FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

Assessing the Impact of Volume- to Weight-Based Household Waste Pricing: A Staggered Difference-in-Differences Approach

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June 2, 2026

Foreword

From February 2025 to June 2026, I conducted my master's thesis at Ghent University, and this master's dissertation is the culmination of that effort. It is written in fulfillment of the requirements for my graduation and the attainment of the academic degree of 'Master of Science in Business Engineering - Operations Management'.

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Jef Bruggeman

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Declaration of scientific integrity

I declare that the research was conducted in accordance with the rules governing scientific and academic integrity.
I confirm that I have familiarized myself with and acted in compliance with the faculty's ethical code.

Abstract

In recent years, political debates have intensified across Flanders regarding the environmental burdens associated with residential refuse collection. To meet the targets outlined in the regional Local Materials Plan (LMP) 2023-2030, local authorities have phased out traditional volume-based refuse bags in favor of differentiated, weight-based tariff models (DIFTAR) utilizing chipped waste containers. Despite international backing for weight-based policies, historical empirical literature from Flanders indicates that initial reduction outcomes decay within five years, while missing granular, multi-fraction insights regarding household substitution behaviors. This master's thesis addresses these gaps by evaluating a comprehensive longitudinal panel dataset tracking 17 household waste streams across 266 non-merged Flemish municipalities from 2017 to 2024. Methodologically, the study implements a conditional staggered Difference-in-Differences estimator framework that corrects for multi-period selection biases and negative weighting issues while controlling for structural and demographic variations through the Belfius Municipal Typology. The findings demonstrate that transitioning to weight-based mechanisms yields a statistically significant overall reduction of 11.80% in residual household waste generation, peaking at 17.27% during the first full year post-implementation. Although a fade-out effect is observed in the last years, this trend remains tentative due to data limitations and a restricted post-treatment timeline for recent adopters. Crucially, the multi-fraction substitution analysis reveals that positive spillovers are isolated to small hazardous waste (+6.97%) and vegetable and animal oils/fats (+5.10%), whereas the majority of the diverted weight falls into the category of net waste prevented or out-of-system diversion, such as home composting. Subgroup stratifications indicate that while rural areas absorb organic waste through home composting and substitute via plastic sorting, urban center residents shift materials into municipal biowaste fractions. Finally, targeted configurations such as non-linear, tiered pricing schemes minimize the traditional fade-out effect and prompt steeper residual waste declines of roughly 20%. These empirical insights provide a foundation for local authorities to adjust operational waste logistics, implement targeted communication campaigns, and optimize strategic public infrastructure plans.

Extended Abstract

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***Abstract*—In response to the Flemish Local Materials Plan 2023–2030, many local authorities are replacing volume-based refuse bags with weight-based pricing models. Despite international backing for weight-based policies, historical empirical literature from Flanders indicates that initial reduction outcomes decay within five years, while missing granular, multi-fraction insights regarding household substitution behaviors.**

This study evaluates the impact of this transition using a comprehensive longitudinal panel dataset tracking 17 waste streams across 266 Flemish municipalities from 2017 to 2024. Employing a conditional staggered Difference-in-Differences framework, we find that weight-based pricing yields an immediate 11.80% reduction in residual household waste, peaking at 17.27% in the first year post-implementation. Although a fade-out effect appears in later years, this trend remains tentative due to data limitations for recent adopters. Multi-fraction analysis reveals that weight diversion primarily represents net waste prevention rather than recycling spillovers, though urban residents significantly shift materials into municipal biowaste. Furthermore, non-linear tiered pricing designs mitigate the fade-out effect, driving sustained reductions near 20%. These findings offer critical insights for optimizing local public waste logistics and policy configurations.

***Keywords*—Waste management, Residential waste, Unit-based pricing, Difference-in-Differences, Household Sorting Behavior**

I. Introduction

Flemish municipalities face increasing pressure to reduce household residual waste in line with the Local Materials Plan (LMP) 2023–2030, which mandates a reduction from 125 kg to 100 kg of residual waste per inhabitant by 2030 [1]. To meet this target, an increasing number of municipalities are abandoning the traditional volume-based refuse bag in favor of weight-based differentiated tariffs (DIFTAR), operationalizing the "polluter pays" principle through chipped, weight-based containers [2].

International economic literature endorses unit-based pricing as an effective instrument for waste prevention. Allers and Hoeben found that weight-based pricing reduces unsorted waste by 39% [3], while Linderhof et al. documented a 56% decline in residual waste in the first Dutch municipality to adopt the system [4]. More recently, Gautier and Salem confirmed that weight-based systems outperform all alternatives in Wallonia, reducing residual waste by 31% relative to volume-based pricing, with non-linear tariff structures suggested as a contributing factor to their superior performance [5]. However, Flemish evidence tells a different story. De Jaeger and Eyckmans found only a transient introduction effect, with no long-term advantage over bag-based systems [6]. Most critically, Sasao, De Jaeger, and De Weerdt demonstrated that while weight-based pricing triggers a 21.4% initial shock, this effect completely fades within five years [7].

Three gaps in the existing literature motivate this study. First, all Flemish evidence predates the current wave of adoption (data up to 2015 at most) and must be re-examined with contemporary data. Second, multi-fraction substitution analyses are either absent or limited to a handful of streams, leaving the precise household behavioral response largely unmapped. Third, the proliferation of distinct tariff architectures, linear weight-plus-frequency, non-linear tiered pricing, and hybrid weight-volume systems, has never been evaluated comparatively in a causal framework.

This thesis addresses these gaps using a comprehensive longitudinal panel dataset tracking 17 household waste streams across 266 non-merged Flemish municipalities from 2017 to 2024.

II. Data and Context

A. Dataset Construction

The dataset was assembled from the central waste registry maintained by the *Openbare Vlaamse Afvalstoffenmaatschappij* (OVAM), supplemented by manual classification of municipal pricing schedules through direct contact with intermunicipal associations. Four distinct weight-based tariff categories are distinguished: WF (weight + frequency), WF NL (non-linear weight + frequency), WV (weight + volume), and W (purely weight-based), alongside the baseline volume-based system (V). The observation window spans 2017–2024, yielding 2,128 municipality-year observations across 17 waste streams for a consolidated dataset of 32,290 data points.

Fifteen municipalities involved in administrative mergers are excluded to safeguard internal validity: a merger creates a structural break that confounds the pricing treatment with a change in the unit of observation. The resulting balanced panel contains 83 municipalities that maintained weight-based pricing throughout, 142 that remained volume-based (the "never-treated" control group), and 41 switchers. The distribution over the different pricing systems can be seen in Table I.

B. Controlling for Heterogeneity

Municipal structural heterogeneity is addressed through the Belfius Municipal Typology, a six-cluster classification derived from over 150 statistical indicators covering demographics, income, housing density, and economic activity [8]. Among the

TABLE I
SAMPLE OVERVIEW: SWITCHING MUNICIPALITIES (2017–2024)

Pricing System	Switchers	Municipalities (2024)
WF (Weight + Freq.)	28	76
WF NL (Non-linear WF)	6	8
WV (Weight + Volume)	4	8
W (Purely weight-based)	3	32
Total switchers	**41**	**124**

266 sampled municipalities, residential municipalities (106) and those with economic activity (63) dominate; rural municipalities (55), urbanized municipalities (22), large and regional cities (12), and coastal municipalities (8) complete the typology. Coastal municipalities contain no switchers during the observation window and are excluded from the heterogeneity analysis.

III. METHODOLOGY

A. Staggered Difference-in-Differences

Standard Two-Way Fixed Effects (TWFE) models are biased under staggered treatment timing when treatment effects are heterogeneous over time [9]. Because prior Flemish evidence strongly suggests a dynamic fade-out, TWFE would produce "forbidden comparisons" using already-treated municipalities as counterfactuals for newly treated ones, potentially reversing the sign of the coefficient. This study therefore employs the Callaway–Sant'Anna staggered Difference-in-Differences (DiD) estimator [10], implemented via the `did` package in R.

The building block is the group-time average treatment effect $ATT(g,t)$, defined for each cohort g (year of adoption) and calendar year t:

$$\begin{aligned} ATT(g,t) = \mathbb{E}_{X|G_i=g}\Big[&\mathbb{E}[\ln(Y_{it}{+}1) \\ &- \ln(Y_{i,g-1}{+}1) \mid X_i, G_i{=}g] \\ &- \mathbb{E}[\ln(Y_{it}{+}1) - \ln(Y_{i,g-1}{+}1) \mid X_i, C_i{=}1]\Big] \end{aligned} \tag{1}$$

where X_i encodes the Belfius typology as a conditioning covariate, ensuring the conditional parallel trends assumption holds. The Belfius dummy variables guarantee that each treated municipality is compared only to structurally similar untreated or not-yet-treated peers. An unconditional version of the model, omitting the Belfius typology covariates, serves as a specification check. The cohort-level effects are then aggregated via cohort-size-weighted averaging into a dynamic event study, anchored at the pre-treatment year ($l = -1$). Log-linear estimates $\hat{\theta}$ are converted to exact percentage changes via $(e^{\hat{\theta}} - 1) \times 100$. Statistical significance is assessed using simultaneous confidence bands based on multiplier bootstrap, which corrects for multiple comparisons across event times at the 5% level.

The same framework is iterated over all other waste streams (substitution analysis), restricted to each Belfius cluster (spatial heterogeneity), and restricted to each pricing mechanism (implementation heterogeneity), yielding a fully consistent comparative architecture. For each waste stream, the analysis includes only municipalities with complete data over the 2017—2024 period.

IV. RESULTS

A. Primary Impact on Residual Waste

The conditional staggered DiD model identifies a statistically significant overall reduction in residual household waste of 11.80% (95% simultaneous band: $[-20.02\%, -2.74\%]$). As shown in Table II, the full effect materializes in the first complete post-treatment year, where the reduction peaks at 17.27%. The policy's impact remains statistically significant through Year 4 (-13.32%), but attenuates and loses significance in Years 5–6. This apparent fade-out must be interpreted cautiously: these later event times are anchored to two 2018 early adopters, and the widening of the simultaneous confidence bands is largely a sample-size artefact rather than a confirmed behavioral relapse.

TABLE II
EXACT % CHANGE IN RESIDUAL WASTE — CONDITIONAL EVENT STUDY

Event Time	Estimate	95% Band	Sig.
-2	$+0.31\%$	$[-1.57\%, +2.21\%]$	
-1	-2.68%	$[-5.95\%, +0.71\%]$	
0	-15.12%	$[-18.80\%, -11.28\%]$	*
$+1$	-17.27%	$[-21.91\%, -12.36\%]$	*
$+2$	-15.15%	$[-20.47\%, -9.47\%]$	*
$+3$	-14.94%	$[-21.56\%, -7.77\%]$	*
$+4$	-13.32%	$[-24.85\%, -0.04\%]$	*
$+5$	-3.84%	$[-44.23\%, +65.83\%]$	
$+6$	-1.72%	$[-26.78\%, +31.93\%]$	
Overall	$\mathbf{-11.80\%}$	$[-20.02\%, -2.74\%]$	*

* 95% simultaneous confidence band excludes zero.

The near-identical magnitude of the unconditional (-11.48%) and conditional (-11.80%) overall estimates confirms that the reduction is driven by the pricing mechanism itself rather than pre-existing structural differences between adopting and non-adopting municipalities.

B. Multi-Fraction Substitution Analysis

Table III summarizes the overall substitution effects across 14 alternative waste streams. Contrary to much of the prior literature, positive spillovers into municipal recycling channels are narrow: only small hazardous waste ($+6.97\%$) and vegetable/animal oils & fats ($+5.10\%$) exhibit significant overall increases. This is economically intuitive: both fractions are collected free of charge by Flemish municipalities, and both carry non-trivial weight under a per-kilogram tariff, creating a strong marginal incentive to separate them. Unexpectedly, several fractions experience significant overall declines following the policy transition. The precise behavioral mechanisms

behind these reductions remain unclear and warrant further investigation, as they defy the standard economic incentive to substitute away from the penalized residual stream.

TABLE III
OVERALL SUBSTITUTION EFFECTS (EXACT % CHANGE)

Waste Fraction	Overall Effect	Sig.
Small Hazardous Waste	$+6.97\%$	*
Vegetable & Animal Oils/Fats	$+5.10\%$	*
Wood Waste	-10.76%	*
Paper & Cardboard	-1.87%	*
Packaging Glass	-3.60%	*
Flat Glass	-5.49%	*
PMC, Batteries, C&D Waste, Textiles, Green Waste, VFG Hard Plastics, Scrap Metal	n.s.	

* 95% simultaneous confidence band excludes zero.

The most consequential finding for waste logistics is that the vast majority of diverted weight constitutes net waste prevented rather than recycling substitution. Translating significant effects to absolute kilograms per capita, the 16.0 kg residual waste reduction is not offset by gains in municipal recycling streams; instead, 24.1 kg of the 24.3 kg total shift is categorized as "net waste prevented or out-of-system diversion" (e.g., home composting). However, it is important to note that this out-of-system diversion may also encompass unobserved evasion behaviors, such as illegal dumping, for which municipal-level data is currently unavailable. The previously expected broad surge in formal recycling does not materialize, a finding that has consequences for logistical planning and infrastructure investment decisions.

C. Spatial and Demographic Heterogeneity

Stratifying by Belfius typology reveals consistent primary effectiveness: weight-based pricing reduces residual waste significantly across all clusters, with overall estimates ranging from -11.09% (large and regional cities) to -21.61% (municipalities with economic activity). A higher degree of urbanization does not systematically worsen or improve the primary reduction. However, spatial characteristics decisively shape how households divert their waste:

- **Rural municipalities:** PMC ($+12.67\%$) and small hazardous waste ($+14.30\%$) increase significantly, while VFG remains unaffected, consistent with widespread home composting as the preferred organic diversion route.
- **Large and regional cities:** VFG collection increases by $+35.49\%$ (insignificant due to small n, but directionally robust), confirming that urban residents lacking outdoor composting space are redirected toward the organic bin.
- **Municipalities with economic activity:** The most responsive cluster, driving hard plastics ($+33.67\%$) and PMC ($+14.32\%$) upward alongside the largest residual waste reduction (-21.61%).

D. Method of Implementation

All four weight-based tariff structures achieve significant residual waste reductions. The standard WF model (-10.06%, $n = 28$ switchers) dominates the aggregate results by virtue of its prevalence. Models imposing stronger financial penalties drive steeper declines, although the differences in effectiveness between the individual structures are not statistically significant:

- **WF NL (non-linear):** -19.32% overall, and the reduction remains statistically significant across all observed post-treatment years (up to t=4), suggesting that the escalating penalty structure mitigates the fade-out effect.
- **W (purely weight-based):** -20.07% overall, with no immediate signs of attenuation, though only 3 switching municipalities constrain inference.
- **WV (hybrid):** -11.22% overall, but uniquely stimulates broad positive substitution across PMC ($+11.39\%$), hard plastics ($+59.62\%$), and packaging glass ($+10.31\%$), though only 4 switching municipalities constrain inference.

V. CONCLUSION AND POLICY IMPLICATIONS

This study provides the most comprehensive causal evaluation of weight-based household waste pricing in Flanders to date. The key empirical contributions are threefold.

Effectiveness: The transition from volume- to weight-based pricing yields a significant and robust 11.80% overall reduction in residual household waste, peaking at 17.27% in the first full post-implementation year. The causal identification is robust to covariate adjustment for municipal typology.

Substitution behavior: Contrary to international literature, positive recycling spillovers are narrow and concentrated in fraction-specific channels (small hazardous waste and oils/fats). The dominant household response is waste prevention or out-of-system diversion rather than increased formal recycling, a finding that challenges the assumption that weight-based pricing stimulates municipal recycling stream utilization.

Design matters: Non-linear tiered pricing (WF NL) sustains significant reductions across all observed post-treatment years at approximately 20%, outperforming the standard flat weight-frequency structure and providing empirical evidence against the fade-out narrative for well-designed tariff architectures.

For policymakers, three actionable recommendations follow. First, municipalities should prioritize non-linear tariff designs over flat per-kilogram rates to sustain long-term behavioral change. Second, infrastructure planning must be spatially differentiated: urban areas need organic waste collection capacity to absorb the VFG substitution that home composting cannot accommodate, while rural areas should reinforce PMC and plastics logistics. Third, targeted communication campaigns are needed to prevent the counterintuitive declines observed in glass and paper collection, reassuring citizens that these fractions remain free to separate.

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List of Acronyms

ATT Average Treatment Effect on the Treated.

CI Confidence Interval.

CVRP Capacitated Vehicle Routing Problem.

DiD Difference-in-Differences.

DIFTAR Differentiated Tariffs.

DVR Differential and Variable Rates.

EU European Union.

LMP Local Materials Plan.

MATIS Materials Information System.

OLS Ordinary Least Squares.

OVAM Openbare Vlaamse Afvalstoffenmaatschappij.

PAYT Pay-As-You-Throw.

PMC Plastic, Metal and beverage Cartons.

SHW Small Hazardous Waste.

SME Small and Medium-sized Enterprises.

TWFE Two-Way Fixed Effects.

UBP Unit-Based Pricing.

VFG Vegetable, Fruit and Garden waste.

VLAREMA Vlaams Reglement betreffende het duurzaam beheer van Materiaalkringlopen en Afvalstoffen.

W Weight-based pricing model.

WBP Weight-Based Pricing.

WEEE Waste Electrical and Electronic Equipment.

WF Weight and Frequency pricing model.

WtE Waste-to-Energy.

WV Weight and Volume pricing model.

1

Introduction

In recent years, the rising financial and environmental costs of household waste collection have introduced public and political debate in Flanders. As municipalities deal with the challenge of reducing their residual waste figures to meet ambitious regional targets, many have opted to abandon the traditional refuse sack in favor of weight-based pricing systems (in Flemish context often referred to as "DIFTAR") utilizing chipped, weight-based containers. This transition, which forces citizens to pay precisely per kilogram of waste they generate, is not always met with approval. As highlighted in regional media, opponents often view the system as a covert tax increase [3]. Conversely, proponents argue that the shift is a necessary modernization, moving away from outdated, torn bags on the street toward the polluter pays principle [4]. These conflicting public sentiments underscore a critical question: when local governments introduce weight-based pricing, does it actually alter household behavior in a meaningful, sustainable way?

The rationale behind these policy shifts is firmly rooted in the European transition toward a circular economy, operationalized locally through the Flemish Materials Decree and the waste hierarchy known as the Ladder of Lansink. To minimize incineration and maximize recycling, the Local Materials Plan (LMP) 2023-2030 has set a strict target for Flemish municipalities to reduce average residual household waste to 100 kg per inhabitant per year by 2030. To achieve this, international economic literature widely supports the use of Unit-Based Pricing (UBP). Studies consistently show that charging households per unit of waste generated—whether by bag, volume, or weight—creates a strong financial incentive to prevent waste and increase the separation of recyclables.

However, a gap exists in the academic literature regarding the specific dynamics of these systems within the modern Flemish context. While international and Walloon studies generally identify weight-based pricing as the single most effective instrument for long-term waste reduction, historical empirical evidence from Flanders presents a markedly different, and somewhat discouraging, picture. Prominent Flemish studies have observed that while weight-based pricing triggers a massive initial drop in residual waste, this reduction acts as a temporary "shock effect" that largely fades out within five years. Furthermore, while the literature frequently discusses the "substitution effect"—whereby households divert waste into free or cheaper recycling streams—it often lacks the granular, multi-fraction analysis required to understand precisely *which* materials are diverted, and whether

this diversion represents genuine recycling or merely the dumping of heavy materials into inappropriate streams. Finally, as the design of weight-based systems has evolved to include complex variations—such as non-linear pricing tiers or hybrid weight-volume models—the "one-size-fits-all" assumption in much of the older literature is no longer sufficient to evaluate modern policy outcomes.

Understanding the precise, sustained behavioral impact of these specific weight-based implementations is not only crucial for environmental policy, but it also holds immense practical relevance for operational logistics. The modern transition to chipped, weight-based containers generates vast amounts of highly granular, household-level data. This data presents a unique opportunity for intermunicipal waste associations to optimize their operations, such as predicting exact bin fill-rates and dynamically routing collection trucks using advanced models like the Capacitated Vehicle Routing Problem (CVRP). However, to accurately leverage this data for such logistical optimization, operators must first empirically understand how a structural change in the pricing tariff alters the exact weight, volume, and frequency of waste presented at the curbside. Without robust, econometric estimates of these policy-driven behavioral shocks, advanced predictive logistical models cannot function optimally.

Therefore, the objective of this study is to quantify the causal impact of transitioning to weight-based pricing on both residual waste reduction and substitution into alternative fractions in Flanders. Utilizing a modern, staggered Difference-in-Differences framework on a comprehensive dataset from 2017 to 2024, this research specifically aims to answer the following central question: *How does the implementation of weight-based pricing affect the quantity and composition of household waste produced by Flemish households?* This overarching question is further divided to address specific nuances: whether the reductions are sustained over time, how effectiveness varies across urban versus rural demographics, and which specific structural implementation method (e.g., standard weight-based vs. non-linear pricing) yields the most substantial environmental outcomes.

The remainder of this thesis is structured as follows: Chapter 2 provides an overview of the institutional and regulatory framework governing household waste management in Flanders, followed by a review of the empirical literature on the effectiveness of different pricing systems and the definition of the research questions. Chapter 3 details the data construction process, the evaluated waste streams, and the sample selection, alongside an exploratory data analysis that contextualizes the policy transitions. Chapter 4 outlines the econometric framework, detailing the staggered Difference-in-Differences methodology, its underlying assumptions, and the empirical implementation. Chapter 5 presents the comprehensive empirical results, evaluating the policy's impact on residual waste reduction, substitution effects across selectively collected fractions, spatial and demographic heterogeneity, and the specific methods of implementation. Finally, the Conclusion synthesizes these findings to answer the central research questions and discusses the policy implications and avenues for future research.

2

Household Waste Management Policy and Collection Systems

This chapter provides an overview of the institutional, regulatory, and operational framework governing household waste management in Flanders. It first situates current practices within the broader European waste policy context, with particular attention to the Waste Framework Directive and the waste hierarchy. The chapter then discusses how this framework is translated into Flemish legislation and implemented in practice through local waste management services. Particular emphasis is placed on residual household waste collection systems and pricing mechanisms, including differentiated tariffs (DIFTAR). Subsequently, the chapter reviews empirical evidence on the effectiveness of different pricing systems in reducing residual waste, with a specific focus on weight-based schemes. Based on the findings and gaps identified in this empirical literature, the chapter concludes by defining the central research questions of this thesis, which aim to address the specific impact of weight-based pricing in the current Flemish context.

2.1 Waste Management Policy

The current waste management policy stems from the European Union's broader environmental legislation, specifically the Waste Framework Directive [5]. This directive establishes the fundamental legal framework for handling waste across member states. It defines key concepts such as waste, recycling, and recovery, and institutionalizes the waste hierarchy as a priority order in waste prevention and management legislation.

2.1.1 Waste Hierarchy

The waste hierarchy, known as the Ladder of Lansink, is shown in Figure 2.1 and was introduced as a policy concept in the 1970s by Dr. Ad Lansink, a member of the Dutch Parliament. The Waste Framework Directive embedded it within EU law and extended its application to all Member States and implicates a priority order for waste removal. Within the waste hierarchy, the highest priority is waste prevention, followed by reuse, which involves

employing materials in their original function, and recovery through alternative applications beyond the original use. The fourth priority is incineration. A distinction is commonly made between incineration for final disposal and incineration with energy recovery. Waste-to-Energy (WtE) systems are preferred over incineration without recovery. The last on the list is landfill [1]. In recent literature, the 4R framework (Reduce, Reuse, Recycle, and Recover) is frequently adopted to link waste management strategies with the principles of the circular economy [6].

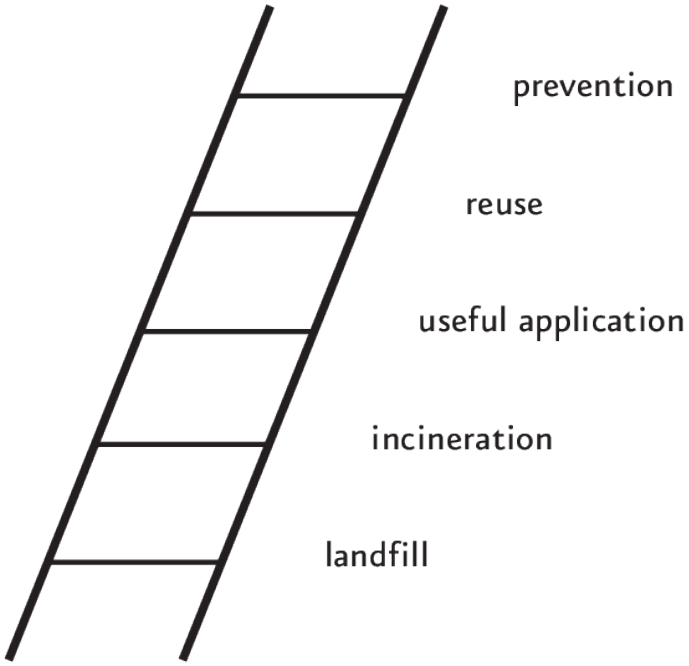


Figure 2.1: Ladder of Lansink [1]

2.1.2 Waste Management Policy in Flanders

In the Flemish region, this European framework is transposed into local law through the Materials Decree (*Materialendecreet*) of December 23, 2011. This decree serves as the legislative backbone, anchoring the principles of sustainable material management and the circular economy in Flemish law. While the Materials Decree sets the strategic goals and legal obligations, the practical implementation and detailed technical regulations are enforced through VLAREMA (*Vlaams Reglement betreffende het duurzaam beheer van Materiaalkringlopen en Afvalstoffen*). Adopted by the Flemish Government in 2012, VLAREMA translates the principles of the Decree into concrete operational rules for the collection, transport, and processing of waste streams. The execution of this legislative framework is entrusted to the Public Waste Agency of Flanders (*Openbare Vlaamse Afvalstoffenmaatschappij* or OVAM). As the central authority, OVAM is responsible for implementing the waste policy, monitoring compliance with the targets set in the Materials Decree, and managing the central data registry to track

waste flows [7].

Recent amendments to the regulatory framework have further intensified the focus on source separation. An example of this is that separate collection of specific household waste streams became mandatory as of January 1, 2024. The most important shift for households in Flanders concerned organic waste collection. Prior to this mandate, the separate collection of organic waste was not universally enforced across all municipalities. Under the new regulations, local authorities are obliged to organize selective collection for this fraction. While a temporary delay was granted to a limited number of municipalities to allow for a transition period, this extension was strictly capped until the beginning of 2026. By enforcing the separation of organic matter, the policy aims to prevent recyclable biomass from ending up in incineration plants, thereby decreasing the total weight of residual waste presented by households. This reduction is a central objective of the Local Materials Plan (LMP) 2023-2030 (*Lokaal Materialenplan 2023-2030*), which sets the specific target of lowering the average residual household waste from 125 kg to 100 kg per inhabitant by 2030 [7].

2.2 Waste Management Services In Flanders

In Flanders, the practical execution of the waste collection is decentralised. The responsibility for the actual collection of household waste lies with the local authorities, specifically the municipalities or their intermunicipal associations (*intercommunales*). These local bodies determine the specific logistical organization within their region, deciding which fractions are collected door-to-door and which must be deposited at recycling parks or neighborhood collection points. Household waste generally consists of two main categories: the specific waste streams that are collected selectively from citizens, representing 71.0% of the total collected weight in 2024, and the residual fraction that remains after sorting [8]. Table 2.1 provides a detailed overview of the composition of selectively collected household waste in 2024. It can be seen that a distinction is made between two bio-waste streams: green waste typically refers to garden waste collected at recycling parks, whereas VFG (Vegetable, Fruit and Garden waste) is collected door-to-door via containers. The processing of these fractions can also differ, though this depends on the specific strategies of the intermunicipal association or municipality. In the following sections, the term "bio-waste" will be used to refer to the organic streams (green waste and VFG), unless a specific distinction is required.

2.2.1 Residual Household Waste Collection Systems

As mentioned in Section 2.1.2, the LMP sets the target of lowering the average residual household waste from 125 kg to 100 kg per inhabitant by 2030. Here, residual household waste is defined in the VLAREMA as the fraction of household waste that is not selectively presented or collected; this includes non-selectively collected waste from public litter bins managed by municipalities or intermunicipal associations, as well as street sweeping waste and waste resulting from the cleanup of illegal dumping [9]. In the remainder of this thesis, when the term 'residual

Table 2.1: Weight distribution of selectively collected household waste fractions in Flanders in 2024

Type of Waste	Percentage
Green waste	18.2%
Paper and cardboard	16.5%
VFG	15.4%
Construction and demolition waste	11.6%
Packaging glass	9.3%
PMC	8.6%
Wood waste	8.5%
E-waste	3.7%
Textile	2.2%
Other	6.0%

waste' is used, this definition applies. To achieve this decrease in residual household waste, there are many possible solutions, one of which is the optimization of waste collection systems. To move up Lansink's Ladder, the way waste is collected is crucial. Research shows that waste collection systems have a major influence on how well materials can be managed and recovered from end-of-life products [10].

Apart from the non-selectively collected waste from public litter bins, street sweeping, and illegal dumping, residual household waste is primarily divided into two categories: bulky waste (*grofvuil*) and regular residual household waste (*huisvuil*). Bulky waste is defined as waste generated by the normal functioning of a private household which, due to its size, nature, or weight, cannot be placed in the standard receptacle for household waste collection [9]. Collection of bulky waste occurs either through house-to-house collection on demand or by citizens delivering it to a civic amenity site [7]. Regular residual household waste consists of the fraction that is not selectively collected. For this category, there are two primary methods of collection: sorting streets and kerbside collection.

The use of sorting streets currently represents a minority of household waste collection. This system involves centralized, often underground, containers and is typically implemented in locations where access for large collection trucks is difficult, in densely populated neighborhoods, or in specific new housing developments. Access is usually controlled electronically. Pricing models in these systems vary; users may pay per opening (paying per bag, as in Pajottegem) or pay based on the exact weight deposited (paying per kilogram, as at Site Saffrou in Oudenaarde). For the pay-per-opening system, a standard conversion is made (60 l = 7.5 kg), enabling the municipality or intermunicipal association to select a tariff within the mandatory range of €0.14 to €0.41 per kilogram defined by VLAREMA to determine the cost per opening [9]. However, unlike the pay-per-opening system, the method where exact weight is used calculates costs based on the actual weight.

The second and most common method is kerbside collection. This approach can be further categorized based on

the recipient used: refuse sacks or containers. When sacks are used, the pricing is volume-based, as the user pays for the specific authorized bag (using the same conversion as mentioned earlier). When containers are used, the cost structure is typically more complex and varies acros municipalities, generally consisting of a fixed monthly usage fee, a per-presentation emptying fee, and a variable weight-based charge per kilogram, although not all components are applied in every municipality.

2.2.2 DIFTAR

To finance the collection and processing of residual household waste, VLAREMA grants local authorities the autonomy to utilize three distinct revenue mechanisms [9]:

- **Variable fees:** Retributions based on actual usage (e.g., retributions per bag, per kilogram, or per emptying)
- **Flat-rate waste taxes:** A fixed tax charged to households regardless of their specific waste generation
- **General municipal funds:** Subsidies drawn from the general budget of the local authority

The first mechanism, where the cost is linked to the quantity of waste presented by the user, is commonly referred to as DIFTAR (Differentiated Tariffs). By tying financial costs to actual usage, whether measured by weight, volume, or frequency of collection, DIFTAR operationalizes the "polluter pays" or the Pay-As-You-Throw (PAYT) principle, as this principle was introduced in the Flemish Waste Decree in 1981 as the Producer Pays Principle [11]. VLAREMA defines the mandatory price ranges for these variable fees [9]. In literature, DIFTAR is often denoted as DVR (Differential and Variable Rates) or unit-based pricing systems [12]. DIFTAR systems are generally categorized based on the specific parameter used to calculate the variable fee. The most common implementations include:

- **Bag-based:** Users pay for specific authorized refuse sacks. The cost is proportional to the volume of waste produced
- **Volume-based:** Users subscribe to a specific container size (e.g., 60 l vs 120 l), paying a fixed fee based on the chosen capacity, regardless of how often it is presented
- **Frequency-based:** Users pay a fee each time the container is presented for emptying, often identified via an electronic chip (pay-per-lift)
- **Weight-based:** The waste is weighed at the moment of collection, and users are charged per kilogram deposited

Regarding the administrative costs of DIFTAR systems, VROM compared 12 Dutch municipalities and found clear differences. The weight-based system is the most expensive to run, costing €6.86 per inhabitant. The bag-based

system is the cheapest at €3.18, while the frequency-based system costs €4.28 [13].[1]

2.2.2.1 Effectiveness of Weight-Based Pricing Systems

Regarding the effectiveness of these systems in reducing residual waste, Van Beukering et al. state that DVR is a cost-effective instrument for waste reduction and more recycling [12]. Fullerton and Kinnaman found that a volume-based pricing program has a substantial effect on the volume but little on the weight, arguing that a weight-based pricing program is likely to be more effective [14]. Extensive empirical literature exists on volume-, bag- and frequency-based pricing, as reviewed by Kinnaman and Fullerton and Allers and Hoeben (2010) [15] [16]. However, as the primary objective of this thesis is to analyze the impact of weight-based DIFTAR, the following discussion will focus on empirical findings that compare the effectiveness of weight-based mechanisms against other pricing models.

Hogg et al. reference a Dutch study by the Dutch Waste Management Council (AOO) from 2001 [2]. This study analyzed data from 1999 to compare the quantities of separated waste and refuse over the different DIFTAR systems. The results can be seen in Figure 2.2.

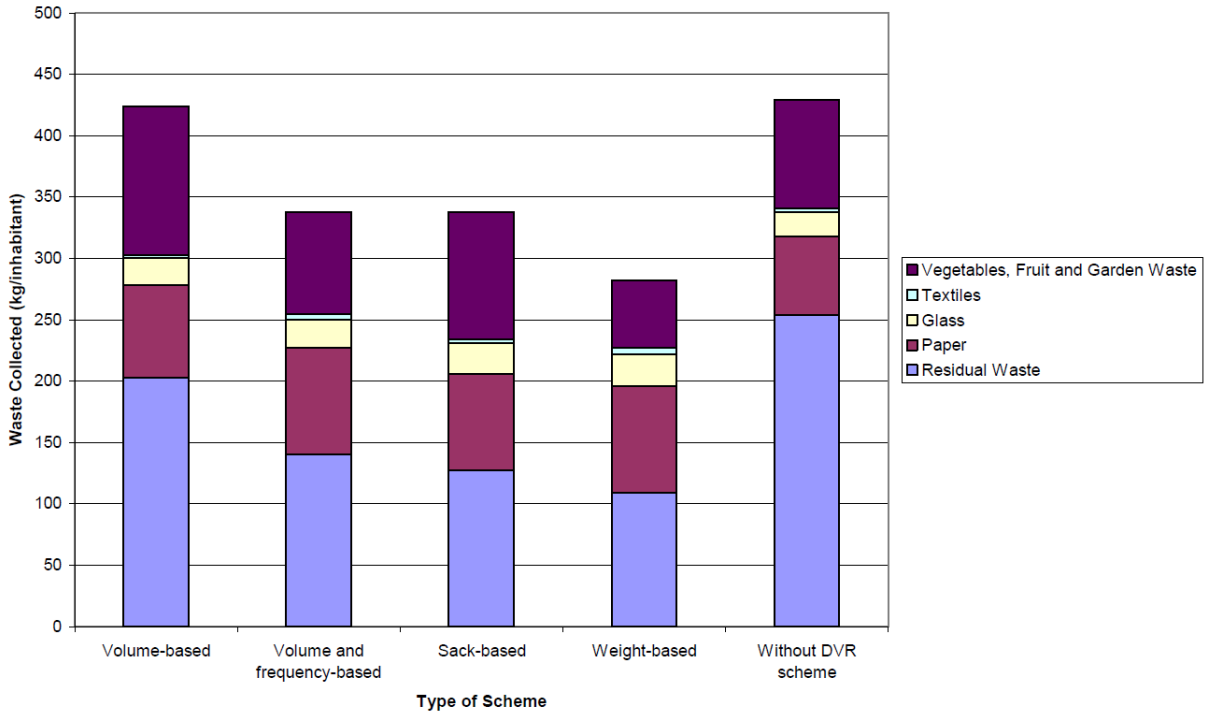


Figure 2.2: Quantities of separated waste and residual waste by charge system type [2]

While the results suggests a clear ranking where weight-based systems outperform volume and frequency-based alternatives, the findings must be interpreted with caution. Hogg et al. note that the municipalities compared

[1] All prices are expressed in year 2000 values.

in the study may not have been strictly comparable, implying that other compounding factors could have influenced the analysis. Furthermore, it is difficult to verify the specific methodology used, such as whether the study addressed only door-to-door collections, as the original source (A00, 2001) is no longer publicly available for review.

Tønning assessed the impact of unit-based pricing systems by comparing data from municipalities using weight-based and volume-based systems with that of chosen reference municipalities that retained traditional flat-rate schemes [17]. Weight-based pricing led to a decrease in residual household waste, a reduction attributed to improved sorting behavior as households increased recycling and home composting. Regarding adverse side effects, the report notes that road authorities observed worse problems with illegal dumping and waste burning in municipalities with weight-based schemes.

Linderhof et al. analyzed the specific impact of weight-based pricing in Oostzaan, the first municipality in the Netherlands to implement such a system [18]. The study compared the waste generation levels under a new pay-per-kilogram model against the baseline scenario where households paid a fixed fee regardless of the amount of waste presented. The results showed a substantial and sustained reduction in waste generation. In the first year following the introduction, the total amount of waste collected per household declined by 30%. This trend continued over time, as three years after implementation, the total annual waste collection had dropped by 42% and stabilized. The system was particularly effective in reducing residual waste, which decreased by 56% compared to the flat-rate baseline. The authors attributed this reduction to behavioral changes, such as increased home composting and improved sorting. While residual waste decreased, the collection of free recyclables increased, with glass collection rising by 36% and tins by 600%. Regarding potential adverse effects, the study found that illegal dumping was virtually non-existent due to effective monitoring, although approximately 4-5% of the waste reduction was attributed to "waste tourism," where waste was transported to neighboring municipalities without weight-based pricing. Finally, the authors suggest that the reduction potential could be even larger in other municipalities, as Oostzaan's high level of environmental activism, reflected in its political affiliation, likely resulted in lower baseline waste levels, leaving less room for further reduction compared to less environmentally conscious communities.

Dijkgraaf and Gradus found that the bag- and weight-based systems performed the best when comparing the four DIFTAR systems compared to a situation without DIFTAR [19]. Weight-based systems were highly effective, achieving a significant reduction in total waste of 38%. This reduction was driven by two main factors. First, compostable waste decreased by over 60%, suggesting a shift toward home composting. Second, the volume of unsorted (residual) waste dropped by nearly 50%. The authors note that while some of this reduction is due to true waste prevention (a net decrease of 29%), a significant portion is attributed to a substitution effect: users redirected recyclable materials (glass, paper, textiles) to free collection streams, which increased by 21%. Bag-based pricing also reduced the amount of total waste, though the magnitude depends heavily on whether compostable waste is also charged. When both unsorted and compostable streams were priced, total waste decreased by 36%,

a result comparable to weight-based systems. However, this reduction dropped to only 14% if compostable waste collection remains free. While unsorted waste decreased by approximately 50% in both scenarios, the behavior toward organic waste differs sharply: it decreased by 61% when priced but increased by 36% when free. The authors suggest that this increase indicates that households "dump" other recyclables into the free compostable bin to avoid the effort of using more distant recycling facilities (e.g., home composting), implying that comprehensive pricing is required to maximize separation efficiency. Thirdly, frequency-based pricing reduced the amount of unsorted waste by 27%, whereas volume-based pricing achieved a reduction of only 6%, driven mainly by a decrease in unsorted waste, with no other significant effects observed. Consequently, the authors concluded that the best option is the bag-based system, as it yields effects comparable to weight-based systems but with lower administrative costs, as mentioned in Section 2.2.2. Finally, the authors caution that reduction figures may be overestimated due to environmental activism, as early adopters often exhibit lower baseline waste levels. Further research by Dijkgraaf and Gradus indicates that this selection bias diminishes over time, confirming that the pricing mechanism remains a sizeable and effective driver for waste reduction even after correcting for these intrinsic motivations [20].

Allers and Hoeben offer a nuanced perspective on the hierarchy of pricing systems, finding that for unsorted waste, weight-based pricing has the strongest effect, reducing quantities by 39% [16]. This significantly outperforms bag-based systems (28% reduction) and frequency-based systems (21% reduction). This contrasts with the findings of Dijkgraaf and Gradus, who observed similar impacts for weight and bag systems. The authors attribute the lower effectiveness of bag- and frequency-based programs to incentives for households to compress waste to fit more into a bag or container rather than reducing the actual mass, an effect known in the literature as stomping [21]. Additionally, Allers and Hoeben note that the price response for biodegradable waste, a 51% reduction under weight-based pricing, is approximately twice that of unsorted waste, a difference they attribute to the easy availability of home composting as a substitute.

