Ede, I have to throw the trash bag in a wheelie bin. Moreover, when I moved to Rotterdam, I no longer had to separate my plastic waste. I became curious as to why municipalities all have their own ways of collecting household waste. In particular, I started wondering what impact these different ways of collecting have on waste quantities and what best incentivizes households to separate. Noticing these differences sparked my interest, and I knew what the subject of my thesis would be.

I would like to thank my supervisor, Tilbe Atav, for her guidance and constructive feedback throughout the research project. Also, I could not have written this thesis without the databases of Rijkswaterstaat. Therefore, I would like to thank Bas van Huet for providing me with additional data and answering my questions.

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# Chapter 1. Introduction

Global warming is a pressing issue that is high on the agenda of governments and other institutions worldwide. As such, all EU member countries have committed to environmental objectives aimed at slowing down global warming (*The European Green Deal*, 2021). Part of these objectives is to realize a reduction in greenhouse gas emissions by at least 55% by 2030, compared to 1990 levels (European Commission, 2024). Municipal solid waste management accounts for approximately 5% of global greenhouse gas emissions (Gautam & Agrawal, 2020). These emissions are driven by the amount of waste. More waste generation leads to more emissions from waste collection, transportation, treatment, and disposal processes. Therefore, adopting policies that minimize waste production or increase resource recovery (e.g. through recycling or separating waste) can be effective strategies to reduce emissions and slow down global warming.

Within the Netherlands we see big differences between municipalities' total household waste and waste separation rates. Furthermore, municipalities within The Netherlands all have their own way of managing household waste. They differ in the way waste is collected and they all tax households differently for the amount of waste they generate, this system is called *Diftar* (rate differentiation system). This makes The Netherlands an interesting context in which to evaluate waste management strategies. Can differences in the household waste quantities and separation rates be explained by differences in waste collection methods and pricing systems? To answer that question, I formulated the following research question:

> *How do different waste management approaches, employed by Dutch municipalities, impact waste reduction and resource recovery?*

Household waste comprises the daily generated waste from households including source-separated recyclables, biowaste and a residual waste fraction (Larsen et al. 2010). In The Netherlands, the average total amount was 455 kg/capita in 2023 (Centraal Bureau voor de Statistiek, 2023). The government's goals were to increase the separation rate to 75% in 2020 and decrease the amount of household residual waste to 100 kg/capita (Ministerie van Infrastructuur en Waterstaat, 2024). These goals were not met: Today, around 60% of household waste is separated by households and the average amount of residual waste is 163 kg/capita. Although the numbers are becoming increasingly better, there is still a long road ahead to meet with national and European standards.

The Dutch government aims to further reduce residual household waste to 30 kg/capita by 2025 (Afval Van Huishoudens, 1985-2022, 2023). This study can perhaps contribute to reaching this goal.

I am interested in examining the impact of various waste management approaches on household residual waste quantities and separation rates. The choice to examine separation rates rather than recycling rates is intentional. The difference between the two is that the former occurs at the beginning of the waste management cycle, while the latter occurs at the end. The separation rate indicates how well households separate recyclables, whereas the recycling rate indicates the percentage of recyclables that are actually recycled at waste treatment centres. The separation rate equals the share of separately collected recyclables in the total amount of household waste. What remains is referred to as residual (i.e. mixed) household waste.

My research aims to investigate how municipalities can effectively utilize their autonomy in establishing waste management practices. There are essentially three main “tools” municipalities have at their disposal to reduce residual waste and enhance the separation of recyclables: waste taxes, different ways of collecting household waste, and the frequency of collecting. The specific details of these approaches and their implementation will be discussed further.

Starting with waste taxes. Household waste collection and processing is very costly. To cover those costs, municipalities impose a tax, known as the *afvalstoffenheffing*. In 2023, on average 96.5% of the costs involved in waste management were covered by the proceedings from the *afvalstoffenheffing* (Rijkswaterstaat, 2024). Historically most municipalities impose a tax based on household size. But an increasing number of municipalities implement a tax based on the amount of residual waste households generate, a system known as Diftar (Milieu Centraal, n.d.). It is equivalent to what is commonly referred to throughout the literature as unit-based pricing. Accordingly, I will adopt this term as well. The Netherlands knows four different unit-based pricing (UBP) systems. Either volume-, weight-, frequency-, or bag-based. Combinations also exist. In 2023, more than half (55%) of Dutch municipalities had implemented a UBP system (Rijkswaterstaat, 2024). Slightly less than half (42%) still used the traditional system based on household size, and the remainder used a fixed rate (3%). For a graphical representation see Figure 1.1.

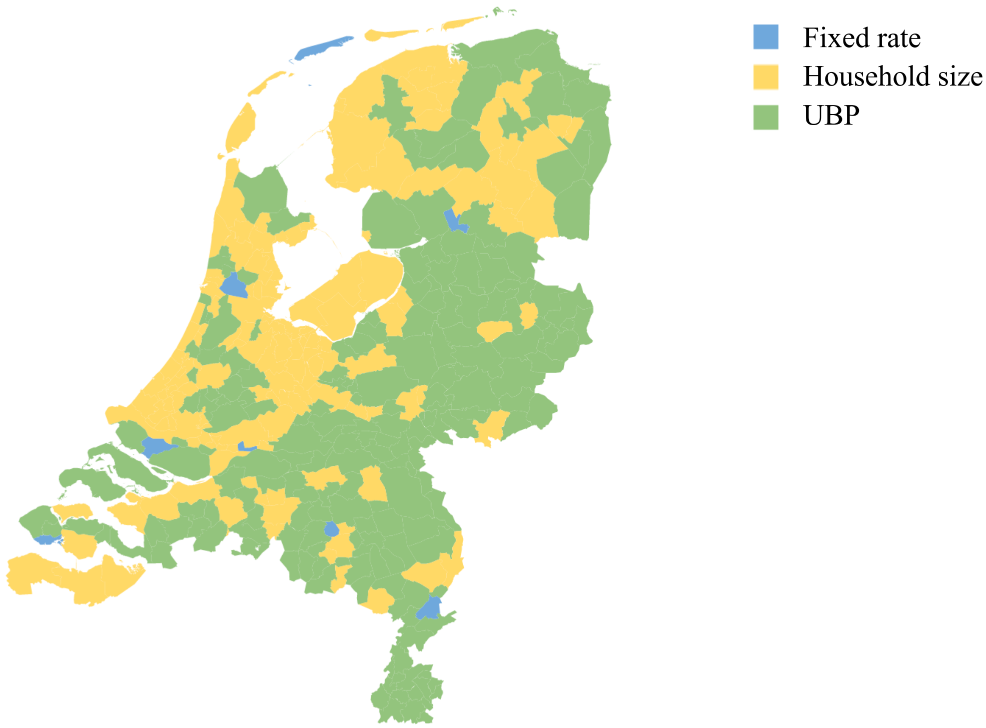



*Figure 1.1 Waste pricing systems per municipality 2023*
*Source: Afvalmonitor Rijkswaterstaat*

Most studies on the effects of implementing UBP have been conducted in the United States. However, two well-known studies have focused on The Netherlands (Dijkgraaf & Gradus, 2004; Allers & Houben, 2009). This paper builds upon the work of Dijkgraaf and Gradus but also takes a different direction. First, my dataset contains more recent and more years of data. Second, the authors note that it would be ideal to use municipality fixed effects but due to very little within variation in the pricing system, they are not able to do so. Alternatively, they include province fixed effects. Conversely, because my data covers an extended time period, I am able to include fixed effects at the municipality level. And most importantly, rather than only estimating the effect on the amount of waste I also estimate the effect on the separation rate. Additionally, while Allers and Hoeben studied the marginal price effect of UBP, my research examines the impact of different pricing systems themselves, without focusing on the price per kilogram or liter. We both include municipality and year fixed effects to control for endogeneity. In addition, I assess the robustness of my results to the use of a different statistical approach using the synthetic control method. To the best of my knowledge, this paper is the first to study the effect of UBP applying the synthetic control method. Moreover, I collected municipality-level data on pricing systems for all municipalities in The Netherlands for a 17-year period (longer than any previous study). It is very interesting to see whether my results align with those found by Dijkgraaf and Gradus, as well as Allers and Houben.

Moving on to another tool municipalities have at their disposal: The collection method. This refers to the way municipalities collect waste or, almost equivalently, the way households dispose of their waste. There are basically two methods: Either municipalities collect the waste from households directly, or households must bring their waste to a collective drop-off point. Multiple studies have researched the potential impact these two methods can have on waste quantities and recycling rates (e.g. Dahlén et al., 2007; Larsen et al., 2010). This paper adds to the existing literature in three ways. First, no study on the collection method for household waste has previously been conducted in The Netherlands. Second, to the best of my knowledge, this paper is the first to distinguish between high-rise and low-rise neighborhoods, proving to be very crucial as will become clear later on. And third, the wide data availability makes this paper unique.

In The Netherlands, the two collection methods take on the following form. Under the "collect" method, households usually present their waste at the curbside in either a trash bag or wheelie bin; this is also called door-to-door collection. For the "bring" method, households have to throw away their waste in underground waste containers (UWCs), which are emptied on a regular basis by either the municipality itself or a contracted firm. In this research, the focus lies on the collection method for residual household waste. A key driver that makes municipalities choose between either a bring- or collect method is the appearance of high-rise buildings (e.g. flats) in a particular neighborhood. I explain this in more detail in the Data chapter. Figure 1.2 shows two maps with the employed collection method for every municipality in neighborhoods with predominantly high- or low-rise buildings, respectively. We can clearly see that there is a relationship between neighborhood building characteristics and the collection method.

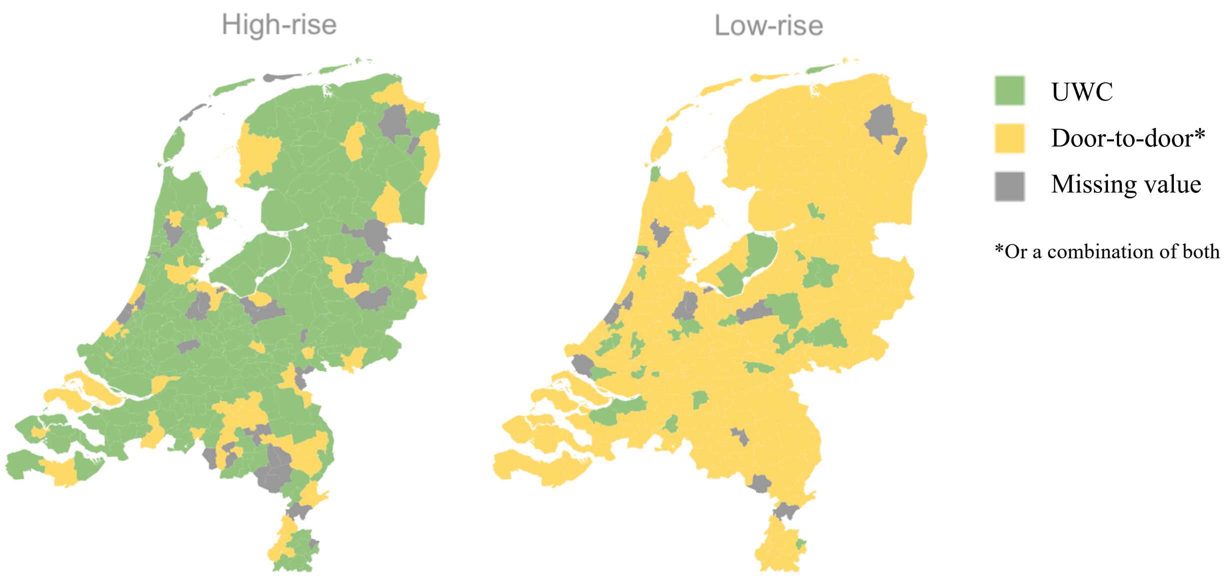



*Figure 1.2 Collection method per municipality 2023*
*Source: Afvalmonitor Rijkswaterstaat*

Lastly, the frequency of collecting residual household waste is examined. Most literature on waste management looks at the municipality side rather than considering the role and behaviors of residents in waste collection. The focus of this paper lies on the latter. As a result, the frequency of collecting is solely examined when residual waste is collected at the curbside. I do not analyze the frequency of emptying UWCs. Municipalities collect household waste either weekly, bi-weekly (i.e. every other week), every three weeks or every four weeks (i.e. monthly). Previous research only looked at weekly versus bi-weekly collecting. Instead, I also examine collecting every three and four weeks. This paper contributes to the limited existing literature by studying the effects of curbside collection frequency in Dutch municipalities. It builds upon the work of Williams and Cole (2013) by analyzing a broader scope and employing a more advanced statistical method.

The remainder of this paper is structured as follows. The next section illustrates the theoretical background and formulates my hypotheses, succeeded by the sections on data and methodology. Thereafter, the empirical results are presented, and conclusions are drawn. Finally, in the last section, I discuss the limitations of my study and provide recommendations for further research.

# Chapter 2. Theoretical Framework

Municipal waste management has been extensively researched throughout the literature, predominantly in the field of Urban Economics and Environmental Economics. The residential waste management cycle involves three central stages and corresponding actors. First, households collect and dispose of the waste they generate. Second, municipalities are responsible for collecting all that waste. Finally, the waste is processed at large disposal sites, which are mostly operated by private firms and regulated by the government. This paper focuses on the role of households in the waste management cycle, particularly examining the effect of different waste management practices implemented by Dutch municipalities.

Continuing, this chapter provides an overview of the existing literature on waste management practices and discusses the main findings. I start by exploring the literature on unit-based pricing followed by an overview of the literature on various waste collection systems. Thereafter, I provide an overview of a less-researched aspect of waste management: the frequency of collecting household waste. Besides these, there are other factors influencing household waste quantities and waste separation rates, primarily socio-economic and demographic municipal characteristics. Accordingly, I explore the literature analyzing these factors which could potentially impact my outcomes. Finally, I present the main empirical results from the literature focused on the cost side of municipal waste management, adding to the economic relevance of my study by providing valuable insights to municipalities and local governments.

## 2.1 Pricing systems and waste

Traditionally, households paid a waste tax, which was either fixed or based on household size. Yet, to incentivize households to recycle more, unit-based pricing was established. In essence, this means that households pay a marginal amount for every additional unit of waste they generate. There are four common types of UBP systems within the waste management sector: bag-based, weight-based, volume-based, and frequency-based.

The systems vary in their respective marginality (Dijkgraaf & Gradus, 2004). Below, I will discuss them in order from least to greatest degree of marginality.

The volume-based system allows households to choose between wheelie bins with different volumes. The standard bin has a volume of 140 liters, but smaller and larger options are available. Households have the option to choose different-sized bins for each waste stream. At the beginning of the contract period, households select their preferred bin size, typically with the option to switch annually. Households are charged for the size of the bin regardless of actual waste quantities (Allers & Houben, 2009).

A more refined form of marginal pricing is the frequency-based system. Households pay for the number of times they present their wheelie bin at the curbside. Similar to the volume-based system the waste tax is independent of the actual amount of waste. Whether the bin is partially filled or completely full, the bill households receive is solely based on the number of times the bin is presented. Note that under the frequency-based system, and less so under the volume-based system, households have a monetary incentive to fill the wheelie bin to its absolute limit, potentially causing issues when emptying because of waste being stuck.

Next, we have the bag-based system. Households have to buy a relatively expensive garbage bag. Each municipality that employs this form of UBP has its own special bag and other bags are not collected. In The Netherlands, the volume of the bag is typically 50 liters. The bag-based system is more refined compared to the frequency-based system, as the volume is significantly smaller. Moreover, the bag cannot be filled to the limit because it might burst.

The most refined marginal pricing system is the weight-based one. The collection vehicle weighs the bin each time it is collected, prompting the household to pay for every additional kilogram of waste it generates.

Two streams of literature can be identified analyzing the effects of unit-based pricing systems on household behavior (Dijkgraaf and Gradus, 2004). One conducts cross-sectional research at the municipality level, whereas the other uses survey data at the household level. Most studies on unit-based pricing analyze the effect of only one pricing system on its own and have a strong focus on bag- and volume-based systems. For example, Strathman et al. (1995), Van Houtven and Morris (1999), Wertz (1976), and Jenkins (1993) all studied the effect of a volume-based system. The effect of a bag-based system has been researched in several studies, including Reschovsky and Stone (1994), Fullerton and Kinnaman (1996), Hong (1999), Kinnaman and Fullerton (1997), Podolsky and Spiegel (1998), and Kinnaman and Fullerton (2000). In addition, Lindelof et al. (2001) is one of the few papers to explore the effects of a weight-based system. Most noticeable is that a direct comparison between unit-based pricing systems is limited to Van Houtven and Morris (1999), who compare bag- and volume-based systems.

It was not until Dijkgraaf and Gradus (2004) that the effects of the four most common unit-based pricing systems were estimated. They examined the effect on household waste collected in Dutch municipalities by estimating a panel model including regional and time fixed effects. Their results show that unit-based pricing is effective in reducing household waste, but large disparities arise between systems. Dijkgraaf and Gradus find that the bag- and weight-based systems show comparable results, which are significantly larger than those of the frequency- and volume-based systems.

In a study comparing six municipalities in southern Sweden, weight-based billing was found to have a significant impact, reducing the amount of residual waste per capita by 50% (Dahlén et al., 2007). Dahlén and Lagerkvist (2010), build on the former research, expanding the scope to include 264 out of all 290 Swedish municipalities. Their research, which compared household waste per capita in the 26 municipalities using weight-based pricing to all other municipalities, revealed a 20% reduction in household waste per capita. Similar to the research conducted in this paper Usui and Takeuchi (2013) use panel data for 665 Japanese cities over eight years. The main goal of their research is to investigate whether the observed effect of unit-based pricing on waste generation and recycling in existing literature remains consistent in the long term. Results show that there is a rebound effect, though a small one.

Perhaps the closest related paper to this one is that of Allers and Hoeben (2009). Their dataset contains information about household waste and recycling rates of all 458 municipalities in The Netherlands across ten years (1997-2006). An instrumental variable (IV) regression and a differences-in-differences (DiD) model are applied to estimate the effect of unit-based pricing on waste quantities and recycling. Allers and Hoeben look at unsorted waste and biodegradable waste. Results show that implementing unit-based pricing reduces the amount of unsorted waste by 24% and biodegradable waste by 46%. For both waste streams, a weight-based system is found to have the largest impact.

Summarizing the literature, I find consistent evidence across multiple studies indicating that the implementation of a unit-based pricing system, compared to, for example, a fixed rate or billing according to household size (i.e., no unit-based pricing), leads to a decrease in household waste quantities. The magnitude of this effect varies between different systems. More recently research has started analyzing the impact of unit-based pricing not only on waste quantities but also on separation rates (Allers & Houben, 2009; Usui & Takeuchi, 2013). The results indicate that unit-based pricing positively impacts separation rates. Therefore, based on these findings, I propose the following hypotheses:

*Hypotheses 1a: Unit-based pricing leads to lower household residual waste quantities, compared to no unit-based pricing.*

And

*Hypothesis 1b: Unit-based pricing leads to a higher separation rate for household waste, compared to no unit-based pricing.*

## 2.2 Collection methods and waste

According to Barrett and Lawlor (1995), there are two main approaches to recycling: “bring” and “collect”. The bring system involves households taking their recyclable waste to a nearby drop-off point. With the collect system, recyclables are collected at the curbside by firms employed by the municipality, who transport the recyclables to a materials recovery facility.

In The Netherlands municipalities can choose whether they collect household waste at the curbside or oblige residents to bring their collected waste to collective (underground) waste containers. Dahlén et al. (2007) studied the effect of curbside collecting compared to drop-off systems in six municipalities in southern Sweden and found that curbside collection has a positive effect on waste separation. In municipalities where recyclables are collected at the curbside, the amount of separately collected recyclables was almost double that of municipalities with drop-off systems. Research done in the municipality of Aarhus (Denmark) investigated the environmental and economic impact of different collection systems for recyclables (Larsen et al., 2010). Results pointed out that curbside collection leads to the highest recycling rates and highest environmental benefits, but a bring system with drop-off containers proved to be a solid alternative. Post-separation of recyclables would lead to a decrease in the overall recycling rate, causing negative environmental impact. Beatty et al. (2007) study the effects of expanding curbside collection throughout California utilizing panel data from 1995-2000. Results are ambiguous, increasing the access to curbside collection has a positive and significant impact on amounts recycled for all materials examined (aluminum, glass, and plastic) at the curb but this effect only holds for plastic when looking at total recycled quantities. A possible explanation given by the authors is that the incremental quantities recycled at the curb previously got recycled at recycling centers. Hinting towards some preliminary evidence that curbside collection may serve as a substitute for recycling centers.

Gallardo et al. (2010) analyzed four different collection systems. By means of a survey Gallardo et al. (2010) found that in Spanish cities with a population greater than 50,000 inhabitants, four systems for collecting household waste are used. In addition to most studies that only focus on quantities they also considered the quality of the recovered materials. Upon comparing the results for the different collection systems, the authors found that a system collecting residual waste and organic waste at the curbside, while glass, paper, and packaging have to be brought to a drop-off point, grants the most favorable results. Following Gallardo et al. (2010), Gallardo et al. (2012) shifted their focus toward Spanish towns with a population between 5000 and 50,000 inhabitants. Furthermore, they added four additional waste collection systems. Apart from the curbside collection done in bins, they also considered door-to-door collection, where residents put their garbage bags outside of their homes at the curbside. Contrary to Gallardo et al. (2010), Gallardo et al. (2012) solely examine waste quantities. Results showed that a waste collection system where residual, organic, paper, and packaging are collected door-to-door, while glass has to be brought to a drop-off point is most beneficial in limiting the amount of waste incorrectly disposed of and maximizing the separation rate.

Note that curbside and door-to-door collection essentially refer to the same concept, both categorized as the “collect” method. Similarly, drop-off points or collective (underground) waste containers both belong to the “bring” method. Throughout the literature most commonly the terms curbside and drop-off point are used; I will adopt these terms accordingly. The aforementioned studies consistently report a negative relationship between curbside collection and waste quantities. Moreover, curbside collection is shown to have a positive effect on waste separation. Accordingly, the second hypothesis is formulated as follows:

*Hypotheses 2a: Curbside collection leads to lower household residual waste quantities, compared to the situation where waste must be brought to a drop-off point.*

And

*Hypothesis 2b: Curbside collection leads to a higher separation rate, compared to the situation where waste must be brought to a drop-off point.*

## 2.3 Frequency of collecting waste

Little research has focused on the effects of the collection frequency on household residual waste and separation rates. Local governments introduce bi-weekly collection of residual and recyclable waste to incentivize households to recycle (Williams & Cole, 2013). Empirical results from the seminal work of Wertz (1976) showed that the frequency of collecting household waste could influence the amounts collected. Later work highlights an increase in recovery rates when the collection frequency of recyclables is increased (Platt et al., 1991; Everett, 1993; Noehammer, 1997).

More recent work by Williams and Cole (2013) showed that a reduction in the collection frequency, from weekly to bi-weekly, positively impacted recycling rates. Two household waste collection trials were conducted between 2008-2009. During both trials, an increase in recycling quantities was observed compared to the same period in the previous year. To arrive at their results, the authors simply calculate the differences in recyclables collected (kg per household) between both the control and test periods. Moreover, the scope of their study was limited to four villages in the district of Lichfield (England). In an earlier study by Wilson and Williams (2007), the authors aim to evaluate the introduction of an alternate collection scheme for residual waste and recyclables. Results showed that alternate collection led to higher set-out rates compared to weekly collection, suggesting higher recycling rates.

Some key drivers of residual household waste and recycling were investigated in the Flemish region of Belgium (Gellynck et al., 2011). Using a logit model the authors estimate the probability of reaching the goal of 150 kg of residual household waste per capita. A dummy indicating whether residual household waste is either collected once a week or bi-weekly shows that collecting residual household waste bi-weekly increases the probability of reaching the 150 kg goal. Put differently, bi-weekly collection compared to weekly collection decreases residual household waste quantities.

As shown above, empirical results are mixed and forming a hypothesis following the literature is not straightforward. Earlier studies commonly suggest that an increase in the collection frequency leads to a greater amount of recyclables collected, whereas more recent research indicates the opposite. I opt to follow the thinking of Williams and Cole (2013) stating that: "residents are being coerced into recycling more because of the reduced collection frequency for residual waste" (p. 30). Accordingly, the third hypothesis reads:

*Hypothesis 3a: Reducing the frequency of collecting household residual waste leads to lower household residual waste quantities.*

And

*Hypothesis 3b: Reducing the frequency of collecting household residual waste leads to a higher separation rate.*

## 2.4 Characteristics of Municipalities

In this section, I provide an overview of the relevant literature regarding socio-economic and demographic characteristics that could potentially have an effect on my dependent variables (household waste quantities and the separation rate). These characteristics are to be controlled for in order to obtain valid estimations.

Beatty et al. (2007) conduct a fixed effect estimation to study the effect of expanding curbside collection on recycling quantities for aluminum, glass, and plastic brought to drop-off centers. They add population density, unemployment, and median family income as controls. Estimations show that population density has a positive and significant effect on the amount of plastic being collected at drop-off centers. Additionally, unemployment is found to have a negative and significant effect on both glass and plastic, while median family income only has a significant negative effect on plastic. Interpreting these results independently is not particularly meaningful. What does it mean that greater population density increases the amount of plastic collected? Does it suggest that households in densely populated areas use more plastic? Does it mean that in higher populated areas households separate their plastic from residual waste better? Or perhaps it simply reflects the overall increase in waste production in densely populated areas, including more plastic waste? To provide a more intuitive explanation I will look at the effects not only on total quantities collected but also on the separation rate. Nonetheless, the findings by Beatty et al. still hold relevance as they indicate municipal factors that I should control for.

Using household data from the city of Portland USA, Hong and Adams (1999) find among other things that income has a positive effect on recycling rates. Similar results were found by Usui and Takeuchi (2013). Moreover, the authors show that the estimated effects of unit-based pricing differ with income groups. Matsumoto (2011) provides us with an extensive overview of the existing literature that uses household-level data to analyze the effects of socio-demographic characteristics on recycling rates. According to the paper commonly examined characteristics include gender, age, education, and income. Throughout the literature, it is found that women are more likely to be involved in recycling activities than men. Additionally, income levels are positively related to recycling and evidence suggests that higher-educated individuals are more likely than less-educated individuals to recycle waste. Furthermore, according to the literature older people are more likely to recycle compared to young people.

To round up this section I analyze the two papers which are most closely related to my research as previously mentioned. Contrary to the literature discussed in the paragraph above, Dijkgraaf and Gradus (2004) find no effect of income on recyclables. They do however find a positive effect of income on total waste. Furthermore, estimations show that the amount of waste per capita increases as the percentage of inhabitants older than 65 increases. Contrary, a larger proportion of non-western foreigners decreases the amount of total waste but also decreases recycling rates. Family size is found to have a negative effect on total waste per capita whereas it has a positive effect on recycling quantities. Moreover, population density has a positive effect on total waste but no effect on recyclables. Finally, a noticeable result is that municipalities with many flats generate smaller amounts of compostable waste per capita, which is as to be expected. Allers and Hoeben (2009) investigate the effect of unit-based pricing on waste quantities and recycling for Dutch municipalities. They include both time and municipal fixed effects in their model. Naturally, they only include control variables that show sufficient variation over time. Besides including fixed effects, the authors control for population density, average household size, the share of ethnic minorities, the share of elderly, the share of children aged three or less, and the number of inhabitants. They are unable to control for income due to a lack of data availability but argue that income only changes gradually over time and is thus corrected for by including municipal fixed effects. Once again, both studies take recycling quantities as their dependent variable. But interpreting these results is not straightforward as I have shown before. On the contrary, my analysis extends beyond mere quantities, also examining the effects on the separation rate. Therewith, providing much more intuitive insights.

### 2.5 Cost side

Municipalities consider not only environmental factors but also the financial costs and benefits associated with specific waste collection methods and unit-based pricing systems. Whilst not separately investigated in this paper I provide an overview of the main findings from the existing literature on waste management practices and their associated costs. By doing so, I aim to provide a more comprehensive understanding of municipal waste management, which may be valuable to municipalities and local governments.

Greco et al. (2015) study the drivers of waste collection costs. Taking a sample of municipalities in Italy they investigate how different types of waste impact collection costs. Results show that for all types of waste, (1) the quantity of waste collected per resident and (2) the separation rate, both significantly affect the costs. Similar results are found by Callan and Thomas (2001), Bel and Fageda (2010), and Dijkgraaf and Gradus (2007). According to Stevens (1978) and Domberger et al. (1986), the amount of waste is the most important determinant of costs. This finding is later strengthened by Reeves and Barrow (2000) who showed that the number of units significantly affects the costs. Even if the authors include the number of units as the only explanatory variable the average estimated $R^2$ is 0.788 compared to 0.85 in the full model. Indicating that most of the variation in total costs can be explained by differences in total waste quantities.

Administrative costs for bag-based pricing systems are much lower than those for weight-based systems (Dijkgraaf & Gradus, 2004). Contrary to their expectations, Reeves and Barrow (2000) find that the use of wheel bins significantly increases collection costs. Throughout the literature, it is found that curbside collection is significantly cheaper compared to backyard collection (e.g. Hirsch, 1965; Stevens, 1978; Dubin and Navarro, 1988). A study conducted more recently by Larsen et al. (2010) showed that curbside collection, compared to four alternative collection systems, led to the most substantial net savings in municipal costs. Another aspect of recycling involves determining the benefits of source-separation versus post-separation. With source-separation, households separate recyclable waste like plastic, glass, and paper from residual waste before collection, whereas with post-separation mixed waste is separated at a treatment plant after collection (Groot et al., 2014). Source separation leads to higher recycling rates (Larsen et al., 2010), but also raises the costs of waste collection (Bošković et al., 2016). These results are in line with Groot et al. who examined all 418 Dutch municipalities in the year 2011. They find that on average the total collection costs for plastic waste are more than two times higher for source-separation compared to post-separation. Furthermore, big differences occur between curbside and drop-off collection within the source-separation system. Curbside collection is more than 2.5 times as expensive as drop-off collection. Consequently, municipalities must navigate a trade-off between environmental and economic consequences.

Empirical results from the seminal work by Hirsch (1965), Clark et al. (1973), and Stevens (1978) show that the frequency of collection significantly affects the costs of collection. Increasing the frequency of collecting from once a week to twice a week results in an increase in costs of more than 25%. Comparable results were found by Domberger et al. (1986) and Dubin and Navarro (1988). Moreover, Dubin and Navarro found that costs are reduced when household waste is collected at the curbside rather than back door. Consistently, Domberger et al. find that curbside collection compared to back door collection reduces total cost by 23%. In a later study analyzing a sample of 110 municipalities in Massachusetts USA, Callan and Thomas (2001) also found that a greater curbside collecting frequency is associated with higher costs. In greater detail, collecting waste more than once a week increases costs by 19% (Dijkgraaf & Gradus, 2003). In addition to the traditional research focusing on waste management costs, Callan and Thomas (2001) investigate the effect of providing joint disposal and recycling services. Results show a 5% reduction in total costs when municipalities offer joint services. More recently, Larsen et al. (2010) found that an increase in the recycling rate leads to a reduction in costs.

In summary, there is no doubt that the amount of waste is the key driver of municipal waste management costs. Moreover, the savings in disposal costs outweigh the increase in administrative costs associated with implementing a unit-based pricing system, particularly given the significant reduction in unsorted waste (Dijkgraaf & Gradus, 2004). Additionally, curbside collection is more costly than drop-off points, and increasing the frequency of collecting household waste leads to higher costs. Upon analyzing the results from this study, I will refer to these findings and discuss the practical implications also from a financial point of view.

# Chapter 3. Data

In this chapter, the data used in this study are discussed. The process of acquiring and transforming the data is explained, and further detail is given on the operationalization of the variables. In addition, descriptive statistics are provided.

### 3.1 Data collection

The panel dataset used in this paper originates from multiple sources. The first dataset is provided by Rijkswaterstaat. Rijkswaterstaat is part of the Ministry of Infrastructure and the Environment in The Netherlands. They are responsible for the management and development of all the national highways and waterways, and they commit to a sustainable environment. Moreover, Rijkswaterstaat manages and monitors the data on waste within The Netherlands. They analyze the data and report on the results. The government uses those reports for the evaluation and further development of waste policy (*Afvalcijfers*, n.d.). Rijkswaterstaat collects its data from the Dutch Central Bureau of Statistics (CBS), which sends out a survey to all Dutch municipalities on a yearly basis. The response rate to this survey varies between 90 and 95 percent. Part of the data was retrieved from a publicly available database called the afvalmonitor which roughly translates to waste monitor. This database contains a wide range of information on waste within The Netherlands at the country, provincial, and municipal level. Apart from the publicly available data, I gathered additional data by contacting Rijkswaterstaat directly. Upon request, I received additional years of data and more detailed information.

Secondly, data on socio-economic and demographic characteristics are obtained from the CBS. It consists of income, population density, unemployment, education, and many more relevant variables. The data is merged on municipality and year.

Data on the main explanatory variables vary in their availability across time. Data on unit-based pricing systems is available for the years 2006-2023, whereas data on the collection system and frequency is only available for 2018-2022. Furthermore, the dataset comprises 507 municipalities. This number exceeds the current total number of municipalities in The Netherlands (342) because, over time, some municipalities have separated or merged. The latter occurs more commonly. Data on the dependent variables, household residual waste quantities, and the separation rate are available for the years 2003-2022. Hence, all observations on unit-based pricing systems in 2023 are dropped. As a consequence, the municipality of Voorne aan Zee is excluded from the dataset, having been formed recently in 2023 through the merger of Brielle, Hellevoetsluis, and Westvoorne. Unfortunately, although not problematic, data on the dependent variables is limited to the 342 municipalities classified as such in 2023. Consequently, observations for all other 165 municipalities are redundant. This resulted in a total of 1487 (21,4%) dropped observations. For a list of all 341 municipalities studied, see Table A1 in Appendix A.

## 3.2 The relevant variables

This section provides an overview of all the variables used in this study. Regarding Table 3.1, these variables are obtained from the RWS database and are used to identify each observation.

The explanatory variables are presented in Table 3.2. The dummy UBP is created by categorizing the different waste billing systems into either unit-based pricing or no unit-based pricing. For an overview of the different pricing systems employed by Dutch municipalities, see Table 3.6 in the descriptive statistics section. In municipalities where billing is based on household size or a fixed rate, households are charged regardless of their actual waste quantities. Thus, under those systems, the costs to households of a marginal increase in garbage will be zero. These two systems are therefore not considered as true UBP systems.

*Table 3.1 Panel identifiers*

| Variable | Definition of Variable | Measurement level/values |
|---|---|---|
| year | The year in which the observation took place | Numeric |
| municipal_code | Corresponding municipal id | Panel id |
| municipal_name | 2023 municipal name | Panel id |

*Table 3.2 Independent variables*

| Variable | Definition of Variable | Measurement level/values |
|---|---|---|
| UBP | Presence of unit-based pricing system | Dummy:<br>UBP (1), no UBP (0) |
| system_id | id number corresponding to different pricing systems | Categorical |
| frequency_lowrise | Collection frequency in neighborhoods with mostly low-rise buildings | Categorical |
| frequency_highrise | Collection frequency in neighborhoods with mostly high-rise buildings | Categorical |
| method_lowrise | Collection method in neighborhoods with mostly low-rise buildings | Categorical |
| method_highrise | Collection method in neighborhoods with mostly high-rise buildings | Categorical |

Table 3.3 presents the dependent variables. RWS splits household waste, into three subcategories:

1. Total household waste
2. Small residual household waste
3. Bulky residual household waste

This study focuses on small (i.e. ordinary) residual household waste. Small residual household waste refers to mixed waste in the ordinary waste bin or garbage bag, i.e., the waste left when households have handled any recyclables separately (Dahlén et al., 2007). I focus on this type of residual household waste for two main reasons. First, municipalities are mainly concerned with lowering the amount of household residual waste and show less concern about the total amount of household waste. Secondly, bulky waste refers to waste that does not fit in a garbage bag, wheelie bin, or UWC. It has to be brought to an environmental park or if you are unable to do so, you can make an appointment with your municipality to come pick it up. Moreover, my variables of interest (and hence my hypotheses), are all centered around small household waste. Data on household waste are unlikely to contain many measurement errors, because municipalities, which supply this information to CBS, pay waste treatment companies according to the weight of their garbage (Allers & Houben, 2009). Additionally, I am interested in the effects on the separation rate, measured as the ratio between source-separated small household waste and total small household waste.

*Table 3.3 Dependent variables*

| Variable | Definition of Variable | Measurement level/values |
|---|---|---|
| residualwaste | Average total amount of residual household waste in kg per resident | Numerical |
| separationrate | Percentage of total household waste collected separately from residual waste | Numerical (0 to 100) |

To obtain valid estimations, I must control for any characteristics that could potentially affect my dependent variables. These control variables are listed in Table 3.4. The variables are chosen based on past research discussed in Chapter 2. Except for population, which was obtained from RWS, all socio-economic and demographic characteristics are retrieved from CBS.

Two datasets are combined to obtain unemployment data for all years under study. The first dataset contains unemployment numbers for the year 2006 and uses the 2019 regional division of municipalities. The second dataset provides unemployment numbers for the years 2007-2022, using the 2023 regional division of municipalities. To integrate both datasets into my main database, I checked for inconsistencies and noted that between 2019 and 2023, four new municipalities were formed as a result of reclassifying 11 existing ones. To account for these changes, I calculated the weighted average of the unemployment rate based on population size for the merged municipalities. For more detail, see Table A2 in Appendix A. The same procedure was followed for the variable higher_edu, as details were also split between two databases: one for the years 2006-2012 and another for 2013-2022, using the 2019 and 2023 regional divisions, respectively. Likewise, data on household income is split between two datasets. The first dataset provides data for the years 2006-2010, and the second for 2011-2022. Even greater inconsistencies were found between these datasets, as the former uses the 2014 regional division of municipalities, and the latter uses the 2023 division. Between 2014 and 2023, a total of 80 municipalities merged, forming 24 new ones. An overview of this reclassification is provided in Table A3 in Appendix A.

Data for all other controls are retrieved directly from one single CBS database, which includes information on regional key figures combining 50 CBS statistics. These figures are available at five geographical levels, ranging from national to municipal. Additionally, two new variables are created by converting the absolute numbers of non-Western immigrants and women into relative values.

*Table 3.4 Control variables*

| Variable | Definition of Variable | Measurement level/values |
|---|---|---|
| population | Number of inhabitants | Numerical |
| pop_dens | Number of inhabitants per km2 | Numerical |
| householdsize | Average household size | Numerical |
| income | Average household disposable income (in thousand EUR) | Numerical |
| unemployment | Share of unemployed inhabitants | Numerical (0 to 100) |
| higher_edu | Share of the population that successfully completed higher education (hbo or wo) | Numerical (0 to 100) |
| women | Share of the population that is a woman | Numerical (0 to 100) |
| preschoolage | Percentage of the total population aged 0 to 4 | Numerical (0 to 100) |
| groenedruk | The ratio between the number of people aged 0 to 20 compared to the number of people aged 20 to 64 years | Numerical (0 to 100) |
| grijzedruk | The ratio between the number of people aged 65 or older compared to the number of people aged 20 to 64 years | Numerical (0 to 100) |
| non_w | Share of inhabitants with a non-Western migration background | Numerical (0 to 100) |

## 3.3 Descriptive statistics

In this section, an overview of the data is presented. Further modifications and cleansing are done to the original dataset to reduce errors and allow for more intuitive interpretations. First, the variables which will not be used in the regression of this study are deleted. Second, after merging the data, I checked for any discrepancies where the name of a municipality was linked to more than one municipal number and vice versa. This included typos, such as 'De Bilt' and 'DeBilt,' both having municipal number 310. Conversely, there were instances where 'Dantumadiel' had municipal number 65 for certain years and 1891 for others, despite being the same municipality. Additionally, data for low- and high-rise neighborhoods is being transformed, creating two separate variables for the collection method and the collection frequency. For this process, see Table D1 in Appendix D.

Furthermore, if any variable had missing or physically impossible values, these were dropped from the dataset. Remarkably, only two physically impossible values – likely attributable to measurement error – were found across all variables. The first one had a residual waste amount of zero, while in all other years for the same municipality, the amount ranged from 111 to 225. The second had a separation rate of 1, while in all other years for the same municipality, the rate varied between 0.41 and 0.58. To ensure the robustness of the models, all observations with missing or physically impossible values were dropped from the database. This resulted in a total of 336 (6,1%) dropped observations. As a result, no observations were left for the municipalities of Maashorst and Schiermonnikoog. The final dataset comprises details on 339 municipalities across 17 years, resulting in a total of 5135 municipal-year observations. This shows that the panel dataset is unbalanced. Descriptive statistics on how the panel dataset looks can be found in Table B1 in Appendix B.