In a study focusing on the effects of unit-based pricing in Wallonia, Gautier and Salem found that the weight-based systems outperformed all other pricing systems and significantly reduced residual waste [22]. Municipalities using a weight-based pricing produce on average 31 % less residual waste than the ones using volume-based pricing. Consequently, they consider it an efficient tool for municipalities to achieve their environmental objectives, noting that high prices for the residual fraction can be efficiently combined with weight-based pricing to further reduce residual volumes and encourage waste sorting. They also note that weight-based systems typically involve non-linear pricing, which may partly explain their superior performance.

In Flanders, research by Gellynck and Verhelst assessed the effectiveness of different collection instruments across Flemish municipalities [23]. Although independent sample t-tests suggested lower average waste levels in municipalities with weight-based fees, the authors found that the regression model showed no significant influence for the weight-based fee dummy variable. Due to violated statistical assumptions in the t-test, they concluded that the data did not allow accepting that weight-based fees had a significant negative impact on collected waste.

Further empirical research regarding weight-based pricing was carried out by De Jaeger, utilizing a dataset of 41 municipalities that adopted the system between 1998 and 2007 [24]. The study evaluated the effectiveness of the system by comparing the residual waste trends of these municipalities against a baseline control group of non-participating Flemish municipalities. The results indicated that, on average, the introduction of weight-based pricing did not lead to a significant additional reduction in residual household waste compared to the control group. The analysis revealed that while participating municipalities historically maintained lower waste levels prior to implementation, their subsequent performance did not significantly outperform that of municipalities using alternative pricing schemes.

In a follow-up study, De Jaeger and Eyckmans revisited the Flemish context using an extended dataset covering the period up to 2010 [25]. By employing a broader set of techniques to correct for selection bias, the authors were able to isolate the specific "introduction effect" of the system. The results indicate that switching to weight-based pricing leads to a significant and substantial immediate reduction in residual waste per capita. However, this initial impact does not appear to be sustained; the study found no robust evidence that the reductions persist in the years following the implementation, as the general participation effect was not significant across different estimation methods. This suggests that while weight-based pricing creates a strong short-term shock, its long-term advantage over bag-based systems is less clear when controlling for the fact that participating municipalities typically have historically lower waste levels.

Building on these earlier findings, Sasao, De Jaeger, and De Weerdt further investigated the evolving impact of weight-based pricing in Flanders using a dynamic panel data analysis with data from Flemish Municipalities up to 2015 [26]. By employing a bias-corrected least squares dummy variables model, the authors were able to separate the immediate shock of the policy from its long-term persistence. The dynamic panel estimations revealed that, on average, continuous participation in a weight-based pricing system decreases residual waste by approximately 10.4%. However, unpacking this average showed that the transition triggers a 21.4% reduction in the first year alone. However, consistent with the 2015 findings, this study provided evidence of a 'shock effect': the initial reduction gradually diminished over time and completely disappeared within five years of the system's introduction. Lastly, the authors demonstrated that traditional, non-dynamic fixed effects models tend to overestimate the long-term benefits of the policy while underestimating the initial short-term shock. This study underscores the necessity of accounting for dynamic, time-varying treatment effects when evaluating waste pricing systems.

While international and Walloon studies generally identify weight-based pricing as the most effective instrument for reducing residual household waste, evidence from Flanders presents a markedly more nuanced picture. Research by Gellynck and Verhelst (2007) found inconclusive evidence regarding the specific impact of weight-based fees, consistent with subsequent studies by De Jaeger (2009), De Jaeger and Eyckmans (2015) and Sasao et al. (2021), which indicate that such systems yield either insignificant reductions or short-term 'shock effects' that are not sustained over time. Moreover, much of the existing literature, both domestic and international, relies on data from the early 2000s. Given that an increasing number of Flemish municipalities are currently adopting

Table 2.2: Overview of studies on waste pricing

Study	Region	Pricing System	Method	Effect on Residual Waste	Remarks
Tønning (2000)	Denmark	Weight; Volume	Comparative analysis	Decrease	Increased illegal dumping and burning reported
Linderhof et al. (2001)	Netherlands (Oostzaan)	Weight	Case study	-56%	"Waste tourism" accounts for 4-5% of reduction, high environmental activism
Dijkgraaf and Gradus (2004)	Netherlands	Bag, Weight, Frequency, Volume	Cross-section	Weight/Bag: -50%; Freq: -27%; Vol: -6%	Possible overestimation due to environmental activism
Dijkgraaf and Gradus (2009)	Netherlands	Bag, Weight, Frequency, Volume	Pooled Cross-section	Sizeable reduction	Pricing remains effective after correcting for activism
Allers and Hoeben (2010)	Netherlands	Weight, Bag, Frequency	Diff-in-Diff	Weight: -39%; Bag: -28%; Frequency: -21%	Volume-based systems less effective due to waste compression
Gautier and Salem (2023)	Wallonia (Belgium)	Bag, Weight, Frequency, Volume	Econometric model	Significant reduction	Non-linear pricing when weight-based pricing is used may explain (part) of the reduction
Gellynck and Verhelst (2007)	Flanders (Belgium)	Weight, Volume	Regression analysis	Inconclusive	Regression showed no significant impact, t-test results unreliable due to violated assumptions
De Jaeger (2009)	Flanders (Belgium)	Weight	Diff-in-Diff	Insignificant	Municipalities that implemented had historically lower waste levels before implementation
De Jaeger and Eyckmans (2015)	Flanders (Belgium)	Weight	OLS, Panel data, Matching Est., Diff-in-Diff	Significant Reduction after initial adoption	No convincing evidence of sustained reduction over time
Sasao et al. (2021)	Flanders (Belgium)	Weight	Dynamic panel analysis	-21.4% initially, fades in 5 years	Non-dynamic models bias results (overestimate long-term, underestimate short-term)

weight-based DIFTAR, there is a need to reassess its effectiveness in the present context. Updated empirical analysis with updated methods is required to determine whether recent implementations generate persistent waste reductions or if the attenuation of effects observed in earlier Flemish studies persists. Table 2.2 provides a structured comparison of the empirical literature, illustrating the contrast between the generally strong performance reported internationally and the mixed evidence observed within Flanders.

2.3 Research Questions

The mixed empirical evidence discussed above in Section 2.2.2.1, particularly regarding the long-term effectiveness of weight-based pricing in Flanders, motivates the research questions addressed in this thesis. Given the increasing adoption of these systems and the need for updated insights, this study aims to answer the following central research question:

How does the implementation of weight-based pricing affect the quantity and composition of household waste produced by Flemish households?

To provide a comprehensive answer, this central question is divided into specific sub-questions focusing on behavioral changes, operational implications, and broader economic and environmental effects:

- **Effectiveness and Substitution:**
  - To what extent does weight-based pricing reduce the weight of residual waste generated by Flemish

households?

  - How does weight-based pricing influence the distribution of waste types, specifically regarding substitution effects between residual waste and selectively collected waste streams (such as PMC, paper, and VFG)?
  - Does the introduction of weight-based pricing lead to a sustained long-term reduction in residual household waste, or are the observed effects limited to short-term behavioral responses that diminish over time?

- **Spatial and Demographic Heterogeneity:**
  - To what extent does the effectiveness of weight-based pricing differ between urban and rural areas, particularly regarding the reduction of residual waste and the potential for home composting?
- **Method of implementation:**
  - How do different implementation strategies of weight-based pricing affect the quantity and composition of household waste?
  - Which approach yields the most significant reduction in residual waste?

3

Data Construction and Sample Selection

This chapter outlines the data collection, classification, and filtering procedures used to build the empirical foundation of this thesis. To evaluate the impact of weight-based pricing on both residual waste reduction and household sorting behavior, a longitudinal dataset of Flemish municipalities was required. Because the data provided by official institutions does not fully capture the nuances of local pricing structures or account for recent administrative changes, data construction and cleaning were necessary.

The chapter proceeds as follows. Section 3.1 details the primary data sources and explains the manual classification of municipal waste policies into five distinct tariff categories. Section 3.2 broadens the analytical scope by defining the 17 specific household waste fractions tracked in this study, which are essential for measuring potential substitution and spillover effects. Section 3.3 discusses the sample selection process, highlighting the exclusion of merged municipalities to safeguard the internal validity of the research. Building on this refined sample, Section 3.4 provides an exploratory data analysis, offering descriptive evidence of policy adoption trends and visually mapping the corresponding evolution of residual waste across different transition cohorts. To account for inherent structural differences between local governments, Section 3.5 introduces the Belfius Municipal Typology as a framework for controlling spatial and demographic heterogeneity. Finally, Section 3.6 summarizes the dimensions of the finalized panel dataset, setting the stage for the empirical methodology and econometric results in the subsequent chapters.

3.1 Data Construction

To analyze the effectiveness of waste collection systems, a longitudinal dataset with the method of collection for residual household waste was constructed covering the period 2017–2024. The data was obtained from OVAM, which manages the central registry of municipal waste statistics. To allow for a more granular analysis of pricing incentives, the data set was extended by categorizing the specific pricing schedules employed within weight-based systems. While the central registry broadly distinguishes between weight-based and volume-based pricing schemes, it does not capture the nuances of the tariff structure. Therefore, manual verification and classification of the pricing mechanisms resulted in five distinct categories based on the specific parameters used to calculate

the waste fee. In instances where the specific pricing parameters were incomplete or ambiguous in the central registry, contact with the responsible intermunicipal associations was done to verify the tariff structure.

The classification distinguishes between standard volume-based pricing **V**, implemented via bags, and four variations of weight-based schemes. The most common weight-based system is the **WF** model, which combines a charge per kilogram with a frequency fee. The frequency component is a fixed service fee charged every time a container is presented for collection, regardless of the weight it contains. Other variations include the **W** model (purely weight-based), the **WF NL** model (a non-linear variation of the WF system where the price per kilogram increases based on weight tiers), and the **WV** model. The WV system represents a hybrid approach offering residents a choice: they can utilize containers (typically >40 l) charged by weight, or opt for authorized small-volume sacks (30 l), for which a fixed fee per bag is charged instead of a weight-based fee. These systems are summarized in Table 3.1.

Table 3.1: Classification of residual household waste pricing schedules in Flanders

Code	Description
V	**Volume-based Pricing:** Residents pay per authorized refuse bag (pricing is proportional to volume).
W	**Weight-based Pricing:** Residents pay strictly based on the weight of waste deposited (per kg).
WF	**Weight + Frequency:** Residents pay a fee per kilogram plus a fixed service fee per presentation (emptying) of the container.
WF NL	**Non-Linear Weight + Frequency:** A variation of the WF system where the tariffs (per kg) vary non-linearly depending on total consumption.
WV	**Weight + Volume:** A hybrid system offering a choice between weight-based containers or small-volume sacks (30 l) charged per unit.

The temporal scope of this analysis is strictly bounded by data availability. OVAM has no records of collection methods prior to 2017. An alternative approach to extend the dataset backwards was explored, based on the rationale that the applied pricing schedule could be derived by analyzing the historical prices of residual waste collection. However, this was ultimately rejected due to the unavailability of pricing data for 2016. Consequently, 2017 serves as the earliest point for which a complete and reliable dataset of collection systems can be established.

3.2 Evaluated Waste Streams

While the primary objective of weight-based pricing is the reduction of residual household waste, evaluating this metric in isolation is insufficient to capture the full impact of the policy. When the marginal cost of disposing of residual waste increases, households are financially incentivized to change their sorting behavior. As highlighted

in the literature review, this can lead to substitution effects, such as the increased sorting of recyclable materials, but it may also induce negative effects, such as the illegal dumping of residual waste into organic bins or public containers.

Previous empirical studies have documented these substitution effects, but they often restrict their analysis to a limited selection of the most common household fractions. For instance, studies such as Linderhof et al. (2001) and Dijkgraaf and Gradus (2004) primarily focused on shifts toward easily observable streams like glass, paper, textiles, and compostable waste [18, 19]. To assess behavioral shifts in the Flemish context, this study extends the analysis beyond these traditional categories to encompass almost all household waste streams collected by the municipalities.

The dataset concerning household waste streams in Flanders was obtained from the OVAM. The data collection process relies on a bottom-up reporting structure. The vast majority of waste collection figures are reported directly to OVAM by the intermunicipal associations. In certain instances, municipalities supplement these reports with data on specific waste streams that they collect and manage independently from the intermunicipal framework. The weighing moment typically takes place when a collection truck unloads its load at a processing facility or at a transfer station.

To centralize, standardize, and verify this reporting, OVAM utilizes the Material Information System (MATIS), which was implemented in 2021 to replace the previous web portal [8]. This centralized platform ensures the aggregation of the data submitted by municipalities, intermunicipal associations, private waste collectors, and specific extended producer responsibility organizations (such as Fost Plus and Recupel). The data in MATIS is then standardized to turn absolute waste volumes into comparable per capita metrics (i.e., kilograms of residual waste per inhabitant). To achieve this, the OVAM dataset integrates official demographic data provided by the Belgian Federal Public Service Economy (Statbel). The population figure utilized as the denominator for any given observation year corresponds to the exact number of registered inhabitants on January 1st of the subsequent calendar year.

Table 3.2 provides an overview of the waste categories included in the dataset that will be tested for substitution and spillover effects. It should be noted that two specific streams are excluded from this analysis: Waste Electrical and Electronic Equipment (WEEE, or AEEA in Dutch) and expired medicines. These fractions are primarily collected via retail stores and pharmacies, respectively. Consequently, accurate, municipality-specific data for these streams is not present. Furthermore, there is currently no municipal data available regarding either the frequency or volume of illegal dumping. It is thus impossible to determine whether the effect on residual waste is partially offset by an increase in negative spillover behavior. In total, the dataset consists of 34,593 observations of per capita waste generation across 17 distinct household waste streams, collected from 286 municipalities over an eight-year period (2017–2024).

To ensure the longitudinal integrity of the estimation, a balanced panel approach is adopted for each specific

Table 3.2: Overview of Analyzed Household Waste Streams in the Dataset

Waste Category (Dutch)	English Translation	Observations
Restafval	**Residual Waste**	2280
PMD	**Plastic, Metal, and Drink Cartons (PMC)**	2275
GFT	**Organic Waste (VFG)**	1616
Papier en karton	**Paper and Cardboard**	2279
Verpakkingsglas	**Packaging Glass**	2280
Groenafval	**Green Waste**	2270
Textiel	**Textiles**	2280
Plantaardige en dierlijke oliën en vetten	**Vegetable and Animal Oils and Fats**	2280
Batterijen	**Batteries**	2278
Bouw- en sloopafval (totaal)	**Construction and Demolition Waste**	2269
KGA (excl. batterijen & rookdetectoren)	**Small Hazardous Household Waste**	2267
Kunststoffen (excl. PMD)	**Hard Plastics**	2263
Houtafval	**Wood Waste**	2261
Metalen (excl. PMD)	**Scrap Metal**	2255
Vlakglas	**Flat Glass**	2230
Matrassen	**Mattresses**	1077
Dierlijk afval	**Animal Waste**	133

waste stream. This means that for any given analysis, only municipalities that reported a complete and uninterrupted dataset for that specific fraction throughout the entire 2017–2024 observation period are included. Consequently, the sample size may vary slightly across different waste streams depending on data availability and reporting consistency within the MATIS system.

3.3 Sample Selection

The starting point for the data collection was the entire population of Flemish municipalities. However, to ensure a robust quantitative analysis, the final dataset consists of a panel of 266 municipalities that excludes the

fifteen entities involved in the administrative mergers of January 1, 2019, as well as the municipalities involved in the recent mergers of January 1, 2025. The exclusion of this last group is necessitated by the fact that OVAM retrospectively aggregated the historical waste data for these newly formed entities, rendering the separate, municipality-specific data of the original entities unavailable for analysis.

The exclusion of the fifteen mergers of January 1, 2019 is a fundamental prerequisite for ensuring the internal validity of the research. Internal validity refers to the confidence with which the observed changes in waste generation can be attributed to the policy intervention (in this thesis the pricing system) rather than extraneous structural changes [27]. In longitudinal research, a municipal merger creates a structural break in the time series where the unit of analysis can change composition mid-stream.

This threat to validity is best illustrated by the varying socio-economic profiles of merging entities. As this study aims to isolate the impact of spatial and demographic heterogeneity, as discussed in Section 2.3, merging diverse municipalities would contaminate the data. The Belfius Municipal Typology provides a clear framework to visualize this issue [28], and is further elaborated in 3.5. An example is the merger of Deinze and Nevele. Prior to 2019, these municipalities were categorized into distinct clusters: Deinze exhibited the characteristics of a small urban center, while Nevele was typified as a rural, residential municipality. Merging two such distinct demographic profiles into a single data point creates a "black box" effect. It becomes impossible to disentangle whether a change in waste figures is due to the new pricing policy or simply the result of mathematically averaging a city population with a rural one. Consequently, to prevent this aggregation bias from confounding the results and to maintain a homogeneous sample for cross-sectional comparison, all municipalities involved in the 2019 mergers were omitted from the analysis.

3.4 Exploratory Data Analysis

3.4.1 Adoption of Weight-Based Pricing Systems (2017-2024)

Based on the final sample defined above, the dataset allows for mapping the transition to weight-based pricing systems in Flemish Municipalities. Figure 3.1 and Table 3.3 illustrate the aggregate trends in the adoption of the defined pricing mechanisms for the non-merged municipalities between 2017 and 2024.

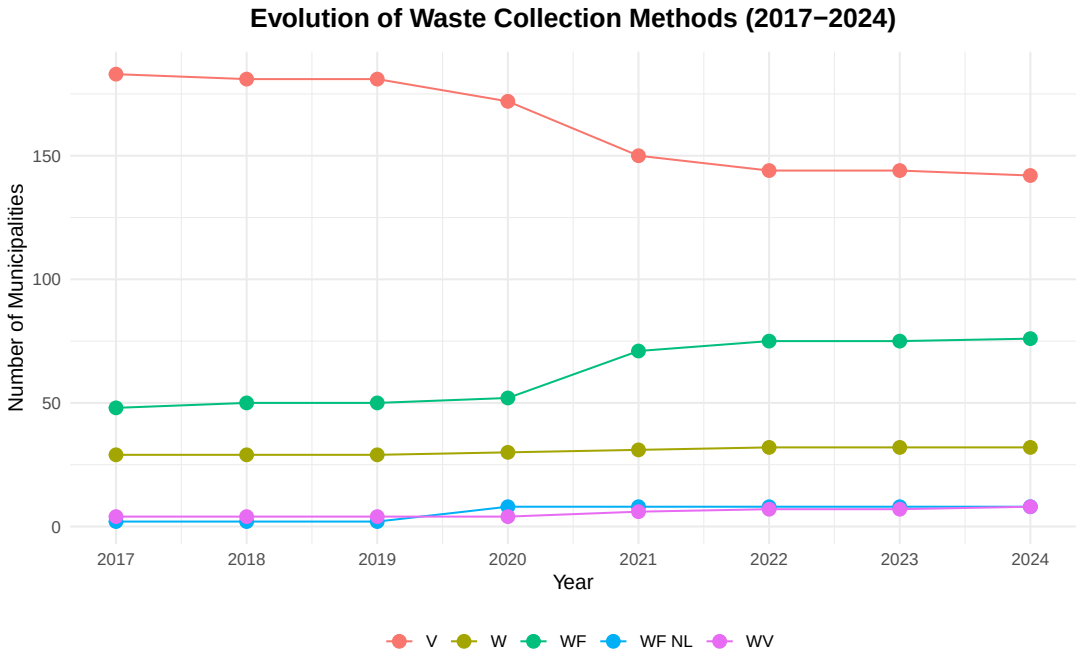


Figure 3.1: Evolution of Waste Collection Methods in Flemish Municipalities (2017-2024)

Table 3.3: Number of Municipalities by Collection Method (2017-2024)

Method	2017	2018	2019	2020	2021	2022	2023	2024
V	183	181	181	172	150	144	144	142
W	29	29	29	30	31	32	32	32
WF	48	50	50	52	71	75	75	76
WF NL	2	2	2	8	8	8	8	8
WV	4	4	4	4	6	7	7	8

The data reveals a shift away from volume-based pricing towards weight-based pricing systems. While volume-based pricing remains the most common method, its prevalence has declined, dropping from 186 municipalities (69.63%) in 2017 to 145 (53.51%) in 2024. This trend reflects the increasing regulatory pressure to reduce residual waste figures, pushing local authorities to abandon sack-based collections in favor of weight-based systems. The WF model has emerged as the preferred alternative, growing from 48 municipalities in 2017 to 76 in 2024. This preference suggests that local authorities favor the two-part tariff structure, incentivizing both waste reduction (weight) and logistical efficiency (frequency), over purely weight-based (W) or hybrid models (WV), which have remained relatively stable over the observed period. The adoption of non-linear pricing (WF NL) also shows a modest increase, indicating a growing experimentation with tariff structures to target heavy polluters.

3.4.2 Evolution of Residual Waste Generation

To contextualize the impact of these policy shifts, it is necessary to examine the corresponding trends in residual waste generation. Rather than broadly grouping all transitioning municipalities together, Figure 3.2 and Table 3.4 stratify the sample into specific groups based on the exact year they changed from volume-based pricing to weight-based pricing. The sample also includes two baseline control groups: municipalities that consistently used volume-based pricing and those that consistently used weight-based pricing throughout the 2017-2024 period.

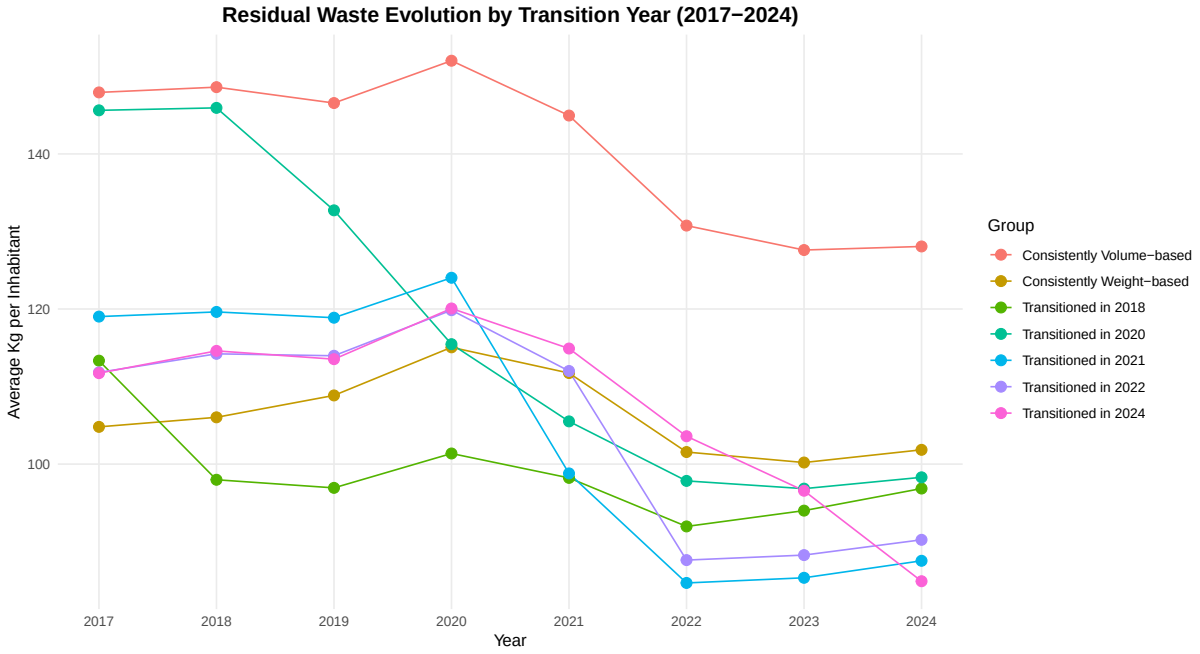


Figure 3.2: Residual Waste Evolution by Transition Year Cohorts (2017-2024)

Table 3.4: Average Residual Waste (kg/inhabitant) by Transition Cohort (2017-2024)

Group	2017	2018	2019	2020	2021	2022	2023	2024
Consistently Volume-based	148.0	149.0	147.0	152.0	145.0	131.0	128.0	128.0
Consistently Weight-based	105.0	106.0	109.0	115.0	112.0	102.0	100.0	102.0
Transitioned in 2018	113.0	98.0	96.9	101.0	98.2	92.0	94.0	96.8
Transitioned in 2020	146.0	146.0	133.0	115.0	106.0	97.8	96.8	98.3
Transitioned in 2021	119.0	120.0	119.0	124.0	98.8	84.7	85.3	87.5
Transitioned in 2022	112.0	114.0	114.0	120.0	112.0	87.6	88.3	90.2
Transitioned in 2024	112.0	115.0	114.0	120.0	115.0	104.0	96.6	84.9

The line chart highlights several critical dynamics regarding the effectiveness of pricing incentives. The munici-

palities that consistently used volume-based pricing establishes the upper bound of residual waste generation. While this group experienced a general downward trend, decreasing from 148.0 kg per inhabitant in 2017 to 128.0 kg in 2024, these municipalities consistently remained the highest waste producer across the entire observation period.

The most crucial insight emerges from comparing the transitioned municipalities against the "Consistently Weight-based" baseline. In 2017, the municipalities that already had a weight-based system in place generated the lowest amount of waste (105.0 kg per inhabitant). However, their performance stagnated over the observed timeframe, ending at 102.0 kg in 2024.

In contrast, the transitioned municipalities demonstrated a pronounced stepwise decrease, where the declines in residual waste align with the year of their policy implementation. For instance, the group transitioning in 2020 saw its waste drop from 133.0 kg in 2019 to 115.0 kg in 2020. The 2021 transition cohort also experienced a big reduction from 124.0 kg in 2020 down to 98.8 kg in 2021. It is important to note that the exact date of transition is unknown, so the full effect can be seen the year after the transition. When looking into Table 3.4 to the year after the implementation, the decrease is even more pronounced.

This trajectory visually isolates the "treatment effect" of the policy change. The fact that sudden reductions occur exactly at the moment of transition for each cohort suggests a causal link between the introduction of weight-based pricing and a structural shift in household sorting behavior. While these descriptive trends visually illustrate the treatment effect, the true impact of the policy change will be formally quantified in Section 5.

3.5 Controlling for Spatial and Demographic Heterogeneity

A challenge in evaluating the impact of municipal waste policies is the spatial and demographic heterogeneity across different municipalities. Waste generation patterns are influenced by local characteristics such as the prevalence of apartments versus detached houses with gardens, since the storage space is different [29]. To isolate the causal effect of weight-based pricing, the underlying socio-economic differences are taken into account.

To address this, the analysis incorporates the Belfius Municipal Typology, a classification used in Belgian policy research. The Belfius Typology categorizes municipalities into distinct clusters using a set of over 150 static and dynamic statistical indicators. Sourced from official institutions such as Statbel, Statistics Flanders, and the Crossroads Bank for Enterprises, these indicators capture a wide array of local characteristics, including demographic structures, income levels, economic activity, and housing density [28]. This classification is widely adopted in other existing literature. For further examples and contextualization, see [30–33].

Table 3.5 presents the distribution of the final sample of 266 municipalities across the six primary Belfius clusters and breaks down the sample by treatment status over the observation period. Appendix A provides a detailed overview of which municipalities adopted which specific pricing system in each year, along with their correspond-

ing Belfius typology cluster. As illustrated in Table 3.5, the sample is predominantly composed of "Residential municipalities" and "Municipalities with economic activity", which together account for over 60% of the observed dataset. "Rural municipalities" form the third-largest group.

Conversely, the more densely populated and highly active areas ("Urbanized municipalities" and "Large and regional cities") represent a smaller segment of the sample but are crucial for understanding waste dynamics in high-density environments where space for sorting and rigid containers is limited. Finally, the "Coastal municipalities" form a unique, isolated cluster. These areas face distinct waste management challenges due to extreme seasonal fluctuations and high volumes of tourist-generated refuse. By mapping the 266 municipalities into these six distinct typologies, the Difference-in-Differences (DiD) framework can control for these cross-sectional variations. Another option or extention of the analysis could be to use the 16 secondary clusters, which are more granular and capture more specific local characteristics. However, the small number of treated municipalities in these secondary clusters would limit the statistical power of the analysis, leading to wide confidence bands. Therefore, the analysis will be performed using the six main clusters.

Table 3.5: Distribution of Municipalities by Belfius Typology and Treatment Group (2017-2024)

Belfius Cluster	Kept W-based	Stayed V-based	Switchers between 2017-2024	Total
Residential municipalities	44	40	22	106
Municipalities with economic activity	13	43	7	63
Rural municipalities	15	36	4	55
Urbanized municipalities	8	9	5	22
Large and regional cities	1	8	3	12
Coastal municipalities	2	6	0	8
Total	**83**	**142**	**41**	**266**

Note: "Switchers" refer to municipalities that transitioned to weight-based pricing during the observation period.

Next, as can be seen in Table 3.5, 41 municipalities are identified that form the treatment group for the analysis, alongside a control group of 142 "never-treated" municipalities. Notably, the distribution reveals a complete absence of switchers among the "Coastal municipalities". Because no coastal municipality transitioned to weight-based pricing between 2017 and 2024, it will not be possible to estimate or draw conclusions regarding the specific effect of the policy for this cluster.

3.6 Summary of the Final Dataset

To conclude, the data construction and filtering processes yield a longitudinal panel dataset structured at the municipality-year-fraction level. By observing the finalized sample of 266 non-merged Flemish municipalities over an eight-year period (2017–2024), the analytical framework encompasses 2,128 distinct municipality-year

observations. Because the dataset tracks the standardized per-capita generation across 17 distinct household waste categories for each of these periods, the final consolidated dataset comprises a theoretical maximum of 36,176 distinct data points. Every observation is cross-referenced with its active pricing mechanism in that year and its corresponding Belfius typology cluster. However, since some municipalities may have missing values or incomplete information, a municipality is only included in the analysis for a given waste stream if complete data is available for that fraction across the entire 2017–2024 period. This results in a total of 32,290 data points. Ultimately, this structure allows for a robust analysis of the causal impact of weight-based pricing on residual waste generation while controlling for spatial and demographic heterogeneity across municipalities.

4

Methodology

This chapter outlines the econometric framework utilized to evaluate the impact of weight-based pricing on household waste generation in Flanders. The empirical literature reviewed in Chapter 2 employs a wide range of methodological approaches to evaluate the impact of waste pricing systems. Earlier studies relied on comparative analyses, case studies, and cross-sectional regressions [17–19], which, while informative, are unable to control for pre-existing differences between municipalities or account for general time trends. More recent Flemish studies have applied panel data techniques and Difference-in-Differences (DiD) estimators [24, 25], representing a methodological improvement. However, as demonstrated by Sasao et. al, traditional non-dynamic fixed effects models remain problematic: they tend to overestimate the long-term benefits of weight-based pricing while underestimating the magnitude of the initial short-term shock. This finding underscores the necessity of adopting a dynamic, time-varying framework when evaluating waste pricing policies [26]. Given the staggered adoption of weight-based pricing across Flemish municipalities over the 2017–2024 period, a standard Two-Way Fixed Effects (TWFE) model would furthermore introduce additional biases through so-called "forbidden comparisons", as detailed in Section 4.1. For these reasons, this study employs the staggered Difference-in-Differences estimator developed by Callaway and Sant'Anna [34], which accounts for treatment timing heterogeneity and avoids the methodological pitfalls identified in the prior literature.

The following sections detail the foundational assumptions of this approach, the mathematical formulations used to isolate primary, substitution, and heterogeneous treatment effects, and the methodological constraints regarding intersectional analysis. Finally, the chapter concludes by outlining the empirical implementation and statistical inference procedures used to compute the estimates and validate their significance.

4.1 Difference-in-Differences method

To estimate the effect of transitioning to weight-based pricing on residual waste generation, the Difference-in-Differences method, one of the most frequently used methods in impact evaluation studies, can be used. This method combines insights from both cross-sectional treatment-control comparisons and before-after studies for a robust identification. Following the logic outlined by Frederiksson and Oliveira, evaluating the true impact of

a policy change requires comparing the targeted group not just against its own past, but against a baseline that represents what would have happened if the policy had never been implemented. With two groups and two periods, the DiD estimate of policy impact can be written as follows [35]:

$$DiD = (\bar{y}_{s=\text{Treatment},\ t=\text{After}} - \bar{y}_{s=\text{Treatment},\ t=\text{Before}}) - (\bar{y}_{s=\text{Control},\ t=\text{After}} - \bar{y}_{s=\text{Control},\ t=\text{Before}}) \quad (4.1)$$

Where:

- y is the outcome variable
- The bar ($\bar{y}$) represents the average value of the outcome variable, averaged over the individuals within the group
- The group is indexed by s, representing whether the group has undergone treatment or is part of the control group
- t represents the time period, indicating if the outcome variable is measured before or after the implementation of the policy change

Equation 4.1 shows that the DiD approach calculates two differences. In the context of the impact of weight-based pricing, the first difference measures the change in residual waste generation over time within the municipalities that transitioned to a weight-based system (the switchers). The difference between their average waste before the transition and their average waste per inhabitant after the transition is calculated. The second difference takes into account the general trend. The method calculates the exact same "before versus after" difference for the municipalities that consistently maintained a volume-based pricing system over the same time period (the control group). This difference shows how much waste generation would have naturally changed without the introduction of weight-based pricing. Equation 4.1 shows an example of the classic DiD method, where two time periods are available and compared (for more examples of this classical DiD method, see [36, 37]). However, as can be seen in Figure 3.2, there are more than two time periods and municipalities adopt the change at different points in time (i.e., treatment timing is staggered).

When standard DiD regression models, typically estimated via TWFE, are applied to data with such staggered treatment timing, severe biases can arise [38]. Roth et. al highlight that TWFE regressions calculate the average policy effect by taking a weighted average of multiple 2x2 comparisons. While this includes "clean" comparisons between newly treated and not-yet-treated municipalities, it also introduces "forbidden comparisons" [38].

A forbidden comparison occurs when a newly treated municipality (e.g., one transitioning to weight-based pricing in 2021) is compared to an "already-treated" municipality (e.g., one that transitioned in 2018). This becomes problematic if the treatment effect is heterogeneous over time. As mentioned in Section 2.2.2.1, De Jaeger and Eyckmans demonstrated that the impact of weight-based pricing in Flanders is primarily a short-term shock: while it

causes an immediate and substantial reduction in residual waste, this initial effect is not sustained in the long run [25]. If treatment effects dynamically fade out over time in this manner, the standard TWFE model will mistakenly use the shifting post-treatment trajectories of early adopters (e.g., a 2018 cohort whose initial reduction is already fading) as the baseline counterfactual for newly treated municipalities (e.g., the 2021 cohort). This dynamic can lead to severe drawbacks such as negative weighting problems. In extreme cases, negative weighting can bias the overall estimate so heavily that it flips the sign of the coefficient. In the context of shifting from volume-based pricing to weight-based pricing this means that the model would falsely conclude that weight-based pricing increases residual waste, even if waste went down in every individual municipality [38]. Consequently, to accurately evaluate the causal impact of the transition across different years without these biases, the staggered DiD method will be used.

4.2 Staggered Difference-in-Differences method

The method described in this section is based on the work of Callaway and Sant'Anna (2021), which provides a framework for estimating treatment effects in settings with staggered treatment timing [34]. The method addresses the biases associated with standard TWFE models by explicitly accounting for the timing of treatment adoption. First, the assumptions of the staggered DiD method are outlined, followed by the mathematical formulations of the different hypotheses tested.

4.2.1 Assumptions

4.2.1.1 Assumption 1: Irreversibility of Treatment

Once a municipality transitions to weight-based pricing, it does not revert back to volume-based pricing during the observation period. This assumption is satisfied in this context, as there are no cases of municipalities switching back to volume-based systems after adopting weight-based pricing. This irreversible nature of the policy adoption underpins the potential outcomes framework utilized by Callaway and Sant'Anna [34]. In this framework, a municipality i has two potential realities at any time t: an untreated outcome $Y_{it}(0)$ (the residual waste generated if they never adopt the policy) and a treated outcome $Y_{it}(g)$ (the residual waste generated if they adopt the policy in year g). Because only one of these outcomes is observed in the real world, the "fundamental problem of causal inference", as defined by Holland (1986), is faced: it is impossible to observe both potential outcomes simultaneously for the same unit [39]. To solve this missing data problem and reconstruct the counterfactual $Y_{it}(0)$, the method must rely on a valid control group. Assumption 1 is crucial in this regard because it categorizes the municipalities, allowing the estimator to use "never-treated" or "not-yet-treated" municipalities to reconstruct the missing untreated outcome [34].

4.2.1.2 Assumption 2: Random Sampling

This assumption requires the dataset to consist of independent and identically distributed (i.i.d.) observations for each unit over time. This condition is satisfied in this study, as the analysis relies on a longitudinal panel dataset. Because the data captures almost the entire population of Flemish municipalities over multiple years, rather than a restricted sample (see Section 3.3), it provides the representative and independent observations required to validly perform the estimation.

4.2.1.3 Assumption 3: Limited Treatment Anticipation

This assumption requires that residents do not systematically alter their waste behavior prior to the policy's implementation date. As Sasao et al. [26] point out, it is not easy for households to anticipate their potential financial savings under weight-based pricing before it begins, because unlike simply counting bags, it requires physically weighing their waste. Because of this it is unlikely that structural behavioral changes occur prior to the actual introduction of the system, meaning that this assumption is likely satisfied in this context.

4.2.1.4 Assumption 4 & 5 : Conditional Parallel Trends Based on a "Never-Treated" Group & Conditional Parallel Trends Based on a "Not-Yet-Treated" Group

The core requirement of the standard DiD framework is that, in the absence of the policy change, the average outcomes of the treated and control groups would have followed parallel paths. However, an unconditional parallel trends assumption is often violated in reality because municipalities that adopt weight-based pricing may systematically differ from those that do not. For example, dense urban centers typically exhibit different natural waste generation trajectories compared to rural villages. To resolve this, Callaway and Sant'Anna introduce a conditional parallel trends assumption [34]. Depending on the data structure, the estimator reconstructs the missing counterfactual by comparing the newly treated units to a "never-treated" group (Assumption 4) or a "not-yet-treated" group (Assumption 5). To satisfy this condition, this study includes the Belfius Municipal Typology as a covariate. By conditioning the parallel trends assumption on this classification, the model ensures that newly treated municipalities are compared strictly to untreated (or not-yet-treated) municipalities with similar characteristics. This covariate-specific matching ensures that the parallel trends assumption plausibly holds.

4.2.1.5 Assumption 6: Overlap

The final identifying assumption requires that for any given set of observed characteristics, there is a positive probability that a unit could be either treated or untreated. In the context of this study, this overlap condition dictates that within any given Belfius Typology cluster, there must be a mix of municipalities that have adopted weight-based pricing and those that have not yet done so. This ensures that the estimator can successfully match treated municipalities with comparable control units. As can be seen in Table 3.5 in Section 3.5, this condition

is satisfied for all clusters except the "Coastal municipalities", which have no treated units. Consequently, the analysis will not be able to estimate the treatment effect for this specific cluster, and any conclusions regarding the impact of weight-based pricing on coastal municipalities will be limited.

4.2.2 Mathematical Formulation

4.2.2.1 Mathematical Formulation: Unconditional Log-Linear Staggered DiD

While the conditional framework (detailed in Section 4.2.2.2) will provide the causal estimates by controlling for municipal characteristics, the unconditional model is introduced first. By stripping away the complexity of covariate-matching, the unconditional framework can be used to explain the intricate mechanics of the staggered DiD estimator. It allows for a step-by-step demonstration of how granular cohort effects are calculated, dynamically aggregated into an event study, and mathematically transformed into exact percentages.

As stated above, the unconditional staggered DiD estimator calculates the treatment effect without adjusting for underlying municipal characteristics or covariates. It relies on the baseline assumption that, without controlling for specific covariates, the unadjusted residual waste generation of the newly treated municipalities and the control group would have followed parallel trajectories in the absence of the policy change. The building block of this framework is the group-time average treatment effect, denoted as. The parameter $ATT(g,t)$ is the group-time average treatment effect in a specific year t for a specific cohort of municipalities first treated in year g. To evaluate the impact on residual waste and to express this impact as a percentage deviation, the outcome variable is transformed using the natural logarithm. The unconditional $ATT(g,t)$ estimator, which compares the evolution of logged outcomes for the treated cohort g against a valid control group, is defined as:

$$ATT(g,t) = \mathbb{E}[\ln(Y_{it}+1) - \ln(Y_{i,g-1}+1)|G_i = g] - \mathbb{E}[\ln(Y_{it}+1) - \ln(Y_{i,g-1}+1)|C_i = 1] \quad (4.2)$$

Where the variables are defined as follows:

- Y_{it}: The amount of residual waste (in kilograms per inhabitant) produced by municipality i in year t.
- $\ln(Y_{it}+1)$: The natural logarithm of the outcome variable. The addition of 1 ensures that any theoretical zero-value observations can be log-transformed without mathematical errors.
- g: The treatment cohort, representing the specific year a municipality first adopts the weight-based pricing system.
- t: The current observation year being evaluated.
- $g-1$: The baseline year, which is the year strictly prior to the treatment adoption for cohort g.

- $G_i = g$: An indicator variable denoting that municipality i belongs to the treatment cohort g.
- $C_i = 1$: An indicator variable denoting that municipality i belongs to the valid control group (e.g., the "never-treated" municipalities that maintained volume-based pricing throughout the observation period).

To summarize the impact of the policy across all municipalities over time, these individual $ATT(g,t)$ estimates are aggregated into an event-study parameter. This aggregation takes a weighted average of the group-specific effects, where the weights are proportional to the size of each transition cohort. This ensures that every individual treated municipality carries an equal weight in the final aggregate estimate. Furthermore, the baseline reference point for this event study is anchored to the year immediately preceding the policy implementation (Year -1). By utilizing a log-linear specification, the event-study point estimates ($\hat{\theta}$) represent proportional differences. To convert these estimates into percentage changes, the mathematical transformation $(\exp(\hat{\theta}) - 1) \times 100$ is applied.

4.2.2.2 Mathematical Formulation: Conditional Log-Linear Staggered DiD

The conditional Staggered DiD estimator calculates the treatment effect while adjusting for underlying municipal characteristics to isolate the true causal impact of the policy. It relies on the assumption that, after controlling for specific covariates, the residual waste generation of the newly treated municipalities and the chosen control group would have followed parallel trajectories in the absence of the policy change (the conditional parallel trends assumption). The core parameter of this framework remains the group-time average treatment effect, denoted as $ATT(g,t)$. However, in the conditional model, this parameter is derived by first conditioning the expected outcomes on a set of covariates, and then averaging those differences over the covariate distribution of the specifically treated cohort.

To evaluate the proportional impact on residual waste, the outcome variable is transformed using the natural logarithm. The conditional $ATT(g,t)$ estimator, which compares the evolution of logged outcomes for the treated cohort g against a covariate-matched control group, is mathematically defined as:

$$ATT(g,t) = \mathbb{E}X|G_i = g\Big[\mathbb{E}[\ln(Yit{+}1){-}\ln(Y_{i,g-1}{+}1)|X_i, G_i = g]{-}\mathbb{E}[\ln(Y_{it}{+}1){-}\ln(Y_{i,g-1}{+}1)|X_i, C_i = 1]\Big] \tag{4.3}$$

Where the newly introducedvariables are defined as follows:

- Y_{it}: The amount of residual waste (in kilograms per inhabitant) produced by municipality i in year t.
- X_i: A vector of strictly pre-treatment or time-invariant covariates for municipality i. In this study, X_i represents the dummy variables encoding the Belfius Municipal Typology.
- $\mathbb{E}_{X|G_i=g}$: The outer expectation taken over the distribution of covariates X specifically among the municipalities in the treated cohort g. This ensures the control units are reweighted or matched to resemble the structural characteristics of the newly treated municipalities.

To summarize the overarching impact of the policy, these covariate-adjusted $ATT(g,t)$ estimates are similarly aggregated into an event-study parameter. The aggregation process, including the cohort-size weighting, the anchoring to the baseline year (Year -1), and the exact percentage transformation of the log-linear estimates via $(\exp(\hat{\theta})-1)\times 100$, is mathematically identical to the procedure detailed for the unconditional model in Section 4.2.2.1.

4.2.2.3 Mathematical Formulation: Substitution and Spillover Effects

To evaluate whether the weight-based pricing of residual waste incentivizes households to divert materials into selectively collected streams, the conditional Staggered DiD framework established in Section 4.2.2.2 is iteratively applied to the alternative household waste fractions.

Because the underlying structural assumptions, baseline anchoring, and covariate-matching procedures (using the Belfius Municipal Typology, X_i) remain completely identical to the primary model, the econometric architecture is preserved. However, the outcome variable is substituted to explicitly quantify the substitution effect, which is the extent to which the implementation of weight-based pricing drives households to increase their use of alternative, selectively collected fractions. The group-time average treatment effect for a specific alternative waste fraction k, denoted as $ATT^k(g,t)$, is mathematically defined as:

$$ATT^k(g,t) = \mathbb{E}_{X|G_i=g}\Big[\mathbb{E}[\ln(F^k_{it}+1)-\ln(F^k_{i,g-1}+1)|X_i, G_i=g]-\mathbb{E}[\ln(F^k_{it}+1)-\ln(F^k_{i,g-1}+1)|X_i, C_i=1]\Big] \tag{4.4}$$

Where the newly introduced variables are defined as:

- $ATT^k(g,t)$: The covariate-adjusted group-time average treatment effect on the alternative waste fraction k (e.g., PMD, GFT, Paper and Cardboard).
- F^k_{it}: The amount of waste belonging to fraction k (in kilograms per inhabitant) collected in municipality i in year t.

In this context, while a negative event-study estimate for residual waste indicates policy success, a positive point estimate ($\hat{\theta}>0$) for a fraction k (such as PMD or GFT) signifies a substitution effect, where households actively redirect recyclable materials away from the residual bin. To ensure consistency and interpretability across all evaluated streams, the resulting aggregated log-linear estimates for each fraction k are converted into exact percentage changes using the mathematical transformation $(\exp(\hat{\theta})-1)\times 100$.

4.2.2.4 Mathematical Formulation: Spatial and Demographic Heterogeneity

To explore whether the impact of weight-based pricing varies across different socio-demographic and spatial environments, the Staggered DiD framework is applied to isolated subsets of the data. Rather than utilizing the Belfius Municipal Typology as a set of covariates to reweight the control group, as done in the conditional model (Section 4.2.2.2), this approach filters the sample.

By restricting the analysis to municipalities belonging to a single, specific cluster c (e.g., "Large and regional cities"), the internal characteristics of municipalities within the subset are held constant. Consequently, the covariate-matching mechanism becomes obsolete, and the estimation reverts to the unconditional framework (Section 4.2.2.1), but evaluated strictly conditional on cluster membership. The group-time average treatment effect for a specific cluster, denoted as $ATT^c(g,t)$, is mathematically defined as:

$$ATT^c(g,t) = \mathbb{E}[\ln(Y_{it}+1) - \ln(Y_{i,g-1}+1) | G_i = g, X_i = c] - \mathbb{E}[\ln(Y_{it}+1) - \ln(Y_{i,g-1}+1) | C_i = 1, X_i = c] \tag{4.5}$$

Where the newly introduced parameters are defined as:

- $ATT^c(g,t)$: The cluster-specific group-time average treatment effect, representing the policy's impact strictly within a defined spatial or demographic subset.
- $X_i = c$: The conditioning statement ensuring that both the treated municipalities ($G_i = g$) and the control municipalities ($C_i = 1$) evaluated in this specific estimation belong exclusively to the chosen Belfius Typology cluster c.

Because this approach physically restricts the sample prior to estimation, the mechanics of the model are preserved. The aggregation into dynamic event-study parameters, the baseline anchoring, and the final conversion into exact percentage changes via $(\exp(\hat{\theta}) - 1) \times 100$ remain mathematically identical to the primary analyses.

4.2.2.5 Mathematical Formulation: Method of Implementation

To evaluate whether the specific design of the weight-based pricing system (e.g., WF, W, WV, WF NL) drives different behavioural responses, the framework is iteratively applied to isolated subsets corresponding to the adopted tariff schedule.

Similar to the spatial heterogeneity approach, this method restricts the treated sample prior to estimation. For a given pricing mechanism m (e.g., the WF system), the dataset is filtered to include only the municipalities that transitioned to this specific method, alongside the baseline control group. Crucially, any municipality that transitioned to an alternative weight-based system ($m' \neq m$) during the observation period is strictly excluded.

This ensures the volume-based control group ($C_i = 1$) remains completely uncontaminated by competing policy interventions.

Because the analysis still aims to isolate the true causal effect by accounting for underlying municipal characteristics, it utilizes the conditional framework established in Section 4.2.2.2. The expected outcomes are conditioned on the Belfius Municipal Typology covariates (X_i) to ensure parallel trends hold. Iterating over each alternative waste fraction k, the covariate-adjusted, method-specific group-time average treatment effect, denoted as $ATT^{m,k}(g,t)$, is mathematically defined as:

$$\begin{aligned} ATT^{m,k}(g,t) = \mathbb{E}_{X|G_i=g,M_i=m}\Big[&\mathbb{E}[\ln(F_{it}^k+1) - \ln(F_{i,g-1}^k+1) \mid X_i, G_i = g, M_i = m] \\ &- \mathbb{E}[\ln(F_{it}^k+1) - \ln(F_{i,g-1}^k+1) \mid X_i, C_i = 1]\Big] \end{aligned} \tag{4.6}$$

Where the newly introduced parameters are defined as:

- $ATT^{m,k}(g,t)$: The covariate-adjusted, method-specific group-time average treatment effect for waste fraction k, representing the policy's impact driven strictly by pricing mechanism m.
- $M_i = m$: The conditioning statement ensuring that the treated municipalities ($G_i = g$) evaluated in this specific estimation adopted exclusively the pricing mechanism m (e.g., the WF system).

As with the preceding conditional models, the aggregation into dynamic event-study parameters, the baseline anchoring, and the final conversion into exact percentage changes via $(\exp(\hat{\theta})-1)\times 100$ remain mathematically identical to the primary analyses.

4.2.3 Intersectional Analysis

While estimating the impact of specific pricing methods within distinct municipal clusters (e.g., the efficacy of non-linear pricing strictly within large cities) would yield highly granular policy insights, this intersectional approach is currently constrained by data scarcity. Table 4.1 illustrates the cross-sectional distribution of the 41 switchers across their municipal typology and their adopted weight-based system.

As the table reveals, subdividing this already restricted cohort splits the dataset, leaving most intersections with zero or only a single municipality. This fragmentation strips the staggered Difference-in-Differences model of the statistical power required to compute reliable estimates, as it would produce wide confidence bands.

An option could be to apply a fractional factorial design, which is a method used in experimental design to estimate the effects of multiple factors and their interactions with a reduced number of experimental runs. However, this method is not suitable for the current observational data for several reasons. The three basic principles of experimental design are randomization, replication and blocking. The first one, randomization, is the cornerstone

Table 4.1: Distribution of Switchers by Municipal Typology and Adopted Pricing System (2017-2024)

Municipal Typology Cluster	WF	WV	W	WF NL	Total
Residential municipalities	18	0	2	2	**22**
Municipalities with economic activity	4	3	0	0	**7**
Urbanized municipalities	4	0	0	1	**5**
Rural municipalities	1	0	1	2	**4**
Large and regional cities	1	1	0	1	**3**
Coastal municipalities	0	0	0	0	**0**
Total Switchers	**28**	**4**	**3**	**6**	**41**

underlying the use of statistical methods in experimental design [40]. Randomization means that both the allocation of the experimental material (in this context the method of implementation for a municipality) and the order in which the individual runs of the experiment are performed (here the year of transition) are randomly determined. This is not the case in this study as municipalities independently choose both their tarrif structure and the timing of their transition as a political decision. Consequently, the dataset is purely observational and retrospective, lacking any element of randomization. This fundamental difference in data structure means that the assumptions and statistical properties that underpin a fractional factorial design do not hold, making it an inappropriate method for analyzing the current dataset. Furthermore, the imbalance and presence of empty cells in the data (e.g., the 'WV' system is absent in residential, urbanized, and rural municipalities) violates the orthogonality requirement of factorial designs. This causes parameter estimates to be correlated and leads to an inflation in the standard errors of the effects [40]. As a result, an intersectional analysis by pricing method and municipal typology would lead to confounding, or aliasing, of the effects, where the impact of one factor (e.g., the pricing method) cannot be statistically separated from the impact of another factor (e.g., the municipal typology). Consequently, analyzing the precise interaction between local demographics and specific tariff structures remains unfeasible until these diverse pricing mechanisms achieve broader adoption across Flanders.

4.2.4 Empirical Implementation and Statistical Inference

To generate the empirical results based on the methodologies outlined in Section 4.2.2, the R package `did` is used, as suggested and developed by Callaway and Sant'Anna [34]. This software operationalizes the staggered Difference-in-Differences framework by computing group-time average treatment effects and dynamically aggregating them to prevent negative weighting biases. To assess statistical significance across multiple event times, the `did` package constructs simultaneous confidence bands using a multiplier bootstrap procedure rather than standard analytical methods. Unlike standard pointwise confidence intervals, these simultaneous bands explicitly correct for the multiple comparisons problem. Because the model tests the policy effect across multiple event

times simultaneously, the bands are appropriately widened. This ensures a conservative measure of statistical significance at the 5% confidence level, preventing false positives across the evaluated timeline. Furthermore, the multiplier bootstrap procedure is utilized because analytical formulas for standard errors often either do not exist for such complex estimators, or they require strict assumptions about the underlying population distribution that are unlikely to hold true in practice [41].

5

Results

This chapter presents the empirical findings regarding the transition from volume-based to weight-based pricing in Flanders. The results are structured to unpack the policy's impact, moving from aggregate effects to context-specific behavioral shifts. First, Section 5.1 establishes the primary treatment effect by quantifying the overarching impact on residual waste generation using both unconditional and conditional staggered DiD models. Building on this foundation, Section 5.2 explores secondary behavioral responses, detailing the substitution and spillover effects across other selectively collected household fractions. Section 5.3 then breaks down these aggregate trends to examine spatial and demographic heterogeneity across distinct municipal clusters. Finally, Section 5.4 isolates the effects of specific tariff designs to determine how the method of implementation drives differing outcomes.

5.1 Results: Impact on Residual Waste

5.1.1 Unconditional Log-Linear Staggered DiD

Before presenting the covariate-adjusted results, this section utilizes the unconditional model to unpack the mechanics of the staggered Difference-in-Differences estimator step-by-step. While this unadjusted model does not fully isolate the causal effect from demographic confounders, it illustrates how the final metrics are constructed. The estimation is broken down into three distinct phases: estimating granular group-time effects, aggregating these into dynamic event-study effects, and transforming the logarithmic estimates into exact percentages. By establishing this foundational process here, subsequent sections can present the definitive conditional results directly through concise summary tables.

5.1.1.1 Phase 1: Group-Time Average Treatment Effects ($ATT(g,t)$)

The building blocks of the staggered DiD estimator are the group-time average treatment effects, denoted as $ATT(g,t)$. Instead of calculating one average, the model first splits the treated municipalities into distinct

"cohorts" based on the year they adopted the policy (the group g). It then compares each cohort's waste generation in a specific year (the time t) against the "never-treated" control group. These results can be seen in Table 5.1.

Table 5.1: Group-Time Average Treatment Effects ($ATT(g,t)$) on Residual Waste

Group	Time	$ATT(g,t)$	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.1270	0.0791	-0.3312	0.0773	
2018	2019	-0.1253	0.0850	-0.3448	0.0942	
2018	2020	-0.1195	0.0940	-0.3624	0.1235	
2018	2021	-0.0992	0.1251	-0.4223	0.2239	
2018	2022	-0.0646	0.1105	-0.3501	0.2209	
2018	2023	-0.0209	0.1081	-0.3002	0.2584	
2018	2024	0.0055	0.1144	-0.2899	0.3009	
2020	2018	-0.0001	0.0078	-0.0202	0.0200	
2020	2019	-0.0868	0.0399	-0.1899	0.0164	
2020	2020	-0.1781	0.0490	-0.3048	-0.0515	*
2020	2021	-0.2066	0.0546	-0.3476	-0.0656	*
2020	2022	-0.1786	0.0619	-0.3384	-0.0187	*
2020	2023	-0.1666	0.0610	-0.3242	-0.0091	*
2020	2024	-0.1557	0.0596	-0.3096	-0.0017	*
2021	2018	0.0022	0.0060	-0.0132	0.0177	
2021	2019	0.0047	0.0083	-0.0168	0.0261	
2021	2020	0.0009	0.0106	-0.0266	0.0284	
2021	2021	-0.1776	0.0190	-0.2268	-0.1284	*
2021	2022	-0.2231	0.0290	-0.2980	-0.1482	*
2021	2023	-0.1946	0.0340	-0.2826	-0.1066	*
2021	2024	-0.1722	0.0372	-0.2682	-0.0761	*
2022	2018	0.0195	0.0110	-0.0089	0.0478	
2022	2019	0.0107	0.0151	-0.0283	0.0497	
2022	2020	0.0026	0.0261	-0.0649	0.0700	
2022	2021	-0.0255	0.0480	-0.1495	0.0985	
2022	2022	-0.1390	0.0396	-0.2414	-0.0366	*
2022	2023	-0.1006	0.0591	-0.2534	0.0522	
2022	2024	-0.0812	0.0595	-0.2349	0.0725	
2024	2018	0.0211	0.0278	-0.0508	0.0930	

Table 5.1 continued from previous page

Group	Time	$ATT(g,t)$	SE	Lower 95% Band	Upper 95% Band	Sig.
2024	2019	0.0013	0.0078	-0.0188	0.0214	
2024	2020	0.0134	0.0232	-0.0464	0.0733	
2024	2021	0.0061	0.0249	-0.0583	0.0704	
2024	2022	-0.0003	0.0128	-0.0335	0.0329	
2024	2023	-0.0463	0.0323	-0.1299	0.0372	
2024	2024	-0.1394	0.1015	-0.4016	0.1227	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% band does not cover 0.

For example, looking at the output for the cohort that transitioned in 2020 ($g = 2020$):

- In 2018 and 2019 (pre-treatment), the ATT estimates are -0.0001 and -0.0868 respectively, and both are statistically insignificant. This confirms that prior to adoption, the 2020 cohort was following a similar trajectory to the control group.
- In 2020 (the year of adoption), the ATT drops to -0.1781 and becomes significant at the 5% confidence level.
- This significant reduction persists for this specific cohort through 2024, maintaining an estimate of -0.1557.

Similar patterns are observable for the other cohorts, where significant reductions align with their respective years of adoption. However, presenting dozens of individual $ATT(g,t)$ estimates across all calendar years makes it difficult to assess the overarching policy impact.

5.1.1.2 Phase 2: Dynamic Aggregation (Event Study)

To summarize these cohort effects into a single cohesive narrative, the individual $ATT(g,t)$ estimates are aggregated relative to the moment of treatment. This shifts the x-axis from standard calendar years to the number of years relative to the policy adoption. Event Time 0 represents the adoption year for every municipality, regardless of whether that occurred in 2018 or 2024. This dynamic aggregation allows for a visualization of the average treatment effect trajectory before and after the policy change, while also providing simultaneous confidence bands to assess statistical significance at each point in time. The results of this event study are presented in Table 5.2 and in Figure 5.1.

The aggregated output from this event study (expressed in log points) is as follows:

- **Pre-treatment (Event Time -6 to -1):** The aggregated estimates are near zero (ranging from -0.0258 to 0.0211) and are all statistically insignificant. This confirms the unconditional parallel trends assumption

Table 5.2: Aggregated Dynamic Effects on Residual Waste (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0211	0.0426	-0.0859	0.1280	
-5	0.0013	0.0071	-0.0166	0.0192	
-4	0.0180	0.0095	-0.0058	0.0418	
-3	0.0042	0.0052	-0.0089	0.0173	
-2	0.0030	0.0062	-0.0126	0.0186	
-1	-0.0258	0.0139	-0.0606	0.0090	
0	-0.1677	0.0159	-0.2076	-0.1279	*
1	-0.1954	0.0247	-0.2575	-0.1334	*
2	-0.1696	0.0271	-0.2377	-0.1015	*
3	-0.1662	0.0324	-0.2474	-0.0850	*
4	-0.1391	0.0543	-0.2755	-0.0027	*
5	-0.0209	0.1148	-0.3091	0.2673	
6	0.0055	0.1195	-0.2944	0.3054	
Overall	**-0.1219**	**0.0452**	**-0.2105**	**-0.0334**	*

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

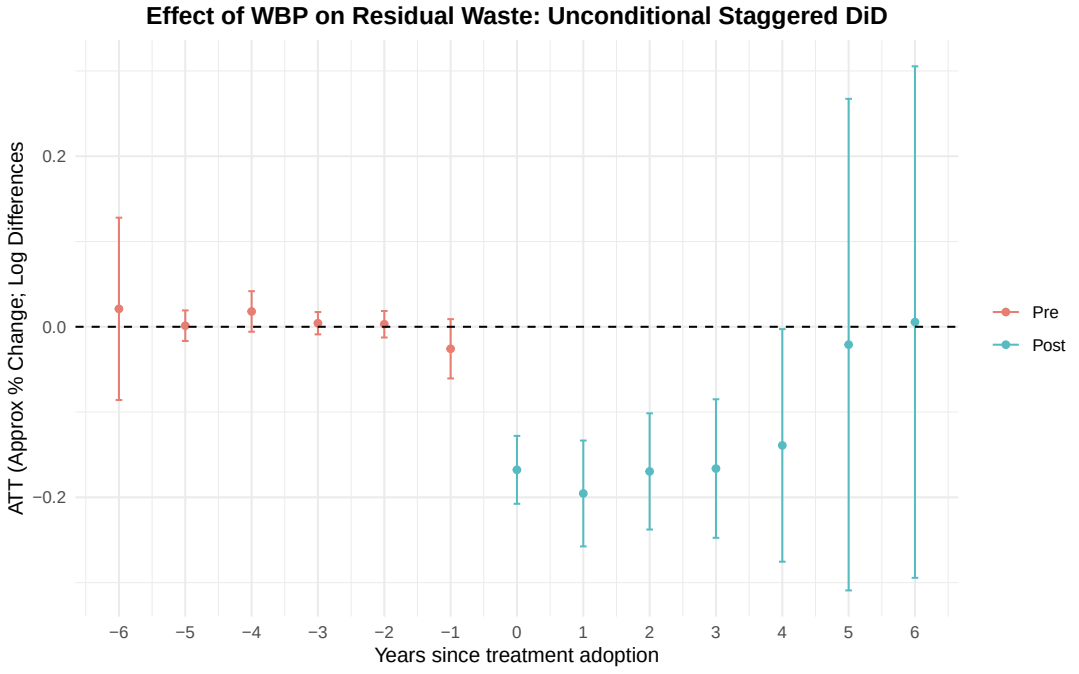


Figure 5.1: Unconditional Impact of Weight-Based Pricing on Residual Waste

across the entire sample.

- **Post-treatment (Event Time 0 to +6):** A statistically significant structural break occurs at Event Time 0 with an aggregated log estimate of -0.1677. This significant reduction persists up to Event Time +4 (-0.1391). As the exact moment of treatment is unknown, the full effect can be observed in the year after the transition, which corresponds to Event Time +1. At this point, the estimate reaches its lowest point at -0.1954, indicating a strong negative effect on residual waste generation immediately following the policy change. However, from Event Time +5 onwards, the estimates lose statistical significance, which may be due to reduced sample size in the later event times.
- **Overall ATT:** Averaging all post-treatment periods yields an overall estimate of -0.1219, indicating a strong significant negative effect on residual waste generation.

5.1.1.3 Phase 3: Exact Percentage Transformation

While the aggregated estimates in Section 5.1.1.2 provide the trajectory and statistical significance of the policy, they are expressed in logarithmic differences. Because the impact of weight-based pricing is substantial, interpreting these values directly as percentages introduces mathematical approximation errors.[1]

To provide accurate and interpretable results, the confidence bands and the point estimates from Phase 2 are transformed using the formula $(\exp(\hat{\theta}) - 1) \times 100$. The final, definitive results of this transformation are presented in Table 5.3.

As shown in Table 5.3, the transition to weight-based pricing triggers an immediate exact reduction of 15.44% in residual waste during the year of adoption (Event Time 0). However, as stated before, because the exact date of implementation within that calendar year is unknown, this number likely captures only a partial year of treatment. Consequently, the full effect of the policy becomes observable from the first full year following the transition (Event Time 1) onwards, where the reduction initially peaks at 17.75%. While the policy's impact remains highly significant through the fourth year, a gradual attenuation is observed in the subsequent periods, with the estimates for Event Times 5 and 6 losing statistical significance. This pattern aligns with previous empirical literature in Flanders, which characterizes the introduction of weight-based pricing as a strong, but fading, short-term behavioral shock. However, a plausible explanation for this perceived fade-out is the reduction in sample size at the end of the observation window. The estimates for these later event times rely on the earliest adopters, a cohort of two municipalities that transitioned in 2018. This restricted sample size introduces uncertainty, which is mathematically reflected in the widened simultaneous confidence bands observed in Years 5 and 6. Consequently, it is difficult to definitively disentangle a genuine long-term behavioral relapse from the statistical noise inherent to

[1] The standard approximation $x \approx \exp(x) - 1$ degrades as x moves further from zero. For instance, the estimate for Event Time 1 is -0.1954. Interpreting this directly yields a 19.54% reduction, whereas the exact transformation yields the true discrete reduction of 17.75%.

Table 5.3: Exact Percentage Change in Residual Waste (Unconditional Event Study)

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	2.13%	-8.23%	13.65%	
-5	0.13%	-1.65%	1.94%	
-4	1.81%	-0.58%	4.26%	
-3	0.42%	-0.89%	1.74%	
-2	0.30%	-1.25%	1.87%	
-1	-2.55%	-5.88%	0.90%	
0	-15.44%	-18.74%	-12.01%	*
1	-17.75%	-22.70%	-12.49%	*
2	-15.60%	-21.16%	-9.65%	*
3	-15.31%	-21.92%	-8.15%	*
4	-12.99%	-24.08%	-0.27%	*
5	-2.07%	-26.59%	30.64%	
6	0.55%	-25.50%	35.72%	
Average Post-Treatment	**-11.48%**	**-18.99%**	**-3.29%**	*

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

small early-adopter cohorts. This remark will keep showing up in the subsequent analyses, as event times 5 and 6 will always rely on a smaller subset of treated municipalities, which introduces a similar uncertainty.

In the following sections, the analysis of the results will be discussed exclusively using tables presenting exact percentage changes. This ensures that the magnitude of the policy impacts remains accurate and interpretable, free from mathematical approximation errors. For completeness and methodological transparency, all underlying logarithmic estimates and dynamic aggregations, analogous to the Phase 1 and Phase 2 outputs discussed above, will be provided in Appendix B for both the primary conditional model and the substitution effects. The full event-study tables containing the exact percentage transformations for these models are also included in the appendix. In the main text, the focus will remain on key findings and interpretations, supported by summary tables to facilitate comparison across all tested scenarios. Finally, for the stratified analyses presented in Sections 5.3 and 5.4, only the event-study tables with the exact percentage changes are included in the appendix. The underlying logarithmic estimates for these specific sub-analyses are not included to maintain a concise appendix, but are available upon request.

5.1.2 Conditional Log-Linear Staggered DiD

While the unconditional event study presented in Section 5.1.1 demonstrated a significant reduction in residual waste following the implementation of weight-based pricing, it relied on the assumption that all municipalities follow the exact same natural waste generation trajectory. As detailed in Section 4.2.1.4, this unconditional assumption is often violated in practice; demographic and structural differences, such as comparing dense urban centers to rural villages, can influence the outcome of a policy intervention.

To address this and isolate the true causal effect of the policy, this section presents the results of the Conditional Log-Linear Staggered DiD model. Following the framework of Callaway and Sant'Anna, this updated model formally incorporates all assumptions, including assumptions 4 and 5, which dictate that parallel trends must hold conditionally based on specific covariates.

To satisfy this requirement, the model introduces the Belfius Municipal Typology as a control variable. Consistent with the reporting structure established in the previous section, the overarching policy impacts will be discussed using exact percentage transformations, while the underlying logarithmic estimates and dynamic aggregations are provided in Appendix B. The results of the conditional event study are presented in Table 5.4. Looking at these

Table 5.4: Exact Percentage Change in Residual Waste (Conditional Event Study)

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	2.00%	-6.08%	10.77%	
-5	1.23%	-1.32%	3.83%	
-4	2.11%	0.18%	4.07%	*
-3	0.39%	-1.06%	1.87%	
-2	0.31%	-1.57%	2.21%	
-1	-2.68%	-5.95%	0.71%	
0	-15.12%	-18.80%	-11.28%	*
1	-17.27%	-21.91%	-12.36%	*
2	-15.15%	-20.47%	-9.47%	*
3	-14.94%	-21.56%	-7.77%	*
4	-13.32%	-24.85%	-0.04%	*
5	-3.84%	-44.23%	65.83%	
6	-1.72%	-26.78%	31.93%	
Average Post-Treatment	**-11.80%**	**-20.02%**	**-2.74%**	*

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

findings, the trajectory of the policy impact closely mirrors the unconditional estimates. The transition to weight-based pricing still triggers a significant reduction in residual waste, peaking at a decrease of 17.27% in the first full year following implementation.

Compared to the unconditional peak of 17.75%, this covariate-adjusted estimate is only fractionally attenuated. This is an interesting finding: it confirms that the observed waste reductions are driven by the pricing mechanism itself, rather than being an artifact of the municipal heterogeneities discussed above. Overall, the average post-treatment reduction of 11.80% remains significant, reaffirming the significant impact of weight-based pricing on residual waste generation. The fade-out effect also persists, with the reduction gradually narrowing to 13.32% by Year 4 before losing statistical significance in Years 5 and 6, a drop-off that is possibly attributable to the limited sample size of the 2018 early-adopter cohort. Overall, the average post-treatment reduction of 11.80% remains significant, reaffirming the significant impact of weight-based pricing on residual waste generation.

Furthermore, the pre-treatment periods in the conditional model largely validate the parallel trends assumption, with most estimates being close to zero and remaining statistically insignificant. A deviation is observed at Event Time -4, showing a 2.11% difference. However, because this isolated fluctuation is bordered entirely by non-significant baseline years, it is likely a statistical artifact rather than a systemic violation of the counterfactual assumption. Ultimately, adjusting for municipal typology reaffirms the effectiveness of the policy.

5.2 Substitution Effects on Collected Fractions

Table 5.5 provides a comprehensive summary of the substitution effects across all selectively collected waste fractions. The table presents the exact percentage changes for each fraction, along with the specific event times at which statistically significant effects were observed. This structured overview allows for a comparison of how changing to weight-based pricing influenced household behavior across different waste streams, highlighting both the magnitude and timing of any substitution effects. The detailed breakdown of significant event times further explains the dynamic nature of these behavioral shifts in response to the policy change. The tables with the exact percentage changes for each fraction are provided in the Appendix B for methodological transparency and completeness. Overall, the results indicate that while some fractions experienced significant substitution effects, others remained unaffected, in contrast to the results of existing literature that reports behavioral spillovers.

It should be noted that the substitution effects observed in this analysis are not necessarily indicative of a direct causal relationship between the policy and changes in specific waste streams. Instead, other factors such as concurrent waste management initiatives could also contribute to these observed changes. While the staggered DiD framework mitigates this risk by employing unit and time fixed effects to account for broad Flemish trends, purely local initiatives are not explicitly captured. An example of a regional initiative during the observation period is the rollout of the “New Blue Bag”, which expanded the types of plastics allowed in PMC collection. While such region-wide shifts are captured by the control group trends, purely local initiatives, such as the introduction of

VFG collection in a specific municipality, facilitated oil or battery collection and local campaigns, are not captured in the dataset. Nevertheless, it is unlikely that such local characteristics would systematically bias the results. For these factors to undermine the causal interpretation, they would need to be implemented in close temporal synchrony with the weight-based pricing transition across a majority of the 41 switching municipalities. While local initiatives may play a role in isolated cases, the observed average treatment effects across the staggered timeline are more reasonably attributed to the structural incentive of the pricing transition itself. Lastly, a higher degree of caution is required when interpreting the stratified analyses in Sections 5.3 and 5.4. In cohorts with a limited number of switchers (e.g., $n = 3$ or $n = 4$), the results are more likely to be influenced by local factors. Consequently, these subgroup analyses should be regarded as exploratory and hypothesis-generating rather than confirmatory. They serve to identify potential divergent behavioral patterns that warrant further investigation as broader adoption of these pricing structures provides more longitudinal data.

Table 5.5: Summary of Substitution Effects on Collected Fractions (Exact Percentage Changes)

Waste Stream	**Overall Effect (%)**	**Significant Event Times & Sign**
Residual Waste	-11.80%*	t=-4 (+), t=0 (-), t=1 (-), t=2 (-), t=3 (-), t=4 (-)
Batteries	-2.08%	
Construction and Demolition Waste	0.62%	
Organic Waste (VFG)	-6.56%	t=-5 (-), t=5 (-), t=6 (-)
Green Waste	-0.76%	
Wood Waste	-10.76%*	t=0 (-), t=4 (-)
Small Hazardous Waste	6.97%*	t=2 (+), t=5 (+), t=6 (+)
Hard Plastics	10.42%	t=-1 (-), t=1 (+), t=2 (+), t=3 (+), t=4 (+)
Scrap Metal	1.69%	t=6 (+)
Paper and Cardboard	-1.87%*	t=-5 (-), t=6 (-)
Vegetable and Animal Oils/Fats	5.10%*	t=3 (+)
PMC	+2.18%	t=-5 (-), t=-1 (+), t=5 (+), t=6 (+)
Textiles	-4.73%	
Packaging Glass	-3.60%*	
Flat Glass	-5.49%*	t=1 (-), t=3 (-)

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

5.2.1 Residual Waste

To establish a baseline for the substitution analysis, the impact on residual waste is re-estimated using the framework outlined in Section 4.2.2.3. Because the model specifications mirror the conditional model, the outcomes

remain unchanged. As shown in Table 5.4, weight-based pricing triggers a peak reduction of 17.27% in residual waste, while having a significant decrease of 11.80% over the 6 year period. This decrease acts as the driver for the behavioral shifts observed in the selectively collected fractions analyzed below.

5.2.2 Batteries

As indicated by the lack of statistical significance across all post-treatment event times and no significant effect over the 6-year period, the implementation of weight-based pricing has no measurable substitution effect on this specific fraction. Unlike the sharp decrease observed in residual waste, the total amount of collected batteries remains unchanged, yielding an insignificant overall effect of -2.08%. This shows that households do not fundamentally alter their battery recycling behavior in response to the increased cost of the residual waste bin.

5.2.3 Construction and Demolition Waste

Similar to the findings for batteries, the results show a lack of statistical significance across all post-treatment periods. The overall aggregated effect is virtually zero (0.62%), with wide confidence bands indicating high natural variance in this waste stream. This confirms that the introduction of weight-based pricing for regular residual waste does not induce any measurable behavioral spillover or substitution effect regarding how households dispose of heavy building and demolition materials.

5.2.4 Organic Waste (VFG)

Unlike batteries or demolition waste, VFG is a frequent, high-volume fraction collected door-to-door at almost all households. As discussed in Section 2.1.2, its separate collection became a obligatory across Flanders on January 1, 2024 (with some exceptions allowed). However, the econometric analysis of this specific fraction is constrained by data availability. While the overarching baseline dataset contains 183 relevant municipalities (142 "never-treated" control units and 41 "switchers"), only 107 of these municipalities reported a complete, uninterrupted VFG dataset for the entire 2017–2024 observation period. This reduced sample size decreases the statistical power of the model, produces wider simultaneous confidence bands, as observed in Table B.11, making it more difficult to isolate and confirm a significant substitution effect. Furthermore, this data restriction introduces a potential selection bias into the analysis. By systematically excluding municipalities that did not have an established door-to-door VFG collection system throughout the observation period, the model does not measure the substitution effects but only the effect at municipalities where there is a door-to-door collection system. Consequently, it fails to capture the effect at municipalities without formal organic waste collection. In these excluded municipalities, residents lack the option to divert organic matter to door-to-door collection of the VFG stream. Consequently, the introduction of weight-based pricing on residual waste likely forces an even more pronounced shift toward home composting (or alternative disposal) in these areas. This could imply that the true overarching drive toward home

composting across Flanders might be even stronger than what can be inferred from this restricted sample.

Given the strict penalization of residual waste under weight-based pricing, a positive substitution effect, where households actively shift organic materials from the residual waste bin into the municipal organic waste bin, was theoretically expected.

However, the results indicate an overall statistically insignificant change of -6.56%. While the later post-treatment periods (Years 5 and 6) show significant decreases of -13.62% and -15.81%, the overarching trend does not support a widespread substitution effect. This finding aligns with the behavioral shifts regarding organic waste identified in earlier empirical literature. For instance, Dijkgraaf and Gradus (2004) demonstrated that household response depends heavily on the pricing of the organic stream itself: they observed a 61% decrease in compostable waste when it was priced, but a 36% increase when it remained free, a spike they attributed to households "dumping" other unpriced materials into the compost bin rather than pure organic substitution [19]. Similarly, Allers and Hoeben (2010) found a 51% reduction in biodegradable waste under weight-based pricing, explicitly citing the easy availability of home composting as a powerful substitute [16]. Tønning (2000) also historically linked the introduction of weight-based systems directly to increased home composting [17].

Crucially, in Flanders, organic waste is not one of the free fractions as municipalities and intermunicipal organizations have the autonomy to set specific tariffs for VFG collection. Because using the collection carries its own financial cost, the absence of a positive substitution effect in the current dataset, eventually turning into a significant decrease in later years, suggests two mechanisms. Modern households might already be maximizing their baseline VFG separation prior to the policy change, or, more likely, the compounded financial burden of paying for both residual and organic waste is successfully driving them away from municipal collection and towards home composting.

5.2.5 Green Waste

Much like the previous alternative fractions, the results indicate a lack of statistical significance across all post-treatment periods. The overall aggregated effect is -0.76%, accompanied by wide confidence bands that reflect the high natural variance in garden waste generation. This confirms that the introduction of weight-based pricing for regular residual waste does not induce households to systematically alter their disposal habits for green waste. This lack of substitution is logical, as garden waste volumes are predominantly dictated by seasonal factors, weather conditions, and existing home composting practices, rather than by the marginal cost shifts of the residual waste bin.

5.2.6 Wood Waste

Unlike the previous alternative fractions which largely displayed statistical insignificance, wood waste exhibits a statistically significant decrease, with an overall aggregated reduction of 10.70%. The dynamic event-study reveals

that this reduction is most pronounced in the immediate implementation year (Event Time 0, -12.30%) and four years post-treatment (Event Time 4, -25.85%).

Crucially, a deeper inspection of the unaggregated group-time average treatment effects (see Table B.15 in Appendix B) reveals that this overarching decline is almost entirely driven by the 2020 treatment cohort. This specific cohort demonstrated significant, and compounding reductions across all its post-treatment years (reaching drops of up to -0.3787 log points by 2024). This indicates the absence of a positive substitution effect. Instead the policy appears to coincide with a negative spillover. While the data captures this reduction, the behavioral mechanisms driving the 2020 cohort specifically remain unclear within the constraints of this dataset and therefore requires the precise cause of this cohort's dramatic reduction in wood waste warrants further investigation.

5.2.7 Small Hazardous Waste

In contrast to previous alternative fractions, Small Hazardous Waste (SHW) exhibits a statistically significant increase, revealing a positive substitution effect. Overall, the implementation of weight-based pricing drives a 6.97% aggregate increase in the separation and proper collection of this fraction. The dynamic event-study demonstrates that this behavioral shift strengthens over time, achieving significant peaks of 4.72% in Year 2, and jumping to 16.73% and 18.86% in Years 5 and 6, respectively. However, it is important to note that the later post-treatment years (Years 5 and 6) rely on a smaller sample size, as stated before in Section 5.1.1.3. Consequently, while the significant increases in these later years are promising, they should be interpreted with caution until further longitudinal data from more municipalities becomes available.

This finding illustrates an effective policy mechanism. When confronted with strict penalization and marginal costs per kilogram for residual waste, households actively change their disposal habits for small hazardous materials, such as paint remnants, chemical products, and motor oils. Rather than illegally or passively discarding these relatively heavy and environmentally toxic items into the regular grey bin, the financial incentive motivates residents to take the extra effort to properly separate them and utilize the designated and free municipal collection channels, such as local recycling parks. This represents an advantage for the weight-based pricing system, proving it can effectively divert polluting materials out of the residual waste stream and into proper treatment facilities.

5.2.8 Hard Plastics

Overall, the implementation of weight-based pricing suggests a positive substitution effect, with an aggregated increase of 10.42%. While this overall estimate misses statistical significance (the lower band dips to -1.16%), the dynamic event-study reveals significant spikes in the years immediately following the policy change. Hard plastics collection increased significantly by 19.04% in Year 1, 22.35% in Year 2, and a peak of 28.31% in Year 3. This indicates that households actively divert hard plastic items from the weight-based residual waste stream toward

other, mostly recycling park alternatives.

However, these results must be interpreted with a degree of caution. First, there is a statistically significant pre-trend reduction of -7.37% in the year immediately prior to implementation (Event Time -1). A closer inspection of the unaggregated group-time average treatment effects in Appendix B (Table B.21) reveals that the significance of this dynamic is almost entirely driven by the 2021 cohort. This specific cohort demonstrated a significant drop prior to treatment, followed by high significant increases in the post-treatment periods. Furthermore, the estimated effect flips to -11.78% by Event Time 6. While this late-stage drop is insignificant, it is accompanied by wide confidence bands (ranging from -29.82% to 10.89%). As stated before, this volatility is largely a limitation of the dataset at Event Times 5 and 6. Consequently, further longitudinal research tracking subsequent cohorts over a longer time horizon is required. Such investigation is necessary to determine whether this late-stage reversal represents a true, widespread decay in the substitution effect across other municipalities, or if it is merely an anomaly driven by the small sample size.