Now, as one can see in Table 3.5, large differences arise between municipalities on residual waste quantities and the separation rate. Figures C1 and C2 in Appendix C show the trends for the average residual waste quantities and separation rate respectively. I directly observe that the quantity of household residual waste has decreased over the period 2006-2022, while conversely, the separation rate has increased. Furthermore, one municipality-year observation has a missing value for the separation rate. Nevertheless, this observation is retained because it still contributes to my estimations on residual waste quantities and appears to be no outlier.

Regarding Table 3.6, a complete overview is presented of the different pricing systems' categories. Over the period under study, there are a total of 2,168 municipality-year observations with a form of UBP and 2,954 without. The trend shows that in 2006, 33.57% of municipalities had implemented UBP, increasing to 55.84% by 2022. The most popular form of UBP is the system which is based on the volume & frequency of collecting. However, the predominant pricing system remains non-UBP and is determined by household size. Municipalities vary in the way they measure household size, with some billing based on the actual number of people and others distinguishing between single or multi-person households. However, this level of detail falls outside the scope of this study. Another notable fact is that over the period 2006-2022, not one municipality implemented a pricing system solely based on the frequency of collecting.

*Table 3.5 Descriptive statistics dependent variables*

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| residualwaste | 5,135 | 178.81 | 67.47 | 5 | 663 |
| separationrate | 5,134 | 54.45 | 14.53 | 9 | 98 |

*Table 3.6 Pricing systems*

| Variable | UBP | Categories | Freq. | Percent |
|---|---|---|---|---|
| system | Yes | Expensive garbage bag | 206 | 4.02 |
| | | Expensive garbage bag & number of people | 105 | 2.05 |
| | | Volume | 353 | 6.89 |
| | | Volume & frequency | 1,142 | 22.30 |
| | | Volume, frequency & number of people | 148 | 2.89 |
| | | Weight | 112 | 2.19 |
| | | Weight & frequency | 92 | 1.80 |
| | | Weight & number of people | 9 | 0.18 |
| | | Other | 1 | 0.02 |
| | No | Fixed rate | 358 | 6.99 |
| | | Number of people | 2,595 | 50.66 |
| | | No fee | 1 | 0.02 |
| | | Total | 5,122 | 100.00 |

Continuing, Table 3.7 summarizes the different collection frequencies and methods. As shown in Figure 1.2 in the introductory chapter, municipalities seem to have endogenous reasons for choosing their collection method. Accordingly, separate analyses are conducted for neighborhoods with predominantly low-rise buildings and neighborhoods with predominantly high-rise buildings. This approach strengthens the robustness of my estimations, as it accounts for endogenous factors influencing the choice of the collection method. Focusing on the collecting frequencies I notice that there are relatively few observations for neighborhoods with mostly high-rise buildings. This is unsurprising, as collection frequencies matter only when residual waste is collected directly from households, i.e. curbside collection. Upon examination of the collection methods, it becomes clear that curbside collection (door-to-door) is most common in neighborhoods with predominantly low-rise buildings, while the use of UWCs is popular in neighborhoods with predominantly high-rise buildings. Furthermore, we observe that the collection of residual waste is primarily done bi-weekly or every four weeks.

*Table 3.7 Residual waste collection frequencies & methods*

| Variable | Categories | Freq. | Percent |
|---|---|---|---|
| frequency_lowrise | Weekly | 49 | 4.40 |
| | Bi-weekly | 551 | 49.51 |
| | Every three weeks | 89 | 8.00 |
| | Every four weeks | 424 | 38.10 |
| | Total | 1,113 | 100.00 |
| frequency_highrise | Weekly | 56 | 33.14 |
| | Bi-weekly | 67 | 39.64 |
| | Every three weeks | 7 | 4.14 |
| | Every four weeks | 39 | 23.08 |
| | Total | 169 | 100.00 |
| method_lowrise | UWC | 131 | 8.58 |
| | door-to-door | 1,113 | 72.89 |
| | door-to-door and UWC | 283 | 18.53 |
| | Total | 1,527 | 100.00 |
| method_highrise | UWC | 1,120 | 74.22 |
| | door-to-door | 169 | 11.20 |
| | door-to-door and UWC | 220 | 14.58 |
| | Total | 1,509 | 100.00 |

Finally, descriptive statistics regarding the controls used are presented in Table 3.8. At first, the minimum value of zero for higher_edu seemed like a measurement error. However, upon closer examination, I discovered that this value appears eight times in my dataset. These occurrences are split equally between two municipalities: Rozendaal and Vlieland. The latter is an island, and both have very small populations (fewer than 1,600 inhabitants). Therefore, I conclude that these are all valid observations.

*Table 3.8 Descriptive statistics control variables*

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| population | 5,135 | 49341.42 | 73413.49 | 1105 | 882633 |
| pop_dens | 5,135 | 909.94 | 1032.19 | 31 | 6712 |
| householdsize | 5,135 | 2.31 | 0.20 | 1.64 | 3.54 |
| income | 5,135 | 42.42 | 8.30 | 25.7 | 109.5 |
| unemployment | 5,135 | 4.86 | 1.60 | 2.5 | 13.5 |
| higher_edu | 5,135 | 25.47 | 7.65 | 0 | 56.9 |
| women | 5,135 | 50.33 | 0.79 | 46.52 | 53.47 |
| preschoolage | 5,135 | 5.17 | 0.92 | 2.7 | 10.7 |
| groenedruk | 5,135 | 40.04 | 5.32 | 22.2 | 80.7 |
| grijzedruk | 5,135 | 32.49 | 8.16 | 11.4 | 67.8 |
| non_w | 5,135 | 6.71 | 5.79 | 0.76 | 39.63 |

# Chapter 4. Methodology

In this chapter, the empirical method used for my research is introduced, and its corresponding assumptions and limitations are addressed.

### 4.1 Fixed effects model

My dataset contains information on numerous variables for all municipalities in The Netherlands across multiple years. While a difference-in-differences (DiD) model is the preferred statistical method to estimate a causal effect when working with panel data, this is not feasible for the hypotheses I am trying to answer, due to the nature of my dataset. As a result, I choose the second-best option and follow the works of Allers and Houben (2009), Dijkgraaf and Gradus (2004), and Beatty et al. (2007) by employing a fixed effects (FE) regression to estimate the impact of municipal waste management practices on household residual waste quantities and the separation rate.

Fixed effects – a within-effects estimator – is preferred over a random effects (RE) model, because a within-effects estimator accounts for unit heterogeneity. It only uses within-variation and as a result, drops all time-invariant variables from the model. It is thus important to assess whether my main variables of interest show enough within variation. This can partially be done by looking at some descriptive statistics specific to panel data. The corresponding tables are presented in Appendix F.

Most important is the "Within Percent" column which gives us a good indication of the within variation of our variables. As an example, we can look at the first row of Table F2, the within percent of 36.34 means that if a municipality ever used pricing system "1" it has used this method 36.34 percent of the time. Moreover, the total within percent is the normalized between weighted average of the within percents. In the case of a time-invariant variable, the total within percent would be 100.00. Given the within percents of my variables of interest I conclude that there is enough within variation to conduct an FE regression.

Even though the FE estimation is possible, a correlated random effects (CRE) regression and a Hausman test should be conducted when choosing between FE and RE. These tests tell us how likely it is that the unobserved heterogeneity is uncorrelated with my variable of interest. If likely, then it is better to use RE since it uses both between and within variation and is therefore more efficient. Results are presented in Appendix E. I reject the null hypothesis for the CRE test meaning that at least one component of the time-variant averages influences the outcome, therefore it is likely that other unobserved components matter. Additionally, rejecting the null hypothesis for the Hausman test indicates a systematic difference between the FE and RE coefficients. This suggests that unobserved heterogeneity likely influences the outcome. Therefore, based on the results of both tests, it is expected that unobserved heterogeneity is correlated with my variable of interest, making the FE model the most appropriate choice in this setting.

The general model has the following form:

$$(1)\ y = \beta_k X_{k,m,t} + \gamma Z_{m,t} + \delta_m + \delta_t + \varepsilon_{m,t}$$

Where y is our dependent variable. Our coefficient of interest $\beta_k$ represents the coefficient for each independent variable's category k. $X_{k,m,t}$ is a dummy variable indicating the presence of category k in municipality m at time t, taking the value 1 if the category is present and 0 otherwise. $\gamma$ represents the coefficient for the control variables and $Z_{m,t}$ is the set of control variables for municipality m at time t. $\delta_m$ and $\delta_t$ are municipality and year fixed effects, respectively. And $\varepsilon_{m,t}$ represents the idiosyncratic error. Standard errors will be clustered at the municipality level, allowing for the correlation of error terms between observations within the same municipality. The inclusion of municipality and year fixed effects controls for time-invariant differences in outcomes between municipalities, as well as any time-variant shocks at the municipality level.

The fixed effects model has one significant limitation, namely the fact that the idiosyncratic shock ($\varepsilon_{m,t}$) must be uncorrelated with my variables of interest for the estimations to be unbiased. There is no statistical method to test this and can thus only be assumed. To decrease the risk of endogeneity, time-variant control variables are included, though we can never be 100% sure that there is no endogeneity bias left.

### 4.2 Econometric issues

This section addresses further econometric issues that might arise with the chosen statistical method. First, there can be no perfect collinearity, meaning that: (1) none of the independent variables is constant, and (2) there are no exact linear relationships between explanatory variables. Collinearity causes the estimated standard errors to be wrong, and the model less precise. I follow a commonly used rule of thumb which states that if the absolute value of the correlation between two independent variables is 0.8 or higher, this is often considered a sign of problematic collinearity. Table F7 in Appendix F contains the pairwise correlations between the variables. There is one correlation coefficient greater than 0.8, namely between householdsize and groenedruk (0.816). This is unsurprising because a higher average household size implies more children on average per household, which in turn implies a higher ratio between the number of people aged 0 to 20 compared to the number of people aged 20 to 64 years, referred to as "groene druk". Luckily, these are control variables, and I can simply drop one from my model to solve potential problematic collinearity issues. I choose to drop groenedruk because it also has a relatively high correlation with preschoolage (0.700), whereas the second highest pairwise correlation for householdsize is 0.546. The new pairwise correlations can be found in Table F8 in Appendix F. Moreover, the correlation between UBP and system_id is very high (-0.967). This is unsurprising because the former is a transformation of the latter. Fortunately, this leads to no collinearity issues because both independent variables are not included in the same model simultaneously.

There is also the concern that the data may not follow a normal distribution or have outliers, which can interfere with the statistical robustness of the model. In this study, I am particularly concerned that my dependent variables may not follow a normal distribution. For histograms of both my dependent variables, see Figures F9 and F10 in Appendix F. According to these figures, both the amount of residual waste (kg/capita) and the separation rate are approximately normally distributed.

Finally, there is the concern of endogeneity. There are three main sources of endogeneity: omitted variable bias, reverse causality and measurement error. For this study, omitted variable bias is of most concern. One of my explanatory variables could be correlated with the error term. By including municipality fixed effects, I control for the potential effects of any time-invariant omitted variable. Additionally, including year fixed effects helps control for time-variant factors that are common across all municipalities. Nevertheless, the fixed effects cannot address biases caused by omitted variables that vary over time within municipalities. Accordingly, important factors that vary over time within municipalities are controlled for, further mitigating potential bias. Besides, it could be that municipalities that experience higher amounts of waste per capita, implement UBP, with the aim of reducing the amounts. This creates a scenario where reverse causality could occur. In reality, municipalities do indeed implement UBP in the hope of reducing the amount of residual household waste. After UBP is implemented, any decrease in waste quantities can generally be attributed to the policy, assuming no significant external factors are influencing waste generation. Leading to the conclusion that bias due to reverse causality does not play a significant role in this study. One solution to tackle both endogeneity concerns would be an instrumental variable (IV), but for this study a strong and valid IV is absent. Lastly, because the data is collected from several sources and not by me, it is difficult to check for measurement errors. However, as discussed before it is very unlikely for the data to contain many measurement errors.

# Chapter 5. Results

In this chapter, the results of the statistical test for my three hypotheses are presented. Additionally, the results are interpreted, discussed, and contextualized. In my discussion of the estimation results, I only consider the fixed-effect estimates. Standard errors are robust to heteroskedasticity and clustered by municipality. Moreover, the results are robust to removing outliers.

## 5.1 Fixed effects estimations

As discussed in section 4.1, the hypotheses are tested by employing the fixed effects (FE) model. I start by testing Hypotheses 1a and 1b, the former stating that unit-based pricing leads to lower household residual waste quantities, compared to no unit-based pricing. And the latter states that unit-based pricing leads to a higher separation rate for household waste, compared to no unit-based pricing. From the regression results in Table 5.1, it can be observed that the dummy UBP has a negative and significant coefficient in the first model. The coefficient shows that, on average, municipalities that employ any form of unit-based pricing generate 53.71 kilograms less residual waste per capita, compared to municipalities that do not have a UBP system. The effect is significant at the 1% level ($F(1,338) = 143.45$, $p < 0.01$). Thus, I cannot reject hypothesis 1a, suggesting that unit-based pricing indeed leads to lower household residual waste quantities, compared to no unit-based pricing. To put the coefficient in context, the mean amount of household residual waste across the period under study is 178.81 kg per capita. Implementing a UBP system can thus lead to a significant reduction in household residual waste, cutting quantities by 30%. This result is slightly larger than previously found in studies (Dahlen & Lager, 2010; Allers & Houben, 2009), which reported effects of 20% and 24%, respectively. One reason could be that people are becoming more environmentally aware each year, intrinsically wanting to reduce the waste they generate and improve the separation of recyclables.

Moving on to hypothesis 1b. From the regression results in Table 5.1, it can be observed that the dummy UBP has a positive and significant coefficient in the second model. The coefficient shows that, on average, employing any form of unit-based pricing increases the separation rate by 9.63 percentage points, compared to municipalities that do not employ a UBP system. The effect is significant at the 1% level ($F(1,338) = 92.97$, $p < 0.01$). Hence, I cannot reject hypothesis 1b, suggesting that unit-based pricing indeed leads to an increase in the separation rate of household waste, compared to no unit-based pricing. To better understand the significance of this effect, the average separation rate across the period under study is 54.45%. Implementing UBP can thus increase the household separation rate by almost 18%.

Combining the above findings, I show that, on average, implementing any form of UBP reduces waste quantities by 30% while the separation rate increases by 18%. As a result, the remaining 12% reduction in waste quantities must be attributed to other factors unrelated to the increase in the separation rate. One such factor previously mentioned is the growing environmental awareness among households. Another contributing factor could be the rising marginal costs to households associated with each additional kilogram or liter of residual waste, an aspect studied in the research by Allers and Houben (2009).

Additionally, the ratio between the number of people aged 65 or older compared to the number of people aged 20 to 64 years and the share of inhabitants with a non-Western migration background significantly impact the amount of household residual waste and the separation rate. Sharing the same "unfavorable" signs, increasing the amount and decreasing the separation rate. Moreover, the population size and household size both negatively impact the separation rate. Especially household size has a very significant and large effect, decreasing the separation rate by 27.81 percentage points per every additional person in a household. Besides, no other control variable shows a significant effect, which might be due to too little within variation. However, this is not concerning, as their primary role in this model is to mitigate potential omitted variable bias.

Finally, I observe that both models fit the data well, with adjusted R-squared values of 0.678 and 0.572, indicating that the model explains 67.8% and 57.2% of the variation in the independent variable, respectively.

*Table 5.1 Fixed effects regression results for unit-based pricing and its impact on residual waste quantities and the separation rate*

| VARIABLES | (1) residualwaste | (2) separationrate |
|---|---|---|
| UBP | -53.71*** | 9.63*** |
| | (4.48) | (1.00) |
| population_1000 | 0.21 | -0.11*** |
| | (0.15) | (0.03) |
| pop_dens | -0.01 | 0.00 |
| | (0.00) | (0.00) |
| householdsize | 35.69 | -27.81*** |
| | (34.19) | (10.26) |
| income | -0.37 | 0.16 |
| | (0.40) | (0.10) |
| unemployment | -1.75 | -0.12 |
| | (1.42) | (0.34) |
| higher_edu | 0.13 | 0.01 |
| | (0.22) | (0.07) |
| women | 4.26 | -0.89 |
| | (4.26) | (1.02) |
| preschoolage | 2.79 | -0.70 |
| | (2.63) | (0.59) |
| grijzedruk | 1.27** | -0.31** |
| | (0.53) | (0.13) |
| non_w | 3.82** | -1.50*** |
| | (1.51) | (0.40) |
| Constant | -119.44 | 174.75*** |
| | (247.81) | (56.14) |
| Observations | 5,135 | 5,134 |
| Adj. $R^2$ | 0.678 | 0.572 |
| Year FE | Yes | Yes |
| Municipality FE | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The variable for population size is transformed and should be interpreted as “per 1000 inhabitants”

After finding that UBP leads to lower amounts of household residual waste and a higher separation rate, it is interesting to determine which specific pricing system has the greatest impact. To do so I include separate dummies for each pricing system, where the fixed rate system forms the base category. First, from the regression results in Table 5.2, it can be observed that almost every UBP system separately has a negative and significant coefficient in the third model and a positive and significant coefficient in the fourth model. Only the volume-based system shows no significant effects. Furthermore, the category “Weight & number of people” is omitted because of collinearity. The reason for this is that this particular UBP system is implemented solely by one municipality

(Eijsden-Margraten), which used this particular UBP system throughout the entire study period. The inclusion of municipality fixed effects prevents the estimation of this coefficient. One should be careful of interpreting the estimated coefficients for “Other” and “No fee” because both are exclusively found across one observation. This limited representation means that the coefficients for these categories will most likely not provide reliable insights, and any conclusions drawn from them should be made with caution. Unsurprisingly, yet disappointingly, the most used pricing system which is based on the number of people shows no significant effects. Additionally, the results indicate that the bag-based system yields the most favorable outcomes, reducing the amount of residual household waste by a staggering 113.42 kg and increasing the separation rate by 26.95 percentage points compared to the municipalities using a fixed rate. These results are somewhat in line with those found by Dijkgraaf and Gradus (2004), who find that the bag- and weight-based systems show comparable results, which are significantly larger than those of the frequency- and volume-based systems. Finally, the estimations are not in line with what I would have expected considering the relative marginalities discussed in section 2.2. I would expect the weight-based system to have a larger effect compared to the bag-based system but the coefficients are not statistically different ($F(1,337) = 1.49$, $p > 0.1$). A possible explanation might be that, although the weight-based system is more refined, individuals may perceive purchasing a relatively expensive garbage bag as more financially burdensome compared to receiving an annual invoice.

Furthermore, I once again observe that both models fit the data well, with adjusted R-squared values of 0.751 and 0.661, indicating that the model explains 75.1% and 66.1% of the variation in the independent variable, respectively.

*Table 5.2 Fixed effects regression results for each pricing system and its impact on residual waste quantities and the separation rate*

| VARIABLES | (3) residualwaste | (4) separationrate |
|---|---|---|
| Expensive garbage bag | -113.42*** | 26.95*** |
| | (8.30) | (2.06) |
| Expensive garbage bag & number of people | -99.61*** | 24.08*** |
| | (11.08) | (3.74) |
| Volume | -8.67 | 1.84 |
| | (6.87) | (1.61) |
| Volume & frequency | -72.48*** | 13.21*** |
| | (6.75) | (1.60) |
| Volume, frequency & number of people | -58.64*** | 11.61*** |
| | (6.91) | (1.69) |
| Weight | -103.17*** | 14.75*** |
| | (8.54) | (2.44) |
| Weight & frequency | -86.78*** | 16.56*** |
| | (7.15) | (2.02) |
| Weight & number of people | - | - |
| Other | -57.72*** | 9.28*** |
| | (4.23) | (1.02) |
| Number of people | -7.60 | 2.06 |
| | (5.94) | (1.43) |
| No fee | -9.69 | 6.94*** |
| | (6.06) | (1.49) |
| Constant | 88.08 | 118.38*** |
| | (212.65) | (44.40) |
| Observations | 5,122 | 5,121 |
| Adj. $R^2$ | 0.751 | 0.661 |
| Controls | Yes | Yes |
| Year FE | Yes | Yes |
| Municipality FE | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Turning to my second hypothesis, which states that curbside collection, compared to the situation where residual household waste must be brought to a drop-off point, leads to (H2a) lower household residual waste quantities and (H2b) a higher separation rate. From the regression results in Table 5.3, it can be observed that the dummy for curbside collection has a positive and significant coefficient in the fifth and seventh model. The coefficient shows that, on average, in municipalities where households must present their residual waste at the curbside rather than bring it to a drop-off point more residual household waste is being collected. This effect appears to be uniform between neighborhoods with predominantly low- and high-rise buildings, although the magnitude of the effect is much smaller within high-rise neighborhoods compared to low-rise neighborhoods. One possible explanation could be that residents living in high-rise buildings need to walk down and exit the building under both collection methods. Conversely, with curbside collection, residents living in low-rise buildings simply need to step outside their front door and place their waste bags (or wheelie-bin) at the curbside, whereas they would have to walk to a collective UWC down the street under the bring method. In other words, the disparity in the effort required for household waste disposal between the drop-off and curbside collection methods is more pronounced in low-rise neighborhoods compared to high-rise neighborhoods. Nevertheless, I reject hypothesis 2a, suggesting that curbside collection does not lead to lower residual waste quantities, compared to waste being collected at drop-off points. However, the magnitude of the increase in residual waste quantities is not very significant, with a 10.04 kg increase in low-rise neighborhoods and a 5.51 kg increase in high-rise neighborhoods.

Shifting my focus to the separation rate, it can be observed that the dummy for curbside collection has a negative and significant coefficient in the sixth and eighth model. It shows that, on average, obliging households to present their residual waste at the curbside rather than them bringing it to a drop-off point leads to a lower separation rate. This effect appears to be uniform between neighborhoods with predominantly low- and high-rise buildings. As a result, I reject hypothesis 2b, suggesting that curbside collection does not lead to a higher separation rate, compared to waste being collected at drop-off points. Once again, the magnitude of the decline in the separation rate is not very significant, with a 2.38 percentage point decrease in low-rise neighborhoods and a 1.01 percentage point decrease in high-rise neighborhoods.

My findings regarding the collection method for household residual waste are not in line with the existing literature. In fact, they indicate the opposite effect. Finding an explanation for these inconsistencies is challenging. A possible reason could be that the previous studies were all conducted outside of The Netherlands (Spain, Sweden, Denmark, US). It may be that The Netherlands has certain unique characteristics that impact waste quantities and separation rates. One such unique characteristic in the context of this study is that The Netherlands is significantly more densely populated than the other countries.

Finally, according to Groot et al. (2014), curbside collection is more than 2.5 times as expensive as the use of drop-off points. Their study comprised all 418 Dutch municipalities in the year 2011.

When combining my results with theirs, I would encourage municipalities to study the possibility of expanding the use of drop-off points.

*Table 5.3 Fixed effects regression results for the collection method for household residual waste and its impact on residual waste quantities and the separation rate*

| | Low-rise | | High-rise | |
|---|---|---|---|---|
| | (5) | (6) | (7) | (8) |
| VARIABLES | residualwaste | separationrate | residualwaste | separationrate |
| Curbside | 10.04** | -2.38** | 5.51* | -1.01* |
| | (4.41) | (1.19) | (2.84) | (0.60) |
| Curbside & drop-off point | 4.88 | -1.04 | -3.00 | 0.95 |
| | (3.56) | (0.94) | (2.95) | (0.67) |
| Constant | 248.73 | 62.37 | 306.61 | 50.48 |
| | (329.91) | (74.48) | (339.69) | (76.37) |
| Observations | 1,527 | 1,527 | 1,509 | 1,509 |
| Adj. $R^2$ | 0.235 | 0.156 | 0.230 | 0.150 |
| Controls | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Municipality FE | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Finally, my third hypothesis is tested. The hypothesis states that reducing the frequency of collecting residual household waste leads to (H3a) lower household residual waste quantities and (H3b) a higher separation rate. From the regression results in Table 5.4, it can be observed that the dummies for "Every three weeks" and "Every four weeks" have negative (positive) and significant coefficients in model nine (ten). The coefficients show that, on average, collecting household residual waste every three weeks leads to a reduction of 34.14 kilograms in residual waste compared to municipalities that collect weekly. Additionally, collecting every three weeks increases the separation rate by 8.74 percentage points compared to weekly collection. Furthermore, according to the F-test, I cannot reject the null hypothesis that the effects are significantly different between collecting every three weeks and every four weeks ($F(1,281) = 0.26$, $p > 0.1$). I cannot reject hypothesis 3, which suggests that reducing the frequency of collection indeed leads to a lower amount of household residual waste and a higher separation rate. To put the estimated effects in context, 34.14 kilograms equals a 19% reduction compared to the mean amount of household residual waste. And 8.74 percentage points equals a 16% increase compared to the mean separation rate. Showing the significant impact reducing the frequency of collection can have. The most straightforward explanation for the findings can be traced back to Williams and Cole (2013), who argued that a reduced collection frequency for residual waste incentivizes residents to separate their waste more effectively. Households generally dislike waste in their homes due to the odor it produces and therefore want to dispose of it as quickly as possible. If the frequency of collection is reduced, they will thus try to generate less waste and separate more effectively.

No significant effects are found in neighborhoods with predominantly high-rise buildings and the magnitudes of the coefficients significantly differ compared to those for low-rise neighborhoods. However, both may very well be the result of limited observations of the collection frequency in high-rise neighborhoods because the most common collection method in these areas is the use of drop-off points, as discussed in the chapter on data. As previously mentioned, the frequency of collection only matters when residual waste is collected at the curbside. Therefore, cautious implications of these results are recommended. Furthermore, the category “Every three weeks” is omitted because of collinearity. This frequency of collecting shows no variation within municipalities over time and its coefficient can therefore not be estimated.

I want to make two final remarks regarding the frequency of collecting waste. First, previous studies have shown that increasing the frequency of collecting household waste significantly raises municipal waste management costs. Combining these findings with the results of this study, it may seem beneficial for municipalities currently collecting residual waste weekly or bi-weekly to transition to collecting every three or four weeks. However, municipalities should keep in mind that reducing the frequency of collection can also cause negative externalities such as littering and health hazards (Coffey & Coad, 2010). Hence, it might be more beneficial for municipalities to prioritize unit-based pricing systems and drop-off points.

*Table 5.4 Fixed effects regression results for the frequency of collecting household residual waste and its impact on residual waste quantities and the separation rate*

| | Low-rise | | High-rise | |
|---|---|---|---|---|
| | (9) | (10) | (11) | (12) |
| VARIABLES | residualwaste | separationrate | residualwaste | separationrate |
| Bi-weekly | -2.69 | 1.63 | 14.37 | -2.59 |
| | (5.05) | (1.15) | (12.19) | (2.75) |
| Every three weeks | -34.14** | 8.74*** | - | - |
| | (13.43) | (3.01) | | |
| Every four weeks | -28.01*** | 7.72*** | -8.14 | 2.17 |
| | (5.72) | (1.34) | (10.48) | (2.23) |
| Constant | 288.75 | 69.87 | 306.69 | 46.18 |
| | (347.69) | (76.98) | (734.28) | (169.04) |
| Observations | 1,113 | 1,113 | 169 | 169 |
| Adj. $R^2$ | 0.390 | 0.342 | 0.272 | 0.268 |
| Controls | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Municipality FE | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

# Chapter 6. Robustness Check

Preferably, a more robust statistical method would be employed. And for part of this study, this would have been possible by utilizing the synthetic control method (SCM).

In essence, the SCM creates a weighted combination of control units that best match the characteristics of the treated unit before the intervention. By ensuring that the synthetic control closely matches the treated unit's pre-intervention characteristics and outcomes, the method effectively controls for both observed and unobserved factors that could be correlated with both the treatment and the outcome. Differences in post-intervention outcomes can be attributed to the intervention itself, rather than to omitted variables. Moreover, since the SCM relies on pre-intervention data to construct the synthetic control unit, it inherently avoids reverse causality. This demonstrates why the SCM is even more robust compared to the FE model. The SCM only relies on the stable unit treatment value assumption (SUTVA). If I assume the SUTVA to hold, the difference in outcomes after the treated unit implemented UBP yields the causal effect.

But, for the results to be reliable and convincing, a sufficient number of time periods is also required. The credibility of the SCM relies on its ability to closely match the treated unit's characteristics and outcomes over an extended time period pre-treatment. Abadie et al. (2014) do not recommend using this method whenever the pretreatment fit is poor, or the number of pretreatment observations is limited. These are the reasons why the SCM cannot be used to test my second and third hypotheses. Data for those independent variables is limited to five time periods, and the changes within municipalities are very random and not consistent.

Conversely, data on the pricing system is available across 17 years, and changes within municipalities persist, making the SCM a feasible method to address my first hypothesis. Although the SCM can be used, it will soon become clear why I employed the fixed effects model as my main methodology and utilized the SCM only as a robustness check. By employing the SCM, I test the sensitivity of my estimates to the use of a different statistical method, thereby increasing the validity of my results.

Before going to the results of the synthetic control method I want to emphasize why I choose this method over a difference-in-differences model. Moreover, I address the SUTVA assumption and why I think the assumption is likely to hold.

Different from Allers and Houben (2009), who apply a difference-in-differences (DiD) model, I choose to use the synthetic control method (SCM). Although very similar, the SCM has some advantages over the DiD in the context of this study. For a DiD regression, I would have to manually find a municipality that matches my treated unit as close as possible. Typically, one would select a municipality adjacent to the treated one. However, since both the treated unit and the control unit must share the same non-UBP system before treatment, finding such a match is very difficult. The challenge becomes even harder because, in addition to the SUTVA assumption, DiD also relies on the parallel-trends assumption. This assumption states that pre-intervention trends for the dependent variables must be parallel in order to obtain unbiased results.

The SCM is feasible because there are municipalities that employ the same non-UBP system throughout the entire study period. These municipalities form the “pool” from which eventually the synthetic control unit is formed. In this pool each unit is assigned a certain weight based on prespecified covariates from which the best synthetic control unit is formed, matching our treated unit as close as possible.

The SUTVA assumption states that: the treatment can only have an effect on the treatment group and no effect on the control group, i.e., there can be no interaction between the treatment and control group. In this study, the “treatment” is the implementation of a unit-based pricing system. Previous literature found no evidence showing that households from municipalities with UBP systems dispose of their waste in surrounding municipalities without UBP systems, a practice also known as waste tourism (Dijkgraaf & Gradus, 2004; Allers & Houben, 2009). Accordingly, Dijkgraaf and Gradus found no spillover effects on the amounts of waste collected when neighboring municipalities implemented UBP. Based on these findings, I conclude that the SUTVA assumption is very likely to hold and that the estimates obtained using the SCM represent the true causal effects.

The SCM requires my panel dataset to be balanced. Accordingly, I began by excluding all municipalities that had missing values for certain years, leaving me with 186 municipalities.[1] To form the pool from which the synthetic control unit is formed I selected all municipalities that billed households based on the number of people (as this was by far the most used non-UBP system) and that used this system throughout the entire study period. Ultimately this pool consists of 58 different municipalities.

Proceeding, in the search for treated units I found 11 municipalities that changed from "Number of people" to "Volume & frequency", four that changed to "Volume, frequency & number of people", two that changed to "Volume", and only one which changed to "Expensive garbage bag". Every single one of these municipalities had at least five periods in which they used the base pricing system (Number of people) and at least three periods in which they used their newly implemented UBP system. Furthermore, the change in the pricing system had to be consistent up until 2022. This shows exactly why I opted to use the fixed effects regression as my main method, as I cannot estimate the effect for the remaining five UBP systems with the SCM.

To provide the most generalizable outcomes, I will identify the most average municipality for each of the four UBP systems I am going to analyze. I do this by calculating the Euclidean distance for each municipality by comparing the values of their socio-economic and demographic characteristics to the mean values derived from all 341 municipalities in my complete dataset. According to the Euclidean distance, the most average municipalities are the municipality of Duiven changing to "Volume & frequency", Renkum changing to "Volume, frequency & number of people", Rheden changing to "Volume", and there was only one municipality changing to "Expensive garbage bag", namely the municipality of Leusden.

The obtain the weights for each municipality in the pool that ultimately forms the synthetic control unit I have to find possible predictors of post-intervention outcomes, which are unaffected by the intervention. I choose the same socio-economic and demographic characteristics previously used as controls in my fixed effect model. Furthermore, following Abadie et al. (2014) I include

[1] Based on a statistical test performed, the estimated coefficients for each pricing system dummy in the main model and this subset do not significantly differ at any of the common levels of significance. See Table G1 in appendix G for the corresponding regression results. Test results are available upon request.

preintervention values of my outcome variable to further increase the fit of my synthetic control unit.

Turning to the results of the SCM, Table 6.1 shows the estimated effects of implementing the volume- & frequency-based pricing system for each year after the treatment took place. Graphical illustration can be found in Figure G1 and Figure G2 in Appendix G. The results indicate that switching from a pricing system based on the number of people in a household to a volume- & frequency-based pricing system leads to a reduction in the amount of household residual waste by 84.23 kg per capita and an increase in the separation rate by 23.83 percentage points in the first year the UBP system was introduced. One cannot immediately check whether these estimates align with those found using the FE model. Recall that the base category in the FE regression was the fixed rate, whereas, with the SCM, the pre-treatment pricing system is based on the number of people in a household. Therefore, I should subtract the FE coefficient “Number of people” from the “Volume & frequency” coefficient, resulting in an average effect of -64.88 for the amount of household residual waste, and an average effect of 11.15 for the separation rate. Furthermore, the SCM allows me to assess the effects over time, while the FE method comments on average effects only. Accordingly, I compare the average effects of -64.88 and 11.15 with the average effects over time from the SCM, which are -59.82 and 20.67 respectively. Leading to the conclusion that the estimates found utilizing the SCM match those obtained from the fixed effects regression with regard to their sign. However, the effects differ substantially with respect to their magnitude.

*Table 6.1 Synthetic control method estimates for the effect of implementing a Volume- & frequency-based pricing system*

| | ESTIMATES | |
|---|---|---|
| YEAR | residualwaste | separationrate |
| 2016 | -84.23** | 23.83*** |
| 2017 | -85.47*** | 24.48*** |
| 2018 | -47.49 | 19.44*** |
| 2019 | -45.43 | 18.44** |
| 2020 | -44.01 | 16.43** |
| 2021 | -44.73 | 18.10*** |
| 2022 | -67.38** | 23.99*** |

*** p<0.01, ** p<0.05, * p<0.1

Second, Table 6.2 shows the estimated effects of implementing the volume-, frequency- & number of people-based pricing system for each year after the treatment took place. Graphical illustration can be found in Figure G3 and Figure G4 in Appendix G. The results indicate that switching from a waste tax based on the number of people in a household to a volume-, frequency- & number of people-based pricing system leads to a reduction in the amount of household residual waste by 87.85 kg per capita and an increase in the separation rate by 24.20 percentage points in the first year the UBP system was introduced. Once again, I subtract the FE coefficient "Number of people" from the "Volume, frequency & number of people" coefficient, resulting in an average effect of -51.04 for the amount of household residual waste, and an average effect of 9.55 for the separation rate. Comparing these with the average effects over time from the SCM, which are -68.23 and 20.24 respectively, shows that the estimates found utilizing the SCM match those obtained from the fixed effects regression with regard to their sign. However, the effects differ substantially with regard to their magnitude.

*Table 6.2 Synthetic control method estimates for the effect of implementing a Volume-, frequency & number of people-based pricing system*

| | ESTIMATES | |
|---|---|---|
| YEAR | residualwaste | separationrate |
| 2017 | -87.85*** | 24.20*** |
| 2018 | -68.18** | 20.50*** |
| 2019 | -59.27* | 19.86** |
| 2020 | -71.83* | 19.84*** |
| 2021 | -65.54* | 19.85*** |
| 2022 | -56.73 | 17.20** |

*** p<0.01, ** p<0.05, * p<0.1

Next, Table 6.3 shows the estimated effects of implementing the volume-based pricing system for each year after the treatment took place. Graphical illustration can be found in Figure G5 and Figure G6 in Appendix G. The results indicate that switching from a pricing system based on the number of people in a household to a volume-based pricing system leads to a reduction in the amount of household residual waste by 39.87 kg per capita and an increase in the separation rate by 7.06 percentage points in the first year the UBP system was introduced. These results are quite surprising, as previous analyses using the FE model found no significant effect for the volume-based pricing system. On top of that, Figures G3 and G4 show striking preliminary results, suggesting that the effects may not persist over time.

Like before, I subtract the FE coefficient "Number of people" from the "Volume" coefficient, resulting in an average (insignificant) effect of -1.07 on the amount of household residual waste, and an average (insignificant) effect of -0.22 on the separation rate. Comparing these with the average effects over time from the SCM, which are -29.26 and 3.32 respectively, shows that the estimates found utilizing the SCM differ significantly from those found employing the FE model.

*Table 6.3 Synthetic control method estimates for the effect of implementing a Volume-based pricing system*

| | ESTIMATES | |
|---|---|---|
| YEAR | residualwaste | separationrate |
| 2013 | -39.87** | 7.06** |
| 2014 | -38.68* | 6.50** |
| 2015 | -33.75 | 5.11 |
| 2016 | -35.73 | 4.40 |
| 2017 | -21.07 | 2.65 |
| 2018 | -38.55 | 5.25 |
| 2019 | -26.81 | 2.21 |
| 2020 | -30.42 | 2.21 |
| 2021 | -18.49 | 0.43 |
| 2022 | -9.19 | -2.59 |

*** p<0.01, ** p<0.05, * p<0.1

Finally, Table 6.4 shows the estimated effects of implementing the bag-based pricing system for each year after the treatment took place. Graphical illustration can be found in Figure G7 and Figure G8 in Appendix G. The results indicate that switching from a pricing system based on the number of people in a household to a bag-based pricing system leads to a reduction in the amount of residual household waste by 65.44 kg per capita and an increase in the separation rate by 13.53 percentage points in the first year the UBP system was introduced. Once more, I subtract the FE coefficient "Number of people" from the "Expensive garbage bag" coefficient, resulting in an average effect of -105.82 on the amount of household residual waste, and an average effect of 24.89 on the separation rate. Comparing these with the average effects over time from the SCM, which are -56.87 and 13.08 respectively, shows that the estimates found utilizing the SCM match those obtained from the fixed effects regression with regard to their sign. However, contrary to before, the magnitudes are almost half of those previously found using the FE model.

*Table 6.4 Synthetic control method estimates for the effect of implementing a bag-based pricing system*

| | ESTIMATES | |
|---|---|---|
| YEAR | residualwaste | separationrate |
| 2018 | -65.44** | 13.53** |
| 2019 | -66.82** | 14.46** |
| 2020 | -60.91* | 14.07* |
| 2021 | -44.11 | 9.98 |
| 2022 | -47.06 | 13.36* |

*** p<0.01, ** p<0.05, * p<0.1

In trying to validate the robustness of my estimates obtained from the fixed effects regression, I found similar estimates utilizing the SCM in terms of their sign. However, I observed significantly higher/lower magnitudes of the estimated effects. Moreover, previous results indicated that the bag-based pricing system has the largest impact on household residual waste quantities and the separation rate. In contrast, the results from the SCM indicate that the volume-, frequency- and number of people-based pricing system yields the most favorable outcomes. These discrepancies may be explained by the fact that the treatment group comprises of only one municipality per treatment. The question arises how representable that specific municipality is for the rest of the Dutch municipalities. Nonetheless, the reliability of the initial estimates can be assessed by considering the consistency of the sign of the effects. Both the FE model and the SCM indicate similar directional impacts, which strengthens the credibility of the initial findings. Despite varying magnitudes, the key takeaway is that implementing UBP has consistently resulted in a decrease in household residual waste quantities and a corresponding increase in the separation rate.

# Chapter 7. Conclusion

In this final chapter, the key findings from this study are summarized, practical implications are discussed, and policy recommendations are provided. The paper concludes by giving relevant recommendations for further research in this field.