Despite these cohort-specific nuances and the data constraints in the later years, the initial post-treatment periods provide evidence of a substantial, short-to-medium-term positive substitution effect for hard plastics.

5.2.9 Scrap Metal

The overall effect of weight-based pricing on scrap metal is a statistically insignificant 1.69%, with the dynamic event-study confirming no significant deviations from the control group during the first five post-treatment years. This lack of a positive substitution effect is expected: because scrap metal holds intrinsic economic value, households often bypass municipal recycling parks to sell these materials to independent scrap dealers. Consequently, increased residual waste costs do not heavily influence municipal collection volumes for this fraction.

Notably, the model estimates a sudden significant spike of 20.37% in Event Time 6. However, this late-stage anomaly must be interpreted with caution due to the small sample size. Given the lack of significance in the preceding five years, this jump is likely driven by local dynamics rather than a delayed, causal policy effect.

5.2.10 Paper and Cardboard

Overall, weight-based pricing is associated with a small but significant 1.87% decrease in paper and cardboard collection, though the first five post-treatment years show no significant deviation from the control group. This lack of a positive substitution effect is logical: the Flemish government advises municipalities to keep paper and cardboard collection free. Because this financial barrier is mostly non-existent, households likely maximize their baseline separation under the previous volume-based pricing, leaving little room for further substitution when transitioning to weight-based fees.

Two anomalies stand out: a pre-treatment decrease at Event Time -5 (driven by 2024 cohort) and a significant

5.16% drop at Event Time 6. As with previous fractions, this late-stage Year 6 estimate relies on just two "switcher" municipalities from the 2018 cohort and could be interpreted as a statistical anomaly. Ultimately, weight-based pricing residual waste does not boost paper and cardboard separation.

5.2.11 Vegetable and Animal Oils/Fats

Overall, the transition to weight-based pricing generates a significant positive substitution effect of 5.10% on the collection of vegetable and animal oils/fats (primarily cooking and frying oils). The dynamic event-study shows this behavioral shift strengthening over the first few post-treatment years, culminating in a significant 10.68% peak at Event Time 3. This positive substitution is logical given the physical properties of the waste and the Flemish legal framework. Used oils and fats are dense, heavy liquids. Under a volume-based system, disposing a bottle of used frying oil in the residual waste bin carries little penalty. However, under a weight-based pricing model, doing so becomes more expensive. Because the Flemish government legally mandates that municipalities collect household frying fats and oils free of charge, the financial incentive to separate this fraction is optimized.

In later post-treatment periods (Event Times 4 through 6), the estimates lose significance and display volatility, with the confidence bands widening drastically (e.g., Year 5 ranges from -6.07% to 44.35%). As explained for previous fractions, these late-stage fluctuations can be driven by the diminishing sample size of "switcher" municipalities available for long-term observation or local factors rather than a definitive reversal in household behavior. Ultimately, pricing residual waste by weight successfully increases the amount of vegetable and animal oils and fats collected seperatly.

5.2.12 PMC

Overall, the transition from volume-based to weight-based pricing yields an insignificant 2.18% increase on the amount of PMC collected, with the first four post-treatment years showing no significant deviation from the control group. This lack of substitution is logical within the Flemish context. Under the volume-based system, the cost of a PMC bag was already lower than the cost of a residual waste bag. Because this financial incentive to separate PMC was already well-established, households had likely maximized their separation habits before the transition to weight-based pricing for residual waste, leaving little room for additional policy-driven substitution.

The dynamic timeline does contain several noisy estimates. The significant pre-treatment fluctuations at Event Times -5 and -1 likely reflect external, cohort-specific shocks, such as the rollout of the expanded "New Blue Bag" between 2019 and 2021, rather than true policy anticipation effects [42]. Furthermore, the significant post-treatment spikes at Event Times 5 and 6 (14.26% and 7.38%, respectively) rely on the two-municipality sample of the 2018 cohort. As with previous fractions, these late-stage estimates can be interpreted as statistical anomalies. Ultimately, moving to weight-based residual waste pricing does not systematically increase PMC separation beyond its already high baseline.

5.2.13 Textiles

Similar to previous fractions, the results of weight-based pricing on textiles show a lack of statistical significance across all post-treatment periods, with an overall aggregated effect of -4.73%. This confirms that transitioning to weight-based pricing for residual waste does not induce measurable behavioral substitution. As noted by the Flemish government, textiles hold intrinsic economic value and are therefore already collected for free via established networks, leaving households with no new financial incentive to alter their disposal habits. This contrasts with the findings of Dijkgraaf and Gradus (2004), who observed a significant increase in textile separation under weight-based pricing, a shift they attributed to the fact that textiles were not collected for free in their Dutch context [19]. In Flanders, the financial incentive to separate textiles was already optimized under the previous volume-based system, leaving little room for further substitution when transitioning to weight-based fees.

5.2.14 Packaging Glass

Overall, the transition from volume-based to weight-based pricing is associated with a significant decrease of 3.60% in packaging glass collection. However, the event-study reveals no significant deviations during any individual post-treatment period. This lack of positive substitution is logical within the local policy context. Similar to paper and cardboard, the Flemish government advises municipalities to refrain from imposing taxes on transparent packaging glass (bottles, jars, and flasks). Because this financial barrier was already non-existent under the prior volume-based regime, households had likely maximized their baseline separation habits before the transition, leaving little room for additional policy-driven substitution when residual waste pricing changed. The observed overall decrease is likely a statistical artifact rather than a true behavioral shift, as it is not supported by any significant post-treatment deviations and lacks a clear economic rationale.

5.2.15 Flat Glass

As can be seen in Table 5.5, the collection of flat glass decreases significantly when residual waste pricing is changed to a weight-based system, resulting in an overall decrease of 5.49% in flat glass collection. The dynamic model reveals negative effects at Event Times 1 and 3, while the unaggregated data in Table B.42 highlights a concentrated drop across multiple cohorts during the calendar year 2022.

Theoretically, charging for residual waste by weight should either increase glass separation or leave it unchanged. A policy-driven decrease defies expected economic incentives. Because the staggered DiD estimator explicitly controls for general trends, this decline cannot be attributed to broad external shocks. Further investigation is required to determine whether this drop is a statistical anomaly driven by localized dynamics in a few municipalities, or if it reflects a true, widespread behavioral change. Given the lack of significance in the preceding and subsequent years, as well as the absence of a clear economic rationale, this decline should be interpreted with caution.

5.2.16 Summary of Substitution Effects

The transition to weight-based pricing in Flanders yields mixed substitution effects. Contrary to some previous literature that suggests widespread positive behavioral spillovers, this analysis reveals that households do not systematically shift recyclable materials out of the residual bin. For a large portion of selectively collected waste streams, the policy did not induce a significant overall change in household behavior. Fractions such as batteries, construction and demolition waste, green waste, and scrap metal remained unaffected. The expected positive substitution effect for VFG did not materialize, likely because households opt to avoid municipal collection fees entirely by turning to cost-free home composting. Similarly, no significant effects were observed for PMC and textiles. The lack of substitution for PMC is logical, as the financial incentive to separate this fraction was already maximized under the previous volume-based system. Furthermore, in contrast to some earlier literature that found positive substitution for textiles, no significant effect was observed here, as textile collection in Flanders is already widely available for free.

However, the financial penalty of weight-based pricing did successfully drive households to separate specific materials more strictly. SHW saw a significant overall increase of 6.97%, indicating that households actively divert these toxic items to free municipal collection channels rather than paying to put them in the residual bin. Vegetable and animal oils and fats also experienced an overall increase of 5.10%, suggesting households are separating these liquids better to avoid weight fees, though this may be partially influenced by local collection initiatives. Additionally, a positive substitution effect resulting in an overall increase of 10.42% is observed for hard plastics, particularly in the short-to-medium term, as households divert bulky plastics away from the residual stream.

Unexpectedly, several fractions experienced significant overall declines following the policy transition. The mechanisms behind these reductions are not entirely clear and warrant further investigation. A decline of 10.76% was observed in wood waste, though the exact cause for this negative spillover remains unknown. Paper and cardboard noted a small but significant decrease of 1.87%, which seems to be a statistical anomaly driven by late-stage data from a limited number of early adopters. Finally, packaging glass and flat glass saw significant overall decreases of 3.60% and 5.49%, respectively. Because glass collection is generally free, a policy-driven decrease defies expected economic incentives, making the behavioral rationale behind this decline unclear.

To translate these results into a more intuitive perspective, Figure 5.2 visualizes these significant effects in absolute kilograms per capita. Alongside the 16.0 kg drop in residual waste, decreases are observed in wood waste (-6.4 kg), with minor drops in paper and cardboard (-0.9 kg) and both glass fractions (-0.9 kg combined). As stated before, the anticipated positive substitution effect is nearly non-existent, with only SHW and oils/fats showing minor increases (+0.1 kg each).

Consequently, of the 24.3 kg total shifted waste, 24.1 kg is categorized as "Net Waste Prevented / Disappeared." This visually underscores a key finding: weight-based pricing primarily drives absolute waste reduction or out-of-system diversion (such as home composting), rather than pushing households to separate more waste into the

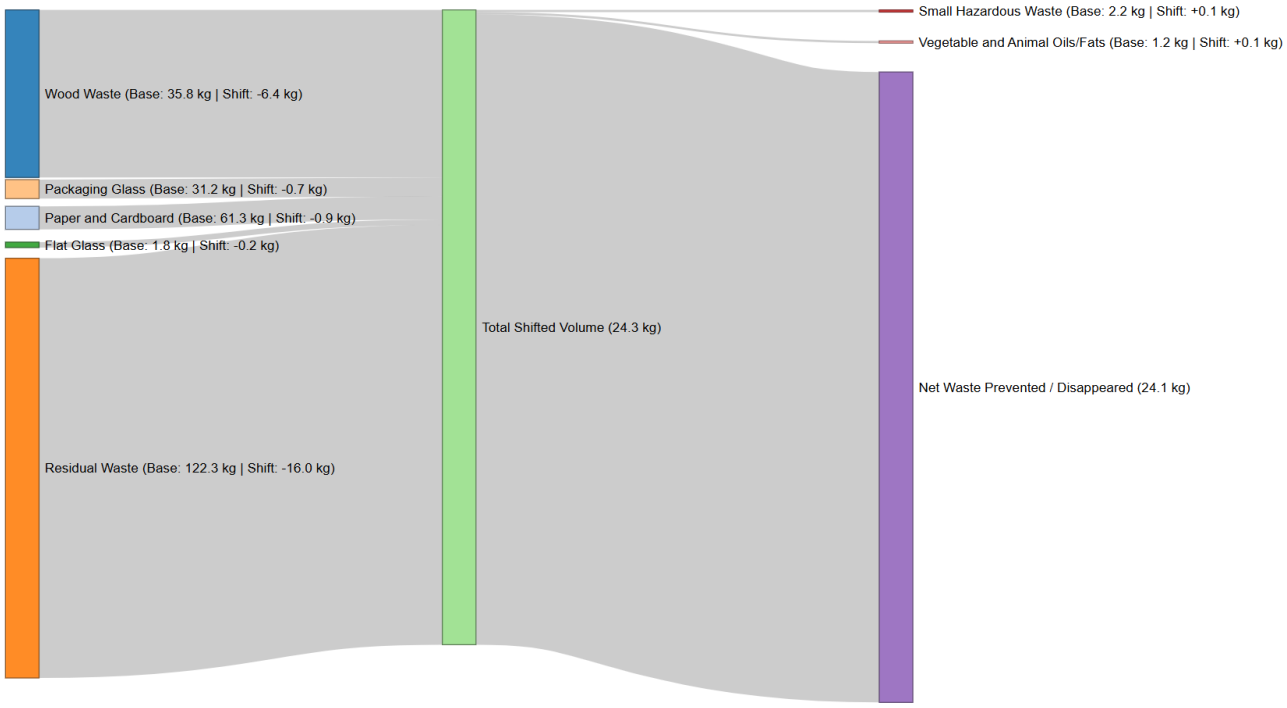


Figure 5.2: Sankey Diagram of Significant Substitution Effects

existing municipal recycling streams.

5.3 Spatial and Demographic Heterogeneity

The preceding analysis established the average treatment effects of weight-based pricing, revealing significant reductions in residual waste and mapping the substitution effects across selectively collected fractions. However, analyzing these aggregate shifts assumes a uniform policy response, which rarely reflects reality. The effectiveness and behavioral impact of WBP can vary depending on spatial and socio-economic characteristics, such as population density and urbanization. To explore this spatial and demographic heterogeneity, this section extends the analysis by leveraging the Belfius Typology, further elaborated on in Section 3.5, to categorize the treated municipalities. By stratifying the dataset rather than controlling for these typologies, this analysis estimates the treatment effects independently within each municipal cluster. This approach isolates spatial and demographic heterogeneity, revealing how different municipal clusters respond differently to weight-based pricing. This will uncover whether certain types of municipalities exhibit differing sensitivities to weight-based pricing, providing insights for targeted waste management policy. For methodological transparency, the exact percentage changes across all pre- and post-treatment periods are provided in Appendix B.

5.3.1 Residential municipalities

Table 5.6: Rollout of Weight-Based Pricing in Residential Municipalities (2017-2024)

Year	Volume-Based	Switchers (First Year)	Already Weight-Based	Total
2017	62	0	44	106
2018	61	1	44	106
2019	61	0	45	106
2020	56	5	45	106
2021	43	13	50	106
2022	41	2	63	106
2023	41	0	65	106
2024	40	1	65	106

Table 5.6 shows the rollout of weight-based pricing within residential municipalities, where in total 22 municipalities switched to weight-based pricing between 2018 and 2024, with the majority of these transitions occurring in the years 2020 and 2021. The summary of the substitution effects on collected fractions within this cluster is provided in Table 5.7, while detailed results are presented in Table B.45 in Appendix B.

The results reveal several insights regarding the impact of adopting weight-based pricing for residual waste in residential municipalities. While the decrease in residual waste is not significant at the 5% confidence level, the estimated average reduction of 4.78% points toward a decline. This is supported by a 95% simultaneous confidence band [-9.41%, 0.09%] that narrowly crosses the zero threshold. When looking into the detailed results, the effect in year 5 and 6 after the policy intervention is positive instead of negative. Here, as stated above multiple times, the small number of observations affects the estimate. Consistent with the overarching analysis in Section 5.2, the policy disincentivizes the disposal of wood waste (-13.73%), paper and cardboard (-2.89%), packaging glass (-3.18%), and flat glass (-9.23%), as these fractions exhibit significant declines. Secondly, a significant increase is observed in vegetable and animal oils/fats (6.77%). However, unlike the aggregated trends, residential areas show distinct evidence of substitution behavior. A significant increase is observed in construction and demolition waste (2.94%). Furthermore, the expected boost in standard at-home recycling is absent. Instead, a small but significant decrease in batteries (-4.54%) is observed. Furthermore, VFG waste decreased significantly by 12.60%. This more likely points towards a broader behavioral shift, such as reduced consumption or alternative disposal routes, rather than increased sorting of these specific fractions. Finally, deviations in fractions like PMC, textiles, and green waste remain statistically insignificant, mirroring their lack of response in the general analysis.

Table 5.7: Summary of Effects on Collected Fractions in Residential Municipalities (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-4.78%	t=-6 (+), t=0 (-), t=1 (-), t=2 (-), t=3 (-), t=5 (-), t=6 (-)
Batteries	-4.54%*	t=5 (-), t=6 (-)
Construction and Demolition Waste	2.94%*	t=5 (+)
Organic Waste (VFG)	-12.60%*	t=3 (-)
Green Waste	-0.74%	t=5 (-), t=6 (+)
Wood Waste	-13.73%*	t=0 (-), t=1 (-), t=2 (-), t=3 (-)
Small Hazardous Waste	4.25%	t=-6 (-), t=-5 (+), t=5 (+), t=6 (+)
Hard Plastics	8.42%	t=-1 (-)
Scrap Metal	-2.70%	t=-6 (-), t=2 (-), t=3 (-)
Paper and Cardboard	-2.89%*	t=-5 (-), t=6 (-)
Vegetable and Animal Oils/Fats	6.77%*	t=-4 (-), t=-1 (-), t=3 (+), t=5 (+)
PMC	-3.00%	t=-6 (+), t=-5 (-), t=-1 (+), t=5 (+), t=6 (+)
Textiles	-10.19%	t=-6 (+), t=5 (-), t=6 (-)
Packaging Glass	-3.18%*	t=-6 (+), t=-5 (-), t=5 (-), t=6 (-)
Flat Glass	-9.23%*	t=-6 (+), t=1 (-), t=3 (-)

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table 5.8: Rollout of Weight-Based Pricing in Municipalities with Economic Activity (2017-2024)

Year	Volume-Based	Switchers (First Year)	Already Weight-Based	Total
2017	50	0	13	63
2018	50	0	13	63
2019	50	0	13	63
2020	50	0	13	63
2021	45	5	13	63
2022	43	2	18	63
2023	43	0	20	63
2024	43	0	20	63

Table 5.9: Summary of Effects on Collected Fractions in Municipalities with Economic Activity (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-21.61%*	t=-4 (+), t=0 (-), t=1 (-), t=2 (-), t=3 (-)
Batteries	-5.47%	
Construction and Demolition Waste	6.91%	t=3 (+)
Organic Waste (VFG)	6.51%	
Green Waste	7.43%*	t=-4 (+), t=2 (+)
Wood Waste	0.15%	
Small Hazardous Waste	0.57%	t=-3 (+)
Hard Plastics	33.67%*	t=0 (+), t=1 (+), t=2 (+), t=3 (+)
Scrap Metal	2.47%	
Paper and Cardboard	-0.35%	
Vegetable and Animal Oils/Fats	5.66%	
PMC	14.32%*	t=1 (+), t=2 (+), t=3 (+)
Textiles	-3.51%	
Packaging Glass	-1.15%	
Flat Glass	-0.54%	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

5.3.2 Municipalities with Economic Activity

Table 5.8 shows the rollout of weight-based pricing within this cluster, where in total 7 municipalities switched to weight-based pricing between 2018 and 2024. Notably, all of these transitions occurred exclusively in the years 2021 and 2022. The summary of the substitution effects on collected fractions within this group is provided in Table 5.9.

The results reveal several insights regarding the impact of adopting weight-based pricing in municipalities with economic activity. Most notably, the policy is effective at its primary goal: residual waste shows a significant overall reduction of 21.61%, with sustained negative effects across all post-treatment years (t=1 through t=3). In contrast to residential areas, the introduction of the policy in these municipalities drives a significant substitution toward standard recycling streams. Hard plastics exhibit a significant overall increase of 33.67%, demonstrating positive effects immediately upon implementation and continuing throughout the observed periods. Similarly, PMC collection experiences a significant overall increase of 14.32%. Green waste also shows a significant overall increase of 7.43%, though the specific event time significance is slightly more scattered. Some minor pre-treatment

significance is noted in fractions like SHW and green waste, but since it some years before the implementation (t=-3 and t=-4 respectively), it is unlikely that there was an anticipation effect. Interestingly, the disincentivizing effect on some fractions observed in the residential analysis is absent here. Fractions such as wood waste, packaging glass, and VFG show no significant overall changes. This suggests that in municipalities with higher economic activity, the behavioral shift is predominantly channeled into the improved sorting of light packaging and plastics, rather than a reduction in the disposal of heavier organic or bulky materials.

5.3.3 Rural municipalities

Table 5.10: Rollout of Weight-Based Pricing in Rural Municipalities (2017-2024)

Year	Volume-Based	Switchers (First Year)	Already Weight-Based	Total
2017	40	0	15	55
2018	39	1	15	55
2019	39	0	16	55
2020	37	2	16	55
2021	37	0	18	55
2022	36	1	18	55
2023	36	0	19	55
2024	36	0	19	55

Table 5.10 shows the rollout of weight-based pricing within rural municipalities, where in total 4 municipalities switched to weight-based pricing between 2018 and 2024. It is important to note that this represents a limited number of adopting municipalities, which restricts the amount of policy variation available for the model and may constrain the statistical power of the estimations in this cluster. The summary of the substitution effects on collected fractions within this group is provided in Table 5.11.

The results for the rural municipalities reveal that despite the limited number of policy adopters, weight-based pricing remains effective at its primary objective. Residual waste exhibits a significant overall reduction of 20.99%, supported by sustained negative estimates across nearly all post-treatment years. In the first year after treatment, the reduction is -23.95%, while in year 6 it is still -17.71%. Alongside this primary reduction, there is evidence of substitution toward specific recycling channels. Both PMC and SHW show strong, significant overall increases of 12.67% and 14.30%, respectively, with multiple significant post-treatment years driving these positive effects. Conversely, the policy appears to disincentivize the collection of certain fractions, as evidenced by significant overall declines in wood waste (-10.55%) and packaging glass (-5.66%). However, these findings must be interpreted with caution due to the limited statistical power inherent in a sample of only four switching municipalities. This constraint is reflected in the scattered pre-treatment significance observed across several fractions (e.g., at t=-

Table 5.11: Summary of Effects on Collected Fractions in Rural Municipalities (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-20.99%*	t=-3 (+), t=0 (-), t=1 (-), t=2 (-), t=4 (-), t=5 (-), t=6 (-)
Batteries	0.07%	
Construction and Demolition Waste	-6.25%	t=-4 (-), t=-3 (+), t=4 (-)
Organic Waste (VFG)	-4.76%	t=5 (-), t=6 (-)
Green Waste	-5.03%	t=-4 (+), t=-1 (-), t=0 (+)
Wood Waste	-10.55%*	t=2 (-), t=3 (-)
Small Hazardous Waste	14.30%*	t=-4 (-), t=1 (+), t=2 (+), t=3 (+), t=5 (+), t=6 (+)
Hard Plastics	0.95%	t=-3 (-)
Scrap Metal	9.68%	t=6 (+)
Paper and Cardboard	-1.04%	t=6 (-)
Vegetable and Animal Oils/Fats	3.10%	t=-4 (+), t=-3 (-), t=6 (+)
PMC	12.67%*	t=-3 (-), t=1 (+), t=5 (+), t=6 (+)
Textiles	8.27%	t=-4 (-), t=5 (+)
Packaging Glass	-5.66%*	t=-4 (-), t=-1 (+), t=4 (-), t=6 (-)
Flat Glass	-0.97%	t=-4 (+), t=-3 (-)

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

3 for residual waste and PMC, and at t=-4 for textiles and packaging glass). While this could partially indicate anticipation behavior by residents preparing for the upcoming pricing shift, it is highly likely exacerbated by the instability of the estimates driven by the small treatment group. Consequently, the majority of the remaining waste streams, such as VFG, green waste, and paper and cardboard, do not display statistically significant overall effects, mirroring this lack of power.

5.3.4 Urbanized municipalities

Table 5.12 shows the rollout of weight-based pricing within this cluster, where in total 5 municipalities switched to weight-based pricing between 2018 and 2024. These transitions took place between 2020 and 2022. While this small sample size limits the statistical power of the estimations, these municipalities represent a large number of inhabitants. The summary of the effects on collected fractions within this group is provided in Table 5.13.

Consistent with the broader sample and other clusters, the policy successfully achieves its primary objective: residual waste exhibits a significant overall reduction of 17.46% in residual waste generation. This strong effect is characterized by an immediate decline upon implementation that is sustained in later post-treatment years.

Table 5.12: Rollout of Weight-Based Pricing in Urbanized Municipalities (2017-2024)

Year	Volume-Based	Switchers (First Year)	Already Weight-Based	Total
2017	14	0	8	22
2018	14	0	8	22
2019	14	0	8	22
2020	13	1	8	22
2021	10	3	9	22
2022	9	1	12	22
2023	9	0	13	22
2024	9	0	13	22

Table 5.13: Summary of Effects on Collected Fractions in Urbanized Municipalities (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-17.46%*	t=0 (-), t=3 (-), t=4 (-)
Batteries	10.34%	
Construction and Demolition Waste	8.98%	t=-4 (+)
Organic Waste (VFG)	14.25%	t=-4 (-), t=-2 (+), t=4 (+)
Green Waste	1.11%	
Wood Waste	-0.80%	
Small Hazardous Waste	3.87%	
Hard Plastics	17.36%	t=-2 (-)
Scrap Metal	3.60%	
Paper and Cardboard	0.56%	
Vegetable and Animal Oils/Fats	1.41%	t=3 (+), t=4 (-)
PMC	-3.12%	t=-4 (+), t=-2 (+)
Textiles	-10.10%	t=4 (-)
Packaging Glass	-9.86%*	t=-1 (+), t=0 (-), t=2 (-), t=4 (-)
Flat Glass	0.46%	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

When examining the substitution effects, the urbanized cluster presents an interesting deviation from the general analysis. In the conditional broad sample, weight-based pricing drove statistically significant diversions toward specific recycling channels, such as SHW and vegetable and animal oils/fats. In contrast, the urbanized municipalities show almost no statistically significant overall increases across these alternative fractions. While the magnitudes of the estimates for VFG (14.25%) and hard plastics (17.36%) hint at similar substitution behaviors in these areas, they fail to reach statistical significance. The only other fraction exhibiting a statistically significant overall effect is packaging glass, which experiences a decline of 9.86%. This mirrors the significant negative trend observed in the broader sample, suggesting a behavioral spillover where households either reduce their consumption of glass packaging or dispose of it through improper channels, even though glass collection typically is free. Finally, the scattered pre-treatment significance observed in fractions such as PMC and construction and demolition waste underscores the volatility of the estimates in this smaller sub-sample. While this could partially indicate anticipation behavior by residents preparing for the upcoming pricing shift, it advises a degree of caution when interpreting the precise dynamic timing of these secondary effects.

5.3.5 Large and Regional Cities

Table 5.14: Rollout of Weight-Based Pricing in Large and Regional Cities (2017-2024)

Year	Volume-Based	Switchers (First Year)	Already Weight-Based	Total
2017	11	0	1	12
2018	11	0	1	12
2019	11	0	1	12
2020	10	1	1	12
2021	9	1	2	12
2022	9	0	3	12
2023	9	0	3	12
2024	8	1	3	12

Table 5.14 outlines the rollout of weight-based pricing within this cluster. Although 3 out of the 12 cities transitioned to weight-based pricing between 2018 and 2024, this cluster remains of importance to the overall analysis. Because large and regional cities account for a large portion of the total population, any behavioral shifts or waste reductions observed in this group have a large impact on the amount of waste that is produced. The summary of the effects on collected fractions within this group is provided in Table 5.15. The results for large and regional cities confirm that weight-based pricing effectively achieves its primary objective, with substitution dynamics tailored to the urban environment. Residual waste exhibits a significant overall reduction of 11.09%, driven by sustained declines in the years following implementation, eventhough it loses significance over time, likely due to the small number (1) of switching municipalities in this specific sub-sample. While this relative percentage de-

Table 5.15: Summary of Effects on Collected Fractions in Large and Regional Cities (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-11.09%*	t=1 (-), t=2 (-), t=3 (-)
Batteries	2.45%	t=-1 (-), t=3 (+), t=4 (-)
Construction and Demolition Waste	-2.02%	t=-4 (+)
Organic Waste (VFG)	35.49%	t=-5 (-), t=-4 (-), t=4 (+)
Green Waste	-19.67%	t=-6 (+), t=-4 (+), t=1 (-), t=4 (-)
Wood Waste	-18.00%*	t=-1 (+), t=4 (-)
Small Hazardous Waste	2.05%	t=-6 (+), t=-2 (+)
Hard Plastics	34.28%	t=-4 (+)
Scrap Metal	-0.26%	t=-4 (+), t=-1 (+)
Paper and Cardboard	0.95%	t=-5 (-), t=2 (+), t=4 (-)
Vegetable and Animal Oils/Fats	-3.00%	t=-4 (+), t=4 (-)
PMC	-4.12%	
Textiles	2.23%	t=-5 (-), t=2 (+)
Packaging Glass	9.79%	t=-6 (-), t=-5 (+), t=4 (+)
Flat Glass	2.75%	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

crease is slightly smaller in magnitude compared to other clusters, it translates to an impactful absolute reduction given the high population densities of these major cities.

When evaluating substitution effects, the most notable deviation from the broader sample occurs within VFG. The model estimates a 35.49% overall increase in VFG collection; however, this is not significant due to the wide confidence bands driven by the small number of switching municipalities. Despite the lack of overall significance, this underlying surge aligns with theoretical expectations. Unlike rural residents, inhabitants of large cities generally lack the garden space required for home composting. Consequently, the financial pressure of weight-based pricing on residual waste forces a more direct diversion of organic matter into the organic waste stream. A significant decrease of 18.00% is observed in wood waste. This trend is also seen at other clusters, and the reason for this pattern is not entirely clear. Finally, the scattered pre-treatment significance across several fractions further highlights the volatility inherent to this restricted sample, advising caution when interpreting the these secondary behaviors, even as the core economic incentives operate as intended.

5.3.6 Coastal Municipalities

As stated before in Section 3.5, there is no treated municipality in the "Coastal" cluster, so this typology is excluded from the heterogeneity analysis.

5.3.7 Summary of Effects of Spatial and Demographic Heterogeneity

The stratified analysis across the Belfius Municipal Typology reveals that weight-based pricing consistently achieves its primary objective of reducing residual waste across all clusters. However, the secondary effects vary across different subgroups. As illustrated in Figure 5.3, the magnitude of this overall reduction is slightly more pronounced in rural areas (-20.99%) and municipalities with economic activity (-21.61%) compared to large regional cities (-11.09%). However, the data does not present a relationship indicating that a higher degree of urbanization worsens or improves the policy's primary effect. When interpreting the dynamic effects across clusters in Figure 5.3, it is crucial to primarily evaluate the first four post-treatment years. The estimates for Years 5 and 6 rely on isolated data points from early adopters. This data scarcity distorts the trend and produces the wide confidence intervals visible in the latter stages of the graph.

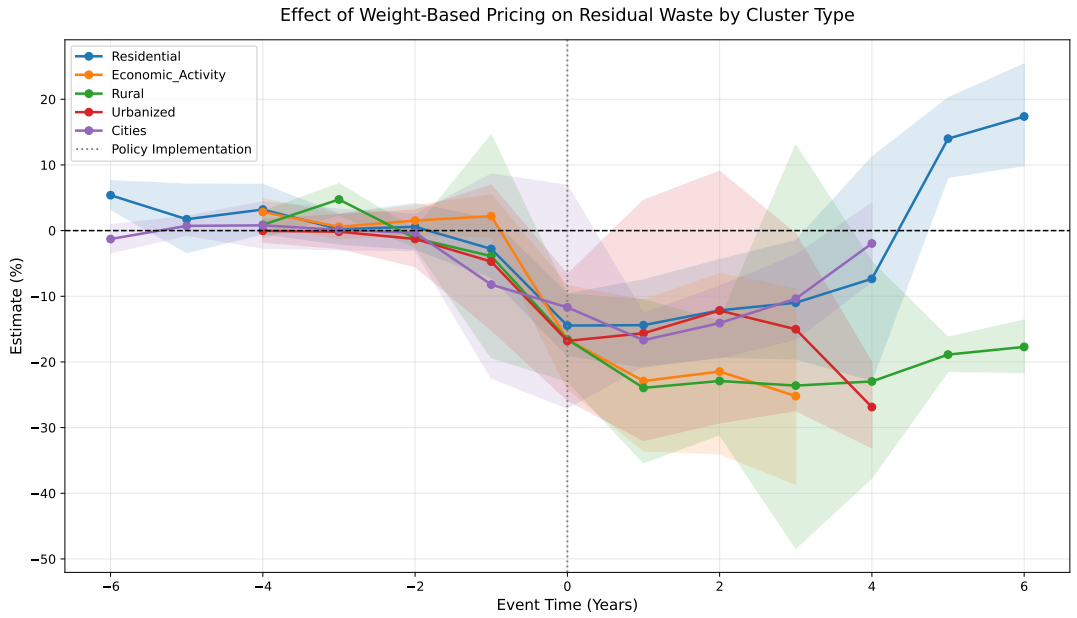


Figure 5.3: Impact of Weight-Based Pricing on Residual Waste by Municipal Cluster with 95% Confidence Bands

Beyond the primary reduction in residual waste, the most striking difference between urban and rural regions lies in their substitution patterns. More rural municipalities predominantly divert waste by increasing the recycling of PMC and hard plastics. In contrast, urbanized municipalities and large regional cities do not mirror this shift toward plastics. Instead, they exhibit an increase toward VFG collection, with large and regional cities and urbanized

municipalities experiencing an estimated underlying insignificant increase of 35.49% and 14.25% respectively. This urban-rural divide is a direct reflection of the spatial potential for home composting. Rural residents generally possess the outdoor space to privately compost organic waste, allowing their formal behavioral shift to focus on light packaging and plastics. Urban residents, lacking the garden space required for home composting, are forced to utilize municipal VFG collection streams to avoid the newly imposed financial penalties on their residual waste.

5.4 Method of Implementation

As explained in Section 3.1, the transition to weight-based pricing in Flanders is not a uniform policy change. Municipalities adopt various tariff structures, ranging from purely weight-based systems (W) to models incorporating frequency fees (WF), non-linear pricing (WF NL), or hybrid choices (WV). While Section 3.4.1 highlighted the growing preference for the WF model, it is crucial to determine whether these different systems drive different behavioral responses among households.

This section evaluates the heterogeneity of the treatment effect based on the specific method of implementation. By segmenting the treated municipalities according to their active pricing schedule, the following analysis investigates whether variations in the policy design, such as penalizing collection frequency or introducing non-linear weight tariffs, significantly alter the magnitude of residual waste reduction and subsequent substitution effects.

5.4.1 Weight and Frequency (WF) Pricing

Table 5.16: Evolution of the Weight and Frequency Based (WF) Pricing System (2017-2024)

Year	Other Systems	Switchers to WF	Already WF	Total
2017	218	0	48	266
2018	216	2	48	266
2019	216	0	50	266
2020	214	2	50	266
2021	195	19	52	266
2022	191	4	71	266
2023	191	0	75	266
2024	190	1	75	266

Table 5.16 shows the evolution of the weight and frequency-based (WF) pricing system across the sample, where in total 28 municipalities switched to this pricing structure between 2018 and 2024, with 19 municipalities transitioning in 2021. The summary of the corresponding substitution effects on collected fractions under this pricing model is provided in Table 5.17. Consistent with the primary policy objective, the introduction of WF pricing leads

Table 5.17: Summary of Effects on Collected Fractions when switching from Volume-Based pricing to Weight and Frequency (WF) Pricing (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-10.06%*	t=-6 (+), t=0 (-), t=1 (-), t=2 (-), t=3 (-)
Batteries	-4.58%	
Construction and Demolition Waste	-0.38%	t=0 (-), t=1 (-), t=5 (+), t=6 (+)
Organic Waste (VFG)	-12.04%*	t=-5 (-), t=0 (-), t=3 (-), t=4 (-), t=5 (-), t=6 (-)
Green Waste	0.03%	t=6 (+)
Wood Waste	-10.32%	t=0 (-), t=1 (-), t=2 (-), t=3 (-)
Small Hazardous Waste	6.41%*	t=-6 (-), t=-5 (+), t=5 (+)
Hard Plastics	2.76%	t=-2 (-), t=-1 (-)
Scrap Metal	0.22%	t=-6 (-), t=6 (+)
Paper and Cardboard	-2.46%*	t=-5 (-), t=6 (-)
Vegetable and Animal Oils/Fats	8.25%*	t=-1 (-), t=2 (+), t=3 (+)
PMC	1.45%	t=-6 (+), t=-5 (-), t=5 (+), t=6 (+)
Textiles	-2.09%	t=-6 (+)
Packaging Glass	-4.41%*	t=-6 (+), t=-5 (-), t=2 (-), t=3 (-), t=6 (-)
Flat Glass	-7.99%*	t=-6 (+), t=1 (-), t=3 (-)

Note: Estimates represent the exact percentage change relative to the control group, adjusted for Belfius Municipal Typology covariates. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

to a significant reduction in residual waste. As detailed in Table 5.17, an overall decrease of 10.06% is observed. Crucially, this reduction manifests immediately upon policy implementation and remains statistically significant and sustained through the first three post-treatment years. After those years, it loses significance, but as stated before, these numbers rely on a smaller number of municipalities that switched in 2018 and 2020, and therefore should be interpreted with caution.

A similar effect is observed in the collection of VFG, which experiences a significant overall reduction of 12.04%. Similar to residual waste, the drop in VFG collection is sustained across multiple post-treatment periods. Weight and frequency-based pricing also triggers significant declines across several specific recycling streams, such as packaging glass (-4.41%), flat glass (-7.99%), and paper and cardboard (-2.46%). Furthermore, while wood waste does not reach overall statistical significance, it exhibits a pattern of significant reductions in the immediate post-treatment years. Conversely, significant substitution effects lead to increased collection in specific alternative fractions. SHW increases significantly by 6.41%, and vegetable and animal oils/fats see a significant increase of 8.25%. While the overall effect on PMC (1.45%) is not statistically significant, the fraction does show a pattern of increased collection in the later post-treatment years, hinting at a positive sorting response. However, this should

be interpreted with caution, as the estimates in these later periods are driven by a smaller subset of municipalities that have reached these post-treatment times.

Finally, the transition to WF pricing yields no effects for several other fractions, notably batteries, construction and demolition waste, green waste, hard plastics, scrap metal, and textiles. While occasional significant pre-treatment coefficients emerge across the analyzed fractions, these dynamics are isolated and do not undermine the internal validity of the structural breaks identified at the time of policy implementation. Crucially, the magnitude and direction of the effects within this WF sub-sample closely mirror the estimates presented in Table 5.5. This alignment is a consequence of the sample composition: of the 41 municipalities that transitioned from volume- to weight-based pricing between 2018 and 2024, 28 adopted the WF system. Consequently, this specific cohort exerts substantial statistical leverage, driving the average treatment effects observed in the aggregate analysis. Isolating the WF system thus provides necessary transparency, confirming that the baseline findings are largely a reflection of this dominant pricing structure rather than an equally distributed effect across all weight-based systems.

5.4.2 Non-Linear Weight and Frequency (WF NL) Pricing

Table 5.18: Evolution of the Weight and Frequency Based with Non-Linear (WF NL) Pricing System (2017-2024)

Year	Other Systems	Switchers to WF NL	Already WF NL	Total
2017	264	0	2	266
2018	264	0	2	266
2019	264	0	2	266
2020	258	6	2	266
2021	258	0	8	266
2022	258	0	8	266
2023	258	0	8	266
2024	258	0	8	266

Table 5.18 shows the evolution of the Non-linear weight and frequency-based (WF NL) pricing system across the sample, where in total 6 municipalities switched to this pricing structure between 2018 and 2024, all of which transitioned in 2020. It is important to note that this represents a limited number of adopting municipalities, which restricts the amount of policy variation available for the model and may strongly constrain the statistical power of the estimations for this specific mechanism. The summary of the corresponding substitution effects on collected fractions under this pricing model is provided in Table 5.19. Consistent with the primary policy objective, the transition to WF NL pricing drives a significant overall reduction of 19.32% in residual waste. Notably, in contrast to the standard WF system where statistical significance faded in later periods, the reduction under the

Table 5.19: Summary of Effects on Collected Fractions when switching from Volume-Based pricing to Non-Linear Weight and Frequency (WF NL) Pricing (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-19.32%*	t=-1 (-), t=0 (-), t=1 (-), t=2 (-), t=3 (-), t=4 (-)
Batteries	6.35%*	t=-1 (-), t=3 (+)
Construction and Demolition Waste	2.02%	
Organic Waste (VFG)	37.57%*	t=-1 (+), t=0 (+), t=1 (+), t=2 (+), t=3 (+), t=4 (+)
Green Waste	-9.91%	t=2 (-)
Wood Waste	-26.31%*	t=0 (-), t=1 (-), t=2 (-), t=3 (-), t=4 (-)
Small Hazardous Waste	6.32%*	t=2 (+)
Hard Plastics	21.15%*	t=1 (+), t=2 (+), t=3 (+), t=4 (+)
Scrap Metal	1.84%	
Paper and Cardboard	0.07%	
Vegetable and Animal Oils/Fats	-2.87%	
PMC	2.01%	t=-1 (+), t=0 (+)
Textiles	-8.83%	t=-1 (+)
Packaging Glass	-1.72%	
Flat Glass	0.83%	

Note: Estimates represent the exact percentage change relative to the control group, adjusted for Belfius Municipal Typology covariates. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

non-linear model remains statistically significant across all observed post-treatment years. While the magnitude of the decrease slightly attenuates over time, moving from a peak reduction of 21.39% to 17.09% by Year 4, the penalizing effect of the non-linear pricing tiers appears successful at sustaining long-term waste reduction. However, a significant negative pre-trend at $t = -1$ suggests minor anticipation effects or pre-existing downward trajectories within this specific 2020 cohort.

A deviation from other pricing mechanisms is observed in organic waste (VFG), which exhibits a significant overall increase of 37.57%. While this suggests a strong positive substitution effect driven by the financial penalty on residual waste, this result must be interpreted with caution. The dynamic event-study reveals that VFG collection was already significantly increasing in the year prior to implementation ($t = -1$). This significant pre-trend indicates that external, cohort-specific factors likely initiated this behavioral shift before the pricing intervention formally took effect. For instance, it could be the case that these municipalities started organic waste collection in 2019, which would explain the significant increase in VFG collection before the implementation of the non-linear tariff. The introduction of the non-linear tariff also triggers significant shifts in other fractions. The system disincentivizes the disposal of heavy bulk items, reflected in a significant 26.31% overall drop in wood waste

that is sustained continuously. Secondly, hard plastics collection increases significantly by 21.15% across the post-treatment horizon. Thirdly, batteries also show a significant increase of 6.35%, while SHW increases significantly by 6.32%, showing that the non-linear pricing structure has a positive impact on the collection of dangerous waste. Finally, the scattered significance observed across multiple fractions exactly one year prior to treatment (such as construction waste, PMC, and textiles) further highlights the volatility inherent to this restricted six-municipality sample, reinforcing the need to interpret the precise timing of these secondary behaviors with caution.

5.4.3 Weight and Volume (WV) Pricing

Table 5.20: Evolution of the Weight and Volume Based (WV) Pricing System (2017-2024)

Year	Other Systems	Switchers to WV	Already WV	Total
2017	262	0	4	266
2018	262	0	4	266
2019	262	0	4	266
2020	262	0	4	266
2021	260	2	4	266
2022	259	1	6	266
2023	259	0	7	266
2024	258	1	7	266

Table 5.20 shows the evolution of the weight and volume-based (WV) pricing system across the sample, where in total 4 municipalities switched to this pricing structure between 2018 and 2024. It should be noted that WV pricing essentially functions as a standard weight-based (W) system, with the distinguishing feature that residents still retain the option to purchase (at a higher price compared to the W system) small 30-liter residual waste bags alongside the weight-based container. The low adoption rate restricts the amount of policy variation available for the model and constrains the statistical power of the estimations for this specific mechanism. The summary of the corresponding substitution effects on collected fractions under this pricing model is provided in Table 5.21. The transition to WV pricing achieves a significant 11.22% overall reduction in residual waste. However, because the policy adopters in this cluster transitioned relatively recently, the dataset only captures up to three years of post-implementation data. While these initial reductions are significant, further observation over an extended time horizon is required to assess the permanence of this behavioral shift.

When looking at the substitution effects, the WV system shows increases across nearly all selectively collected fractions. Unlike the standard WF system, which decreased the collection of waste streams, the WV system drives households to increase their separation efforts. Significant overall increases are observed across bulky and organic streams, including hard plastics (59.62%), VFG (20.14%), construction and demolition waste (20.14%), green

Table 5.21: Summary of Effects on Collected Fractions when switching from Volume-Based pricing to Weight and Volume (WV) Pricing (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-11.22%*	t=0 (-), t=1 (-), t=2 (-), t=3 (-)
Batteries	6.16%	t=2 (+), t=3 (+)
Construction and Demolition Waste	18.83%*	t=-4 (+), t=1 (+), t=2 (+), t=3 (+)
Organic Waste (VFG)	20.14%*	t=-5 (-), t=-3 (+), t=1 (+), t=2 (+), t=3 (+)
Green Waste	14.08%*	t=-6 (+), t=-4 (+), t=2 (+), t=3 (+)
Wood Waste	67.05%	
Small Hazardous Waste	8.70%	t=-6 (+), t=-3 (+), t=1 (+)
Hard Plastics	59.62%*	t=0 (+), t=1 (+), t=2 (+), t=3 (+)
Scrap Metal	11.29%*	t=2 (+), t=3 (+)
Paper and Cardboard	3.93%	t=-5 (-), t=-3 (+), t=1 (+), t=2 (+)
Vegetable and Animal Oils/Fats	-1.51%	
PMC	11.39%*	t=-5 (-), t=-4 (-), t=1 (+), t=2 (+), t=3 (+)
Textiles	16.05%	t=3 (+)
Packaging Glass	10.31%*	t=-6 (-), t=-5 (+), t=1 (+), t=2 (+), t=3 (+)
Flat Glass	7.89%*	

Note: Estimates represent the exact percentage change relative to the control group, adjusted for Belfius Municipal Typology covariates. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

waste (14.08%), and scrap metal (11.29%). While wood waste exhibits a 67.05% increase, this estimate fails to reach statistical significance. This is entirely due to wide confidence bands, reflecting high variance due to the the small sample size of the four switching municipalities. Furthermore, the dynamic event-study reveals a distinct and positive pattern of behavioral reversal in standard household recycling streams. Fractions such as PMC (11.39%) and packaging glass (10.31%) yield significant overall increases. Crucially, as these fractions exhibited significant negative pre-trends prior to implementation, this reversed into significant positive increases following the policy change. This provides a strong signal that the WV system successfully forces residents to strictly separate valuable materials that they were previously neglecting or throwing in the residual bin.

While these substitution effects are strong and point toward improved sorting behaviors, they must be contextualized. The constraints of analyzing only four municipalities, combined with a short post-treatment horizon, advise a degree of caution when extrapolating these magnitudes to the broader population.

Table 5.22: Evolution of the purely Weight-Based (W) Pricing System (2017-2024)

Year	Other Systems	Switchers to W	Already W	Total
2017	237	0	29	266
2018	237	0	29	266
2019	237	0	29	266
2020	236	1	29	266
2021	235	1	30	266
2022	234	1	31	266
2023	234	0	32	266
2024	234	0	32	266

Table 5.23: Summary of Effects on Collected Fractions when switching from Volume-Based pricing to purely Weight-Based (W) Pricing (Exact Percentage Changes)

Waste Stream	Overall Effect (%)	Significant Event Times & Sign
Residual Waste	-20.07%*	t=-4 (+), t=1 (-), t=2 (-), t=3 (-), t=4 (-)
Batteries	3.89%*	t=-4 (+), t=0 (-), t=2 (+), t=3 (+), t=4 (+)
Construction and Demolition Waste	-8.55%	t=-4 (-), t=-3 (+), t=2 (-), t=3 (-)
Organic Waste (VFG)	-34.75%*	t=-4 (-), t=-1 (-), t=1 (-), t=2 (-), t=3 (-), t=4 (-)
Green Waste	-1.71%	t=-4 (+), t=4 (-)
Wood Waste	-15.74%	t=-4 (+), t=-3 (+), t=1 (-), t=4 (-)
Small Hazardous Waste	1.73%	t=-4 (-), t=1 (+), t=4 (-)
Hard Plastics	33.16%	t=0 (-), t=4 (+)
Scrap Metal	-12.30%	t=2 (-)
Paper and Cardboard	-4.53%*	t=-1 (+), t=0 (-), t=1 (-), t=2 (-), t=3 (-)
Vegetable and Animal Oils/Fats	-4.23%	t=-4 (+), t=-2 (-), t=4 (-)
PMC	12.33%*	t=-4 (+), t=1 (+), t=2 (+), t=3 (+), t=4 (+)
Textiles	-36.25%*	t=-4 (-), t=-3 (+), t=1 (-), t=3 (-), t=4 (-)
Packaging Glass	1.88%	t=-4 (-), t=1 (+), t=3 (+)
Flat Glass	-9.11%*	t=-4 (+), t=1 (-), t=4 (-)

Note: Estimates represent the exact percentage change relative to the control group, adjusted for Belfius Municipal Typology covariates. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

5.4.4 Purely Weight-based (W) Pricing

Table 5.22 shows the evolution of the purely weight-based (W) pricing system across the sample, where in total 3 municipalities switched to this specific pricing structure between 2018 and 2024. While this very limited number of recent switchers constrains the statistical power of the estimations, understanding the effects of this specific mechanism remains crucial given its widespread prevalence, with 32 municipalities actively employing it at the time of analysis. The summary of the corresponding substitution effects on collected fractions under this pricing model is provided in Table 5.23. Consistent with the other weight-based pricing systems, the purely weight-based system triggers a significant overall reduction in residual waste, here of 20.07%. Notably, this decrease remains statistically significant across all observed post-treatment years fluctuating around -20%, showing no immediate signs of the fade-out effect observed under the standard WF pricing model. However, given the small sample size of only three switching municipalities, this apparent long-term stability must be interpreted with caution.

Regarding selective collection streams, the evidence for positive behavioral spillover or substitution is weak under the purely weight-based system. PMC collection exhibits a significant positive increase of 12.33%, with sustained positive effects across all post-treatment years. Secondly, hard plastics show a nominal increase of 33.16%, but extreme variance within this restricted switcher sample produces wide confidence bands, preventing the estimate from reaching overall statistical significance and highlighting the volatility of the model. Similar to other weight-based configurations, decreases are observed across various other household fractions. This is evidenced by significant overall declines in textiles (-36.25%), flat glass (-9.11%), and paper and cardboard (-4.53%). Wood waste also experiences a nominal reduction of 15.74%, though it fails to reach overall statistical significance. The dynamic event-study timelines for several of these fractions remain volatile, often exhibiting significant pre-treatment fluctuations, which underscores the noise inherent to analyzing a restricted cohort of three switching municipalities.

Finally, VFG experiences a significant 34.75% overall reduction. While the dynamic event-study reveals statistically significant negative anticipation effects in the years prior to implementation (specifically at t=-1 and t=-4), the true causal impact of the policy remains robust. The magnitude of the reduction increases post-treatment, confirming that the intervention triggered a distinct behavioral shift rather than merely continuing a pre-existing downward trajectory. Crucially, this decline stands in contrast to the positive substitution effects observed for VFG under both the WV and WF NL pricing models. This can be due to noise in the estimates given the small sample size, but it may also reflect a more direct diversion of organic waste into alternative disposal routes such as home composting, which is more feasible in the rural and residential municipalities that adopted the purely weight-based system.

5.4.5 Summary of Effects of Method of Implementation

To address the research question regarding how different implementation strategies of weight-based pricing affect the quantity and composition of household waste, the analysis demonstrates that while all methods successfully reduce residual waste, their secondary effects and long-term trajectories vary significantly. As illustrated in Figure 5.4, all four pricing models trigger immediate declines in residual waste following policy implementation. The standard WF system, which is the most widely adopted with 28 switching municipalities, dictates the general trend observed in the broader sample. It achieves a significant initial reduction of 10.06%, though the estimates for Years 5 and 6 suggest a potential fade-out effect. However, it is crucial to note that the data points for these later years rely on two early adopters, meaning this upward shift can reflect statistical noise rather than a decline in policy effectiveness.

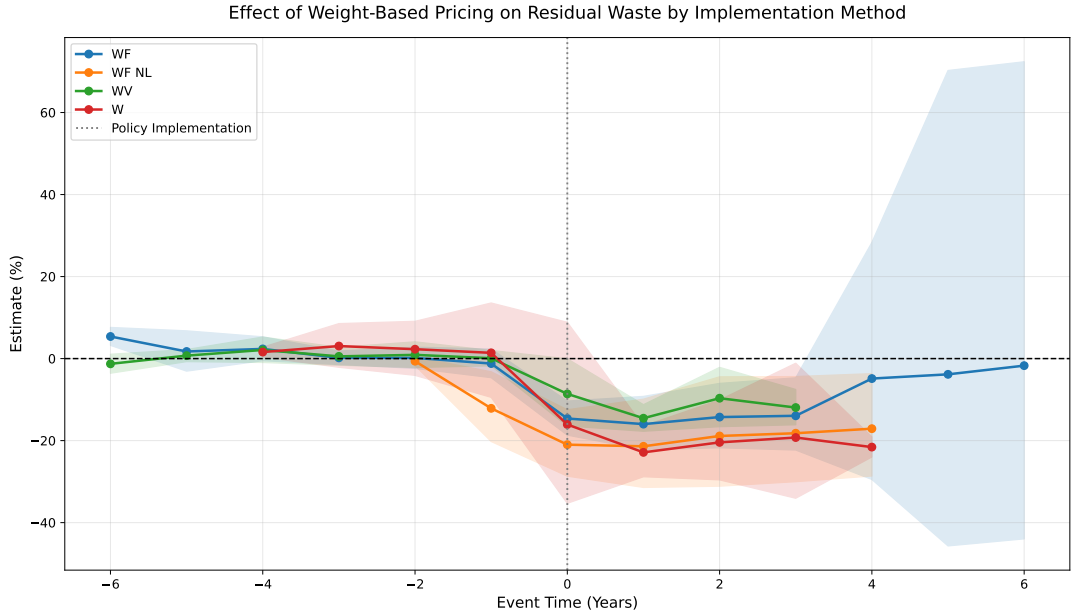


Figure 5.4: Impact of Weight-Based Pricing on Residual Waste by Implementation Method with 95% Confidence Bands

Regarding which approach yields the most significant reduction in residual waste, the data indicates that systems imposing targeted financial penalties, specifically the purely weight-based and non-linear models, drive steeper declines than the standard WF model, reaching approximate reductions of 20%. As seen in Figure 5.4, the WF NL system sustains a statistically significant reduction across all post-treatment years. While a significant pre-trend at $t = -1$ suggests some anticipation behavior prior to the formal rollout of the non-linear tariffs, the subsequent downward trajectory confirms the policy's robust impact. The purely weight-based system also achieves a significant overall reduction of 20.07%, with no immediate signs of fading. However, given the small sample size of only three switching municipalities, this apparent long-term stability must be interpreted with caution. Fur-

thermore, these reductions are not significantly different from the 10.06% reduction achieved under the standard WF system, as the confidence intervals of these estimates overlap. Therefore, while the data suggests that these targeted financial penalties could yield steeper reductions, it does not provide conclusive evidence that these approaches are statistically superior to the standard WF model in terms of residual waste reduction.

Beyond residual waste, alternative pricing methods prove more effective at stimulating positive substitution behavior than the WF system. The standard WF model drives absolute waste reduction without triggering broad increases in standard recycling streams. In contrast, targeted structures yield different outcomes, particularly concerning organic waste. The W system causes a 34.75% drop in VFG collection, likely pushing rural and residential households toward home composting. Conversely, the WF NL and WV systems drive residents to increase their separation efforts. The WF NL system triggers a 37.57% increase in VFG collection, while the WV model uniquely stimulates broad positive substitution across standard recycling streams such as PMC and hard plastics. Ultimately, while the WF system establishes the baseline trend, these alternatives demonstrate that a more targeted financial incentive could lead to superior sorting and recycling outcomes. However, drawing definitive conclusions about these substitution effects remains challenging, as explained in Section 5.2.

5.5 Data Limitations and Directions for Future Research

Evaluating staggered policy implementations requires more data than often assumed to reliably avoid magnitude exaggeration and wrong sign errors [43]. This data requirement poses a limitation for the stratified analyses in Chapter 5. By partitioning the sample into specific clusters or pricing models, the number of treated units drops, leaving only 3 or 4 switchers for the W and WV systems, or within rural municipalities. With such sparse data, subgroup estimates become volatile and underpowered. Furthermore, analyzing the policy's long-term sustainability is constrained. While historical evidence indicates that the initial shock effects of weight-based pricing completely decay within five years, the current dataset's estimates for post-treatment years 5 and 6 rely entirely on just two early-adopting municipalities. To draw definitive conclusions about specific subgroup behaviors or long-term fade-out effects without risking errors, future research must track larger cohorts of switchers for at least five uninterrupted post-treatment years.

6

Conclusion

This thesis provides an econometric evaluation of the transition from volume-based to weight-based pricing for household waste in Flanders. By applying a staggered Difference-in-Differences framework to a longitudinal dataset spanning from 2017 to 2024, this research identifies how financial incentives reshape disposal behavior across different waste streams and municipal contexts. The findings confirm that the implementation of weight-based pricing is an effective policy instrument for waste reduction. Across the broad Flemish sample, the transition triggers a statistically significant overall reduction in residual waste of 11.80%. This reduction is both immediate and robust, reaching a peak decrease of 17.27% during the first full year post-implementation. Furthermore, the data supports weight-based pricing as a powerful and sustainable instrument for at least four years following adoption. While the magnitude of the reduction narrows in later years and loses statistical significance after Year 4, this "fade-out" effect must be interpreted with caution. The estimates for Years 5 and 6 rely on a highly restricted sample of only two early-adopting municipalities, suggesting that the apparent relapse may reflect statistical noise or localized dynamics rather than a genuine, widespread behavioral decay.

Beyond the primary reduction in residual waste, the anticipated positive substitution effect, whereby households divert waste into existing municipal recycling streams to avoid financial penalties, is largely absent across the general population. Rather than a broad surge in recycling, positive spillovers are isolated to a few specific fractions, namely small hazardous waste (+6.97%) and vegetable and animal oils/fats (+5.10%). Conversely, the policy transition coincides with a reduction in the collection of several other fractions, resulting in significant declines in wood waste (-10.76%), paper and cardboard (-1.87%), packaging glass (-3.60%) and flat glass (-5.49%). This represents a behavioral shift that currently defies standard economic incentives. Ultimately, the vast majority of the diverted weight falls into the category of "net waste prevented or disappeared." This indicates that households adapt to weight-based fees primarily through waste prevention, altered consumption habits, or alternative disposal routes like home composting, rather than through increased sorting into established municipal recycling channels.

Furthermore, the behavioral response to these financial incentives is dictated by local spatial and demographic characteristics. In rural municipalities, while households achieve significant reductions in residual waste, an in-

crease is observed in PMC (+12.67%) collection. Conversely, VFG exhibits almost no growth in these areas as residents in these greener zones can absorb organic waste through home composting. In contrast, inhabitants of urbanized areas and regional cities face constraints due to a lack of outdoor space, making home composting unfeasible. When switching to weight-based pricing in large and regional cities, an increase is observed in VFG (+35.49%). Municipalities characterized by economic activity demonstrate the most robust response. They achieve the largest overall reduction in residual waste (-21.61%) while driving significant increases in multiple streams, including PMC (+14.32%) and Hard Plastics (+33.67%). Ultimately, the data confirms that weight-based pricing consistently achieves its primary objective of reducing residual waste across all clusters. A higher degree of urbanization does not systematically worsen or improve the reduction in residual waste. Rather than dictating whether the policy succeeds, local spatial characteristics dictate how households divert their waste, contrasting the rural increase in PMC and plastics with the urban increase in VFG collection.

Finally, the structural design of the tariff system itself plays a role in the final outcome, although these findings must be contextualized by the limited adoption rates of certain models. While the dominant Weight and Frequency (WF) system provides a stable baseline with a 10.06% overall reduction, models imposing escalating penalties achieve significantly larger decreases. However, it must be stressed that alternative structures were adopted by a very limited number of transitioning municipalities during the observation period: only 3 for the purely weight-based (W) system, 4 for the hybrid Weight and Volume (WV) system, and 6 for the non-linear (WF NL) model. Due to these low sample sizes, particularly for the W and WV systems, the magnitude of their secondary effects should be interpreted with caution. Despite this statistical constraint, the available data highlights divergent behavioral responses. The hybrid WV system, for instance, succeeds with an 11.22% residual waste reduction while stimulating positive substitution across standard recycling streams such as PMC and hard plastics. The purely W system, while reducing residual waste by 20.22%, causes a 36.18% drop in VFG collection. Lastly, the WF NL system offers another alternative. By implementing tiered pricing, the WF NL model realizes a 19.32% reduction in residual waste while simultaneously triggering a 37.57% increase in VFG collection.

Based on these empirical findings, several actionable recommendations emerge for policymakers and local governments considering the transition to weight-based waste pricing.

Prioritize weight-based systems with non-linear prices: The evidence confirms that abandoning volume-based systems in favor of weight-based DIFTAR is an effective strategy for driving down residual waste. Furthermore, municipalities should look beyond flat-rate systems. The implementation of non-linear tariff structures, which impose escalating financial penalties for excessive waste generation, proved to be effective. By utilizing tiered pricing, these non-linear models achieve nearly double the residual waste reduction of standard flat-rate systems.

Tailor infrastructure to demographic realities: The finding that spatial characteristics dictate how households divert their waste implies that waste management strategies cannot be one-size-fits-all. In dense urban areas where home composting is unfeasible, the introduction of weight-based penalties causes an increase in VFG collection. Urban municipalities must therefore ensure that their organic waste collection infrastructure has the

capacity to handle this structural shift. Conversely, rural municipalities should focus on optimizing their PMC and hard plastics collection capabilities, while continuing to promote home composting initiatives.

Implement communication campaigns: While the policy successfully drives positive substitution effects in specific fractions like small hazardous waste and vegetable/animal oils, it inadvertently coincides with a reduction in the collection of glass and paper. To mitigate this unintended behavioral shift, municipalities can couple the introduction of weight-based pricing with targeted awareness campaigns. Citizens must be educated and reminded that fractions such as glass and paper remain free to selectively dispose of, neutralizing any perceived financial incentive to discard them improperly or reduce their separation.

Future Work

While this study provides a robust evaluation of weight-based waste pricing, several limitations present clear opportunities for future research. First, regarding data availability, the current dataset provides standardized figures from 2017 onwards. Future research could benefit from manually collecting and integrating 2016 data directly from municipal authorities or intermunicipal associations, extending the pre-treatment observation window back to 2013. This would allow for a more rigorous validation of pre-treatment trends.

Secondly, the long-term sustainability of the policy requires further investigation. Because the estimates for Event Times 5 and 6 rely on a restricted sample of two municipalities, the observed attenuation of the treatment effect cannot be separated from statistical noise. As the staggered transition progresses over time, future studies with extended longitudinal data will be crucial to evaluate the true long-term behavioral persistence of these financial incentives.

Thirdly, the precise mechanisms driving the declines in several free or intrinsically valuable fractions, such as glass, paper, and wood waste, warrant deeper qualitative or granular econometric research. Crucially, as municipal data on the incidence and volume of illegal dumping is currently unavailable, future research must attempt to quantify these negative spillovers to determine whether the reduction in residual waste is partially offset by illicit disposal methods.

Finally, as alternative tariff structures such as the purely weight-based (W) and non-linear (WF NL) systems achieve broader adoption across Flanders, future research should leverage larger sample sizes to calculate exact price elasticities and isolate the causal impact of specific pricing tiers.

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Appendices

Appendix A

Table A.1: Classification and Weight-Based Pricing Transitions of Sample Municipalities

Municipality	Belfius Typology Cluster	Status	New System	Year
Aalst	Large and regional cities	Switcher	WF	2021
Aarschot	Urbanized municipalities	Already Weight-Based	-	-
Aartselaar	Municipalities with economic activity	Switcher	WF	2021
Affligem	Residential municipalities	Switcher	WF	2021
Alken	Residential municipalities	Stayed Volume-Based	-	-
Alveringem	Rural municipalities	Already Weight-Based	-	-
Anzegem	Municipalities with economic activity	Stayed Volume-Based	-	-
Ardooie	Rural municipalities	Stayed Volume-Based	-	-
Arendonk	Residential municipalities	Already Weight-Based	-	-
As	Residential municipalities	Already Weight-Based	-	-
Asse	Municipalities with economic activity	Stayed Volume-Based	-	-
Assenede	Rural municipalities	Already Weight-Based	-	-
Avelgem	Residential municipalities	Already Weight-Based	-	-
Baarle-Hertog	Residential municipalities	Already Weight-Based	-	-
Balen	Residential municipalities	Already Weight-Based	-	-
Beernem	Rural municipalities	Already Weight-Based	-	-
Beerse	Municipalities with economic activity	Already Weight-Based	-	-
Beersel	Municipalities with economic activity	Stayed Volume-Based	-	-
Begijnendijk	Residential municipalities	Already Weight-Based	-	-
Bekkevoort	Rural municipalities	Already Weight-Based	-	-
Beringen	Municipalities with economic activity	Already Weight-Based	-	-
Berlaar	Residential municipalities	Already Weight-Based	-	-
Berlare	Residential municipalities	Switcher	WF	2021
Bertem	Residential municipalities	Already Weight-Based	-	-
Bever	Rural municipalities	Stayed Volume-Based	-	-
Bierbeek	Residential municipalities	Already Weight-Based	-	-
Blankenberge	Coastal municipalities	Stayed Volume-Based	-	-
Bocholt	Rural municipalities	Already Weight-Based	-	-
Boechout	Residential municipalities	Stayed Volume-Based	-	-
Bonheiden	Residential municipalities	Switcher	WF	2021

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Table A.1 – *Continued from previous page*

Municipality	Belfius Typology Cluster	Status	New System	Year
Boom	Urbanized municipalities	Stayed Volume-Based	-	-
Boortmeerbeek	Residential municipalities	Already Weight-Based	-	-
Bornem	Municipalities with economic activity	Already Weight-Based	-	-
Boutersem	Residential municipalities	Already Weight-Based	-	-
Brakel	Residential municipalities	Stayed Volume-Based	-	-
Brasschaat	Residential municipalities	Stayed Volume-Based	-	-
Bree	Municipalities with economic activity	Already Weight-Based	-	-
Brecht	Residential municipalities	Already Weight-Based	-	-
Bredene	Coastal municipalities	Stayed Volume-Based	-	-
Brugge	Large and regional cities	Stayed Volume-Based	-	-
Buggenhout	Residential municipalities	Switcher	WF	2021
Damme	Rural municipalities	Already Weight-Based	-	-
De Haan	Coastal municipalities	Stayed Volume-Based	-	-
De Panne	Coastal municipalities	Already Weight-Based	-	-
Deerlijk	Municipalities with economic activity	Already Weight-Based	-	-
Denderleeuw	Urbanized municipalities	Switcher	WF	2021
Dendermonde	Municipalities with economic activity	Already Weight-Based	-	-
Dentergem	Rural municipalities	Already Weight-Based	-	-
Dessel	Municipalities with economic activity	Already Weight-Based	-	-
Destelbergen	Residential municipalities	Switcher	WF	2021
Diepenbeek	Residential municipalities	Already Weight-Based	-	-
Diest	Municipalities with economic activity	Already Weight-Based	-	-
Diksmuide	Municipalities with economic activity	Already Weight-Based	-	-
Dilbeek	Municipalities with economic activity	Stayed Volume-Based	-	-
Dilsen-Stokkem	Residential municipalities	Already Weight-Based	-	-
Drogenbos	Municipalities with economic activity	Stayed Volume-Based	-	-
Duffel	Municipalities with economic activity	Stayed Volume-Based	-	-
Edegem	Municipalities with economic activity	Stayed Volume-Based	-	-
Eeklo	Municipalities with economic activity	Already Weight-Based	-	-
Erpe-Mere	Residential municipalities	Switcher	WF	2021
Essen	Residential municipalities	Already Weight-Based	-	-
Evergem	Urbanized municipalities	Already Weight-Based	-	-
Gavere	Rural municipalities	Already Weight-Based	-	-

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Table A.1 – *Continued from previous page*

Municipality	Belfius Typology Cluster	Status	New System	Year
Geel	Municipalities with economic activity	Already Weight-Based	-	-
Geetbets	Residential municipalities	Already Weight-Based	-	-
Genk	Large and regional cities	Already Weight-Based	-	-
Gent	Large and regional cities	Stayed Volume-Based	-	-
Geraardsbergen	Urbanized municipalities	Already Weight-Based	-	-
Gingelom	Residential municipalities	Already Weight-Based	-	-
Gistel	Rural municipalities	Already Weight-Based	-	-
Glabbeek	Rural municipalities	Already Weight-Based	-	-
Grimbergen	Municipalities with economic activity	Stayed Volume-Based	-	-
Grobbendonk	Municipalities with economic activity	Stayed Volume-Based	-	-
Haacht	Residential municipalities	Already Weight-Based	-	-
Haaltert	Residential municipalities	Switcher	WF	2021
Halen	Residential municipalities	Already Weight-Based	-	-
Halle	Municipalities with economic activity	Already Weight-Based	-	-
Hamme	Urbanized municipalities	Already Weight-Based	-	-
Hamont-Achel	Rural municipalities	Already Weight-Based	-	-
Harelbeke	Municipalities with economic activity	Already Weight-Based	-	-
Hasselt	Large and regional cities	Stayed Volume-Based	-	-
Hechtel-Eksel	Residential municipalities	Already Weight-Based	-	-
Heers	Residential municipalities	Already Weight-Based	-	-
Heist-Op-Den-Berg	Urbanized municipalities	Already Weight-Based	-	-
Hemiksem	Urbanized municipalities	Stayed Volume-Based	-	-
Herent	Residential municipalities	Already Weight-Based	-	-
Herentals	Municipalities with economic activity	Already Weight-Based	-	-
Herenthout	Residential municipalities	Already Weight-Based	-	-
Herk-De-Stad	Residential municipalities	Already Weight-Based	-	-
Herselt	Residential municipalities	Switcher	WF	2021
Herstappe	Rural municipalities	Already Weight-Based	-	-
Herzele	Residential municipalities	Switcher	WF	2021
Heuvelland	Rural municipalities	Already Weight-Based	-	-
Heusden-Zolder	Municipalities with economic activity	Already Weight-Based	-	-
Hoegaarden	Residential municipalities	Already Weight-Based	-	-
Hoeilaart	Residential municipalities	Switcher	W	2021

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Table A.1 – *Continued from previous page*

Municipality	Belfius Typology Cluster	Status	New System	Year
Holsbeek	Residential municipalities	Already Weight-Based	-	-
Hooglede	Rural municipalities	Already Weight-Based	-	-
Hoogstraten	Municipalities with economic activity	Already Weight-Based	-	-
Horebeke	Rural municipalities	Stayed Volume-Based	-	-
Houthalen-Helchteren	Municipalities with economic activity	Already Weight-Based	-	-
Houthulst	Rural municipalities	Already Weight-Based	-	-
Hove	Residential municipalities	Stayed Volume-Based	-	-
Huldenberg	Residential municipalities	Switcher	WF NL	2020
Hulshout	Residential municipalities	Switcher	WF	2021
Ichtegem	Rural municipalities	Already Weight-Based	-	-
Ieper	Municipalities with economic activity	Already Weight-Based	-	-
Ingelmunster	Municipalities with economic activity	Already Weight-Based	-	-
Izegem	Municipalities with economic activity	Already Weight-Based	-	-
Jabbeke	Rural municipalities	Already Weight-Based	-	-
Kalmthout	Residential municipalities	Already Weight-Based	-	-
Kampenhout	Residential municipalities	Already Weight-Based	-	-
Kapelle-Op-Den-Bos	Residential municipalities	Switcher	WF	2021
Kapellen	Residential municipalities	Already Weight-Based	-	-
Kaprijke	Rural municipalities	Already Weight-Based	-	-
Kasterlee	Rural municipalities	Stayed Volume-Based	-	-
Keerbergen	Residential municipalities	Already Weight-Based	-	-
Kinrooi	Rural municipalities	Already Weight-Based	-	-
Kluisbergen	Residential municipalities	Already Weight-Based	-	-
Knokke-Heist	Coastal municipalities	Stayed Volume-Based	-	-
Koekelare	Rural municipalities	Already Weight-Based	-	-
Koksijde	Coastal municipalities	Already Weight-Based	-	-
Kontich	Municipalities with economic activity	Stayed Volume-Based	-	-
Kortenaken	Residential municipalities	Already Weight-Based	-	-
Kortenberg	Residential municipalities	Already Weight-Based	-	-
Kortemark	Rural municipalities	Already Weight-Based	-	-
Kortrijk	Large and regional cities	Stayed Volume-Based	-	-
Kraainem	Residential municipalities	Stayed Volume-Based	-	-
Kuurne	Municipalities with economic activity	Already Weight-Based	-	-

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Table A.1 – *Continued from previous page*

Municipality	Belfius Typology Cluster	Status	New System	Year
Laakdal	Municipalities with economic activity	Already Weight-Based	-	-
Laarne	Residential municipalities	Switcher	WF	2021
Lanaken	Urbanized municipalities	Already Weight-Based	-	-
Landen	Residential municipalities	Already Weight-Based	-	-
Langemark-Poelkapelle	Rural municipalities	Already Weight-Based	-	-
Lebbeke	Residential municipalities	Switcher	WF	2021
Lede	Residential municipalities	Switcher	WF	2021
Ledegem	Rural municipalities	Already Weight-Based	-	-
Lendelede	Municipalities with economic activity	Already Weight-Based	-	-
Lennik	Rural municipalities	Switcher	WF NL	2020
Leopoldsburg	Urbanized municipalities	Already Weight-Based	-	-
Leuven	Large and regional cities	Already Weight-Based	-	-
Lichtervelde	Rural municipalities	Already Weight-Based	-	-
Liedekerke	Residential municipalities	Switcher	WF NL	2020
Lier	Municipalities with economic activity	Switcher	WF	2021
Lierde	Residential municipalities	Stayed Volume-Based	-	-
Lille	Residential municipalities	Switcher	WF	2021
Linkebeek	Residential municipalities	Stayed Volume-Based	-	-
Lint	Residential municipalities	Stayed Volume-Based	-	-
Linter	Residential municipalities	Already Weight-Based	-	-
Lo-Reninge	Rural municipalities	Already Weight-Based	-	-
Lommel	Municipalities with economic activity	Already Weight-Based	-	-
Londerzeel	Residential municipalities	Switcher	WF	2021
Lubbeek	Residential municipalities	Already Weight-Based	-	-
Lummen	Rural municipalities	Already Weight-Based	-	-
Maarkedal	Rural municipalities	Stayed Volume-Based	-	-
Maaseik	Urbanized municipalities	Already Weight-Based	-	-
Maasmechelen	Urbanized municipalities	Already Weight-Based	-	-
Machelen	Municipalities with economic activity	Stayed Volume-Based	-	-
Maldegem	Rural municipalities	Already Weight-Based	-	-
Malle	Municipalities with economic activity	Already Weight-Based	-	-
Mechelen	Large and regional cities	Switcher	WV	2021
Meerhout	Residential municipalities	Already Weight-Based	-	-

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Table A.1 – *Continued from previous page*

Municipality	Belfius Typology Cluster	Status	New System	Year
Meise	Residential municipalities	Stayed Volume-Based	-	-
Menen	Urbanized municipalities	Already Weight-Based	-	-
Merchtem	Residential municipalities	Stayed Volume-Based	-	-
Merksplas	Rural municipalities	Already Weight-Based	-	-
Mesen	Residential municipalities	Already Weight-Based	-	-
Middelkerke	Coastal municipalities	Stayed Volume-Based	-	-
Mol	Urbanized municipalities	Already Weight-Based	-	-
Moorslede	Rural municipalities	Already Weight-Based	-	-
Mortsel	Municipalities with economic activity	Stayed Volume-Based	-	-
Niel	Urbanized municipalities	Stayed Volume-Based	-	-
Nieuwerkerken	Residential municipalities	Already Weight-Based	-	-
Nieuwpoort	Coastal municipalities	Stayed Volume-Based	-	-
Nijlen	Residential municipalities	Already Weight-Based	-	-
Ninove	Urbanized municipalities	Switcher	WF	2021
Olen	Municipalities with economic activity	Stayed Volume-Based	-	-
Oosterzele	Rural municipalities	Switcher	WF NL	2020
Oostkamp	Municipalities with economic activity	Switcher	WV	2021
Oostrozebeke	Municipalities with economic activity	Already Weight-Based	-	-
Oostende	Large and regional cities	Stayed Volume-Based	-	-
Opwijk	Residential municipalities	Switcher	WF	2021
Oud-Heverlee	Residential municipalities	Already Weight-Based	-	-
Oud-Turnhout	Residential municipalities	Already Weight-Based	-	-
Oudenaarde	Municipalities with economic activity	Switcher	WV	2022
Oudenburg	Rural municipalities	Already Weight-Based	-	-
Overijse	Residential municipalities	Switcher	W	2021
Peer	Rural municipalities	Already Weight-Based	-	-
Pepingen	Rural municipalities	Stayed Volume-Based	-	-
Pittem	Rural municipalities	Already Weight-Based	-	-
Poperinge	Municipalities with economic activity	Already Weight-Based	-	-
Putte	Residential municipalities	Switcher	WF	2021
Ranst	Residential municipalities	Already Weight-Based	-	-
Ravels	Rural municipalities	Already Weight-Based	-	-
Retie	Residential municipalities	Already Weight-Based	-	-

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Table A.1 – *Continued from previous page*

Municipality	Belfius Typology Cluster	Status	New System	Year
Riemst	Residential municipalities	Already Weight-Based	-	-
Rijkevorsel	Rural municipalities	Already Weight-Based	-	-
Roeselare	Large and regional cities	Already Weight-Based	-	-
Ronse	Urbanized municipalities	Switcher	WF	2021
Roosdaal	Residential municipalities	Stayed Volume-Based	-	-
Rotselaar	Residential municipalities	Already Weight-Based	-	-
Rumst	Residential municipalities	Switcher	WF	2020
Schelle	Municipalities with economic activity	Switcher	WF	2021
Scherpenheuvel-Zichem	Residential municipalities	Already Weight-Based	-	-
Schilde	Residential municipalities	Stayed Volume-Based	-	-
Schoten	Municipalities with economic activity	Stayed Volume-Based	-	-
Sint-Genesius-Rode	Residential municipalities	Stayed Volume-Based	-	-
Sint-Gillis-Waas	Residential municipalities	Already Weight-Based	-	-
Sint-Katelijne-Waver	Municipalities with economic activity	Switcher	WF	2022
Sint-Laureins	Rural municipalities	Already Weight-Based	-	-
Sint-Lievens-Houtem	Residential municipalities	Switcher	WF	2020
Sint-Martens-Latem	Residential municipalities	Stayed Volume-Based	-	-
Sint-Niklaas	Large and regional cities	Switcher	WF NL	2020
Sint-Pieters-Leeuw	Municipalities with economic activity	Stayed Volume-Based	-	-
Sint-Truiden	Municipalities with economic activity	Already Weight-Based	-	-
Spiere-Helkijn	Rural municipalities	Switcher	W	2020
Stabroek	Residential municipalities	Stayed Volume-Based	-	-
Staden	Rural municipalities	Already Weight-Based	-	-
Steenokkerzeel	Residential municipalities	Switcher	WF	2022
Stekene	Residential municipalities	Already Weight-Based	-	-
Temse	Urbanized municipalities	Switcher	WF	2020
Ternat	Residential municipalities	Stayed Volume-Based	-	-
Tervuren	Residential municipalities	Switcher	WF	2024
Tielt-Winge	Residential municipalities	Already Weight-Based	-	-
Tienen	Municipalities with economic activity	Stayed Volume-Based	-	-
Torhout	Urbanized municipalities	Already Weight-Based	-	-
Tremelo	Residential municipalities	Already Weight-Based	-	-
Turnhout	Large and regional cities	Stayed Volume-Based	-	-

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Table A.1 – *Continued from previous page*

Municipality	Belfius Typology Cluster	Status	New System	Year
Veurne	Municipalities with economic activity	Already Weight-Based	-	-
Vilvoorde	Municipalities with economic activity	Stayed Volume-Based	-	-
Vleteren	Rural municipalities	Already Weight-Based	-	-
Voeren	Rural municipalities	Already Weight-Based	-	-
Vorselaar	Residential municipalities	Already Weight-Based	-	-
Vosselaar	Residential municipalities	Already Weight-Based	-	-
Waasmunster	Rural municipalities	Already Weight-Based	-	-
Waregem	Municipalities with economic activity	Already Weight-Based	-	-
Wellen	Residential municipalities	Already Weight-Based	-	-
Wemmel	Residential municipalities	Stayed Volume-Based	-	-
Wervik	Residential municipalities	Already Weight-Based	-	-
Westerlo	Municipalities with economic activity	Already Weight-Based	-	-
Wetteren	Municipalities with economic activity	Already Weight-Based	-	-
Wevelgem	Municipalities with economic activity	Already Weight-Based	-	-
Wezembeek-Oppem	Residential municipalities	Stayed Volume-Based	-	-
Wichelen	Residential municipalities	Switcher	WF	2020
Wielsbeke	Municipalities with economic activity	Already Weight-Based	-	-
Wijnegem	Municipalities with economic activity	Stayed Volume-Based	-	-
Willebroek	Urbanized municipalities	Already Weight-Based	-	-
Wommelgem	Municipalities with economic activity	Stayed Volume-Based	-	-
Wortegem-Petegem	Rural municipalities	Already Weight-Based	-	-
Wuustwezel	Rural municipalities	Already Weight-Based	-	-
Zandhoven	Rural municipalities	Already Weight-Based	-	-
Zaventem	Municipalities with economic activity	Stayed Volume-Based	-	-
Zedelgem	Municipalities with economic activity	Already Weight-Based	-	-
Zele	Municipalities with economic activity	Already Weight-Based	-	-
Zelzate	Urbanized municipalities	Stayed Volume-Based	-	-
Zemst	Residential municipalities	Switcher	WF	2020
Zoersel	Residential municipalities	Already Weight-Based	-	-
Zonhoven	Residential municipalities	Already Weight-Based	-	-
Zonnebeke	Rural municipalities	Already Weight-Based	-	-
Zottegem	Urbanized municipalities	Switcher	WF NL	2022
Zoutleeuw	Residential municipalities	Already Weight-Based	-	-

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Table A.1 – *Continued from previous page*

Municipality	Belfius Typology Cluster	Status	New System	Year
Zuienkerke	Rural municipalities	Already Weight-Based	-	-
Zulte	Rural municipalities	Switcher	WF	2022
Zutendaal	Residential municipalities	Already Weight-Based	-	-
Zwalm	Rural municipalities	Already Weight-Based	-	-
Zwevegem	Municipalities with economic activity	Already Weight-Based	-	-

Appendix B

This appendix provides the unmodified statistical outputs generated by the log-linear Staggered Difference-in-Differences models discussed in the main text.