## 7.1 Conclusion

The aim of this paper was to study the impact of municipal waste management practices. More precisely, the research question addressed in this study reads:

> *"How do different waste management approaches, employed by Dutch municipalities, impact waste reduction and resource recovery?"*

To be able to answer this research question three hypotheses were formulated based on the findings in the existing literature on this topic. The research conducted in this study focused on three parts of municipal waste management: the pricing system (i.e. waste tax), the collection method, and the frequency of collecting. The key results and their implications are now discussed.

Applying a fixed effects model, the effects of unit-based pricing on household residual waste quantities and the separation rate were estimated. Results showed that in municipalities that implement a form of UBP, on average, households generate less residual waste per capita per year, compared to municipalities that do not use UBP, reducing quantities by 30%. In practical terms, this reduction could mean that if a municipality normally collects 150 kg of residual waste per capita each year, implementing UBP could reduce this amount to 105 kg. Such a substantial decrease could lead to significant cost savings for the municipality and limit the municipality's environmental impact. Additionally, municipalities implementing UBP show a 18% higher separation rate, compared to municipalities that do not employ UBP.

I continued by analyzing the effects of each pricing system on its own, comparing them to the case where the municipality would employ a fixed rate. The bag-based system was found to have the greatest effect, reducing waste quantities by a remarkable 63% and increasing the separation rate by almost 50%. The volume-, frequency- & number of people-based pricing system showed the smallest effect, yet still reducing waste quantities by 33% and increasing the separation rate by

21%. The signs of the effects were robust to relaxing assumptions of the main model utilizing the synthetic control method.

To conclude, this study has shown the promising effects of implementing UBP. The results suggest that it may be beneficial for municipalities currently not using UBP to explore the possibilities of implementing a form of UBP, and for municipalities already using UBP to consider whether switching to a different UBP system could yield even greater benefits.

The research continued by analyzing the effects of different methods of collecting household residual waste. Contrary to the study's expectations, a "collect" method where households present their residual waste at the curbside, increased rather than decreased the amount of waste, compared to a "bring" method where households bring their waste to a collective drop-off point. Besides, curbside collection also leads to a lower separation rate. We saw that the presence of high-rise buildings is an important factor for municipalities to choose for drop-off points rather than curbside collection. However, in neighborhoods with predominantly low-rise buildings, curbside collection is the most popular method. Based on the results, it might be beneficial for municipalities to start collecting household residual waste at drop-off points also in these areas. This can reduce costs and limit their environmental impact.

Finally, the frequency of collecting is examined. This is done solely in the case where household residual waste is collected at the curbside. Due to a small number of observations no valid conclusions can be drawn for neighborhoods with predominantly high-rise buildings. Hence, in neighborhoods with predominantly high-rise buildings, the preferred collection method is the use of drop-off points. For neighborhoods with predominantly low-rise buildings results suggest that a lower frequency of collecting – every three or four weeks versus weekly or bi-weekly – leads to a decrease in the amount of residual waste and an increase in the separation rate. Nevertheless, municipalities should keep in mind that reducing the frequency of collection can also cause negative externalities such as littering and health hazards. Hence, it might be more beneficial for municipalities to prioritize unit-based pricing systems and drop-off points.

### 7.2 Limitations and further research

The results found in this research are subject to the dataset, the constraints of the methods used, and the assumptions made. Therefore, one must be careful in deriving inferences. In a different setting and under different conditions the conclusions drawn may not be credible. Future studies may conduct this research in other countries to increase the external validity.

The main limitation lies in the practicality of the results. Even though results point towards the use of UBP. In some municipalities, this might just not be feasible. For instance, implementing the bag-based pricing system could lead to the illegal dumping of household waste. The success of municipal waste management depends on the circumstances to which municipalities must adapt, such as infrastructural, demographical, political, and cultural conditions (Timlett & Williams, 2011). Moreover, implementing a UBP system requires large upfront investments. Although the savings in disposal costs will likely outweigh the increase in administrative costs (Dijkgraaf & Gradus, 2004), transitioning to another pricing system might be too costly, especially for smaller municipalities that typically have limited budgets.

This study focused on household residual waste. Future studies may perform this research analyzing different waste streams, such as glass, paper, organic waste, and plastic, metals and drink cartons (PMD). Some municipalities do not ask their residents to separate recyclables themselves, referred to as source-separation, but rather collect waste mixed and separate it at the materials recovery facility, known as post-separation. This is very common when it comes to PMD. Although several studies have already addressed this phenomenon (Larsen et al., 2010; Dijkgraaf & Gradus, 2020), the rapid technological changes and the emergence of AI calls for ongoing research in this field.

Finally, one of the regressions from the SCM indicated that the effects of implementing a volume-based pricing system do not persist over time. Usui and Takeuchi (2013) previously only found a small rebound effect. The preliminary rebound effect found in this study is an interesting starting point for further research.

Despite the limitations, the results yield important insights regarding the research question. It suggests that various waste management practices certainly do have an impact on household residual waste quantities and the separation rate. As is often the case in research, there is not a simple answer to what the best practice is moving forward. While the results are subject to this study's design, this paper does shed new light on municipal waste management and contributes to the body of knowledge within Environmental Economics. Future studies in this field can use the results of this study as comparison material to aid their research.

## References


Abadie, A., Diamond, A., & Hainmueller, J. (2014). Comparative Politics and the synthetic control Method. *American Journal of Political Science*, *59*(2), 495–510. https://doi.org/10.1111/ajps.12116

*Afval van huishoudens, 1985-2022*. (2023, August 3). Compendium Voor De Leefomgeving. https://www.clo.nl/indicatoren/nl014038-afval-van-huishoudens-1985-2022

*Afvalcijfers*. (n.d.). Afval Circulair. https://www.afvalcirculair.nl/monitoring-en- cijfers/afvalcijfers/

Allers, M., & Hoeben, C. (2009). Effects of Unit-Based Garbage Pricing: A Differences-in-Differences approach. *Environmental & Resource Economics*, *45*(3), 405–428. https://doi.org/10.1007/s10640-009-9320-6

Barrett, A., & Lawlor, J. (1995). The economics of solid waste management in Ireland. *Research Series*. https://ideas.repec.org/b/esr/resser/prs26.html

Beatty, T. K. M., Berck, P., & Shimshack, J. P. (2007). CURBSIDE RECYCLING IN THE PRESENCE OF ALTERNATIVES. *Economic Inquiry*, *45*(4), 739–755. https://doi.org/10.1111/j.1465-7295.2007.00055.x

Bel, G., & Fageda, X. (2010). Empirical analysis of solid management waste costs: Some evidence from Galicia, Spain. *Resources, Conservation and Recycling*, *54*(3), 187–193. https://doi.org/10.1016/j.resconrec.2009.07.015

Beliën, J., De Boeck, L., & Van Ackere, J. (2014). Municipal Solid Waste Collection and Management Problems: A Literature review. *Transportation Science*, *48*(1), 78–102. https://doi.org/10.1287/trsc.1120.0448

Bošković, G., Jovičić, N., Jovanović, S., & Šimović, V. (2016). Calculating the costs of waste collection: A methodological proposal. *Waste Management & Research*, *34*(8), 775–783. https://doi.org/10.1177/0734242x16654980

Callan, S. J., & Thomas, J. M. (2001). Economies of Scale and Scope: A cost analysis of Municipal solid Waste services. *Land Economics*, *77*(4), 548–560. https://doi.org/10.2307/3146940

Centraal Bureau voor de Statistiek. (2023, October 19). Minder huishoudelijk afval per inwoner in 2022. *Centraal Bureau Voor De Statistiek*. https://www.cbs.nl/nl-nl/nieuws/2023/42/minder-huishoudelijk-afval-per-inwoner-in-2022

Clark, R. M., Grupenhoff, B. L., Garland, G. A., & Klee, A. J. (1971). Cost of residential solid waste collection. *Journal of the Sanitary Engineering Division*, *97*(5), 563–568. https://doi.org/10.1061/jsedai.0001306

Coffey, M., & Coad, A. (2010). *Collection of municipal solid waste in developing countries*. https://unhabitat.org/sites/default/files/2021/02/2010_collection-msw-developing-countries_un-habitat.pdf

Dahlén, L., & Lagerkvist, A. (2010). Pay as you throw. *Waste Management*, *30*(1), 23–31. https://doi.org/10.1016/j.wasman.2009.09.022

Dahlén, L., Vukicevic, S., Meijer, J., & Lagerkvist, A. (2007). Comparison of different collection systems for sorted household waste in Sweden. *Waste Management*, *27*(10), 1298–1305. https://doi.org/10.1016/j.wasman.2006.06.016

Das, S. K., & Bhattacharyya, B. (2015). Optimization of municipal solid waste collection and transportation routes. *Waste Management*, *43*, 9–18. https://doi.org/10.1016/j.wasman.2015.06.033

Dijkgraaf, E., & Gradus, R. H. (2003). Cost savings of contracting out refuse collection. *Empirica, 30*(2), 149-161.

Dijkgraaf, E., & Gradus, R. (2004). Cost savings in unit-based pricing of household waste. *Resource and Energy Economics*, *26*(4), 353–371. https://doi.org/10.1016/j.reseneeco.2004.01.001

Dijkgraaf, E., & Gradus, R. (2007). Collusion in the Dutch waste collection market. *Local Government Studies*, *33*(4), 573–588. https://doi.org/10.1080/03003930701417601

Dijkgraaf, E., & Gradus, R. (2020). Post-collection separation of plastic waste: better for the environment and lower collection costs? *Environmental & Resource Economics*, *77*(1), 127–142. https://doi.org/10.1007/s10640-020-00457-6

Domberger, S., Meadowcroft, S., & Thompson, D. (1986). Competitive tendering and efficiency: the case of refuse collection. *Fiscal Studies*, *7*(4), 69–87. https://doi.org/10.1111/j.1475-5890.1986.tb00530.x

Dubin, J. A., & Navarro, P. (1988). How markets for impure public goods organize: The case of household refuse collection. *Journal of Law, Economics, & Organization*. https://doi.org/10.1093/oxfordjournals.jleo.a036951

*EU 2030 climate and environmental targets within reach*. (2024, March 13). Environment. https://environment.ec.europa.eu/news/eu-2030-climate-and-environmental-targets-within-reach-2024-03-13_en

Everett, J. (1993). Curbside recycling in the U.S.A.: convenience and mandatory participation. *Waste Management & Research*, *11*(1), 49–61. https://doi.org/10.1006/wmre.1993.1006

Fullerton, D., & Kinnaman, T.C. (1996). Household responses to pricing garbage by the bag. *American Economic Review 86*, 971–984.

Gallardo, A., Bovea, M. D., Ortega-Colomer, F. J., Prades, M., & Carlos, M. (2010). Comparison of different collection systems for sorted household waste in Spain. *Waste Management*, *30*(12), 2430–2439. https://doi.org/10.1016/j.wasman.2010.05.026

Gallardo, A., Bovea, M. D., Ortega-Colomer, F. J., & Prades, M. (2012). Analysis of collection systems for sorted household waste in Spain. *Waste Management*, *32*(9), 1623–1633. https://doi.org/10.1016/j.wasman.2012.04.006

Gautam, M., & Agrawal, M. (2020). Greenhouse Gas Emissions from Municipal Solid Waste Management: A Review of Global Scenario. *Environmental Footprints and Eco-design of Products and Processes*, 123–160. https://doi.org/10.1007/978-981-15-9577-6_5

Gellynck, X., Jacobsen, R., & Verhelst, P. (2011). Identifying the key factors in increasing recycling and reducing residual household waste: A case study of the Flemish region of Belgium. *Journal of Environmental Management*, *92*(10), 2683–2690. https://doi.org/10.1016/j.jenvman.2011.06.006

Golden, B. L., Assad, A. A., & Wasil, E. (2002). 10. Routing Vehicles in the Real World: Applications in the Solid Waste, Beverage, Food, Dairy, and Newspaper Industries. In *Society for Industrial and Applied Mathematics eBooks* (pp. 245–286). https://doi.org/10.1137/1.9780898718515.ch10

Greco, G., Allegrini, M., Del Lungo, C., Savellini, P. G., & Gabellini, L. (2015). Drivers of solid waste collection costs. Empirical evidence from Italy. *Journal of Cleaner Production*, *106*, 364–371. https://doi.org/10.1016/j.jclepro.2014.07.011

Groot, J., Bing, X., Bos-Brouwers, H., & Bloemhof, J. (2014). A comprehensive waste collection cost model applied to post-consumer plastic packaging waste. *Resources, Conservation and Recycling*, *85*, 79–87. https://doi.org/10.1016/j.resconrec.2013.10.019

Han, H., & Cueto, E. P. (2015). Waste Collection Vehicle Routing Problem: Literature review. *Promet*, *27*(4), 345–358. https://doi.org/10.7307/ptt.v27i4.1616

Hirsch, W. Z. (1965). Cost functions of an urban government service: refuse collection. *The Review of Economics and Statistics*, *47*(1), 87. https://doi.org/10.2307/1924127

Hong, S. (1999). The effects of unit pricing system upon household solid waste management: The Korean experience. *Journal of Environmental Management*, *57*(1), 1–10. https://doi.org/10.1006/jema.1999.0286

Hong, S., & Adams, R. M. (1999). Household responses to price incentives for recycling: Some further evidence. *Land Economics*, *75*(4), 505. https://doi.org/10.2307/3147062

Jenkins, R.R. (1993). The Economics of Solid Waste Reduction: the Impact of User Fees, Edward Elgar, Aldershot.

Kim, B., Kim, S., & Sahoo, S. (2006). Waste collection vehicle routing problem with time windows. *Computers & Operations Research*, *33*(12), 3624–3642. https://doi.org/10.1016/j.cor.2005.02.045

Kinnaman, T. C., & Fullerton, D. (1997). *Garbage and Recycling in Communities with Curbside Recycling and Unit-Based Pricing*. https://doi.org/10.3386/w6021

Kinnaman, T. C., & Fullerton, D. (2000). Garbage and Recycling with Endogenous Local Policy. *Journal of Urban Economics*, *48*(3), 419–442. https://doi.org/10.1006/juec.2000.2174

Larsen, A. W., Merrild, H. K., Møller, J. S., & Christensen, T. H. (2010). Waste collection systems for recyclables: An environmental and economic assessment for the municipality of Aarhus (Denmark). *Waste Management*, *30*(5), 744–754. https://doi.org/10.1016/j.wasman.2009.10.021

Linderhof, V., Kooreman, P., Allers, M., & Wiersma, D. (2001). Weight-based pricing in the collection of household waste: the Oostzaan case. *Resource and Energy Economics*, *23*(4), 359–371. https://doi.org/10.1016/s0928-7655(01)00044-6

Matsumoto, S. (2011). Waste separation at home: Are Japanese municipal curbside recycling policies efficient? *Resources, Conservation and Recycling*, *55*(3), 325–334. https://doi.org/10.1016/j.resconrec.2010.10.005

Milieu Centraal. (n.d.). *Bronscheiding, nascheiding en diftar*. https://www.milieucentraal.nl/minder-afval/afval-scheiden/bronscheiding-nascheiding-en-diftar/

Ministerie van Infrastructuur en Waterstaat. (2024, April 8). *Huishoudelijk afval scheiden en recyclen*. Afval | Rijksoverheid.nl. https://www.rijksoverheid.nl/onderwerpen/afval/huishoudelijk-afval

Noehammer, H. (1997). EFFECT OF DESIGN VARIABLES ON PARTICIPATION IN RESIDENTIAL CURBSIDE RECYCLING PROGRAMS. *Waste Management & Research*, *15*(4), 407–427. https://doi.org/10.1006/wmre.1996.0096

Platt, B., Docherty, C., Broughton, A.C., & Morris, D. (1991). *Beyond 40 Percent: Record Setting Recycling and Composting Programs.* Institute for Local Self-Reliance.

Podolsky, M.J., & Spiegel, M. (1998). Municipal waste disposal: unit-pricing and recycling opportunities. *Public Works Management and Policy 3*, 27–39.

Quistorff, B., & S. Galiani. (2017). The synth_runner package: Utilities to automate synthetic control estimation using synth. *Stata Journal 17*, 834-849.

Reeves, E., & Barrow, M. (2000). The impact of contracting out on the costs of refuse collection services: the case of Ireland. *The Economic and Social Review*, *31*(2), 129–150. https://www.esr.ie/vol31_2/2Reeves.pdf

Reschovsky, J.D., & Stone, S.E. (1994). Market incentives to encourage household waste recycling: paying for what you throw away. *Journal of Policy Analysis and Management 13*, 120–139.

Rijkswaterstaat. (2024). Afvalstoffenheffing 2023. In *Afvalcirculair*. Ministerie van Infrastructuur en Waterstaat. https://www.afvalcirculair.nl/publicaties/

Stevens, B. J. (1978). Scale, market structure, and the cost of refuse collection. *The Review of Economics and Statistics*, *60*(3), 438. https://doi.org/10.2307/1924169

Strathman, J.G., Rufolo, A.M., & Mildner, G.C.S. (1995). The demand for solid waste disposal. *Land Economics 71*, 57–64.

*The European Green Deal*. (2021, July 14). European Commission. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en

Timlett, R., & Williams, I. (2011). The ISB model (infrastructure, service, behaviour): A tool for waste practitioners. *Waste Management*, *31*(6), 1381–1392. https://doi.org/10.1016/j.wasman.2010.12.010

Usui, T., & Takeuchi, K. (2013). Evaluating Unit-Based Pricing of Residential solid Waste: A panel data analysis. *Environmental & Resource Economics*, *58*(2), 245–271. https://doi.org/10.1007/s10640-013-9702-7

Van Houtven, G., & Morris, G. E. (1999). Household Behavior under Alternative Pay-as-You-Throw Systems for Solid Waste Disposal. *Land Economics*, *75*(4), 515. https://doi.org/10.2307/3147063

Van Vliet, T. (2021, August 20). *Effects of Underground Waste Containers on neighbourhood attractiveness and the Utrecht housing market: the case of 'Het Nieuwe Inzamelen'*. https://thesis.eur.nl/pub/59270

Wertz, K.L. (1976). Economic factors influencing households' production of refuse. *Journal of Environmental Economics and Management 2*, 263–272.