To prioritize readability and prevent mathematical approximation errors when interpreting substantial policy impacts, the results chapters exclusively present the treatment effects transformed into exact percentage changes. Consequently, this appendix serves as the repository for the underlying econometric data. It contains all logarithmic estimates (expressed in log points), standard errors, and simultaneous confidence bands produced by the `did` package.

The tables enclosed below include the granular Group-Time Average Treatment Effects ($ATT(g,t)$) as well as the Phase 2 dynamically aggregated event studies for both the conditional models. These outputs are provided to ensure complete methodological transparency, allowing for a detailed review of the baseline estimates and pre-treatment trends prior to their discrete percentage transformation. For the sake of brevity, the tables that contain the results from the Staggered DiD models on the different clusters of municipalities and the methods of implementation are only presented using the exact percentage changes.

Full Econometric Output Conditional Log-Linear Staggered DiD

Table B.1: Group-Time Average Treatment Effects ($ATT(g,t)$) on Residual Waste (Conditional Model)

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.1325	0.0824	-0.3426	0.0776	
2018	2019	-0.1287	0.0966	-0.3752	0.1177	
2018	2020	-0.1249	0.1023	-0.3859	0.1361	
2018	2021	-0.1061	0.1441	-0.4737	0.2615	
2018	2022	-0.0678	0.1351	-0.4125	0.2769	
2018	2023	-0.0391	0.1339	-0.3808	0.3026	
2018	2024	-0.0173	0.1401	-0.3748	0.3401	
2020	2018	-0.0033	0.0081	-0.0240	0.0173	
2020	2019	-0.0826	0.0375	-0.1783	0.0130	
2020	2020	-0.1775	0.0485	-0.3013	-0.0537	*
2020	2021	-0.2057	0.0555	-0.3472	-0.0643	*
2020	2022	-0.1759	0.0642	-0.3398	-0.0120	*
2020	2023	-0.1733	0.0615	-0.3301	-0.0165	*
2020	2024	-0.1597	0.0614	-0.3163	-0.0031	*

Table B.1 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2021	2018	0.0028	0.0064	-0.0136	0.0191	
2021	2019	0.0077	0.0121	-0.0231	0.0386	
2021	2020	-0.0037	0.0121	-0.0344	0.0271	
2021	2021	-0.1716	0.0199	-0.2222	-0.1209	*
2021	2022	-0.2132	0.0290	-0.2871	-0.1393	*
2021	2023	-0.1867	0.0312	-0.2663	-0.1070	*
2021	2024	-0.1622	0.0350	-0.2515	-0.0729	*
2022	2018	0.0210	0.0095	-0.0031	0.0452	
2022	2019	0.0091	0.0170	-0.0342	0.0524	
2022	2020	-0.0012	0.0281	-0.0730	0.0705	
2022	2021	-0.0219	0.0469	-0.1416	0.0979	
2022	2022	-0.1376	0.0347	-0.2260	-0.0491	*
2022	2023	-0.0993	0.0561	-0.2424	0.0438	
2022	2024	-0.0775	0.0667	-0.2477	0.0927	
2024	2018	0.0198	0.0306	-0.0583	0.0979	
2024	2019	0.0122	0.0107	-0.0152	0.0396	
2024	2020	0.0204	0.0136	-0.0143	0.0550	
2024	2021	0.0008	0.0134	-0.0335	0.0351	
2024	2022	-0.0072	0.0167	-0.0499	0.0354	
2024	2023	-0.0516	0.0519	-0.1840	0.0808	
2024	2024	-0.1303	0.1982	-0.6360	0.3754	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.2: Aggregated Dynamic Effects on Residual Waste (Logarithmic Estimates, Conditional Model)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0198	0.0332	-0.0627	0.1023	
-5	0.0122	0.0102	-0.0133	0.0376	
-4	0.0209	0.0077	0.0018	0.0399	*
-3	0.0039	0.0059	-0.0107	0.0185	
-2	0.0030	0.0076	-0.0158	0.0219	
-1	-0.0271	0.0138	-0.0614	0.0071	
0	-0.1640	0.0178	-0.2083	-0.1197	*
1	-0.1896	0.0232	-0.2474	-0.1319	*
2	-0.1642	0.0261	-0.2290	-0.0995	*
3	-0.1618	0.0326	-0.2428	-0.0808	*
4	-0.1430	0.0574	-0.2856	-0.0004	*
5	-0.0391	0.2193	-0.5840	0.5058	
6	-0.0173	0.1185	-0.3117	0.2771	
Overall	**-0.1256**	**0.0499**	**-0.2234**	**-0.0278**	*

Note: Estimates are expressed in log points, conditional on the Belfius Municipal Typology. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

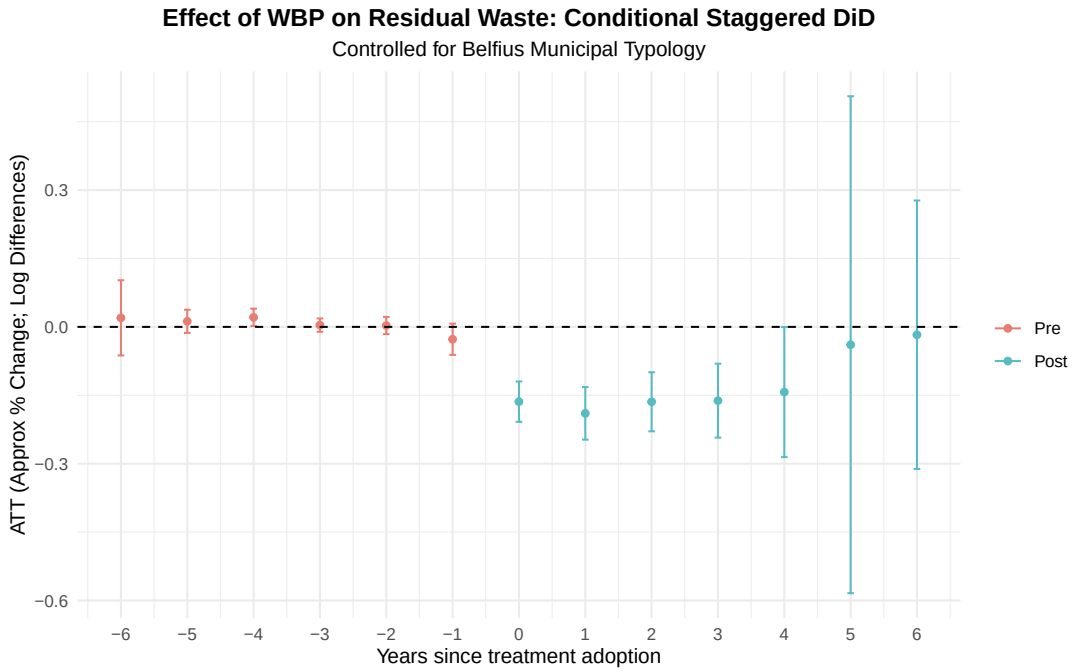


Figure B.1: Conditional Impact of Weight-Based Pricing on Residual Waste

Full Econometric Output Conditional Log-Linear Staggered DiD: Subsitution Effects on Collected Fractions

Batteries

Table B.3: Group-Time Average Treatment Effects ($ATT(g,t)$) on Batteries

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.0468	0.0411	-0.1543	0.0608	
2018	2019	-0.0329	0.0491	-0.1611	0.0954	
2018	2020	-0.0358	0.0461	-0.1563	0.0847	
2018	2021	-0.0349	0.0231	-0.0952	0.0255	
2018	2022	-0.0841	0.0592	-0.2387	0.0706	
2018	2023	-0.0718	0.0790	-0.2783	0.1348	
2018	2024	-0.0447	0.0188	-0.0940	0.0045	
2020	2018	0.0139	0.0194	-0.0368	0.0647	
2020	2019	-0.0510	0.0299	-0.1291	0.0271	
2020	2020	0.0285	0.0321	-0.0554	0.1124	

Table B.3 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	0.0330	0.0242	-0.0302	0.0961	
2020	2022	0.0091	0.0319	-0.0743	0.0926	
2020	2023	0.0484	0.0419	-0.0613	0.1580	
2020	2024	0.0469	0.0531	-0.0920	0.1858	
2021	2018	-0.0020	0.0126	-0.0348	0.0309	
2021	2019	0.0163	0.0118	-0.0146	0.0472	
2021	2020	0.0121	0.0155	-0.0283	0.0525	
2021	2021	-0.0368	0.0154	-0.0772	0.0036	
2021	2022	-0.0445	0.0254	-0.1110	0.0220	
2021	2023	-0.0116	0.0340	-0.1004	0.0772	
2021	2024	-0.0066	0.0334	-0.0939	0.0807	
2022	2018	0.0688	0.0655	-0.1025	0.2401	
2022	2019	0.0471	0.0471	-0.0762	0.1703	
2022	2020	-0.0828	0.0437	-0.1971	0.0315	
2022	2021	-0.0165	0.0256	-0.0835	0.0505	
2022	2022	-0.0655	0.0427	-0.1772	0.0462	
2022	2023	-0.0376	0.1086	-0.3215	0.2463	
2022	2024	-0.0606	0.1721	-0.5106	0.3894	
2024	2018	0.0109	0.0221	-0.0469	0.0687	
2024	2019	0.0043	0.0096	-0.0209	0.0296	
2024	2020	-0.0040	0.0093	-0.0283	0.0203	
2024	2021	-0.0665	0.0149	-0.1054	-0.0277	*
2024	2022	0.0273	0.0462	-0.0935	0.1481	
2024	2023	-0.0207	0.0087	-0.0435	0.0022	
2024	2024	0.1072	0.0473	-0.0165	0.2308	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.4: Aggregated Dynamic Effects on Batteries (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0109	0.0221	-0.0443	0.0662	
-5	0.0043	0.0096	-0.0196	0.0283	
-4	0.0506	0.0527	-0.0813	0.1825	
-3	0.0035	0.0136	-0.0305	0.0376	
-2	0.0011	0.0115	-0.0277	0.0298	
-1	-0.0086	0.0126	-0.0401	0.0230	
0	-0.0201	0.0136	-0.0541	0.0138	
1	-0.0249	0.0241	-0.0852	0.0353	
2	-0.0156	0.0316	-0.0946	0.0634	
3	0.0067	0.0286	-0.0648	0.0782	
4	0.0231	0.0465	-0.0931	0.1393	
5	-0.0718	0.1041	-0.3323	0.1887	
6	-0.0447	0.0188	-0.0918	0.0023	
Overall	**-0.0211**	**0.0225**	**-0.0651**	**0.0230**	

Note: Estimates are expressed in log points.significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

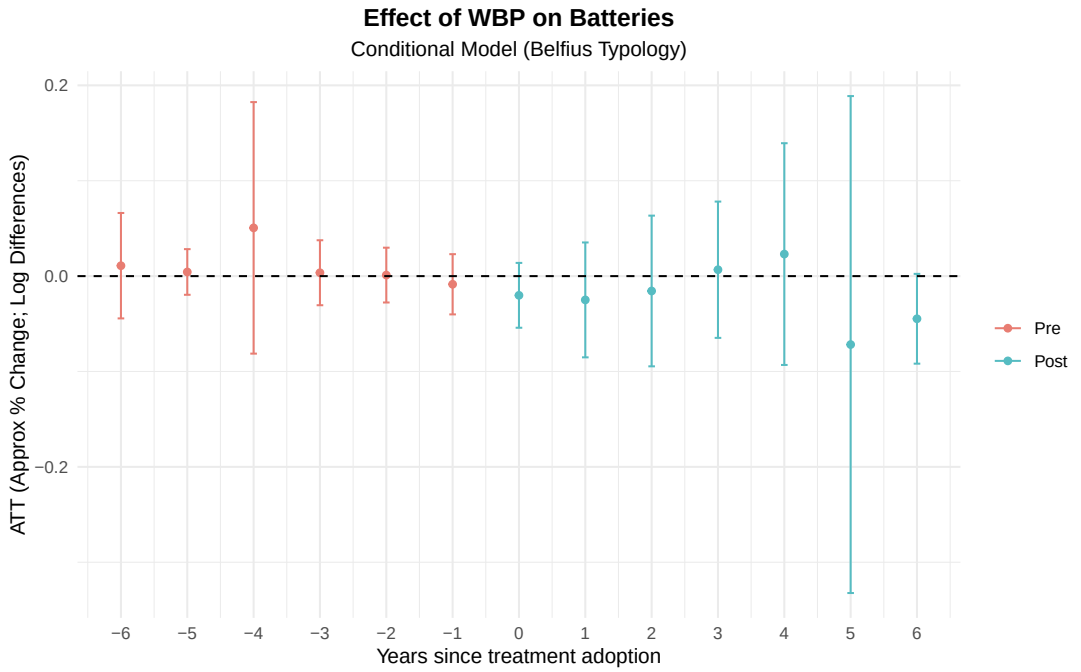


Figure B.2: Impact of Weight-Based Pricing on Batteries

Table B.5: Exact Percentage Change in Batteries

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	1.10%	-4.34%	6.84%	
-5	0.44%	-1.94%	2.87%	
-4	5.19%	-7.81%	20.02%	
-3	0.35%	-3.01%	3.83%	
-2	0.11%	-2.73%	3.03%	
-1	-0.85%	-3.93%	2.33%	
0	-1.99%	-5.27%	1.39%	
1	-2.46%	-8.16%	3.59%	
2	-1.55%	-9.02%	6.55%	
3	0.67%	-6.27%	8.13%	
4	2.34%	-8.89%	14.95%	
5	-6.92%	-28.27%	20.77%	
6	-4.37%	-8.77%	0.24%	
Overall	**-2.08%**	**-6.30%**	**2.32%**	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Construction and Demolition Waste

Table B.6: Group-Time Average Treatment Effects ($ATT(g,t)$) on Construction and Demolition Waste

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	0.0078	0.0414	-0.1036	0.1192	
2018	2019	-0.0494	0.0536	-0.1938	0.0950	
2018	2020	0.0708	0.1003	-0.1991	0.3406	
2018	2021	0.0313	0.1657	-0.4148	0.4775	
2018	2022	0.1096	0.1700	-0.3481	0.5673	
2018	2023	0.1270	0.1530	-0.2847	0.5388	
2018	2024	0.1071	0.1397	-0.2690	0.4831	
2020	2018	0.0071	0.0372	-0.0931	0.1074	
2020	2019	0.0614	0.0617	-0.1047	0.2276	
2020	2020	0.0900	0.0515	-0.0487	0.2286	

Table B.6 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	0.1015	0.0882	-0.1359	0.3389	
2020	2022	0.0538	0.0935	-0.1979	0.3055	
2020	2023	-0.0553	0.1221	-0.3840	0.2735	
2020	2024	-0.1504	0.1459	-0.5432	0.2425	
2021	2018	0.0759	0.0311	-0.0079	0.1597	
2021	2019	0.0225	0.0308	-0.0603	0.1054	
2021	2020	0.1014	0.0523	-0.0393	0.2421	
2021	2021	-0.1242	0.0381	-0.2269	-0.0215	*
2021	2022	-0.0898	0.0658	-0.2669	0.0872	
2021	2023	-0.0071	0.0706	-0.1971	0.1828	
2021	2024	-0.0252	0.0706	-0.2154	0.1649	
2022	2018	0.0298	0.0592	-0.1295	0.1891	
2022	2019	0.0080	0.0588	-0.1501	0.1662	
2022	2020	-0.0062	0.1099	-0.3021	0.2897	
2022	2021	-0.2087	0.1789	-0.6903	0.2728	
2022	2022	0.0173	0.0516	-0.1215	0.1561	
2022	2023	0.0428	0.0827	-0.1798	0.2653	
2022	2024	-0.0204	0.1056	-0.3047	0.2639	
2024	2018	0.0332	0.0398	-0.0739	0.1402	
2024	2019	0.0253	0.0588	-0.1329	0.1835	
2024	2020	0.2248	0.0427	0.1098	0.3398	*
2024	2021	0.0226	0.1200	-0.3003	0.3456	
2024	2022	0.0122	0.0538	-0.1327	0.1570	
2024	2023	0.0306	0.0734	-0.1671	0.2283	
2024	2024	0.0089	0.0824	-0.2129	0.2307	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.7: Aggregated Dynamic Effects on Construction and Demolition Waste (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0332	0.0403	-0.0684	0.1348	
-5	0.0253	0.0573	-0.1191	0.1698	
-4	0.0785	0.0577	-0.0669	0.2240	
-3	0.0588	0.0241	-0.0019	0.1195	
-2	0.0140	0.0244	-0.0476	0.0756	
-1	0.0408	0.0448	-0.0721	0.1538	
0	-0.0435	0.0289	-0.1164	0.0293	
1	-0.0232	0.0458	-0.1387	0.0923	
2	0.0089	0.0588	-0.1392	0.1570	
3	-0.0300	0.0686	-0.2030	0.1430	
4	-0.1031	0.1272	-0.4236	0.2175	
5	0.1270	0.1716	-0.3056	0.5597	
6	0.1071	0.1342	-0.2311	0.4452	
Overall	**0.0062**	**0.0611**	**-0.1136**	**0.1259**	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

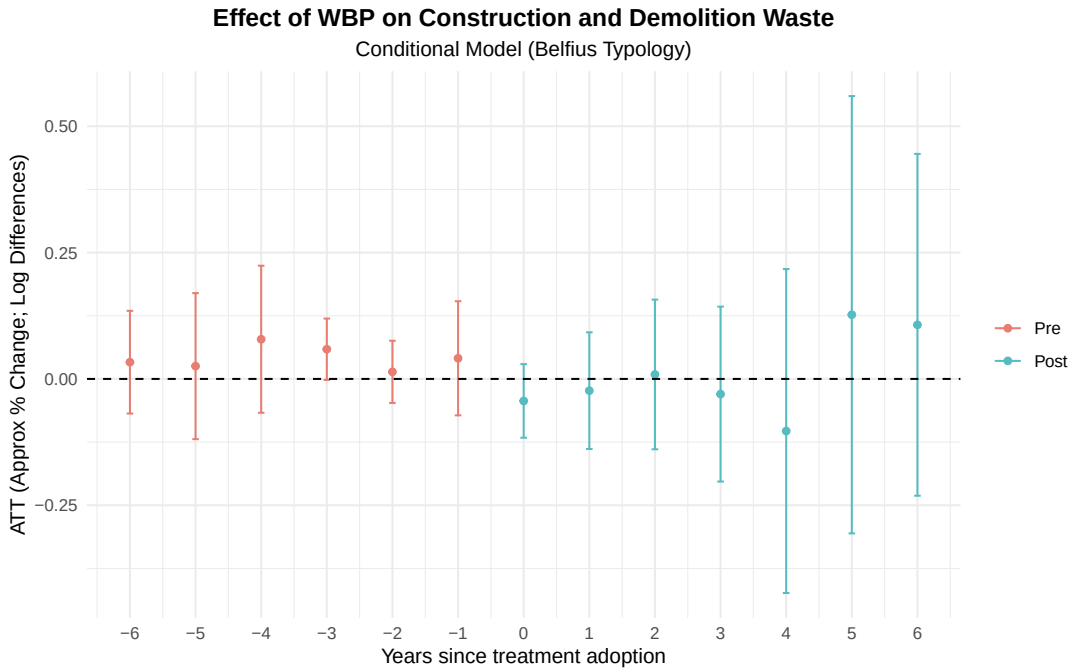


Figure B.3: Impact of Weight-Based Pricing on Construction and Demolition Waste

Table B.8: Exact Percentage Change in Construction and Demolition Waste

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	3.37%	-6.62%	14.43%	
-5	2.57%	-11.23%	18.51%	
-4	8.17%	-6.48%	25.11%	
-3	6.05%	-0.19%	12.69%	
-2	1.41%	-4.64%	7.85%	
-1	4.17%	-6.96%	16.62%	
0	-4.26%	-10.99%	2.98%	
1	-2.29%	-12.95%	9.67%	
2	0.89%	-13.00%	17.00%	
3	-2.96%	-18.37%	15.37%	
4	-9.80%	-34.53%	24.29%	
5	13.55%	-26.33%	75.01%	
6	11.30%	-20.64%	56.09%	
Overall	**0.62%**	**-10.74%**	**13.42%**	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Organic Waste (VFG)

Table B.9: Group-Time Average Treatment Effects ($ATT(g,t)$) on Organic Waste (VFG)

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.0181	0.0316	-0.1101	0.0740	
2018	2019	-0.0175	0.0187	-0.0718	0.0369	
2018	2020	0.0159	0.0265	-0.0612	0.0930	
2018	2021	-0.0698	0.0415	-0.1906	0.0511	
2018	2022	-0.1194	0.0532	-0.2744	0.0357	
2018	2023	-0.1464	0.0524	-0.2991	0.0063	
2018	2024	-0.1721	0.0524	-0.3248	-0.0195	*
2020	2018	0.0088	0.0112	-0.0237	0.0414	
2020	2019	0.1245	0.0476	-0.0143	0.2633	
2020	2020	0.2329	0.0622	0.0518	0.4141	*

Table B.9 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	0.1340	0.1217	-0.2204	0.4884	
2020	2022	0.1629	0.1471	-0.2654	0.5912	
2020	2023	0.1555	0.1452	-0.2675	0.5785	
2020	2024	0.0674	0.1301	-0.3116	0.4464	
2021	2018	-0.0030	0.0142	-0.0444	0.0383	
2021	2019	-0.0152	0.0149	-0.0587	0.0282	
2021	2020	0.0273	0.0153	-0.0173	0.0720	
2021	2021	-0.0750	0.0376	-0.1845	0.0345	
2021	2022	-0.0833	0.0619	-0.2636	0.0970	
2021	2023	-0.1008	0.0630	-0.2842	0.0826	
2021	2024	-0.1494	0.0606	-0.3258	0.0269	
2022	2018	-0.0226	0.0227	-0.0887	0.0435	
2022	2019	-0.0031	0.0183	-0.0562	0.0501	
2022	2020	0.0021	0.0196	-0.0549	0.0590	
2022	2021	-0.0325	0.0229	-0.0991	0.0341	
2022	2022	-0.0700	0.0546	-0.2291	0.0891	
2022	2023	-0.1098	0.0688	-0.3101	0.0905	
2022	2024	-0.1153	0.0739	-0.3306	0.1000	
2024	2018	-0.0013	0.0071	-0.0220	0.0194	
2024	2019	-0.0447	0.0123	-0.0806	-0.0087	*
2024	2020	0.0031	0.0187	-0.0514	0.0575	
2024	2021	-0.0514	0.0241	-0.1216	0.0188	
2024	2022	0.1529	0.1719	-0.3477	0.6536	
2024	2023	-0.0643	0.0226	-0.1302	0.0017	
2024	2024	-0.1012	0.1394	-0.5072	0.3048	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.10: Aggregated Dynamic Effects on Organic Waste (VFG) (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	-0.0013	0.0072	-0.0200	0.0175	
-5	-0.0447	0.0137	-0.0801	-0.0093	*
-4	-0.0162	0.0202	-0.0686	0.0362	
-3	-0.0062	0.0119	-0.0371	0.0246	
-2	0.0012	0.0161	-0.0406	0.0430	
-1	0.0311	0.0166	-0.0119	0.0740	
0	-0.0174	0.0343	-0.1061	0.0714	
1	-0.0429	0.0495	-0.1712	0.0854	
2	-0.0470	0.0548	-0.1888	0.0949	
3	-0.0754	0.0618	-0.2356	0.0847	
4	0.0259	0.1077	-0.2531	0.3049	
5	-0.1464	0.0532	-0.2841	-0.0087	*
6	-0.1721	0.0595	-0.3263	-0.0180	*
Overall	**-0.0679**	**0.0459**	**-0.1579**	**0.0221**	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

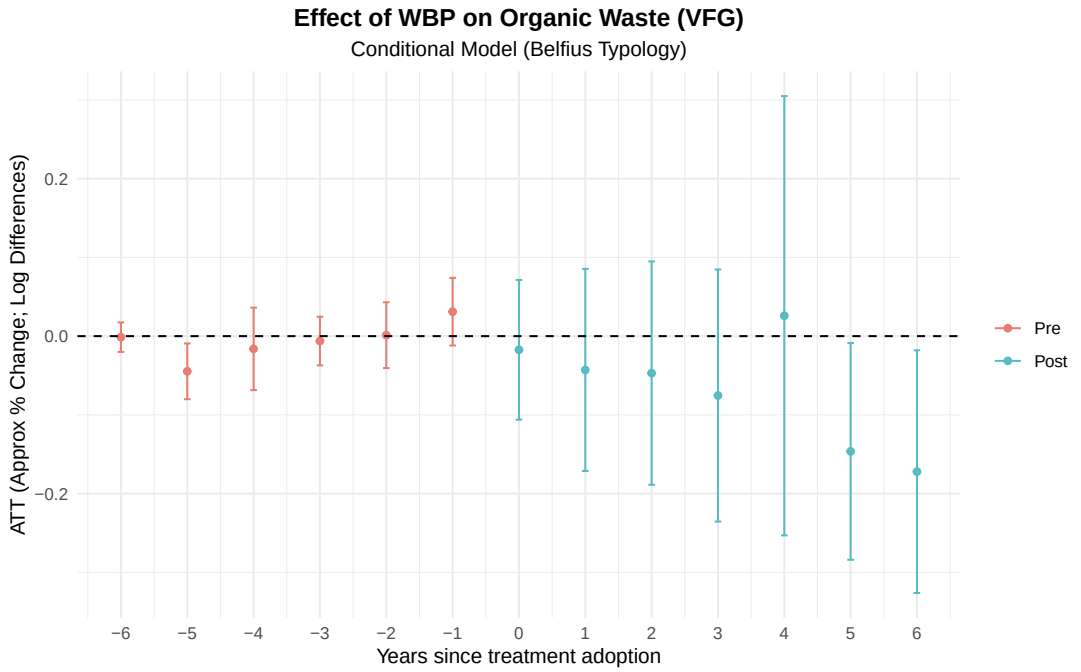


Figure B.4: Impact of Weight-Based Pricing on Organic Waste (VFG)

Table B.11: Exact Percentage Change in Organic Waste (VFG)

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	-0.13%	-1.98%	1.76%	
-5	-4.37%	-7.69%	-0.93%	*
-4	-1.60%	-6.63%	3.69%	
-3	-0.62%	-3.65%	2.50%	
-2	0.12%	-3.98%	4.40%	
-1	3.15%	-1.18%	7.68%	
0	-1.72%	-10.06%	7.40%	
1	-4.20%	-15.74%	8.92%	
2	-4.59%	-17.21%	9.96%	
3	-7.27%	-20.99%	8.84%	
4	2.63%	-22.36%	35.65%	
5	-13.62%	-24.73%	-0.87%	*
6	-15.81%	-27.84%	-1.78%	*
Overall	**-6.56%**	**-14.60%**	**2.23%**	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Green Waste

Table B.12: Group-Time Average Treatment Effects ($ATT(g,t)$) on Green Waste

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	0.0472	0.0430	-0.0673	0.1616	
2018	2019	-0.0262	0.0550	-0.1725	0.1201	
2018	2020	0.0585	0.0566	-0.0922	0.2092	
2018	2021	0.0065	0.0420	-0.1054	0.1184	
2018	2022	0.1595	0.1237	-0.1697	0.4887	
2018	2023	-0.1686	0.1241	-0.4988	0.1617	
2018	2024	0.1906	0.0920	-0.0543	0.4355	
2020	2018	0.0892	0.1213	-0.2336	0.4120	
2020	2019	-0.0841	0.0453	-0.2047	0.0364	
2020	2020	-0.0081	0.0700	-0.1944	0.1781	

Table B.12 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	-0.0654	0.0939	-0.3152	0.1845	
2020	2022	-0.1895	0.0892	-0.4270	0.0480	
2020	2023	-0.1748	0.1201	-0.4944	0.1447	
2020	2024	-0.1566	0.1140	-0.4599	0.1466	
2021	2018	0.0596	0.0252	-0.0075	0.1268	
2021	2019	0.0552	0.0798	-0.1571	0.2676	
2021	2020	0.0377	0.0502	-0.0959	0.1713	
2021	2021	-0.0237	0.0321	-0.1090	0.0616	
2021	2022	-0.0318	0.0363	-0.1285	0.0648	
2021	2023	0.0574	0.0447	-0.0616	0.1765	
2021	2024	0.0742	0.0469	-0.0505	0.1990	
2022	2018	0.1835	0.0999	-0.0823	0.4494	
2022	2019	-0.0398	0.0409	-0.1485	0.0690	
2022	2020	-0.0568	0.0845	-0.2817	0.1680	
2022	2021	-0.1864	0.2350	-0.8118	0.4390	
2022	2022	0.1035	0.0513	-0.0330	0.2400	
2022	2023	0.1007	0.0678	-0.0796	0.2810	
2022	2024	0.2123	0.1323	-0.1398	0.5645	
2024	2018	0.0922	0.1316	-0.2579	0.4424	
2024	2019	0.0054	0.0367	-0.0922	0.1029	
2024	2020	0.1487	0.1819	-0.3355	0.6328	
2024	2021	-0.0049	0.0451	-0.1248	0.1151	
2024	2022	0.0337	0.0318	-0.0510	0.1185	
2024	2023	0.1223	0.0304	0.0414	0.2032	*
2024	2024	0.2744	0.4606	-0.9514	1.5003	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.13: Aggregated Dynamic Effects on Green Waste (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0922	0.0902	-0.1362	0.3206	
-5	0.0054	0.0389	-0.0931	0.1038	
-4	0.1748	0.0788	-0.0249	0.3746	
-3	0.0355	0.0194	-0.0137	0.0846	
-2	0.0447	0.0555	-0.0959	0.1853	
-1	-0.0205	0.0450	-0.1346	0.0935	
0	0.0163	0.0302	-0.0602	0.0929	
1	-0.0189	0.0343	-0.1059	0.0681	
2	0.0243	0.0445	-0.0884	0.1371	
3	0.0022	0.0552	-0.1377	0.1421	
4	-0.0992	0.1073	-0.3709	0.1726	
5	-0.1686	0.1294	-0.4964	0.1593	
6	0.1906	0.0933	-0.0457	0.4269	
Overall	**-0.0076**	**0.0391**	**-0.0843**	**0.0691**	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

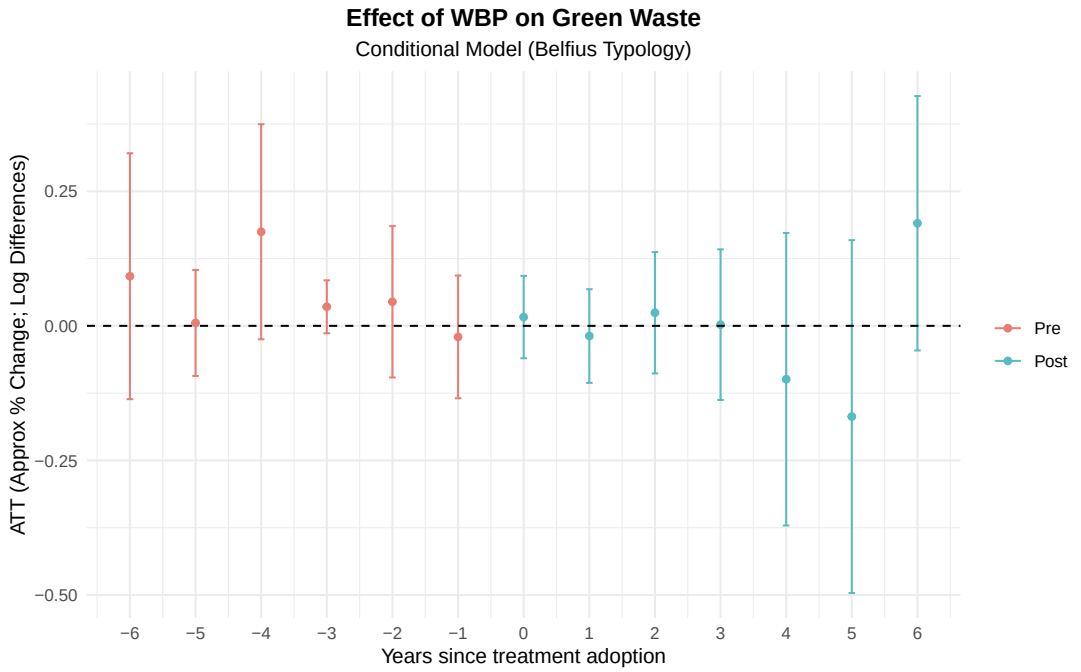


Figure B.5: Impact of Weight-Based Pricing on Green Waste

Table B.14: Exact Percentage Change in Green Waste

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	9.66%	-12.73%	37.80%	
-5	0.54%	-8.89%	10.94%	
-4	19.10%	-2.46%	45.43%	
-3	3.61%	-1.36%	8.83%	
-2	4.57%	-9.14%	20.36%	
-1	-2.03%	-12.59%	9.80%	
0	1.65%	-5.84%	9.73%	
1	-1.87%	-10.05%	7.05%	
2	2.46%	-8.46%	14.69%	
3	0.22%	-12.87%	15.27%	
4	-9.44%	-30.99%	18.84%	
5	-15.51%	-39.13%	17.26%	
6	21.00%	-4.47%	53.25%	
Overall	**-0.76%**	**-8.08%**	**7.15%**	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Wood Waste

Table B.15: Group-Time Average Treatment Effects ($ATT(g,t)$) on Wood Waste

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.0219	0.0233	-0.0812	0.0374	
2018	2019	-0.0346	0.0372	-0.1291	0.0599	
2018	2020	0.0269	0.0556	-0.1145	0.1684	
2018	2021	-0.0395	0.0726	-0.2242	0.1451	
2018	2022	0.0589	0.1089	-0.2180	0.3358	
2018	2023	0.0382	0.0848	-0.1775	0.2539	
2018	2024	0.0468	0.0843	-0.1676	0.2613	
2020	2018	-0.0278	0.0232	-0.0868	0.0311	
2020	2019	0.0440	0.0374	-0.0510	0.1389	
2020	2020	-0.2239	0.0902	-0.4534	0.0055	

Table B.15 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	-0.2685	0.0718	-0.4511	-0.0858	*
2020	2022	-0.2951	0.0799	-0.4984	-0.0919	*
2020	2023	-0.2985	0.1026	-0.5594	-0.0376	*
2020	2024	-0.3787	0.1115	-0.6621	-0.0953	*
2021	2018	0.0069	0.0255	-0.0578	0.0717	
2021	2019	0.0266	0.0314	-0.0534	0.1065	
2021	2020	-0.0511	0.0683	-0.2247	0.1226	
2021	2021	-0.1320	0.0716	-0.3140	0.0499	
2021	2022	-0.1212	0.1045	-0.3868	0.1443	
2021	2023	-0.1102	0.1039	-0.3744	0.1539	
2021	2024	-0.1359	0.1043	-0.4013	0.1294	
2022	2018	0.0173	0.0311	-0.0619	0.0964	
2022	2019	-0.0312	0.0233	-0.0904	0.0280	
2022	2020	-0.0546	0.1041	-0.3192	0.2101	
2022	2021	-0.0696	0.1023	-0.3296	0.1905	
2022	2022	-0.0685	0.0383	-0.1660	0.0290	
2022	2023	-0.0189	0.0641	-0.1818	0.1441	
2022	2024	-0.0524	0.0647	-0.2168	0.1120	
2024	2018	-0.0321	0.0230	-0.0906	0.0264	
2024	2019	0.0343	0.0344	-0.0531	0.1217	
2024	2020	0.0267	0.0633	-0.1343	0.1876	
2024	2021	-0.0488	0.2370	-0.6515	0.5539	
2024	2022	-0.0994	0.0135	-0.1338	-0.0650	*
2024	2023	-0.0224	0.0855	-0.2399	0.1951	
2024	2024	-0.0032	0.0232	-0.0623	0.0559	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.16: Aggregated Dynamic Effects on Wood Waste (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	-0.0321	0.0226	-0.0876	0.0234	
-5	0.0343	0.0316	-0.0435	0.1121	
-4	0.0196	0.0247	-0.0412	0.0804	
-3	-0.0044	0.0226	-0.0599	0.0511	
-2	-0.0049	0.0231	-0.0616	0.0518	
-1	-0.0305	0.0413	-0.1322	0.0712	
0	-0.1313	0.0437	-0.2386	-0.0239	*
1	-0.1350	0.0601	-0.2829	0.0129	
2	-0.1370	0.0639	-0.2943	0.0203	
3	-0.1744	0.0802	-0.3716	0.0227	
4	-0.2991	0.1149	-0.5817	-0.0165	*
5	0.0382	0.0778	-0.1532	0.2295	
6	0.0468	0.0807	-0.1517	0.2454	
Overall	**-0.1131**	**0.0506**	**-0.2123**	**-0.0140**	*

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

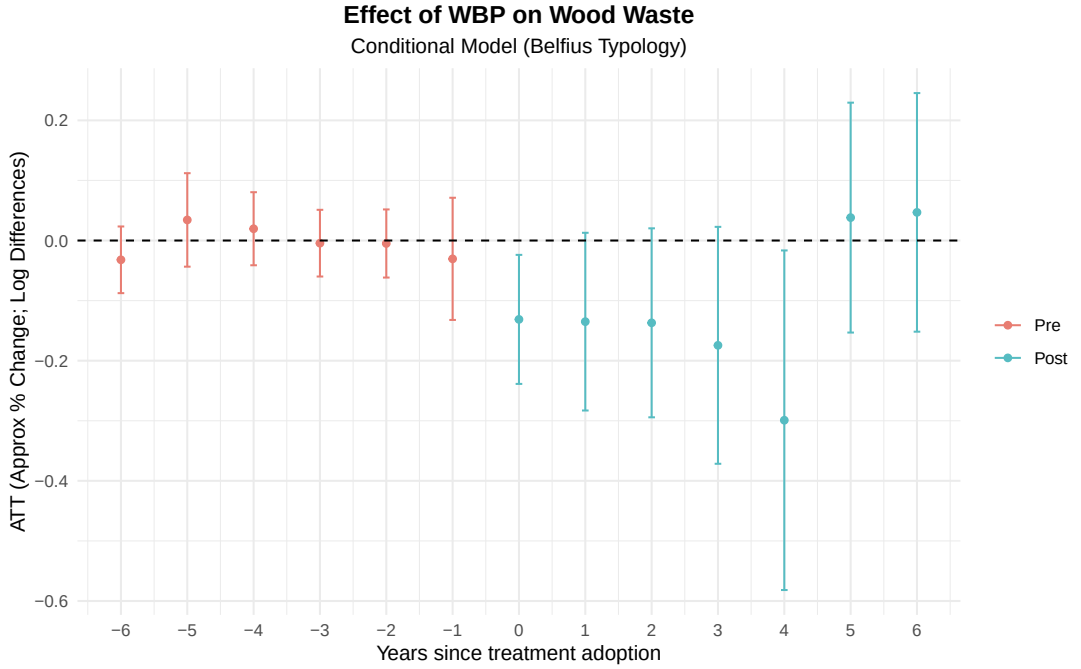


Figure B.6: Impact of Weight-Based Pricing on Wood Waste

Table B.17: Exact Percentage Change in Wood Waste

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	-3.16%	-8.38%	2.37%	
-5	3.49%	-4.26%	11.86%	
-4	1.98%	-4.03%	8.37%	
-3	-0.44%	-5.82%	5.24%	
-2	-0.49%	-5.98%	5.31%	
-1	-3.00%	-12.38%	7.38%	
0	-12.30%	-21.23%	-2.36%	*
1	-12.63%	-24.64%	1.30%	
2	-12.80%	-25.49%	2.05%	
3	-16.01%	-31.04%	2.30%	
4	-25.85%	-44.11%	-1.64%	*
5	3.89%	-14.20%	25.79%	
6	4.80%	-14.08%	27.82%	
Overall	**-10.70%**	**-19.12%**	**-1.39%**	*

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Small Hazardous Waste

Table B.18: Group-Time Average Treatment Effects ($ATT(g,t)$) on Small Hazardous Waste

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.0019	0.0305	-0.0829	0.0791	
2018	2019	0.0356	0.0156	-0.0059	0.0771	
2018	2020	0.1010	0.0447	-0.0176	0.2196	
2018	2021	0.1177	0.0333	0.0292	0.2062	*
2018	2022	0.1680	0.0456	0.0469	0.2891	*
2018	2023	0.1547	0.0277	0.0812	0.2282	*
2018	2024	0.1728	0.0670	-0.0052	0.3507	
2020	2018	-0.0536	0.0777	-0.2601	0.1530	
2020	2019	-0.0182	0.0294	-0.0964	0.0599	
2020	2020	0.0684	0.0378	-0.0320	0.1689	

Table B.18 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	0.0147	0.0450	-0.1048	0.1342	
2020	2022	0.0884	0.0465	-0.0351	0.2119	
2020	2023	-0.0022	0.0598	-0.1610	0.1566	
2020	2024	0.0000	0.0503	-0.1337	0.1338	
2021	2018	0.0047	0.0150	-0.0352	0.0446	
2021	2019	0.0345	0.0194	-0.0170	0.0860	
2021	2020	0.0413	0.0187	-0.0084	0.0910	
2021	2021	-0.0021	0.0174	-0.0483	0.0442	
2021	2022	0.0277	0.0183	-0.0209	0.0764	
2021	2023	0.0235	0.0206	-0.0314	0.0783	
2021	2024	0.0030	0.0246	-0.0624	0.0683	
2022	2018	0.0102	0.0232	-0.0513	0.0717	
2022	2019	0.0065	0.0263	-0.0635	0.0764	
2022	2020	-0.0865	0.0710	-0.2752	0.1022	
2022	2021	-0.0158	0.0597	-0.1745	0.1429	
2022	2022	0.0587	0.0472	-0.0667	0.1840	
2022	2023	0.0828	0.0430	-0.0314	0.1971	
2022	2024	0.0474	0.0441	-0.0697	0.1645	
2024	2018	-0.0081	0.0629	-0.1753	0.1592	
2024	2019	0.0331	0.0410	-0.0758	0.1420	
2024	2020	-0.0367	0.0313	-0.1199	0.0464	
2024	2021	0.0061	0.0467	-0.1181	0.1303	
2024	2022	-0.0095	0.0229	-0.0704	0.0514	
2024	2023	-0.0594	0.0157	-0.1011	-0.0176	*
2024	2024	0.0573	0.0545	-0.0876	0.2023	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.19: Aggregated Dynamic Effects on Small Hazardous Waste (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	-0.0081	0.0327	-0.0906	0.0744	
-5	0.0331	0.0409	-0.0700	0.1362	
-4	-0.0016	0.0203	-0.0526	0.0495	
-3	0.0052	0.0122	-0.0256	0.0359	
-2	-0.0067	0.0228	-0.0643	0.0509	
-1	0.0136	0.0167	-0.0284	0.0556	
0	0.0252	0.0143	-0.0107	0.0611	
1	0.0336	0.0164	-0.0077	0.0749	
2	0.0461	0.0181	0.0005	0.0917	*
3	0.0085	0.0220	-0.0470	0.0640	
4	0.0306	0.0469	-0.0876	0.1487	
5	0.1547	0.0295	0.0802	0.2292	*
6	0.1728	0.0681	0.0010	0.3445	*
Overall	**0.0674**	**0.0200**	**0.0281**	**0.1066**	*****

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

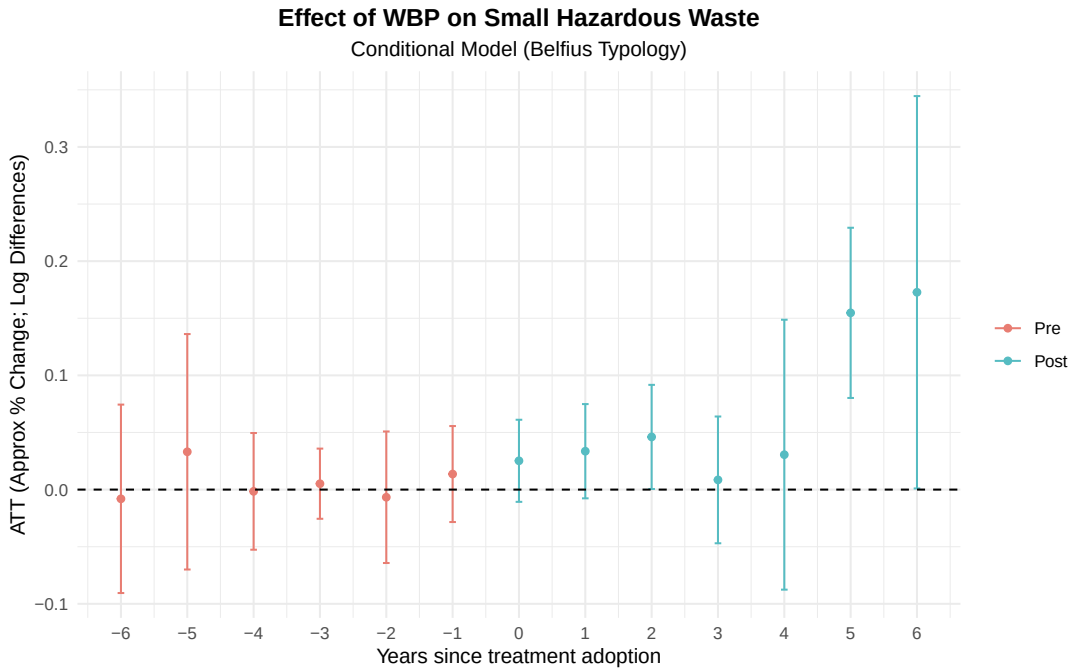


Figure B.7: Impact of Weight-Based Pricing on Small Hazardous Waste

Table B.20: Exact Percentage Change in Small Hazardous Waste

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	-0.80%	-8.66%	7.73%	
-5	3.37%	-6.76%	14.59%	
-4	-0.16%	-5.13%	5.08%	
-3	0.52%	-2.52%	3.65%	
-2	-0.67%	-6.22%	5.22%	
-1	1.37%	-2.80%	5.72%	
0	2.55%	-1.07%	6.31%	
1	3.42%	-0.76%	7.77%	
2	4.72%	0.05%	9.60%	*
3	0.85%	-4.59%	6.61%	
4	3.10%	-8.39%	16.03%	
5	16.73%	8.35%	25.76%	*
6	18.86%	0.10%	41.13%	*
Overall	**6.97%**	**2.85%**	**11.25%**	*

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Hard Plastics

Table B.21: Group-Time Average Treatment Effects ($ATT(g,t)$) on Hard Plastics

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	0.1511	0.1430	-0.2886	0.5909	
2018	2019	0.0738	0.2041	-0.5536	0.7011	
2018	2020	0.1115	0.2362	-0.6147	0.8377	
2018	2021	-0.0492	0.0620	-0.2398	0.1414	
2018	2022	-0.0660	0.0599	-0.2500	0.1180	
2018	2023	-0.0794	0.0613	-0.2679	0.1091	
2018	2024	-0.1254	0.0955	-0.4190	0.1682	
2020	2018	-0.0161	0.0445	-0.1530	0.1209	
2020	2019	0.0269	0.0370	-0.0870	0.1408	
2020	2020	0.0091	0.0545	-0.1585	0.1766	

Table B.21 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	0.0496	0.1271	-0.3412	0.4404	
2020	2022	0.1857	0.1644	-0.3197	0.6910	
2020	2023	0.2698	0.1879	-0.3080	0.8476	
2020	2024	0.2388	0.2001	-0.3762	0.8539	
2021	2018	-0.0215	0.0424	-0.1518	0.1088	
2021	2019	-0.0804	0.0345	-0.1866	0.0258	
2021	2020	-0.1095	0.0292	-0.1993	-0.0197	*
2021	2021	0.1978	0.0422	0.0680	0.3275	*
2021	2022	0.3256	0.0699	0.1108	0.5405	*
2021	2023	0.3195	0.0662	0.1158	0.5232	*
2021	2024	0.2680	0.0661	0.0647	0.4713	*
2022	2018	0.1869	0.0752	-0.0441	0.4180	
2022	2019	-0.0989	0.1354	-0.5152	0.3173	
2022	2020	-0.0267	0.0365	-0.1389	0.0855	
2022	2021	-0.1181	0.1440	-0.5608	0.3246	
2022	2022	-0.1542	0.1310	-0.5570	0.2487	
2022	2023	-0.1603	0.1456	-0.6079	0.2872	
2022	2024	-0.1758	0.1259	-0.5630	0.2113	
2024	2018	0.0075	0.1115	-0.3354	0.3505	
2024	2019	-0.0230	0.0415	-0.1507	0.1047	
2024	2020	0.0624	0.0600	-0.1220	0.2467	
2024	2021	-0.1830	0.2365	-0.9101	0.5440	
2024	2022	-0.0668	0.1099	-0.4047	0.2711	
2024	2023	-0.0555	0.0212	-0.1207	0.0098	
2024	2024	-0.0597	0.0352	-0.1679	0.0484	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.22: Aggregated Dynamic Effects on Hard Plastics (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0075	0.1097	-0.2748	0.2899	
-5	-0.0230	0.0408	-0.1279	0.0819	
-4	0.1558	0.0639	-0.0087	0.3202	
-3	-0.0478	0.0486	-0.1728	0.0773	
-2	-0.0566	0.0266	-0.1252	0.0120	
-1	-0.0766	0.0291	-0.1516	-0.0016	*
0	0.0900	0.0394	-0.0115	0.1916	
1	0.1743	0.0665	0.0031	0.3454	*
2	0.2018	0.0714	0.0179	0.3856	*
3	0.2493	0.0755	0.0548	0.4438	*
4	0.1834	0.1745	-0.2659	0.6327	
5	-0.0794	0.0581	-0.2291	0.0703	
6	-0.1254	0.0888	-0.3541	0.1033	
Overall	**0.0991**	**0.0566**	**-0.0117**	**0.2100**	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

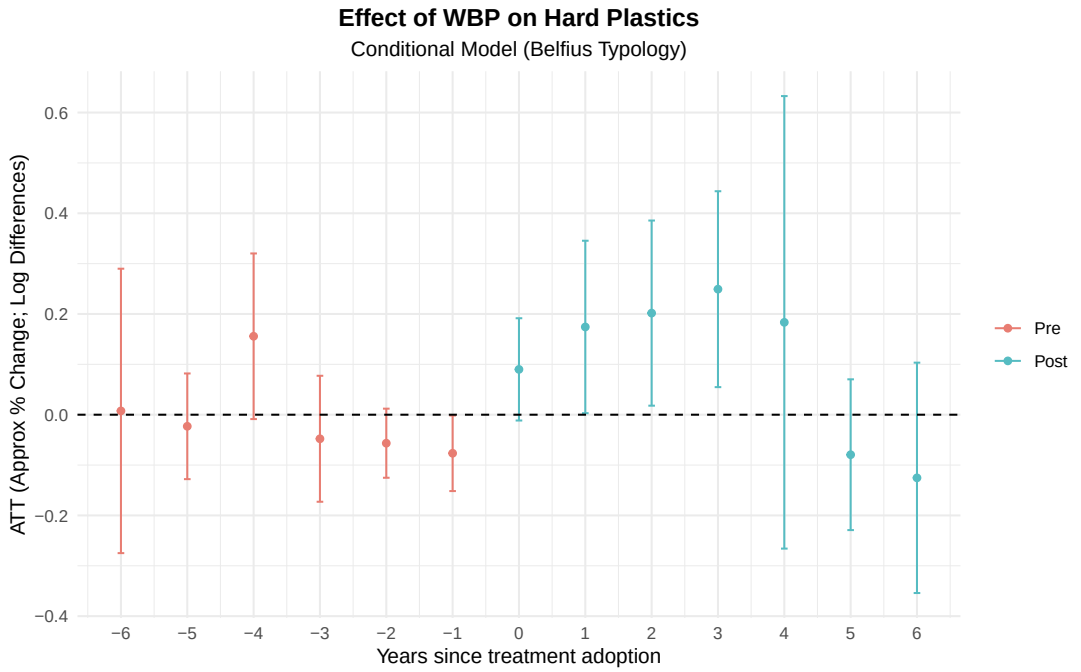


Figure B.8: Impact of Weight-Based Pricing on Hard Plastics

Table B.23: Exact Percentage Change in Hard Plastics

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	0.76%	-24.03%	33.63%	
-5	-2.28%	-12.01%	8.54%	
-4	16.86%	-0.86%	37.74%	
-3	-4.66%	-15.87%	8.04%	
-2	-5.50%	-11.77%	1.21%	
-1	-7.37%	-14.07%	-0.16%	*
0	9.42%	-1.15%	21.12%	
1	19.04%	0.31%	41.26%	*
2	22.35%	1.81%	47.05%	*
3	28.31%	5.63%	55.86%	*
4	20.13%	-23.35%	88.27%	
5	-7.64%	-20.48%	7.28%	
6	-11.78%	-29.82%	10.89%	
Overall	**10.42%**	**-1.16%**	**23.36%**	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Scrap Metal

Table B.24: Group-Time Average Treatment Effects ($ATT(g,t)$) on Scrap Metal

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	0.0121	0.0164	-0.0323	0.0564	
2018	2019	0.0085	0.0201	-0.0460	0.0630	
2018	2020	0.1162	0.0501	-0.0197	0.2521	
2018	2021	0.0492	0.0394	-0.0576	0.1560	
2018	2022	0.1333	0.0415	0.0210	0.2457	*
2018	2023	0.0747	0.0338	-0.0169	0.1663	
2018	2024	0.1854	0.0340	0.0933	0.2776	*
2020	2018	0.0382	0.0182	-0.0110	0.0874	
2020	2019	-0.0049	0.0223	-0.0652	0.0555	
2020	2020	0.0262	0.0359	-0.0712	0.1236	

Table B.24 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	0.0122	0.0892	-0.2295	0.2539	
2020	2022	-0.0302	0.0831	-0.2554	0.1950	
2020	2023	-0.0468	0.1079	-0.3392	0.2456	
2020	2024	-0.0537	0.1073	-0.3445	0.2370	
2021	2018	0.0136	0.0132	-0.0222	0.0494	
2021	2019	0.0178	0.0207	-0.0384	0.0739	
2021	2020	-0.0115	0.0203	-0.0666	0.0437	
2021	2021	-0.0645	0.0244	-0.1306	0.0015	
2021	2022	-0.0388	0.0304	-0.1211	0.0435	
2021	2023	-0.0782	0.0327	-0.1669	0.0105	
2021	2024	-0.0607	0.0310	-0.1448	0.0233	
2022	2018	0.0097	0.0190	-0.0419	0.0613	
2022	2019	-0.0040	0.0460	-0.1287	0.1207	
2022	2020	-0.0812	0.0626	-0.2509	0.0885	
2022	2021	-0.1000	0.0809	-0.3191	0.1192	
2022	2022	0.0423	0.0685	-0.1433	0.2278	
2022	2023	0.0395	0.0485	-0.0919	0.1710	
2022	2024	0.0270	0.0683	-0.1582	0.2122	
2024	2018	-0.0273	0.0388	-0.1324	0.0777	
2024	2019	0.0115	0.0163	-0.0327	0.0556	
2024	2020	0.1144	0.0251	0.0463	0.1825	*
2024	2021	-0.0276	0.1024	-0.3052	0.2499	
2024	2022	-0.0140	0.0200	-0.0681	0.0401	
2024	2023	-0.0089	0.0299	-0.0898	0.0721	
2024	2024	0.0569	0.0228	-0.0048	0.1186	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.25: Aggregated Dynamic Effects on Scrap Metal (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	-0.0273	0.0306	-0.1058	0.0511	
-5	0.0115	0.0170	-0.0321	0.0551	
-4	0.0359	0.0242	-0.0262	0.0980	
-3	0.0074	0.0130	-0.0258	0.0405	
-2	0.0056	0.0164	-0.0365	0.0477	
-1	-0.0234	0.0158	-0.0639	0.0170	
0	-0.0193	0.0187	-0.0673	0.0286	
1	-0.0126	0.0279	-0.0841	0.0590	
2	-0.0410	0.0314	-0.1215	0.0395	
3	-0.0503	0.0347	-0.1390	0.0385	
4	-0.0197	0.0963	-0.2663	0.2269	
5	0.0747	0.0342	-0.0128	0.1622	
6	0.1854	0.0314	0.1051	0.2658	*
Overall	**0.0168**	**0.0248**	**-0.0318**	**0.0653**	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

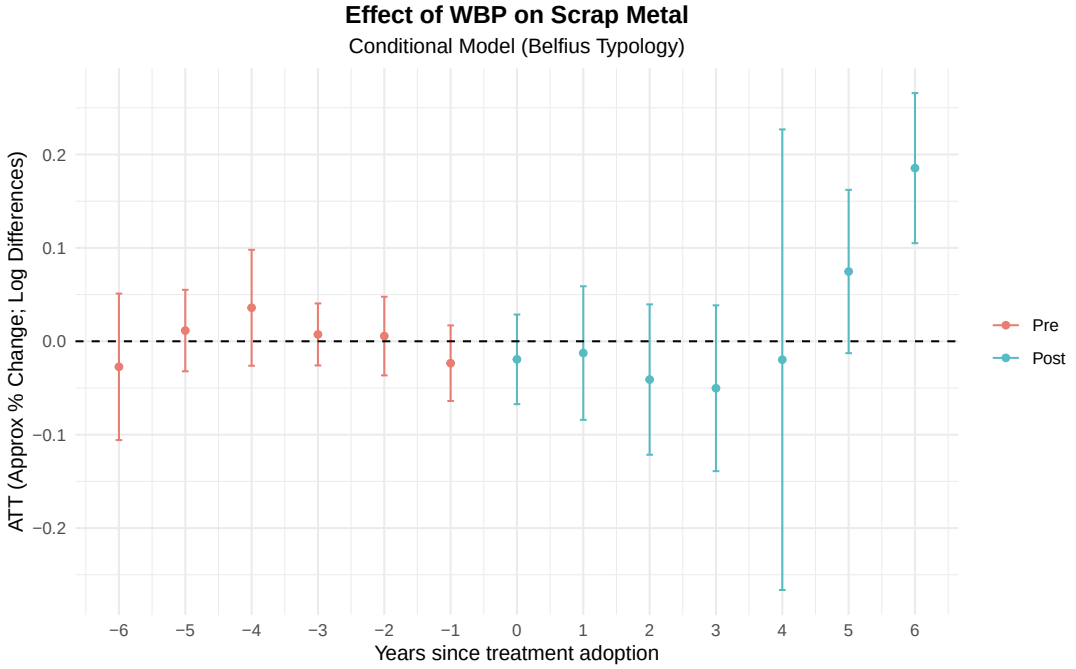


Figure B.9: Impact of Weight-Based Pricing on Scrap Metal

Table B.26: Exact Percentage Change in Scrap Metal

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	-2.70%	-10.04%	5.24%	
-5	1.16%	-3.16%	5.66%	
-4	3.66%	-2.58%	10.29%	
-3	0.74%	-2.55%	4.14%	
-2	0.56%	-3.58%	4.89%	
-1	-2.32%	-6.19%	1.72%	
0	-1.91%	-6.51%	2.91%	
1	-1.25%	-8.07%	6.07%	
2	-4.01%	-11.44%	4.03%	
3	-4.90%	-12.98%	3.93%	
4	-1.95%	-23.38%	25.47%	
5	7.76%	-1.27%	17.61%	
6	20.37%	11.08%	30.44%	*
Overall	**1.69%**	**-3.13%**	**6.75%**	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Paper and Cardboard

Table B.27: Group-Time Average Treatment Effects ($ATT(g,t)$) on Paper and Cardboard

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	0.0129	0.0097	-0.0132	0.0390	
2018	2019	-0.0584	0.0267	-0.1303	0.0135	
2018	2020	-0.0755	0.0235	-0.1387	-0.0124	*
2018	2021	-0.0876	0.0197	-0.1405	-0.0346	*
2018	2022	-0.0745	0.0183	-0.1238	-0.0253	*
2018	2023	-0.0119	0.0149	-0.0519	0.0282	
2018	2024	-0.0530	0.0108	-0.0819	-0.0240	*
2020	2018	-0.0210	0.0093	-0.0461	0.0041	
2020	2019	0.0187	0.0091	-0.0057	0.0431	
2020	2020	0.0136	0.0171	-0.0323	0.0596	

Table B.27 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	-0.0297	0.0209	-0.0860	0.0267	
2020	2022	-0.0098	0.0259	-0.0796	0.0600	
2020	2023	-0.0146	0.0199	-0.0683	0.0390	
2020	2024	-0.0105	0.0198	-0.0637	0.0426	
2021	2018	0.0118	0.0143	-0.0267	0.0503	
2021	2019	-0.0243	0.0117	-0.0558	0.0072	
2021	2020	0.0204	0.0121	-0.0121	0.0529	
2021	2021	-0.0298	0.0174	-0.0765	0.0170	
2021	2022	-0.0002	0.0113	-0.0307	0.0304	
2021	2023	-0.0008	0.0100	-0.0278	0.0261	
2021	2024	-0.0116	0.0131	-0.0469	0.0236	
2022	2018	-0.0170	0.0168	-0.0623	0.0282	
2022	2019	-0.0150	0.0185	-0.0647	0.0348	
2022	2020	-0.0035	0.0071	-0.0226	0.0155	
2022	2021	-0.0862	0.0537	-0.2307	0.0584	
2022	2022	-0.0192	0.0566	-0.1716	0.1331	
2022	2023	0.0094	0.0502	-0.1258	0.1445	
2022	2024	0.0120	0.0459	-0.1115	0.1354	
2024	2018	0.0043	0.0057	-0.0111	0.0197	
2024	2019	-0.0245	0.0057	-0.0397	-0.0093	*
2024	2020	0.0274	0.0164	-0.0168	0.0715	
2024	2021	-0.0075	0.0263	-0.0783	0.0633	
2024	2022	0.0353	0.0217	-0.0231	0.0936	
2024	2023	-0.0157	0.0051	-0.0293	-0.0021	*
2024	2024	0.0009	0.0124	-0.0325	0.0343	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.28: Aggregated Dynamic Effects on Paper and Cardboard (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0043	0.0059	-0.0111	0.0197	
-5	-0.0245	0.0058	-0.0395	-0.0096	*
-4	-0.0059	0.0147	-0.0441	0.0322	
-3	0.0052	0.0104	-0.0218	0.0321	
-2	-0.0173	0.0073	-0.0363	0.0017	
-1	0.0018	0.0123	-0.0303	0.0338	
0	-0.0151	0.0114	-0.0449	0.0146	
1	-0.0085	0.0117	-0.0388	0.0219	
2	-0.0048	0.0111	-0.0335	0.0240	
3	-0.0171	0.0115	-0.0469	0.0127	
4	-0.0222	0.0187	-0.0707	0.0263	
5	-0.0119	0.0143	-0.0492	0.0254	
6	-0.0530	0.0105	-0.0802	-0.0258	*
Overall	**-0.0189**	**0.0075**	**-0.0336**	**-0.0042**	*

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

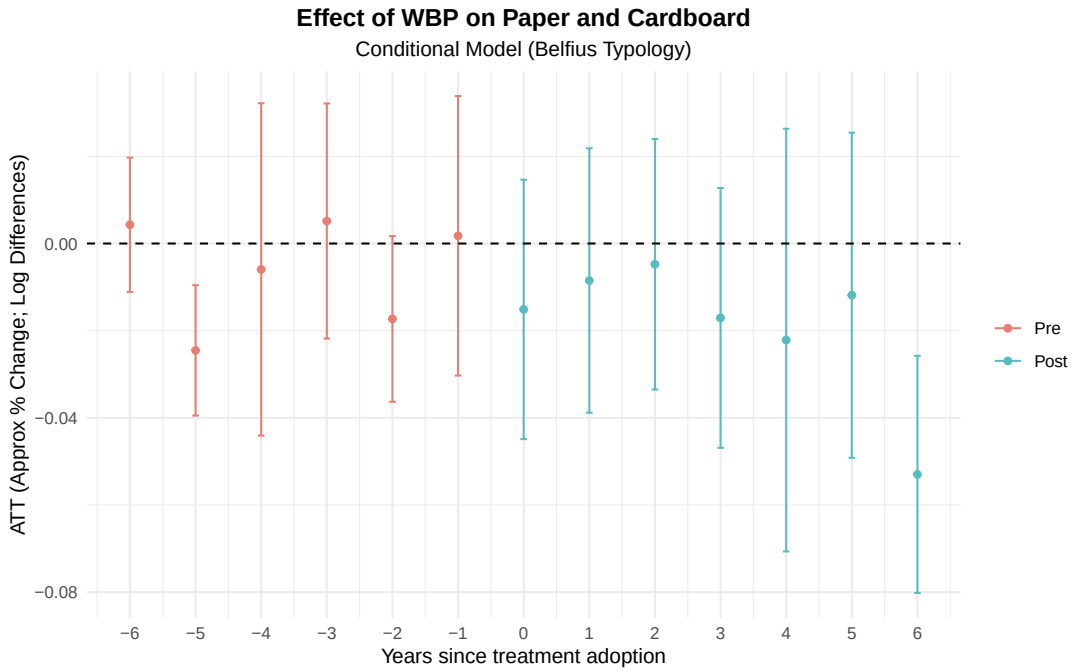


Figure B.10: Impact of Weight-Based Pricing on Paper and Cardboard

Table B.29: Exact Percentage Change in Paper and Cardboard

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	0.43%	-1.10%	1.99%	
-5	-2.42%	-3.87%	-0.95%	*
-4	-0.59%	-4.31%	3.27%	
-3	0.52%	-2.16%	3.27%	
-2	-1.72%	-3.57%	0.17%	
-1	0.18%	-2.98%	3.44%	
0	-1.50%	-4.39%	1.47%	
1	-0.85%	-3.81%	2.21%	
2	-0.47%	-3.29%	2.43%	
3	-1.69%	-4.58%	1.28%	
4	-2.19%	-6.82%	2.67%	
5	-1.18%	-4.80%	2.58%	
6	-5.16%	-7.71%	-2.54%	*
Overall	**-1.87%**	**-3.30%**	**-0.42%**	*

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Vegetable and Animal Oils/Fats

Table B.30: Group-Time Average Treatment Effects ($ATT(g,t)$) on Vegetable and Animal Oils/Fats (Conditional Model)

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.0347	0.0342	-0.1274	0.0580	
2018	2019	-0.0306	0.0188	-0.0816	0.0203	
2018	2020	0.1099	0.0681	-0.0747	0.2945	
2018	2021	0.1181	0.0658	-0.0602	0.2963	
2018	2022	0.1320	0.0632	-0.0392	0.3031	
2018	2023	0.1522	0.0743	-0.0490	0.3534	
2018	2024	0.0205	0.0420	-0.0931	0.1342	
2020	2018	-0.0064	0.0260	-0.0768	0.0641	
2020	2019	0.0197	0.0325	-0.0684	0.1079	

Table B.30 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2020	-0.0236	0.0573	-0.1787	0.1315	
2020	2021	-0.0683	0.0488	-0.2005	0.0640	
2020	2022	-0.0882	0.0644	-0.2627	0.0863	
2020	2023	0.0379	0.0788	-0.1755	0.2512	
2020	2024	-0.0754	0.0461	-0.2003	0.0494	
2021	2018	-0.0115	0.0148	-0.0515	0.0285	
2021	2019	0.0200	0.0155	-0.0220	0.0620	
2021	2020	-0.1186	0.0226	-0.1798	-0.0574	*
2021	2021	0.0519	0.0184	0.0020	0.1018	*
2021	2022	0.0771	0.0316	-0.0085	0.1628	
2021	2023	0.1131	0.0314	0.0281	0.1980	*
2021	2024	0.1260	0.0210	0.0691	0.1829	*
2022	2018	0.0023	0.0378	-0.1002	0.1047	
2022	2019	-0.0074	0.0285	-0.0846	0.0698	
2022	2020	-0.0274	0.0443	-0.1474	0.0925	
2022	2021	0.0212	0.0911	-0.2255	0.2679	
2022	2022	0.0630	0.0854	-0.1682	0.2943	
2022	2023	0.0713	0.0764	-0.1357	0.2783	
2022	2024	0.0218	0.0549	-0.1270	0.1705	
2024	2018	0.0123	0.0257	-0.0571	0.0818	
2024	2019	-0.0116	0.0347	-0.1056	0.0824	
2024	2020	0.0354	0.1123	-0.2689	0.3396	
2024	2021	-0.0038	0.0181	-0.0529	0.0454	
2024	2022	0.1937	0.1628	-0.2472	0.6346	
2024	2023	0.0098	0.0384	-0.0941	0.1138	
2024	2024	-0.1651	0.0354	-0.2610	-0.0692	*

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.31: Aggregated Dynamic Effects on Vegetable and Animal Oils/Fats (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0123	0.0267	-0.0588	0.0835	
-5	-0.0116	0.0364	-0.1088	0.0855	
-4	0.0106	0.0388	-0.0929	0.1140	
-3	-0.0101	0.0113	-0.0402	0.0199	
-2	0.0155	0.0159	-0.0269	0.0580	
-1	-0.0586	0.0227	-0.1190	0.0019	
0	0.0221	0.0217	-0.0357	0.0800	
1	0.0372	0.0267	-0.0341	0.1085	
2	0.0524	0.0273	-0.0205	0.1253	
3	0.1015	0.0264	0.0310	0.1720	*
4	-0.0377	0.0474	-0.1642	0.0888	
5	0.1522	0.0806	-0.0626	0.3670	
6	0.0205	0.0586	-0.1358	0.1768	
Overall	**0.0498**	**0.0192**	**0.0121**	**0.0874**	*

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

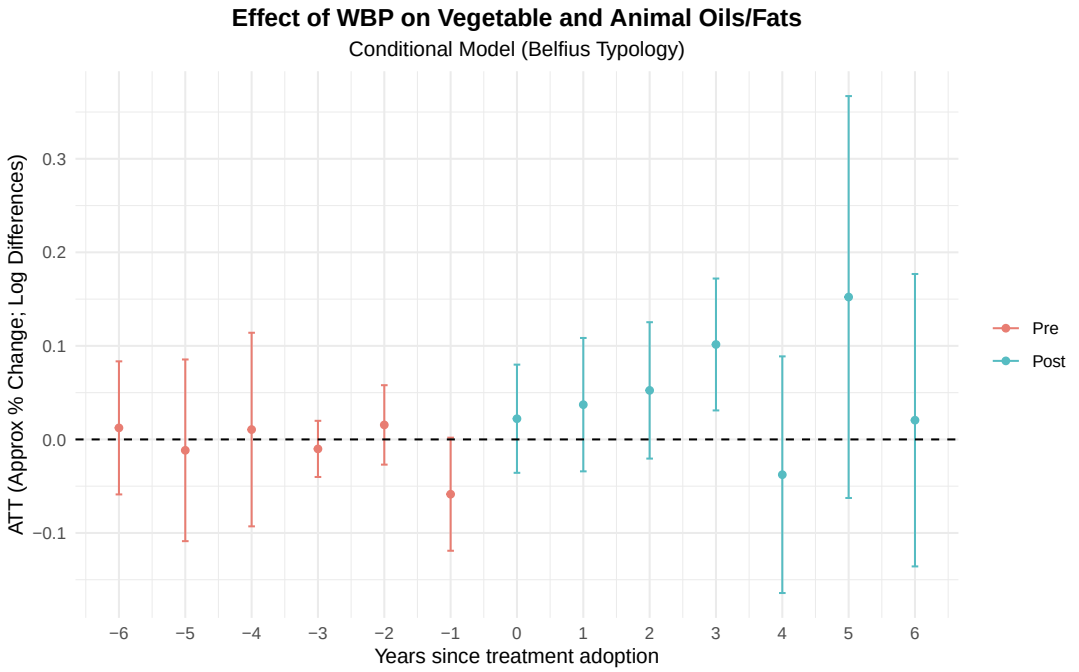


Figure B.11: Impact of Weight-Based Pricing on Vegetable and Animal Oils/Fats

Table B.32: Exact Percentage Change in Vegetable and Animal Oils/Fats

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	1.24%	-5.71%	8.71%	
-5	-1.16%	-10.31%	8.92%	
-4	1.06%	-8.87%	12.08%	
-3	-1.01%	-3.94%	2.01%	
-2	1.56%	-2.66%	5.97%	
-1	-5.69%	-11.22%	0.19%	
0	2.24%	-3.51%	8.32%	
1	3.79%	-3.35%	11.46%	
2	5.38%	-2.03%	13.35%	
3	10.68%	3.15%	18.77%	*
4	-3.70%	-15.14%	9.28%	
5	16.44%	-6.07%	44.35%	
6	2.08%	-12.69%	19.35%	
Overall	**5.10%**	**1.21%**	**9.14%**	*

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

PMC

Table B.33: Group-Time Average Treatment Effects ($ATT(g,t)$) on PMC

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	0.0543	0.0221	-0.0029	0.1116	
2018	2019	0.0511	0.1412	-0.3149	0.4172	
2018	2020	0.0989	0.2362	-0.5136	0.7113	
2018	2021	0.1844	0.1001	-0.0751	0.4439	
2018	2022	0.1520	0.0448	0.0359	0.2682	*
2018	2023	0.1333	0.0653	-0.0361	0.3027	
2018	2024	0.0712	0.0139	0.0352	0.1071	*
2020	2018	0.0000	0.0103	-0.0268	0.0268	
2020	2019	0.1180	0.0600	-0.0376	0.2737	
2020	2020	0.1426	0.0601	-0.0131	0.2983	

Table B.33 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	0.0555	0.0340	-0.0327	0.1437	
2020	2022	-0.0039	0.0422	-0.1135	0.1056	
2020	2023	-0.0104	0.0437	-0.1237	0.1029	
2020	2024	-0.0204	0.0506	-0.1515	0.1107	
2021	2018	-0.0092	0.0125	-0.0417	0.0233	
2021	2019	0.0688	0.0274	-0.0023	0.1398	
2021	2020	0.0483	0.0221	-0.0091	0.1058	
2021	2021	-0.0684	0.0367	-0.1636	0.0269	
2021	2022	-0.0510	0.0492	-0.1786	0.0766	
2021	2023	-0.0572	0.0488	-0.1836	0.0693	
2021	2024	-0.0951	0.0512	-0.2278	0.0375	
2022	2018	0.0321	0.0233	-0.0282	0.0925	
2022	2019	-0.0348	0.0402	-0.1391	0.0695	
2022	2020	-0.0504	0.0218	-0.1068	0.0060	
2022	2021	0.0444	0.0460	-0.0750	0.1638	
2022	2022	0.0766	0.0372	-0.0200	0.1731	
2022	2023	0.0746	0.0316	-0.0073	0.1566	
2022	2024	0.0715	0.0299	-0.0061	0.1490	
2024	2018	0.0101	0.0225	-0.0482	0.0683	
2024	2019	-0.0666	0.0127	-0.0996	-0.0337	*
2024	2020	-0.0542	0.0164	-0.0967	-0.0117	*
2024	2021	0.1197	0.0654	-0.0499	0.2893	
2024	2022	0.0051	0.0217	-0.0512	0.0615	
2024	2023	0.0150	0.0133	-0.0194	0.0495	
2024	2024	0.0215	0.0101	-0.0047	0.0477	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.34: Aggregated Dynamic Effects on PMC (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0101	0.0309	-0.0710	0.0911	
-5	-0.0666	0.0135	-0.1022	-0.0311	*
-4	0.0106	0.0230	-0.0499	0.0710	
-3	-0.0057	0.0134	-0.0408	0.0294	
-2	0.0313	0.0175	-0.0147	0.0774	
-1	0.0621	0.0203	0.0088	0.1154	*
0	0.0095	0.0275	-0.0627	0.0817	
1	-0.0018	0.0327	-0.0878	0.0841	
2	-0.0171	0.0315	-0.0998	0.0656	
3	-0.0551	0.0379	-0.1547	0.0445	
4	0.0110	0.0476	-0.1140	0.1359	
5	0.1333	0.0267	0.0633	0.2034	*
6	0.0712	0.0136	0.0355	0.1069	*
Overall	**0.0216**	**0.0243**	**-0.0260**	**0.0692**	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

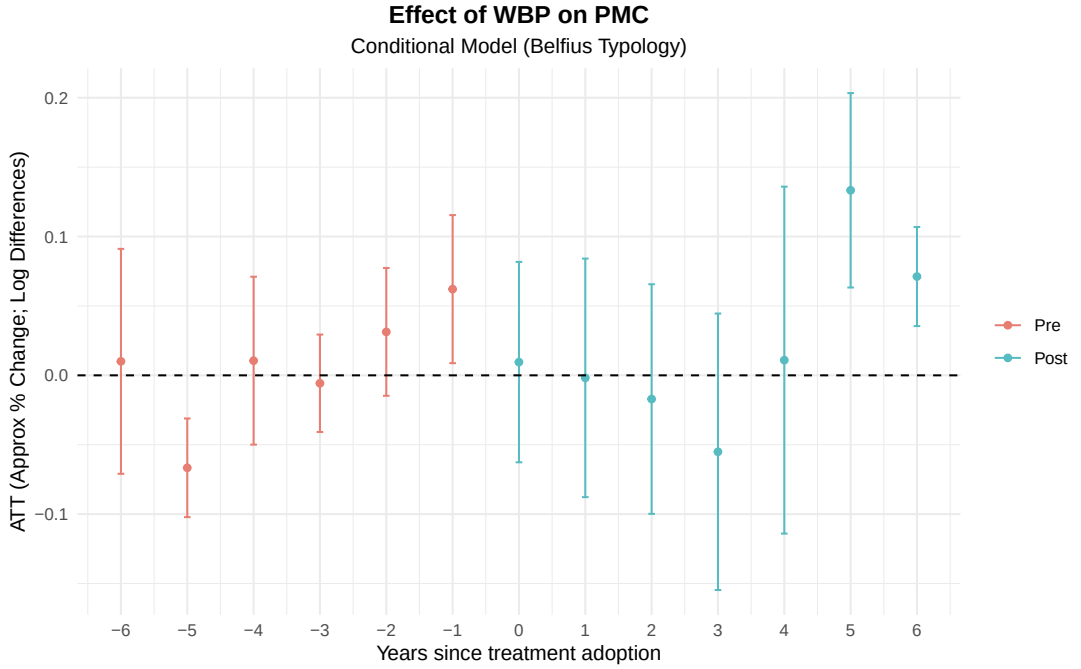


Figure B.12: Impact of Weight-Based Pricing on PMC

Table B.35: Exact Percentage Change in PMC

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	1.01%	-6.85%	9.54%	
-5	-6.45%	-9.71%	-3.06%	*
-4	1.06%	-4.87%	7.36%	
-3	-0.57%	-4.00%	2.98%	
-2	3.18%	-1.46%	8.04%	
-1	6.41%	0.88%	12.24%	*
0	0.96%	-6.07%	8.51%	
1	-0.18%	-8.40%	8.77%	
2	-1.69%	-9.50%	6.78%	
3	-5.36%	-14.33%	4.55%	
4	1.10%	-10.78%	14.56%	
5	14.26%	6.53%	22.55%	*
6	7.38%	3.61%	11.28%	*
Overall	**2.18%**	**-2.57%**	**7.16%**	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Textiles

Table B.36: Group-Time Average Treatment Effects ($ATT(g,t)$) on Textiles

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	0.1564	0.0553	-0.1386	0.4513	
2018	2019	0.2470	0.0479	-0.0085	0.5025	
2018	2020	-0.1634	0.0583	-0.4746	0.1479	
2018	2021	-0.4525	0.0831	-0.8959	-0.0091	*
2018	2022	-0.1945	0.0600	-0.5147	0.1257	
2018	2023	-0.0256	0.0819	-0.4625	0.4112	
2018	2024	-0.1016	0.0780	-0.5180	0.3147	
2020	2018	-0.0259	0.0447	-0.2644	0.2126	
2020	2019	0.1117	0.0403	-0.1032	0.3266	
2020	2020	-0.0908	0.0596	-0.4088	0.2271	

Table B.36 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	-0.1089	0.1888	-1.1165	0.8986	
2020	2022	-0.2491	0.1275	-0.9298	0.4316	
2020	2023	-0.1993	0.1524	-1.0127	0.6140	
2020	2024	-0.1385	0.1292	-0.8282	0.5512	
2021	2018	0.0184	0.0365	-0.1763	0.2132	
2021	2019	0.0787	0.0354	-0.1102	0.2676	
2021	2020	-0.1069	0.0438	-0.3407	0.1270	
2021	2021	-0.0256	0.1162	-0.6460	0.5948	
2021	2022	0.0568	0.0538	-0.2302	0.3438	
2021	2023	0.1441	0.0633	-0.1937	0.4819	
2021	2024	-0.0492	0.0950	-0.5564	0.4579	
2022	2018	0.0050	0.0326	-0.1691	0.1792	
2022	2019	0.0371	0.0265	-0.1045	0.1787	
2022	2020	-0.0715	0.0297	-0.2302	0.0872	
2022	2021	-0.0117	0.0761	-0.4179	0.3946	
2022	2022	-0.0043	0.0806	-0.4344	0.4258	
2022	2023	0.0877	0.1374	-0.6459	0.8212	
2022	2024	0.0833	0.0784	-0.3353	0.5019	
2024	2018	0.0235	0.0330	-0.1525	0.1996	
2024	2019	-0.0368	0.0392	-0.2458	0.1722	
2024	2020	-0.0707	0.0411	-0.2902	0.1488	
2024	2021	0.1720	0.1629	-0.6973	1.0413	
2024	2022	-0.2172	0.1584	-1.0627	0.6283	
2024	2023	-0.1083	0.0410	-0.3269	0.1103	
2024	2024	0.3466	0.0614	0.0187	0.6745	*