Williams, I., & Cole, C. (2013). The impact of alternate weekly collections on waste arisings. *Science of the Total Environment*, *445–446*, 29–40. https://doi.org/10.1016/j.scitotenv.2012.12.024

Wilson, C., & Williams, I. (2007). Kerbside collection: A case study from the north-west of England. *Resources, Conservation and Recycling*, *52*(2), 381–394. https://doi.org/10.1016/j.resconrec.2007.02.006

# Appendices

## Appendix A: Municipal details

*Table A1: List of all 341 municipalities studied*

| | | | | |
|---|---|---|---|---|
| 's-Gravenhage | Deventer | Hollands Kroon | Oisterwijk | Twenterand |
| 's-Hertogenbosch | Diemen | Hoogeveen | Oldambt | Tynaarlo |
| Aa en Hunze | Dijk en Waard | Hoorn | Oldebroek | Tytsjerksteradiel |
| Aalsmeer | Dinkelland | Horst aan de Maas | Oldenzaal | Uitgeest |
| Aalten | Doesburg | Houten | Olst-Wijhe | Uithoorn |
| Achtkarspelen | Doetinchem | Huizen | Ommen | Urk |
| Alblasserdam | Dongen | Hulst | Oost Gelre | Utrecht |
| Albrandswaard | Dordrecht | IJsselstein | Oosterhout | Utrechtse Heuvelrug |
| Alkmaar | Drechterland | Kaag en Braassem | Ooststellingwerf | Vaals |
| Almelo | Drimmelen | Kampen | Oostzaan | Valkenburg aan de Geul |
| Almere | Dronten | Kapelle | Opmeer | Valkenswaard |
| Alphen aan den Rijn | Druten | Katwijk | Opsterland | Veendam |
| Alphen-Chaam | Duiven | Kerkrade | Oss | Veenendaal |
| Altena | Echt-Susteren | Koggenland | Oude IJsselstreek | Veere |
| Ameland | Edam-Volendam | Krimpen aan den IJssel | Ouder-Amstel | Veldhoven |
| Amersfoort | Ede | Krimpenerwaard | Oudewater | Velsen |
| Amstelveen | Eemnes | Laarbeek | Overbetuwe | Venlo |
| Amsterdam | Eemsdelta | Land van Cuijk | Papendrecht | Venray |
| Apeldoorn | Eersel | Landgraaf | Peel en Maas | Vijfheerenlanden |
| Arnhem | Eijsden-Margraten | Landsmeer | Pekela | Vlaardingen |
| Assen | Eindhoven | Lansingerland | Pijnacker-Nootdorp | Vlieland |
| Asten | Elburg | Laren | Purmerend | Vlissingen |
| Baarle-Nassau | Emmen | Leeuwarden | Putten | Voerendaal |
| Baarn | Enkhuizen | Leiden | Raalte | Voorschoten |
| Barendrecht | Enschede | Leiderdorp | Reimerswaal | Voorst |
| Barneveld | Epe | Leidschendam-Voorburg | Renkum | Vught |
| Beek | Ermelo | Lelystad | Renswoude | Waadhoeke |
| Beekdaelen | Etten-Leur | Leudal | Reusel-De Mierden | Waalre |
| Beesel | Geertruidenberg | Leusden | Rheden | Waalwijk |
| Berg en Dal | Geldrop-Mierlo | Lingewaard | Rhenen | Waddinxveen |
| Bergeijk | Gemert-Bakel | Lisse | Ridderkerk | Wageningen |
| Bergen (L.) | Gennep | Lochem | Rijssen-Holten | Wassenaar |
| Bergen (NH.) | Gilze en Rijen | Loon op Zand | Rijswijk | Waterland |
| Bergen op Zoom | Goeree-Overflakkee | Lopik | Roerdalen | Weert |
| Berkelland | Goes | Losser | Roermond | West Betuwe |
| Bernheze | Goirle | Maasdriel | Roosendaal | West Maas en Waal |

| | | | | |
|---|---|---|---|---|
| Best | Gooise Meren | Maasgouw | Rotterdam | Westerkwartier |
| Beuningen | Gorinchem | Maashorst | Rozendaal | Westerveld |
| Beverwijk | Gouda | Maassluis | Rucphen | Westervoort |
| Bladel | Groningen | Maastricht | Schagen | Westerwolde |
| Blaricum | Gulpen-Wittem | Medemblik | Scherpenzeel | Westland |
| Bloemendaal | Haaksbergen | Meerssen | Schiedam | Weststellingwerf |
| Bodegraven-Reeuwijk | Haarlem | Meierijstad | Schiermonnikoog | Wierden |
| Boekel | Haarlemmermeer | Meppel | Schouwen-Duiveland | Wijchen |
| Borger-Odoorn | Halderberge | Middelburg | Simpelveld | Wijdemeren |
| Borne | Hardenberg | Midden-Delfland | Sint-Michielsgestel | Wijk bij Duurstede |
| Borsele | Harderwijk | Midden-Drenthe | Sittard-Geleen | Winterswijk |
| Boxtel | Hardinxveld-Giessendam | Midden-Groningen | Sliedrecht | Woensdrecht |
| Breda | Harlingen | Moerdijk | Sluis | Woerden |
| Bronckhorst | Hattem | Molenlanden | Smallingerland | Wormerland |
| Brummen | Heemskerk | Montferland | Soest | Woudenberg |
| Brunssum | Heemstede | Montfoort | Someren | Zaanstad |
| Bunnik | Heerde | Mook en Middelaar | Son en Breugel | Zaltbommel |
| Bunschoten | Heerenveen | Neder-Betuwe | Stadskanaal | Zandvoort |
| Buren | Heerlen | Nederweert | Staphorst | Zeewolde |
| Capelle aan den IJssel | Heeze-Leende | Nieuwegein | Stede Broec | Zeist |
| Castricum | Heiloo | Nieuwkoop | Steenbergen | Zevenaar |
| Coevorden | Hellendoorn | Nijkerk | Steenwijkerland | Zoetermeer |
| Cranendonck | Helmond | Nijmegen | Stein | Zoeterwoude |
| Culemborg | Hendrik-Ido-Ambacht | Nissewaard | Stichtse Vecht | Zuidplas |
| Dalfsen | Hengelo | Noardeast-Fryslân | Súdwest-Fryslân | Zundert |
| Dantumadiel | Het Hogeland | Noord-Beveland | Terneuzen | Zutphen |
| De Bilt | Heumen | Noordenveld | Terschelling | Zwartewaterland |
| De Fryske Marren | Heusden | Noordoostpolder | Texel | Zwijndrecht |
| De Ronde Venen | Hillegom | Noordwijk | Teylingen | Zwolle |
| De Wolden | Hilvarenbeek | Nuenen, Gerwen en Nederwetten | Tholen | |
| Delft | Hilversum | Nunspeet | Tiel | |
| Den Helder | Hoeksche Waard | Oegstgeest | Tilburg | |
| Deurne | Hof van Twente | Oirschot | Tubbergen | |

*Table A2: Reclassification of municipalities between 2019 and 2023*

| Before merging (2019) | After merging (2023) |
|---|---|
| Heerhugowaard<br>Langedijk | Dijk en Waard |
| Appingedam<br>Delfzijl<br>Loppersum | Eemsdelta |
| Boxmeer<br>Cuijk<br>Sint Anthonis<br>Mill en Sint Hubert<br>Grave | Land van Cuijk |
| Landerd<br>Uden | Maashorst |

*Table A3: Reclassification of municipalities between 2014 and 2023*

| Before merging (2014) | After merging (2023) |
|---|---|
| Heerhugowaard<br>Langedijk | Dijk en Waard |
| Appingedam<br>Delfzijl<br>Loppersum | Eemsdelta |
| Boxmeer<br>Cuijk<br>Sint Anthonis<br>Mill en Sint Hubert<br>Grave | Land van Cuijk |
| Landerd<br>Uden | Maashorst |
| Aalburg<br>Werkendam<br>Woudrichem | Altena |
| Onderbanken<br>Schinnen<br>Nuth | Beekdaelen |
| Groesbeek<br>Millingen aan de Rijn<br>Ubbergen | Berg en Dal |
| Goosterlân-Sleat<br>Lemsterland<br>Skarsterlân | De Fryske Marren |
| Bussum<br>Naarden<br>Muiden | Gooise Meren |
| Bedum<br>Eemsmond<br>De Marne<br>Winsum | Het Hogeland |
| Oud-Beijerland<br>Korendijk<br>Strijen<br>Cromstrijen | |

| | |
|---|---|
| Binnenmaas | |
| ’s-Gravendeel* | Hoeksche Waard |
| Schijndel | |
| Sint-Oedenrode | |
| Veghel | Meierijstad |
| Slochteren | |
| Menterwolde | |
| Hoogezand-Sappermeer | Midden-Groningen |
| Molenwaard | |
| Giessenlanden | Molenlanden |
| Dongeradeel | Noardeast-Fryslân |
| Ferwerderadiel | |
| Kollumerland | |
| Nieuwkruisland | |
| Leerdam | |
| Vianen | |
| Zederik | Vijheerenlanden |
| Franekeradeel | |
| het Bildt | |
| Menaldumadeel | |
| Littenseradiel | Waadhoeke |
| Geldermalsen | |
| Neerijnen | |
| Lingewaal | West Betuwe |
| Grootegast | |
| Leek | |
| Marum | |
| Zuidhorn | |
| Winsum | Westerkwartier |
| Bellingwedde | |
| Vlagtwedde | Westerwolde |
| Goedereede | |
| Dirksland | |
| Middelharnis | |
| Oostflakkee | Goeree-Overflakkee |
| Wieringen | |
| Wieringermeer | |
| Anna Paulowna | |
| Niedorp | Hollands Kroon |
| Nederlek | |
| Ouderkerk | |
| Vlist | |
| Berambacht | |
| Schoonhoven | Krimpenerwaard |
| Spijkenisse | |
| Bernisse | Nissewaard |

*’s-Gravendeel and Binnenmaas already merged on 1 January 2007 to form the newly created municipality of Binnenmaas

## Appendix B: Panel dataset

*Table B1: Descriptive statistics panel dataset*

```
municipal_code:  14, 34, ..., 1982                          n =        339
    year:  2006, 2007, ..., 2022                            T =         17
           Delta(year) = 1 unit
           Span(year)  = 17 periods
           (municipal_code*year uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         1       5      15        17        17      17      17

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+-------------------
      186     54.87   54.87 |  11111111111111111
       14      4.13   59.00 |  111111111111111.11
       11      3.24   62.24 |  111111111111111.1
        9      2.65   64.90 |  .1111111111111111
        9      2.65   67.55 |  1111111111111111.
        6      1.77   69.32 |  .............1111
        6      1.77   71.09 |  11.11111111111111
        4      1.18   72.27 |  ................1
        4      1.18   73.45 |  ...11111111111111
       90     26.55  100.00 | (other patterns)
 ---------------------------+-------------------
      339    100.00         |  XXXXXXXXXXXXXXXXX
```

## Appendix C: Trendlines

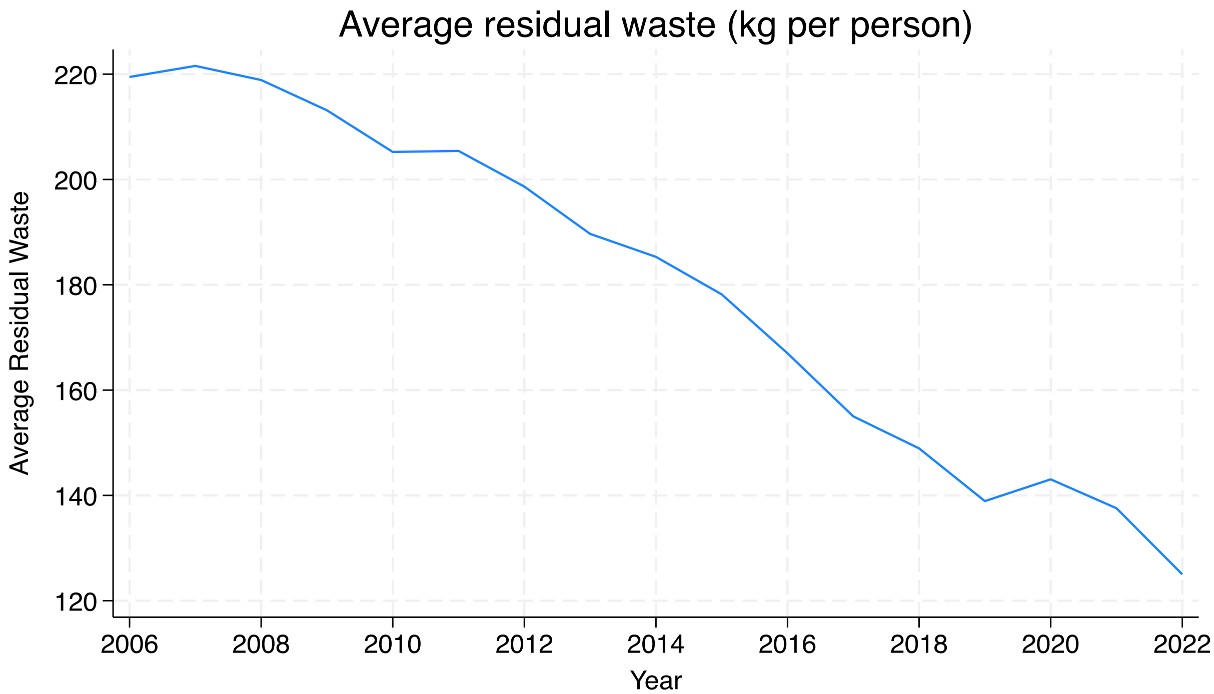



*Figure C1 Average amount of small residual household waste*

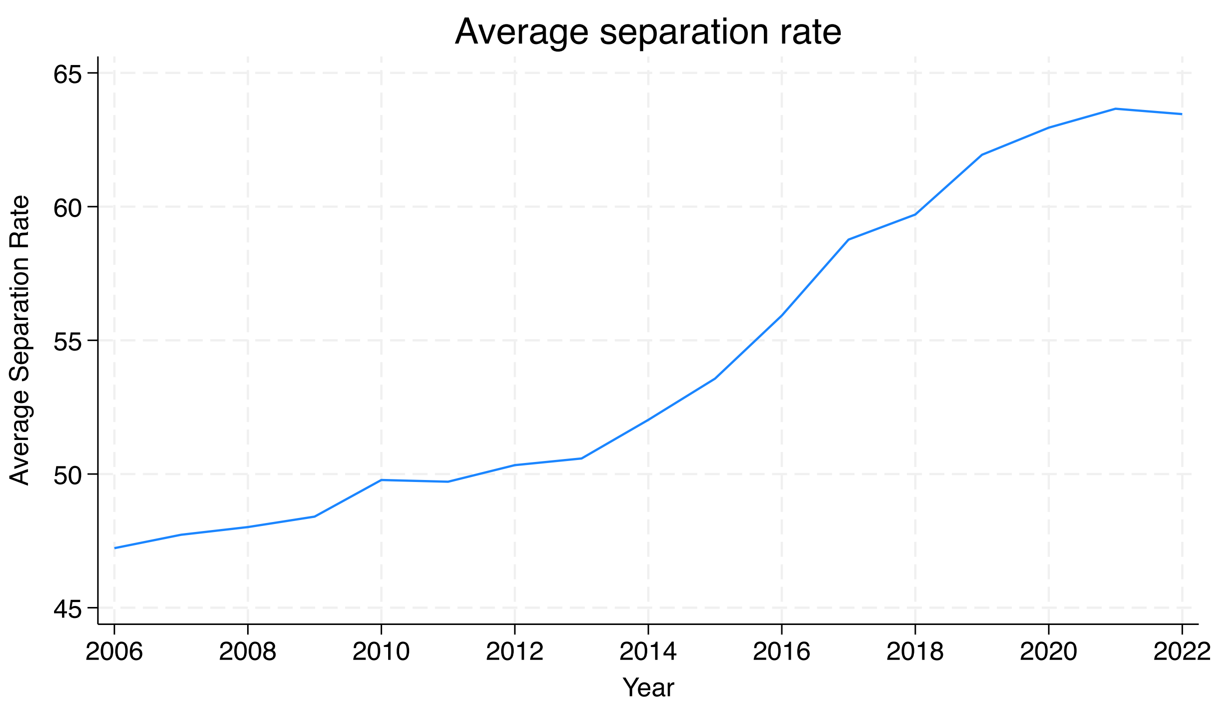



*Figure C2 Average separation rate of small household waste*

## Appendix D: Variable transformations

*Table D1 Transformation of data for low- and high-rise neighborhoods*

| Original values | Created values for: frequency_lowrise frequency_highrise | Created values for: method_lowrise method_highrise |
|---|---|---|
| UWC | - | UWC |
| Weekly | Weekly | door-to-door |
| Weekly & UWC | - | door-to-door and UWC |
| Bi-weekly | Bi-weekly | door-to-door |
| Bi-weekly & UWC | - | door-to-door and UWC |
| Every three weeks | Every three weeks | door-to-door |
| Every three weeks & UWC | - | door-to-door and UWC |
| Every four weeks | Every four weeks | door-to-door |
| Every four weeks & UWC | - | door-to-door and UWC |

In essence, the original value is split up to create separate values for collection frequency and method

## Appendix E: Choice between FE and RE

Note: Test results are only presented for the combination of residualwaste and system_id. Test results for all other combinations of dependent/independent variables lead to the same conclusion: Random Effects is likely to be biased due to unobserved heterogeneity, so better to use Fixed Effects.

*Table E1 CRE model*

| | | | |
|---|---|---|---|
| Random-effects GLS regression | | Number of obs = | **5,122** |
| Group variable: **municipal~de** | | Number of groups = | **338** |
| R-squared: | | Obs per group: | |
| Within = **0.7293** | | min = | **1** |
| Between = **0.7167** | | avg = | **15.2** |
| Overall = **0.7331** | | max = | **17** |
| | | Wald chi2(**31**) = | **13655.74** |
| corr(u_i, X) = **0** (assumed) | | Prob > chi2 = | **0.0000** |

| residualwaste | Coefficient | Std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| system_id | | | | | | |
| 2 | 14.99598 | 5.173537 | 2.90 | 0.004 | 4.856035 | 25.13593 |
| 3 | 121.4633 | 3.745881 | 32.43 | 0.000 | 114.1215 | 128.8051 |
| 4 | 117.2142 | 22.29569 | 5.26 | 0.000 | 73.51549 | 160.913 |
| 5 | 110.1017 | 2.770854 | 39.74 | 0.000 | 104.671 | 115.5325 |
| 6 | 62.02028 | 22.22267 | 2.79 | 0.005 | 18.46464 | 105.5759 |
| 7 | 108.3176 | 3.121999 | 34.69 | 0.000 | 102.1986 | 114.4366 |
| 8 | 42.45138 | 2.492595 | 17.03 | 0.000 | 37.56599 | 47.33678 |
| 9 | 58.65483 | 3.288215 | 17.84 | 0.000 | 52.21004 | 65.09961 |
| 10 | 13.09156 | 4.897617 | 2.67 | 0.008 | 3.492406 | 22.69071 |
| 11 | 30.48177 | 5.26904 | 5.79 | 0.000 | 20.15464 | 40.8089 |
| 12 | 60.62859 | 32.81675 | 1.85 | 0.065 | -3.691056 | 124.9482 |
| preschoolage | 3.689763 | 1.007254 | 3.66 | 0.000 | 1.715581 | 5.663945 |
| groenedruk | .8375105 | .3632299 | 2.31 | 0.021 | .125593 | 1.549428 |
| grijzedruk | -1.470672 | .186323 | -7.89 | 0.000 | -1.835858 | -1.105485 |
| pop_dens | -.0080691 | .003341 | -2.42 | 0.016 | -.0146173 | -.0015209 |
| householdsize | 31.00613 | 16.03757 | 1.93 | 0.053 | -.4269228 | 62.43918 |
| unemployment | -.1851521 | .2406738 | -0.77 | 0.442 | -.656864 | .2865599 |
| higher_edu | -.0988708 | .1215726 | -0.81 | 0.416 | -.3371488 | .1394072 |
| income | -1.64475 | .1395044 | -11.79 | 0.000 | -1.918173 | -1.371326 |
| women | 11.08475 | 1.773288 | 6.25 | 0.000 | 7.609173 | 14.56033 |
| non_w | -2.819309 | .4838071 | -5.83 | 0.000 | -3.767553 | -1.871064 |
| avg_preschoolage | -7.08808 | 6.953556 | -1.02 | 0.308 | -20.7168 | 6.540639 |
| avg_groenedruk | 3.258692 | 1.205456 | 2.70 | 0.007 | .8960414 | 5.621342 |
| avg_grijzedruk | 1.001808 | .5885931 | 1.70 | 0.089 | -.1518128 | 2.15543 |
| avg_pop_dens | .0159562 | .004322 | 3.69 | 0.000 | .0074853 | .0244272 |
| avg_householdsize | -217.4148 | 31.71405 | -6.86 | 0.000 | -279.5732 | -155.2564 |
| avg_unemployment | -14.80543 | 4.030839 | -3.67 | 0.000 | -22.70573 | -6.905132 |
| avg_higher_edu | -2.988223 | .4440439 | -6.73 | 0.000 | -3.858533 | -2.117913 |
| avg_income | .9247701 | .6151756 | 1.50 | 0.133 | -.2809519 | 2.130492 |
| avg_women | -1.663835 | 3.665069 | -0.45 | 0.650 | -8.847238 | 5.519567 |
| avg_non_w | 3.785174 | .8189171 | 4.62 | 0.000 | 2.180126 | 5.390222 |
| _cons | 88.94106 | 166.3214 | 0.53 | 0.593 | -237.0428 | 414.9249 |
| sigma_u | 31.297105 | | | | | |
| sigma_e | 21.414752 | | | | | |
| rho | .68111294 | (fraction of variance due to u_i) | | | | |

*Table E2 CRE test*

```
 ( 1)  avg_preschoolage - avg_groenedruk = 0
 ( 2)  avg_preschoolage - avg_grijzedruk = 0
 ( 3)  avg_preschoolage - avg_pop_dens = 0
 ( 4)  avg_preschoolage - avg_householdsize = 0
 ( 5)  avg_preschoolage - avg_unemployment = 0
 ( 6)  avg_preschoolage - avg_higher_edu = 0
 ( 7)  avg_preschoolage - avg_income = 0
 ( 8)  avg_preschoolage - avg_women = 0
 ( 9)  avg_preschoolage - avg_non_w = 0
 (10)  avg_preschoolage = 0

           chi2( 10) =  193.82
         Prob > chi2 =    0.0000
```

*Table E2 Hausman test*

| | Coefficients (b) fe | Coefficients (B) re | (b-B) Difference | sqrt(diag(V_b-V_B)) Std. err. |
|---|---|---|---|---|
| system_id | | | | |
| 2 | 18.0315 | 15.01766 | 3.013835 | 1.575297 |
| 3 | 121.1583 | 124.0131 | -2.854775 | 1.055854 |
| 4 | 115.5132 | 121.6929 | -6.179748 | . |
| 5 | 108.4256 | 113.1515 | -4.725924 | .6953766 |
| 6 | 62.17472 | 63.5841 | -1.409386 | . |
| 7 | 107.993 | 110.768 | -2.774985 | .5204135 |
| 8 | 42.14496 | 43.17951 | -1.034555 | .2819107 |
| 9 | 57.78017 | 60.0968 | -2.316628 | .3185546 |
| 10 | 8.10675 | 14.964 | -6.857253 | 1.628821 |
| 11 | 27.41177 | 32.3072 | -4.895428 | 1.778402 |
| preschoolage | 3.58959 | 3.730441 | -.1408515 | . |
| groenedruk | .8349236 | 1.188849 | -.3539256 | .1665616 |
| grijzedruk | -1.480023 | -1.542642 | .0626187 | .0868498 |
| pop_dens | -.0080397 | .0029596 | -.0109993 | .0026524 |
| households~e | 32.78321 | -31.20764 | 63.99086 | 10.20261 |
| unemployment | -.1787744 | -.538166 | .3593916 | .0083503 |
| higher_edu | -.1030355 | -.2132197 | .1101842 | .0376998 |
| income | -1.642609 | -2.161742 | .5191335 | .0627906 |
| women | 11.11691 | 13.43592 | -2.319007 | 1.000773 |
| non_w | -2.801674 | -1.133547 | -1.668127 | .3438402 |

```
                         b = Consistent under H0 and Ha; obtained from xtreg.
          B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

   chi2(20) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            = 229.17
Prob > chi2 = 0.0000
(V_b-V_B is not positive definite)
```

## Appendix F: Methodological concerns

*Table F1 Between- and within-variation for UBP*

| | Overall | | Between | | Within |
|---|---|---|---|---|---|
| UBP | Freq. | Percent | Freq. | Percent | Percent |
| 0 | 2967 | 57.78 | 235 | 69.32 | 83.99 |
| 1 | 2168 | 42.22 | 193 | 56.93 | 73.38 |
| Total | 5135 | 100.00 | 428 | 126.25 | 79.21 |
| | | | (n = 339) | | |

*Table F2 Between- and within-variation for system*

| | Overall | | Between | | Within |
|---|---|---|---|---|---|
| system_id | Freq. | Percent | Freq. | Percent | Percent |
| 1 | 206 | 4.02 | 38 | 11.24 | 36.34 |
| 2 | 105 | 2.05 | 13 | 3.85 | 53.41 |
| 3 | 358 | 6.99 | 32 | 9.47 | 71.84 |
| 4 | 1 | 0.02 | 1 | 0.30 | 6.25 |
| 5 | 2595 | 50.66 | 211 | 62.43 | 80.92 |
| 6 | 1 | 0.02 | 1 | 0.30 | 5.88 |
| 7 | 353 | 6.89 | 36 | 10.65 | 60.84 |
| 8 | 1142 | 22.30 | 119 | 35.21 | 64.71 |
| 9 | 148 | 2.89 | 42 | 12.43 | 22.28 |
| 10 | 112 | 2.19 | 13 | 3.85 | 58.48 |
| 11 | 92 | 1.80 | 11 | 3.25 | 59.29 |
| 12 | 9 | 0.18 | 1 | 0.30 | 100.00 |
| Total | 5122 | 100.00 | 518 | 153.25 | 65.25 |
| | | | (n = 338) | | |

*Table F3 Between- and within-variation for frequency_lowrise*

| | Overall | | Between | | Within |
|---|---|---|---|---|---|
| frequen~d | Freq. | Percent | Freq. | Percent | Percent |
| 1 | 551 | 49.51 | 165 | 58.51 | 85.76 |
| 2 | 89 | 8.00 | 30 | 10.64 | 69.39 |
| 3 | 424 | 38.10 | 132 | 46.81 | 79.97 |
| 4 | 49 | 4.40 | 31 | 10.99 | 45.54 |
| Total | 1113 | 100.00 | 358 | 126.95 | 78.77 |
| | | | (n = 282) | | |

*Table F4 Between- and within-variation for frequency_highrise*

| | Overall | | Between | | Within |
|---|---|---|---|---|---|
| frequen~d | Freq. | Percent | Freq. | Percent | Percent |
| 1 | 67 | 39.64 | 31 | 44.93 | 84.14 |
| 2 | 7 | 4.14 | 3 | 4.35 | 100.00 |
| 3 | 39 | 23.08 | 18 | 26.09 | 85.65 |
| 4 | 56 | 33.14 | 28 | 40.58 | 87.50 |
| Total | 169 | 100.00 | 80 | 115.94 | 86.25 |
| | | | (n = 69) | | |

*Table F5 Between- and within-variation for method_lowrise*

| method_~d | Overall Freq. | Overall Percent | Between Freq. | Between Percent | Within Percent |
|---|---|---|---|---|---|
| 1 | 131 | 8.58 | 47 | 13.86 | 62.87 |
| 2 | 1113 | 72.89 | 282 | 83.19 | 87.90 |
| 3 | 283 | 18.53 | 110 | 32.45 | 55.97 |
| Total | 1527 | 100.00 | 439 | 129.50 | 77.22 |
| | | | (n = 339) | | |

*Table F6 Between- and within-variation for method_highrise*

| method_~d | Overall Freq. | Overall Percent | Between Freq. | Between Percent | Within Percent |
|---|---|---|---|---|---|
| 1 | 1120 | 74.22 | 283 | 84.23 | 87.84 |
| 2 | 169 | 11.20 | 69 | 20.54 | 55.60 |
| 3 | 220 | 14.58 | 91 | 27.08 | 53.90 |
| Total | 1509 | 100.00 | 443 | 131.85 | 75.85 |
| | | | (n = 336) | | |

*Table F7 Pairwise Correlations*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) UBP | 1.000 | | | | | | | | | | | | | | | | |
| (2) system_id | -0.967 | 1.000 | | | | | | | | | | | | | | | |
| (3) frequency_lowr~d | 0.020 | -0.005 | 1.000 | | | | | | | | | | | | | | |
| (4) frequency_high~d | -0.290 | 0.331 | 0.521 | 1.000 | | | | | | | | | | | | | |
| (5) method_lowrise~d | 0.033 | -0.032 | | 0.000 | 1.000 | | | | | | | | | | | | |
| (6) method_highris~d | 0.028 | -0.027 | 0.022 | | 0.151 | 1.000 | | | | | | | | | | | |
| (7) population | -0.166 | 0.151 | 0.098 | 0.231 | -0.001 | 0.029 | 1.000 | | | | | | | | | | |
| (8) pop_dens | -0.283 | 0.265 | -0.054 | 0.328 | -0.053 | 0.029 | 0.535 | 1.000 | | | | | | | | | |
| (9) householdsize | 0.145 | -0.142 | 0.004 | 0.028 | 0.066 | -0.075 | -0.405 | -0.411 | 1.000 | | | | | | | | |
| (10) income | 0.074 | -0.078 | -0.025 | 0.136 | 0.084 | 0.098 | -0.155 | -0.101 | 0.084 | 1.000 | | | | | | | |
| (11) unemployment | -0.076 | 0.080 | -0.037 | 0.053 | -0.027 | 0.004 | 0.272 | 0.232 | -0.327 | -0.272 | 1.000 | | | | | | |
| (12) higher_edu | -0.110 | 0.103 | -0.083 | 0.107 | -0.001 | 0.084 | 0.251 | 0.322 | -0.398 | 0.470 | 0.002 | 1.000 | | | | | |
| (13) women | -0.243 | 0.235 | -0.148 | 0.205 | -0.017 | 0.045 | 0.133 | 0.420 | -0.388 | 0.066 | 0.136 | 0.454 | 1.000 | | | | |
| (14) preschoolage | -0.227 | 0.202 | -0.002 | 0.402 | 0.061 | -0.106 | 0.138 | 0.187 | 0.546 | -0.186 | -0.115 | -0.126 | -0.026 | 1.000 | | | |
| (15) groenedruk | -0.076 | 0.060 | -0.067 | 0.188 | 0.120 | -0.071 | -0.250 | -0.196 | 0.816 | 0.178 | -0.207 | -0.114 | -0.077 | 0.700 | 1.000 | | |
| (16) grijzedruk | 0.163 | -0.140 | 0.013 | -0.315 | 0.015 | 0.108 | -0.293 | -0.263 | -0.279 | 0.550 | -0.047 | 0.186 | 0.158 | -0.668 | -0.234 | 1.000 | |
| (17) non_w | -0.294 | 0.266 | -0.019 | 0.389 | -0.057 | -0.026 | 0.720 | 0.733 | -0.506 | -0.046 | 0.299 | 0.348 | 0.340 | 0.151 | -0.259 | -0.264 | 1.000 |

*Table F8 Pairwise Correlations without "groenedruk"*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) UBP | 1.000 | | | | | | | | | | | | | | | |
| (2) system_id | -0.967 | 1.000 | | | | | | | | | | | | | | |
| (3) frequency_lowr~d | 0.020 | -0.005 | 1.000 | | | | | | | | | | | | | |
| (4) frequency_high~d | -0.290 | 0.331 | 0.521 | 1.000 | | | | | | | | | | | | |
| (5) method_lowrise~d | 0.033 | -0.032 | | 0.000 | 1.000 | | | | | | | | | | | |
| (6) method_highris~d | 0.028 | -0.027 | 0.022 | | 0.151 | 1.000 | | | | | | | | | | |
| (7) population | -0.166 | 0.151 | 0.098 | 0.231 | -0.001 | 0.029 | 1.000 | | | | | | | | | |
| (8) pop_dens | -0.283 | 0.265 | -0.054 | 0.328 | -0.053 | 0.029 | 0.535 | 1.000 | | | | | | | | |
| (9) householdsize | 0.145 | -0.142 | 0.004 | 0.028 | 0.066 | -0.075 | -0.405 | -0.411 | 1.000 | | | | | | | |
| (10) income | 0.074 | -0.078 | -0.025 | 0.136 | 0.084 | 0.098 | -0.155 | -0.101 | 0.084 | 1.000 | | | | | | |
| (11) unemployment | -0.076 | 0.080 | -0.037 | 0.053 | -0.027 | 0.004 | 0.272 | 0.232 | -0.327 | -0.272 | 1.000 | | | | | |
| (12) higher_edu | -0.110 | 0.103 | -0.083 | 0.107 | -0.001 | 0.084 | 0.251 | 0.322 | -0.398 | 0.470 | 0.002 | 1.000 | | | | |
| (13) women | -0.243 | 0.235 | -0.148 | 0.205 | -0.017 | 0.045 | 0.133 | 0.420 | -0.388 | 0.066 | 0.136 | 0.454 | 1.000 | | | |
| (14) preschoolage | -0.227 | 0.202 | -0.002 | 0.402 | 0.061 | -0.106 | 0.138 | 0.187 | 0.546 | -0.186 | -0.115 | -0.126 | -0.026 | 1.000 | | |
| (15) grijzedruk | 0.163 | -0.140 | 0.013 | -0.315 | 0.015 | 0.108 | -0.293 | -0.263 | -0.279 | 0.550 | -0.047 | 0.186 | 0.158 | -0.668 | 1.000 | |
| (16) non_w | -0.294 | 0.266 | -0.019 | 0.389 | -0.057 | -0.026 | 0.720 | 0.733 | -0.506 | -0.046 | 0.299 | 0.348 | 0.340 | 0.151 | -0.264 | 1.000 |

*Table F9 Histogram "residualwaste"*

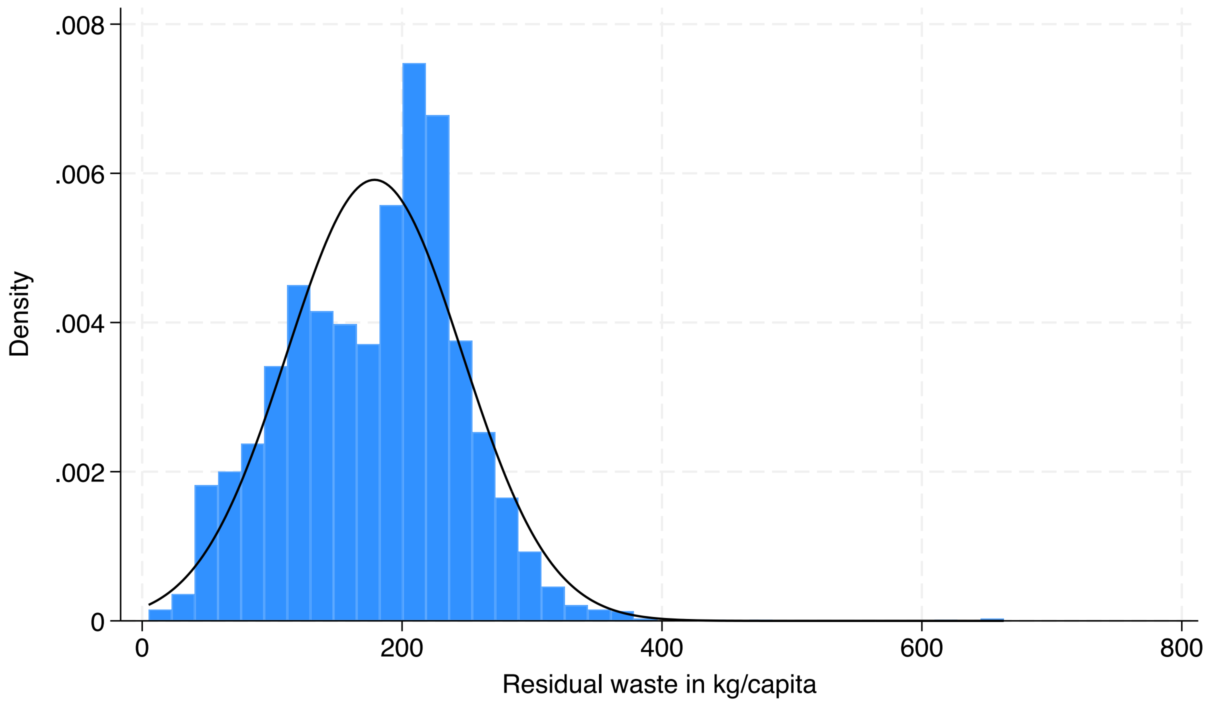
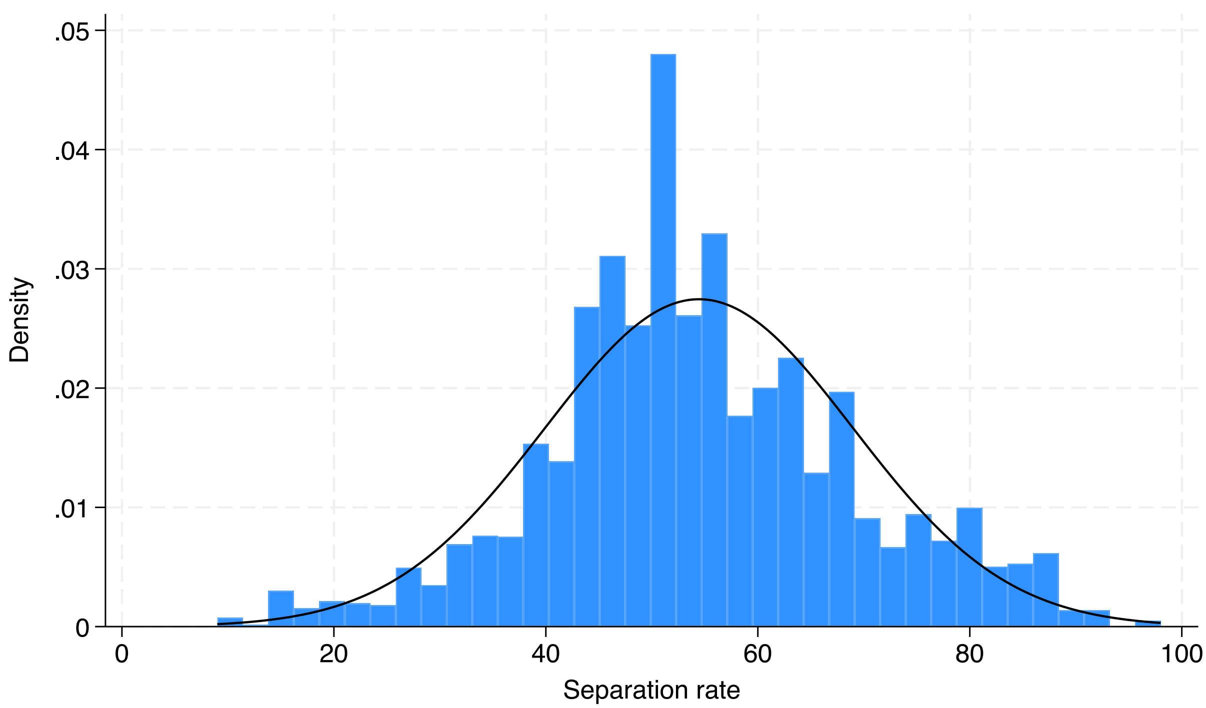



*Table F10 Histogram "separationrate"*



## Appendix G: Robustness check - Synthetic control method

*Table G1 Fixed effects regression results on the balanced subset for each pricing system and its impact on residual waste quantities and the separation rate*

| VARIABLES | (3) residualwaste | (4) separationrate |
|---|---|---|
| Expensive garbage bag | -99.12*** | 23.22*** |
| | (8.39) | (2.21) |
| Expensive garbage bag & number of people | -93.75*** | 23.20*** |
| | (13.51) | (4.51) |
| Volume | -6.30 | 0.34 |
| | (5.18) | (1.28) |
| Volume & frequency | -65.01*** | 10.41*** |
| | (5.98) | (1.42) |
| Volume, frequency & number of people | -53.49*** | 9.71*** |
| | (5.27) | (1.47) |
| Weight | -99.40*** | 13.51*** |
| | (11.06) | (2.00) |
| Weight & frequency | -85.27*** | 15.37*** |
| | (11.22) | (2.54) |
| Constant | -472.55* | 201.02*** |
| | (241.27) | (63.76) |
| Observations | 2,822 | 2,822 |
| Adj. $R^2$ | 0.790 | 0.700 |
| Controls | Yes | Yes |
| Year FE | Yes | Yes |
| Municipality FE | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Some categories are missing due to data limitations of the subset

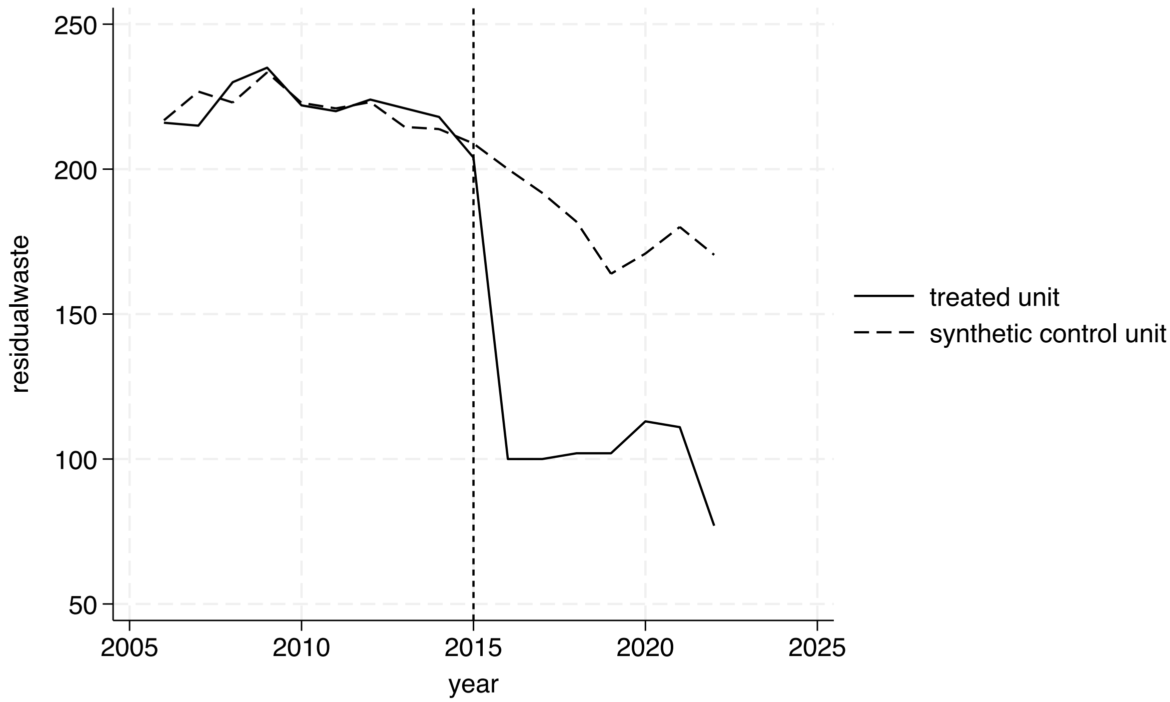



*Figure G1 Synthetic control method results for the effect of implementing a Volume- & frequency-based pricing system on residual waste quantities (kg/capita)*

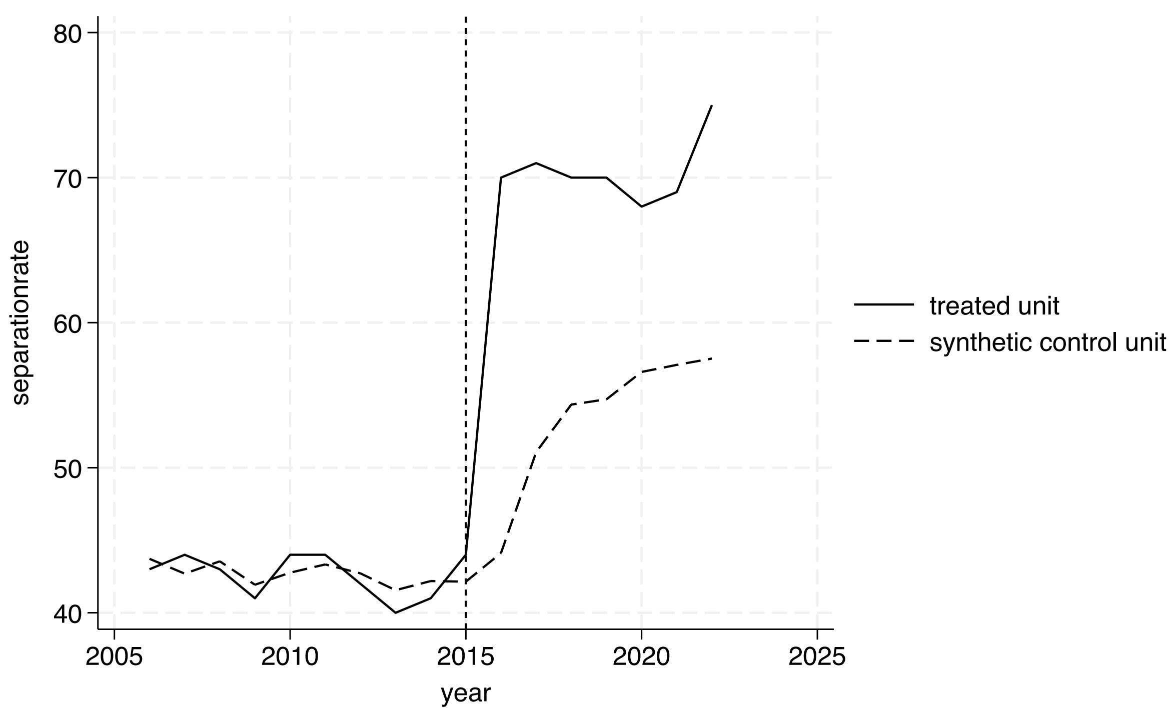



*Figure G2 Synthetic control method results for the effect of implementing a Volume- & frequency-based pricing system on the separation rate*

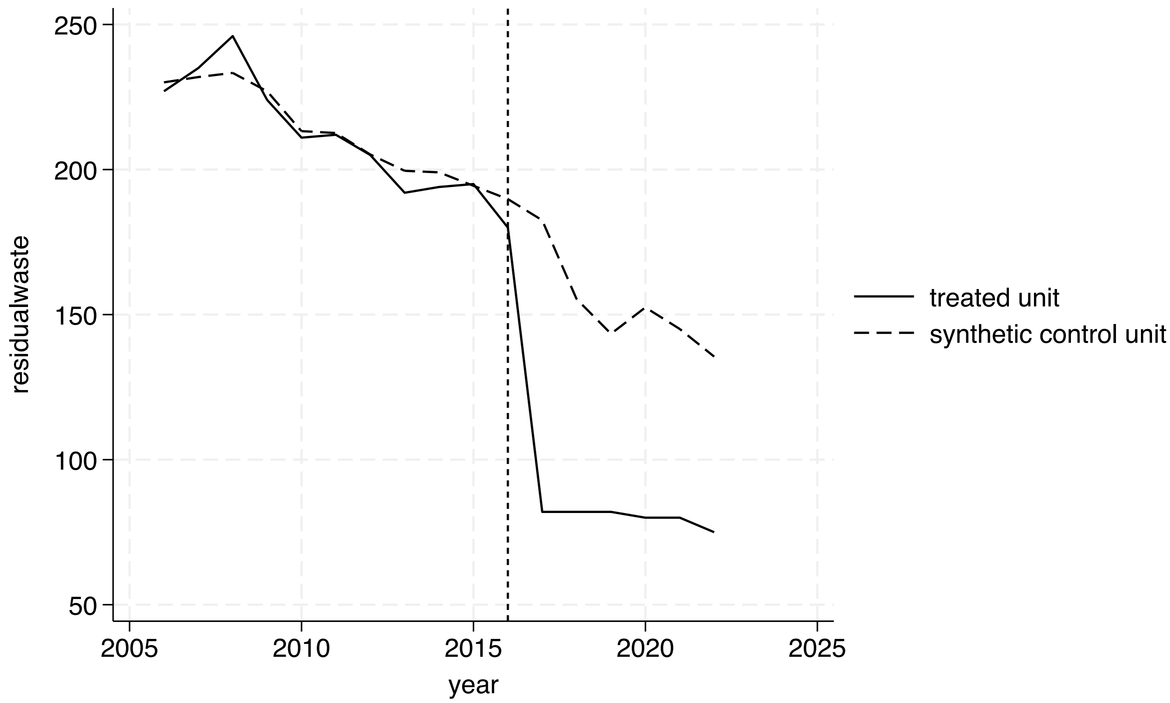



*Figure G3 Synthetic control method results for the effect of implementing a Volume-, frequency & number of people-based pricing system on residual waste quantities (kg/capita)*

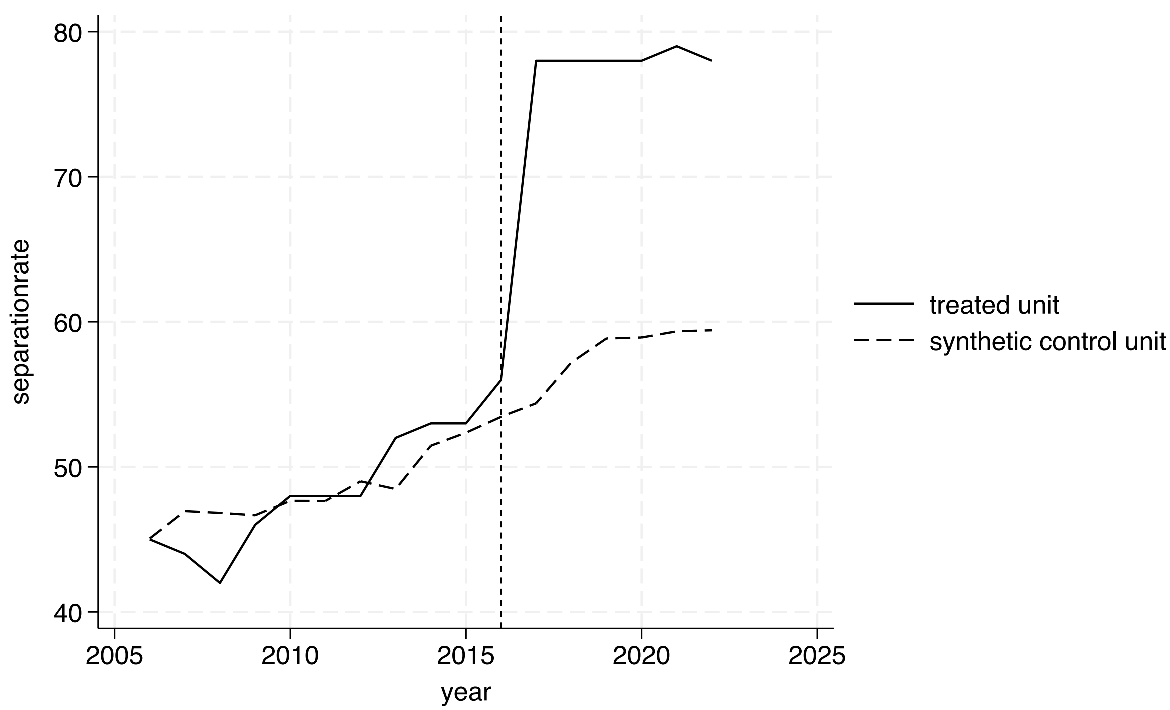



*Figure G4 Synthetic control method results for the effect of implementing a Volume-, frequency and number of people-based pricing system on the separation rate*

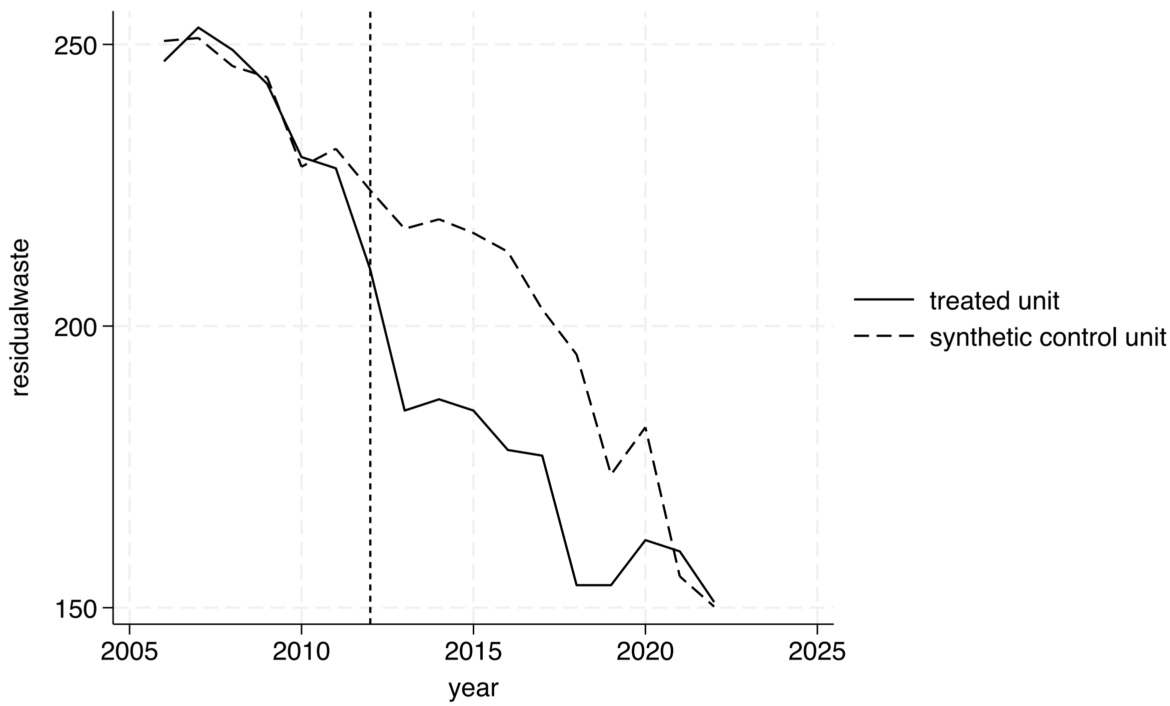



*Figure G3 Synthetic control method results for the effect of implementing a Volume-based pricing system on residual waste quantities (kg/capita)*

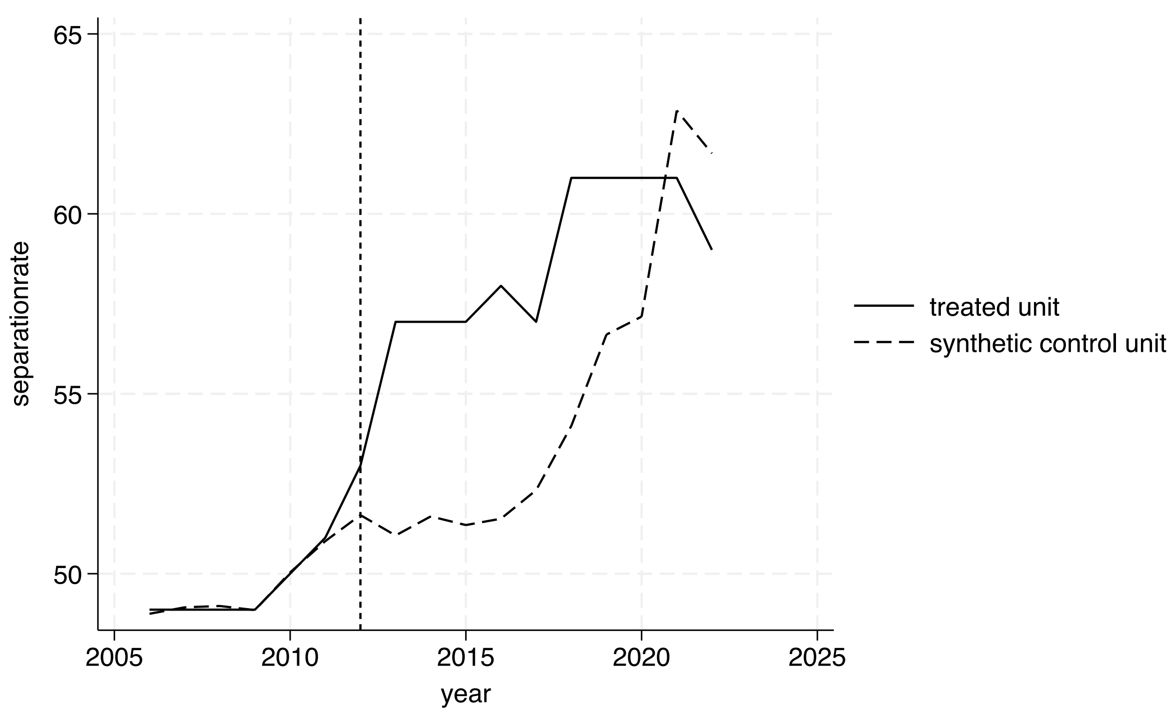



*Figure G4 Synthetic control method results for the effect of implementing a Volume-based pricing system on the separation rate*

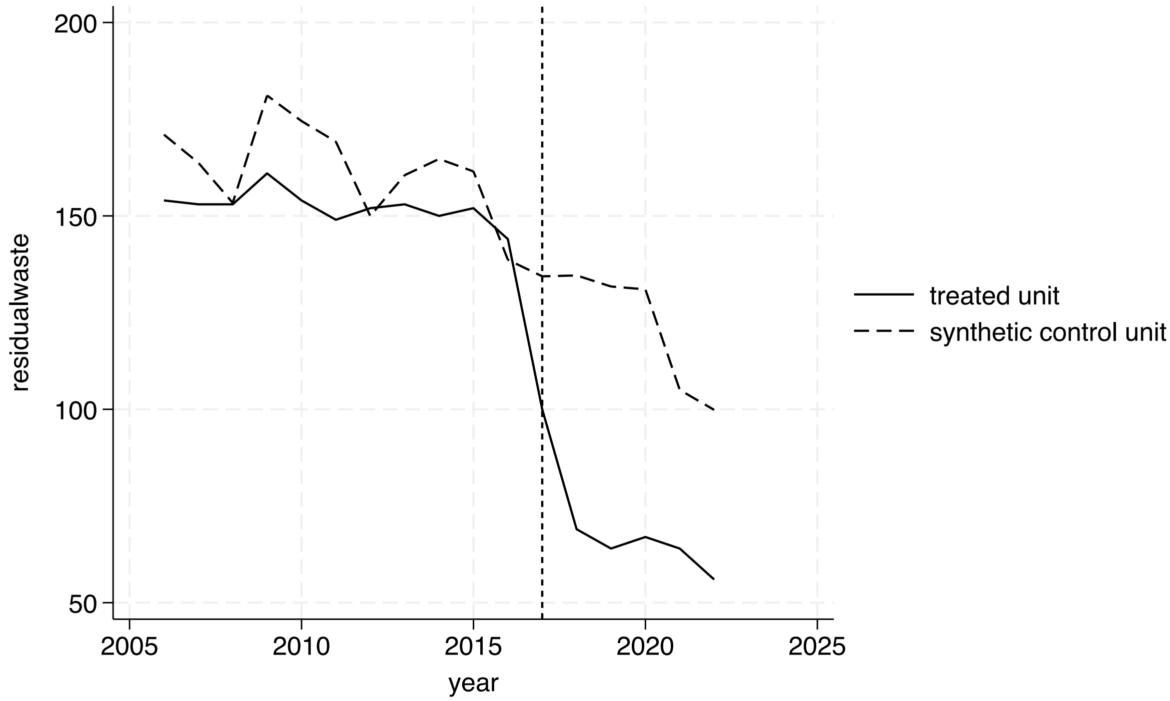



*Figure G5 Synthetic control method results for the effect of implementing a Bag-based pricing system on residual waste quantities (kg/capita)*

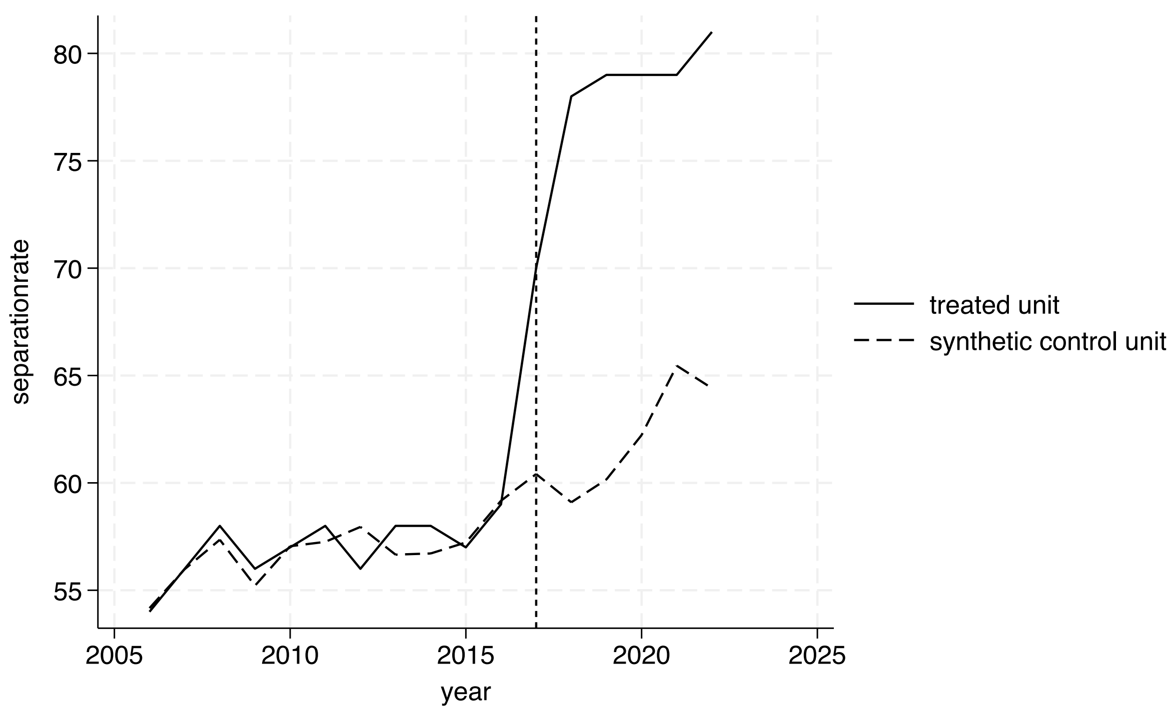



*Figure G6 Synthetic control method results for the effect of implementing a Bag-based pricing system on the separation rate*