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.37: Aggregated Dynamic Effects on Textiles (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0235	0.0338	-0.0587	0.1058	
-5	-0.0368	0.0383	-0.1299	0.0563	
-4	-0.0139	0.0298	-0.0864	0.0586	
-3	0.0324	0.0317	-0.0448	0.1096	
-2	0.0163	0.0291	-0.0546	0.0872	
-1	-0.0419	0.0325	-0.1209	0.0372	
0	-0.0098	0.0675	-0.1740	0.1544	
1	0.0330	0.0526	-0.0951	0.1612	
2	0.0282	0.0557	-0.1073	0.1637	
3	-0.1146	0.0738	-0.2941	0.0649	
4	-0.1487	0.1168	-0.4330	0.1356	
5	-0.0256	0.0957	-0.2585	0.2072	
6	-0.1016	0.0927	-0.3272	0.1240	
Overall	**-0.0484**	**0.0525**	**-0.1514**	**0.0545**	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

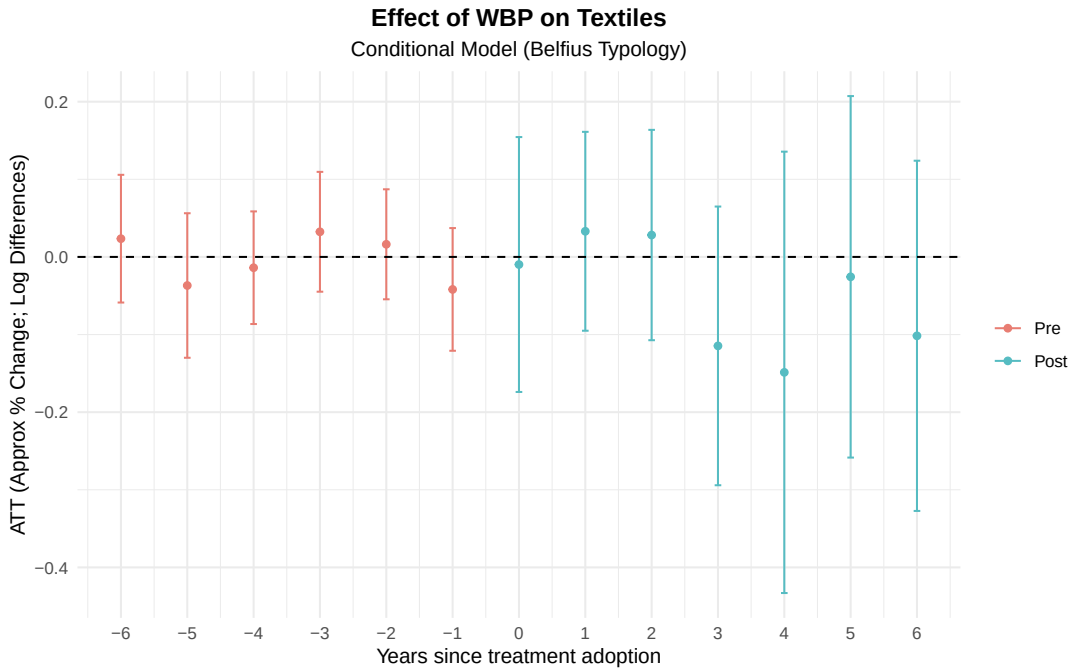


Figure B.13: Impact of Weight-Based Pricing on Textiles

Table B.38: Exact Percentage Change in Textiles

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	2.38%	-5.70%	11.16%	
-5	-3.61%	-12.18%	5.79%	
-4	-1.38%	-8.28%	6.04%	
-3	3.29%	-4.38%	11.58%	
-2	1.64%	-5.31%	9.11%	
-1	-4.10%	-11.39%	3.79%	
0	-0.97%	-15.97%	16.70%	
1	3.36%	-9.07%	17.49%	
2	2.86%	-10.17%	17.79%	
3	-10.83%	-25.48%	6.71%	
4	-13.82%	-35.14%	14.52%	
5	-2.53%	-22.78%	23.03%	
6	-9.66%	-27.91%	13.20%	
Overall	**-4.73%**	**-14.05%**	**5.60%**	

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Packaging Glass

Table B.39: Group-Time Average Treatment Effects ($ATT(g,t)$) on Packaging Glass

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.0240	0.0707	-0.2711	0.2232	
2018	2019	-0.0135	0.0086	-0.0436	0.0167	
2018	2020	-0.0622	0.0142	-0.1120	-0.0125	*
2018	2021	-0.0001	0.0234	-0.0818	0.0815	
2018	2022	-0.0639	0.0165	-0.1217	-0.0062	*
2018	2023	-0.0745	0.0727	-0.3285	0.1796	
2018	2024	-0.0867	0.0368	-0.2153	0.0418	
2020	2018	-0.1186	0.0743	-0.3784	0.1413	
2020	2019	0.0477	0.0332	-0.0683	0.1638	
2020	2020	0.0135	0.0323	-0.0993	0.1263	

Table B.39 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	-0.0072	0.0433	-0.1585	0.1442	
2020	2022	-0.0147	0.0467	-0.1781	0.1486	
2020	2023	-0.0416	0.0417	-0.1872	0.1040	
2020	2024	-0.0363	0.0336	-0.1539	0.0814	
2021	2018	0.0057	0.0107	-0.0317	0.0430	
2021	2019	-0.0231	0.0148	-0.0749	0.0286	
2021	2020	0.0207	0.0150	-0.0317	0.0731	
2021	2021	0.0015	0.0173	-0.0588	0.0618	
2021	2022	0.0043	0.0147	-0.0469	0.0556	
2021	2023	-0.0247	0.0202	-0.0953	0.0458	
2021	2024	-0.0327	0.0261	-0.1239	0.0584	
2022	2018	-0.0293	0.0225	-0.1079	0.0493	
2022	2019	-0.0005	0.0211	-0.0743	0.0733	
2022	2020	-0.0512	0.0185	-0.1160	0.0135	
2022	2021	0.0343	0.0233	-0.0471	0.1157	
2022	2022	-0.0203	0.0302	-0.1261	0.0854	
2022	2023	0.0029	0.0328	-0.1117	0.1174	
2022	2024	-0.0198	0.0403	-0.1608	0.1212	
2024	2018	0.0243	0.0169	-0.0347	0.0833	
2024	2019	-0.0209	0.0126	-0.0648	0.0231	
2024	2020	-0.0556	0.0264	-0.1479	0.0366	
2024	2021	0.0296	0.0264	-0.0628	0.1220	
2024	2022	0.0069	0.0131	-0.0387	0.0526	
2024	2023	-0.0213	0.0124	-0.0645	0.0219	
2024	2024	0.0480	0.0206	-0.0242	0.1202	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.40: Aggregated Dynamic Effects on Packaging Glass (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.0243	0.0155	-0.0149	0.0635	
-5	-0.0209	0.0336	-0.1058	0.0640	
-4	-0.0359	0.0225	-0.0928	0.0211	
-3	0.0060	0.0088	-0.0162	0.0282	
-2	-0.0479	0.0199	-0.0982	0.0024	
-1	0.0269	0.0122	-0.0039	0.0576	
0	0.0020	0.0118	-0.0278	0.0318	
1	0.0005	0.0135	-0.0335	0.0346	
2	-0.0236	0.0164	-0.0650	0.0178	
3	-0.0332	0.0205	-0.0850	0.0187	
4	-0.0413	0.0293	-0.1153	0.0327	
5	-0.0745	0.0432	-0.1839	0.0349	
6	-0.0867	0.0376	-0.1818	0.0083	
Overall	**-0.0367**	**0.0126**	**-0.0613**	**-0.0121**	*

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

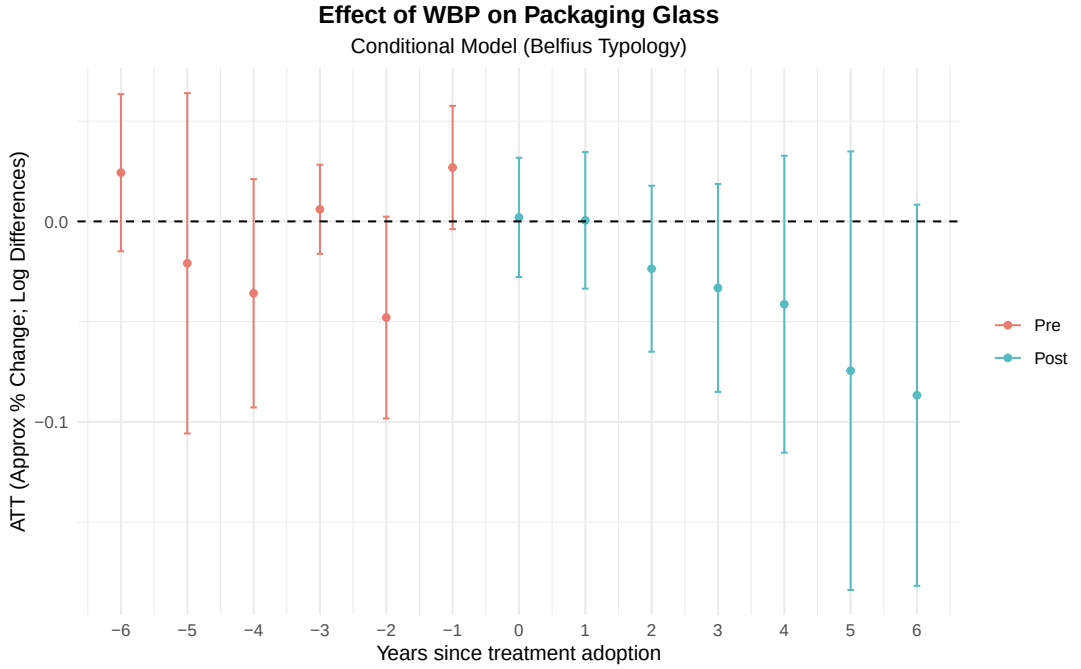


Figure B.14: Impact of Weight-Based Pricing on Packaging Glass

Table B.41: Exact Percentage Change in Packaging Glass

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	2.46%	-1.48%	6.56%	
-5	-2.07%	-10.04%	6.61%	
-4	-3.52%	-8.86%	2.13%	
-3	0.60%	-1.60%	2.86%	
-2	-4.68%	-9.36%	0.24%	
-1	2.72%	-0.39%	5.93%	
0	0.20%	-2.74%	3.23%	
1	0.05%	-3.30%	3.52%	
2	-2.33%	-6.29%	1.79%	
3	-3.26%	-8.15%	1.89%	
4	-4.05%	-10.89%	3.33%	
5	-7.18%	-16.80%	3.56%	
6	-8.31%	-16.62%	0.84%	
Overall	**-3.60%**	**-5.94%**	**-1.20%**	*

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Flat Glass

Table B.42: Group-Time Average Treatment Effects ($ATT(g,t)$) on Flat Glass

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2018	2018	-0.0385	0.0238	-0.1027	0.0256	
2018	2019	-0.0859	0.0411	-0.1969	0.0251	
2018	2020	-0.0243	0.0290	-0.1025	0.0539	
2018	2021	-0.1015	0.0389	-0.2064	0.0034	
2018	2022	-0.1008	0.0334	-0.1908	-0.0108	*
2018	2023	0.0386	0.0291	-0.0399	0.1172	
2018	2024	-0.0555	0.0320	-0.1418	0.0308	
2020	2018	-0.0771	0.0650	-0.2525	0.0984	
2020	2019	0.0901	0.0597	-0.0711	0.2513	
2020	2020	0.0828	0.0450	-0.0387	0.2044	

Table B.42 continued from previous page

Group	Time	ATT(g,t)	SE	Lower 95% Band	Upper 95% Band	Sig.
2020	2021	-0.0266	0.0639	-0.1991	0.1458	
2020	2022	-0.0708	0.0690	-0.2572	0.1155	
2020	2023	-0.0875	0.0780	-0.2979	0.1229	
2020	2024	-0.1301	0.0878	-0.3671	0.1069	
2021	2018	0.0364	0.0332	-0.0532	0.1260	
2021	2019	0.0416	0.0403	-0.0672	0.1504	
2021	2020	-0.0034	0.0305	-0.0859	0.0790	
2021	2021	-0.0912	0.0383	-0.1945	0.0121	
2021	2022	-0.1165	0.0405	-0.2257	-0.0073	*
2021	2023	-0.0496	0.0415	-0.1615	0.0624	
2021	2024	-0.0950	0.0415	-0.2071	0.0172	
2022	2018	-0.0156	0.0665	-0.1950	0.1638	
2022	2019	0.0567	0.1068	-0.2317	0.3452	
2022	2020	-0.0350	0.0715	-0.2279	0.1580	
2022	2021	-0.1046	0.1022	-0.3805	0.1713	
2022	2022	0.0364	0.0816	-0.1838	0.2567	
2022	2023	0.0014	0.0544	-0.1455	0.1482	
2022	2024	-0.0344	0.0626	-0.2034	0.1347	
2024	2018	0.2353	0.3234	-0.6377	1.1084	
2024	2019	-0.0833	0.0535	-0.2278	0.0611	
2024	2020	0.0235	0.0338	-0.0676	0.1146	
2024	2021	0.0216	0.0443	-0.0979	0.1411	
2024	2022	-0.0728	0.1004	-0.3439	0.1982	
2024	2023	0.0302	0.0575	-0.1250	0.1853	
2024	2024	-0.1210	0.1013	-0.3945	0.1525	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Table B.43: Aggregated Dynamic Effects on Flat Glass (Logarithmic Estimates)

Event Time	Estimate	SE	Lower 95% Band	Upper 95% Band	Sig.
-6	0.2353	0.1910	-0.2673	0.7379	
-5	-0.0833	0.0516	-0.2192	0.0525	
-4	-0.0059	0.0545	-0.1492	0.1375	
-3	0.0395	0.0299	-0.0393	0.1182	
-2	-0.0034	0.0285	-0.0784	0.0716	
-1	0.0043	0.0249	-0.0612	0.0699	
0	-0.0332	0.0272	-0.1047	0.0383	
1	-0.0761	0.0278	-0.1492	-0.0029	*
2	-0.0508	0.0288	-0.1267	0.0251	
3	-0.0933	0.0329	-0.1799	-0.0067	*
4	-0.1248	0.0676	-0.3028	0.0532	
5	0.0386	0.0300	-0.0403	0.1176	
6	-0.0555	0.0335	-0.1437	0.0327	

Note: Estimates are expressed in log points. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

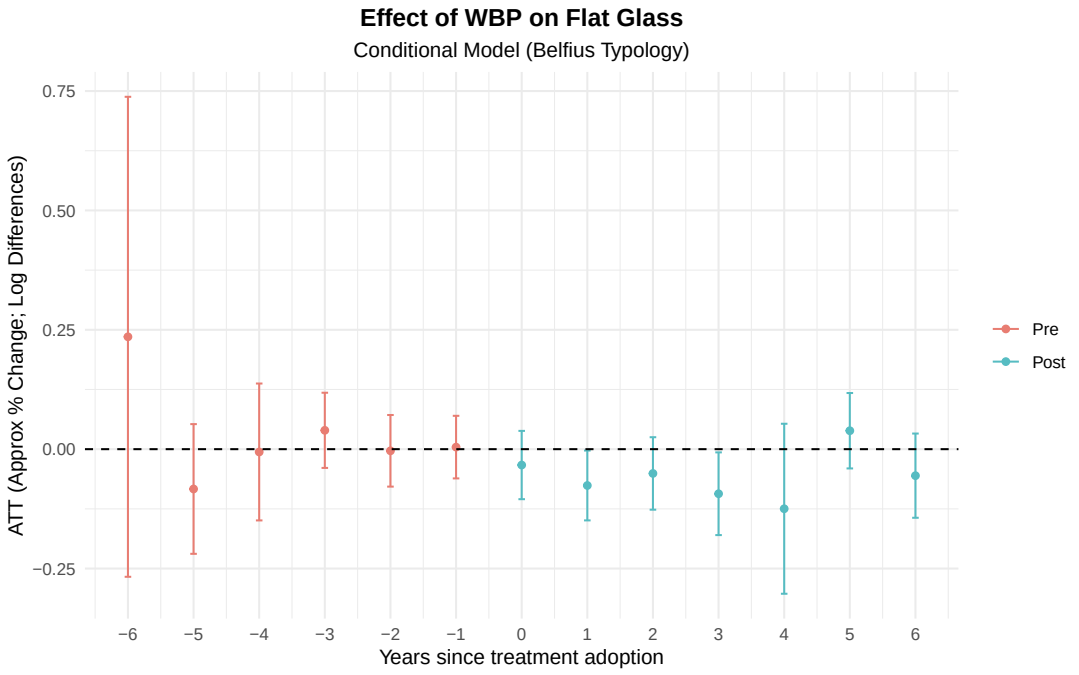


Figure B.15: Impact of Weight-Based Pricing on Flat Glass

Table B.44: Exact Percentage Change in Flat Glass

Event Time	Exact % Change	Lower 95% Band	Upper 95% Band	Significance
-6	26.53%	-23.45%	109.16%	
-5	-8.00%	-19.68%	5.39%	
-4	-0.58%	-13.86%	14.74%	
-3	4.03%	-3.85%	12.55%	
-2	-0.34%	-7.54%	7.42%	
-1	0.43%	-5.94%	7.24%	
0	-3.27%	-9.94%	3.91%	
1	-7.32%	-13.86%	-0.29%	*
2	-4.96%	-11.90%	2.54%	
3	-8.91%	-16.47%	-0.67%	*
4	-11.73%	-26.12%	5.47%	
5	3.94%	-3.95%	12.48%	
6	-5.40%	-13.38%	3.32%	
Overall	**-5.49%**	**-9.93%**	**-0.82%**	*

Note: Estimates represent the exact percentage change relative to the control group. Significance (*) indicates that the 95% simultaneous confidence band does not cover 0.

Full Econometric Output Stratified Log-Linear Staggered DiD: Subsitution Effects on Collected Fractions

Residential Municipalities

Table B.45: Exact Percentage Change for All Fractions (Residential Municipalities)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-6	-1.25	[-4.42, 2.03]	
-5	-0.10	[-2.22, 2.06]	
-4	0.31	[-3.71, 4.51]	
-3	0.39	[-3.82, 4.79]	
-2	0.62	[-2.84, 4.21]	
-1	-0.65	[-4.70, 3.57]	

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Table B.45 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
0	-2.12	[-6.84, 2.83]	
1	-3.95	[-10.49, 3.08]	
2	-3.16	[-10.84, 5.19]	
3	-2.40	[-7.52, 3.01]	
4	2.88	[-8.61, 15.81]	
5	-15.69	[-23.64, -6.92]	*
6	-6.29	[-10.78, -1.58]	*
Overall	**-4.54**	**[-7.99, -0.97]**	*
Panel B: Construction and Demolition Waste			
-6	-0.78	[-9.73, 9.06]	
-5	3.13	[-4.00, 10.80]	
-4	9.01	[-11.26, 33.90]	
-3	4.35	[-4.69, 14.23]	
-2	3.93	[-5.83, 14.70]	
-1	1.36	[-16.56, 23.14]	
0	-6.73	[-17.22, 5.09]	
1	-5.18	[-21.95, 15.20]	
2	-5.22	[-21.15, 13.93]	
3	-10.85	[-27.94, 10.30]	
4	-10.35	[-47.18, 52.16]	
5	38.36	[3.27, 85.39]	*
6	32.13	[-1.37, 77.00]	
Overall	**2.94**	**[-11.99, 20.40]**	
Panel C: Organic Waste (VFG)			
-6	-0.92	[-3.15, 1.37]	
-5	-5.65	[-8.97, -2.21]	*
-4	-0.48	[-6.20, 5.59]	
-3	-1.47	[-5.16, 2.36]	
-2	-2.36	[-5.78, 1.19]	
-1	2.94	[-1.84, 7.94]	
0	-6.68	[-16.09, 3.79]	

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Table B.45 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
1	-13.56	[-26.82, 2.10]	
2	-15.94	[-29.71, 0.52]	
3	-18.61	[-33.19, -0.85]	*
4	-10.64	[-36.61, 25.98]	
5	-9.45	[-24.04, 7.95]	
6	-12.77	[-25.72, 2.44]	
Overall	**-12.60**	**[-22.47, -1.47]**	*****
Panel D: Green Waste			
-6	-2.02	[-6.83, 3.04]	
-5	-2.57	[-11.91, 7.75]	
-4	0.75	[-24.61, 34.66]	
-3	6.47	[-0.57, 14.01]	
-2	11.39	[-7.98, 34.84]	
-1	-5.98	[-23.42, 15.44]	
0	-0.39	[-9.90, 10.13]	
1	-2.03	[-15.64, 13.77]	
2	5.61	[-13.11, 28.36]	
3	1.50	[-19.17, 27.44]	
4	-5.19	[-42.69, 56.84]	
5	-28.27	[-40.61, -13.36]	*
6	33.49	[8.26, 64.59]	*
Overall	**-0.74**	**[-11.91, 11.86]**	
Panel E: Wood Waste			
-6	-2.51	[-10.71, 6.45]	
-5	5.30	[-3.93, 15.41]	
-4	-3.44	[-12.39, 6.43]	
-3	-2.24	[-10.42, 6.68]	
-2	1.40	[-6.73, 10.23]	
-1	-5.39	[-19.25, 10.84]	
0	-16.38	[-24.79, -7.04]	*
1	-19.31	[-27.87, -9.74]	*

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Table B.45 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
2	-20.74	[-30.49, -9.63]	*
3	-25.76	[-36.60, -13.07]	*
4	-31.00	[-56.38, 9.14]	
5	13.34	[-9.91, 42.60]	
6	14.56	[-8.52, 43.45]	
Overall	**-13.73**	**[-24.40, -1.56]**	*
Panel F: Small Hazardous Waste			
-6	-7.06	[-10.88, -3.07]	*
-5	8.44	[3.97, 13.10]	*
-4	2.09	[-9.82, 15.59]	
-3	-2.02	[-6.51, 2.68]	
-2	-1.47	[-10.81, 8.85]	
-1	-0.19	[-5.87, 5.83]	
0	2.99	[-1.55, 7.74]	
1	3.80	[-2.43, 10.44]	
2	2.96	[-3.49, 9.85]	
3	-1.55	[-8.84, 6.33]	
4	-0.02	[-16.52, 19.75]	
5	13.03	[7.43, 18.92]	*
6	9.27	[1.26, 17.92]	*
Overall	**4.25**	**[-0.18, 8.88]**	
Panel G: Hard Plastics			
-6	-4.51	[-18.91, 12.46]	
-5	-6.37	[-15.62, 3.89]	
-4	20.89	[-7.44, 57.89]	
-3	-1.62	[-15.30, 14.27]	
-2	-4.62	[-12.39, 3.83]	
-1	-10.69	[-19.55, -0.85]	*
0	7.55	[-7.87, 25.55]	
1	16.32	[-11.26, 52.46]	
2	24.30	[-7.80, 67.58]	

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Table B.45 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
3	27.43	[-9.10, 78.63]	
4	19.45	[-47.65, 172.53]	
5	-8.03	[-29.34, 19.69]	
6	-19.11	[-36.49, 3.03]	
Overall	**8.42**	**[-9.88, 30.44]**	
Panel H: Scrap Metal			
-6	-6.89	[-10.08, -3.60]	*
-5	0.14	[-5.01, 5.57]	
-4	1.95	[-10.37, 15.97]	
-3	0.22	[-4.86, 5.57]	
-2	3.15	[-3.79, 10.60]	
-1	-3.73	[-10.38, 3.42]	
0	-3.79	[-10.72, 3.68]	
1	-3.96	[-14.19, 7.50]	
2	-9.98	[-18.84, -0.16]	*
3	-12.28	[-22.33, -0.93]	*
4	-14.06	[-38.51, 20.09]	
5	11.65	[4.76, 18.99]	*
6	17.93	[9.12, 27.44]	*
Overall	**-2.70**	**[-9.26, 4.34]**	
Panel I: Paper and Cardboard			
-6	1.05	[-0.20, 2.32]	
-5	-1.89	[-3.65, -0.10]	*
-4	-0.77	[-12.18, 12.11]	
-3	-0.27	[-2.96, 2.49]	
-2	-1.08	[-3.18, 1.06]	
-1	-1.20	[-6.01, 3.86]	
0	-2.63	[-7.55, 2.54]	
1	-2.72	[-7.28, 2.07]	
2	-1.00	[-5.46, 3.66]	
3	-3.38	[-6.69, 0.05]	

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Table B.45 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
4	-3.46	[-7.61, 0.88]	
5	-2.70	[-5.34, 0.01]	
6	-4.33	[-7.10, -1.49]	*
Overall	**-2.89**	**[-4.82, -0.93]**	*****
Panel J: Vegetable and Animal Oils/Fats			
-6	-0.12	[-5.20, 5.24]	
-5	2.95	[-2.16, 8.31]	
-4	-9.36	[-14.63, -3.77]	*
-3	-1.48	[-6.10, 3.37]	
-2	3.24	[-3.97, 10.99]	
-1	-9.93	[-17.57, -1.59]	*
0	2.51	[-6.21, 12.04]	
1	4.89	[-5.30, 16.17]	
2	8.64	[-2.66, 21.25]	
3	12.21	[2.53, 22.80]	*
4	-3.71	[-20.57, 16.73]	
5	30.72	[19.79, 42.65]	*
6	-4.11	[-10.39, 2.61]	
Overall	**6.77**	**[1.72, 12.08]**	*****
Panel K: PMC			
-6	3.84	[2.57, 5.13]	*
-5	-6.73	[-10.31, -3.02]	*
-4	4.04	[-1.97, 10.42]	
-3	-1.83	[-6.12, 2.66]	
-2	6.12	[-0.54, 13.22]	
-1	7.69	[-0.22, 16.22]	
0	-3.23	[-13.01, 7.65]	
1	-6.60	[-17.29, 5.48]	
2	-8.23	[-18.39, 3.19]	
3	-11.38	[-22.72, 1.63]	
4	-2.58	[-17.34, 14.81]	

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Table B.45 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
5	6.21	[3.01, 9.51]	*
6	6.22	[2.98, 9.57]	*
Overall	**-3.00**	**[-8.17, 2.45]**	
Panel L: Residual Waste			
-6	5.39	[3.23, 7.59]	*
-5	1.73	[-3.34, 7.07]	
-4	3.21	[-0.47, 7.03]	
-3	0.22	[-2.05, 2.53]	
-2	0.58	[-2.84, 4.12]	
-1	-2.79	[-7.11, 1.74]	
0	-14.46	[-19.01, -9.65]	*
1	-14.40	[-20.77, -7.51]	*
2	-12.15	[-19.26, -4.42]	*
3	-10.98	[-19.53, -1.53]	*
4	-7.34	[-22.78, 11.19]	
5	14.00	[8.12, 20.20]	*
6	17.38	[9.91, 25.37]	*
Overall	**-4.78**	**[-9.41, 0.09]**	
Panel M: Textiles			
-6	6.31	[0.08, 12.93]	*
-5	0.86	[-4.11, 6.08]	
-4	-1.98	[-13.90, 11.59]	
-3	6.11	[-7.22, 21.37]	
-2	-2.73	[-11.78, 7.25]	
-1	-2.60	[-10.18, 5.63]	
0	3.08	[-19.22, 31.54]	
1	3.24	[-9.93, 18.33]	
2	0.95	[-17.33, 23.28]	
3	-14.24	[-35.09, 13.31]	
4	-22.41	[-49.70, 19.68]	
5	-18.72	[-25.86, -10.90]	*

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Table B.45 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
6	-18.91	[-27.59, -9.19]	*
Overall	**-10.19**	**[-19.48, 0.17]**	
Panel N: Packaging Glass			
-6	7.82	[5.26, 10.44]	*
-5	-4.87	[-6.85, -2.84]	*
-4	-4.01	[-14.19, 7.38]	
-3	-0.20	[-3.63, 3.36]	
-2	-5.15	[-10.16, 0.14]	
-1	0.76	[-3.27, 4.96]	
0	2.63	[-0.98, 6.38]	
1	0.56	[-3.12, 4.38]	
2	-1.69	[-6.01, 2.83]	
3	-2.37	[-8.51, 4.18]	
4	-1.35	[-5.09, 2.54]	
5	-14.72	[-17.40, -11.94]	*
6	-4.31	[-7.88, -0.59]	*
Overall	**-3.18**	**[-5.20, -1.12]**	*
Panel O: Flat Glass			
-6	61.07	[51.18, 71.62]	*
-5	-12.60	[-23.90, 0.39]	
-4	-3.15	[-9.36, 3.49]	
-3	6.24	[-1.79, 14.93]	
-2	-0.16	[-10.22, 11.02]	
-1	0.19	[-9.80, 11.28]	
0	-6.40	[-14.80, 2.82]	
1	-12.85	[-22.16, -2.42]	*
2	-9.40	[-18.86, 1.17]	
3	-14.73	[-23.80, -4.58]	*
4	-19.72	[-38.42, 4.65]	
5	5.32	[-5.42, 17.28]	

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Table B.45 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
6	-4.75	[-15.10, 6.86]	
Overall	**-9.23**	**[-14.81, -3.30]**	*

Municipalities with Economic Activity

Table B.46: Exact Percentage Change for All Fractions (Municipalities with Economic Activity)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-4	18.03	[-8.37, 52.03]	
-3	1.47	[-6.88, 10.58]	
-2	-3.42	[-11.58, 5.48]	
-1	2.38	[-4.09, 9.30]	
0	-6.37	[-13.62, 1.48]	
1	-6.30	[-21.22, 11.44]	
2	-7.58	[-28.90, 20.12]	
3	-1.49	[-8.18, 5.69]	
Overall	**-5.47**	**[-17.34, 8.12]**	
Panel B: Construction and Demolition Waste			
-4	8.45	[-1.80, 19.77]	
-3	5.30	[-2.42, 13.64]	
-2	1.69	[-7.09, 11.30]	
-1	9.93	[-10.65, 35.25]	
0	-2.22	[-11.50, 8.03]	
1	0.73	[-17.92, 23.61]	
2	11.99	[-5.28, 32.41]	
3	18.43	[0.95, 38.93]	*
Overall	**6.91**	**[-5.14, 20.48]**	
Panel C: Organic Waste (VFG)			

Continued on next page

Table B.46 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-4	2.66	[-2.60, 8.21]	
-3	2.59	[-3.44, 9.00]	
-2	-1.89	[-5.56, 1.92]	
-1	4.45	[-1.82, 11.11]	
0	5.18	[-7.77, 19.95]	
1	8.83	[-7.79, 28.45]	
2	6.40	[-13.15, 30.35]	
3	5.66	[-19.73, 39.09]	
Overall	**6.51**	**[-8.26, 23.66]**	
Panel D: Green Waste			
-4	24.84	[12.79, 38.18]	*
-3	-2.02	[-12.43, 9.61]	
-2	-9.35	[-42.49, 42.88]	
-1	15.92	[-12.10, 52.88]	
0	2.21	[-4.33, 9.19]	
1	6.01	[-4.97, 18.25]	
2	9.27	[0.24, 19.10]	*
3	12.51	[-0.70, 27.49]	
Overall	**7.43**	**[0.76, 14.55]**	*
Panel E: Wood Waste			
-4	4.60	[-0.15, 9.57]	
-3	1.25	[-3.21, 5.92]	
-2	1.41	[-8.10, 11.90]	
-1	-8.18	[-29.73, 19.99]	
0	-5.53	[-38.99, 46.27]	
1	0.50	[-47.61, 92.77]	
2	0.24	[-47.11, 89.97]	
3	5.72	[-53.74, 141.62]	
Overall	**0.15**	**[-45.55, 84.20]**	
Panel F: Small Hazardous Waste			

Continued on next page

Table B.46 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-4	-2.02	[-5.45, 1.53]	
-3	5.50	[0.11, 11.18]	*
-2	-0.69	[-7.56, 6.68]	
-1	3.65	[-4.21, 12.16]	
0	-1.42	[-8.35, 6.03]	
1	-1.07	[-7.71, 6.04]	
2	2.27	[-5.35, 10.51]	
3	2.59	[-14.31, 22.81]	
Overall	**0.57**	**[-6.92, 8.67]**	
Panel G: Hard Plastics			
-4	29.28	[-5.41, 76.68]	
-3	-6.23	[-29.12, 24.06]	
-2	-0.86	[-11.26, 10.76]	
-1	-2.85	[-21.81, 20.71]	
0	23.96	[4.97, 46.39]	*
1	35.50	[2.85, 78.52]	*
2	34.37	[4.89, 72.13]	*
3	41.45	[7.51, 86.12]	*
Overall	**33.67**	**[8.85, 64.15]**	*
Panel H: Scrap Metal			
-4	0.31	[-4.02, 4.82]	
-3	1.34	[-2.81, 5.67]	
-2	-3.92	[-8.20, 0.56]	
-1	-2.70	[-7.54, 2.39]	
0	-0.63	[-9.62, 9.24]	
1	5.00	[-9.91, 22.37]	
2	3.54	[-4.89, 12.73]	
3	2.06	[-7.94, 13.13]	
Overall	**2.47**	**[-4.56, 10.02]**	
Panel I: Paper and Cardboard			

Continued on next page

Table B.46 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-4	-0.73	[-2.23, 0.79]	
-3	3.07	[-5.16, 12.01]	
-2	-4.12	[-9.94, 2.08]	
-1	2.54	[-3.19, 8.61]	
0	-2.10	[-6.08, 2.05]	
1	2.35	[-2.27, 7.20]	
2	0.84	[-4.33, 6.28]	
3	-2.42	[-8.23, 3.76]	
Overall	**-0.35**	**[-4.20, 3.65]**	
Panel J: Vegetable and Animal Oils/Fats			
-4	3.38	[-10.10, 18.88]	
-3	-0.45	[-5.40, 4.76]	
-2	-0.34	[-5.78, 5.42]	
-1	2.73	[-8.61, 15.48]	
0	1.82	[-13.82, 20.30]	
1	8.74	[-6.38, 26.29]	
2	6.83	[-7.78, 23.77]	
3	5.37	[-4.33, 16.05]	
Overall	**5.66**	**[-2.81, 14.87]**	
Panel K: PMC			
-4	-2.12	[-6.39, 2.34]	
-3	-1.29	[-8.13, 6.05]	
-2	-6.44	[-13.19, 0.84]	
-1	-0.66	[-6.02, 5.00]	
0	8.94	[-0.18, 18.90]	
1	17.28	[9.02, 26.18]	*
2	16.85	[10.04, 24.08]	*
3	14.41	[7.46, 21.81]	*
Overall	**14.32**	**[8.73, 20.21]**	*
Panel L: Residual Waste			

Continued on next page

Table B.46 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-4	2.82	[0.80, 4.88]	*
-3	0.58	[-1.21, 2.41]	
-2	1.52	[-0.72, 3.81]	
-1	2.21	[-0.90, 5.42]	
0	-16.59	[-24.06, -8.39]	*
1	-22.91	[-33.55, -10.58]	*
2	-21.46	[-33.99, -6.55]	*
3	-25.20	[-38.62, -8.86]	*
Overall	**-21.61**	**[-31.56, -10.20]**	*****
Panel M: Textiles			
-4	3.09	[-9.39, 17.29]	
-3	1.95	[-7.47, 12.32]	
-2	13.12	[-4.54, 34.06]	
-1	-4.82	[-15.88, 7.70]	
0	-10.94	[-43.04, 39.26]	
1	-2.55	[-25.04, 26.68]	
2	5.21	[-22.74, 43.26]	
3	-5.05	[-42.52, 56.85]	
Overall	**-3.51**	**[-33.22, 39.43]**	
Panel N: Packaging Glass			
-4	-1.89	[-10.50, 7.54]	
-3	2.56	[-0.74, 5.98]	
-2	-1.74	[-9.34, 6.50]	
-1	1.00	[-2.55, 4.68]	
0	-0.73	[-5.55, 4.33]	
1	0.43	[-7.75, 9.34]	
2	0.09	[-9.80, 11.05]	
3	-4.29	[-24.17, 20.79]	
Overall	**-1.15**	**[-9.44, 7.91]**	
Panel O: Flat Glass			

Continued on next page

Table B.46 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-4	-1.51	[-36.56, 52.92]	
-3	8.73	[-12.69, 35.42]	
-2	4.25	[-2.74, 11.73]	
-1	-1.10	[-10.79, 9.65]	
0	-0.82	[-15.77, 16.79]	
1	-3.75	[-15.56, 9.71]	
2	-2.99	[-17.05, 13.45]	
3	5.65	[-14.41, 30.40]	
Overall	**-0.54**	**[-12.69, 13.29]**	

Rural Municipalities

Table B.47: Exact Percentage Change for All Fractions (Rural Municipalities)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-4	6.42	[2.53, 10.46]	*
-3	-7.31	[-9.99, -4.54]	*
-2	-0.12	[-6.11, 6.26]	
-1	-1.43	[-5.18, 2.47]	
0	-1.86	[-5.67, 2.10]	
1	-1.20	[-6.81, 4.76]	
2	-1.92	[-7.23, 3.69]	
3	2.45	[-2.19, 7.32]	
4	2.86	[-7.61, 14.52]	
5	2.76	[-1.30, 6.98]	
6	-2.41	[-6.67, 2.04]	
Overall	**0.07**	**[-2.24, 2.44]**	
Panel B: Construction and Demolition Waste			
-4	-17.99	[-29.22, -4.99]	*

Continued on next page

Table B.47 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-3	11.45	[0.48, 23.61]	*
-2	-2.23	[-14.65, 12.01]	
-1	8.90	[-4.98, 24.82]	
0	2.15	[-9.00, 14.68]	
1	-6.60	[-17.10, 5.23]	
2	-8.81	[-33.39, 24.85]	
3	-3.86	[-25.74, 24.46]	
4	-12.93	[-22.88, -1.69]	*
5	-6.82	[-20.44, 9.13]	
6	-6.25	[-21.52, 12.00]	
Overall	**-6.25**	**[-14.40, 2.67]**	
Panel C: Organic Waste (VFG)			
-4	-2.90	[-7.15, 1.54]	
-3	-2.63	[-6.66, 1.58]	
-2	1.76	[-2.56, 6.27]	
-1	6.47	[-3.98, 18.07]	
0	0.27	[-36.57, 58.52]	
1	-1.41	[-26.55, 32.32]	
2	0.05	[-25.38, 34.15]	
3	6.72	[-16.91, 37.08]	
4	0.60	[-24.53, 34.10]	
5	-17.60	[-28.60, -4.90]	*
6	-18.75	[-30.25, -5.35]	*
Overall	**-4.76**	**[-23.33, 18.32]**	
Panel D: Green Waste			
-4	66.60	[46.63, 89.29]	*
-3	-10.58	[-28.94, 12.53]	
-2	24.65	[-34.87, 138.57]	
-1	-15.23	[-27.51, -0.87]	*
0	10.07	[2.83, 17.82]	*
1	-13.16	[-27.79, 4.44]	

Continued on next page

Table B.47 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
2	-10.77	[-22.38, 2.57]	
3	-22.34	[-40.50, 1.37]	
4	-3.61	[-23.97, 22.19]	
5	-0.49	[-13.66, 14.69]	
6	9.67	[-6.08, 28.06]	
Overall	**-5.03**	**[-14.68, 5.71]**	
Panel E: Wood Waste			
-4	5.82	[-0.97, 13.08]	
-3	-0.09	[-6.17, 6.39]	
-2	-4.54	[-12.28, 3.88]	
-1	3.44	[-5.85, 13.63]	
0	-7.66	[-18.49, 4.61]	
1	-13.83	[-28.56, 3.93]	
2	-14.30	[-25.43, -1.50]	*
3	-11.46	[-19.79, -2.26]	*
4	-16.85	[-30.91, 0.07]	
5	-4.78	[-12.71, 3.87]	
6	-4.13	[-12.60, 5.15]	
Overall	**-10.55**	**[-17.65, -2.83]**	*
Panel F: Small Hazardous Waste			
-4	-4.32	[-8.33, -0.13]	*
-3	2.76	[-2.85, 8.69]	
-2	-4.01	[-8.45, 0.64]	
-1	-3.29	[-9.38, 3.22]	
0	9.90	[-7.12, 30.03]	
1	4.82	[0.04, 9.83]	*
2	16.17	[0.82, 33.86]	*
3	9.23	[0.80, 18.37]	*
4	11.89	[-9.01, 37.61]	
5	20.56	[15.20, 26.18]	*

Continued on next page

Table B.47 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
6	29.29	[20.79, 38.38]	*
Overall	**14.30**	**[8.72, 20.18]**	*****
Panel G: Hard Plastics			
-4	-0.24	[-5.59, 5.42]	
-3	7.41	[0.49, 14.81]	*
-2	4.08	[-3.06, 11.75]	
-1	-4.99	[-26.42, 22.68]	
0	-2.03	[-19.43, 19.13]	
1	-1.40	[-22.27, 25.08]	
2	-8.85	[-29.11, 17.20]	
3	18.07	[-14.09, 62.27]	
4	15.19	[-15.91, 57.80]	
5	-7.24	[-22.23, 10.65]	
6	-3.79	[-21.49, 17.89]	
Overall	**0.95**	**[-13.32, 17.58]**	
Panel H: Scrap Metal			
-4	4.07	[-2.89, 11.53]	
-3	-2.05	[-7.33, 3.52]	
-2	-1.49	[-7.56, 4.99]	
-1	3.24	[-1.71, 8.43]	
0	4.94	[-4.24, 15.00]	
1	-4.40	[-12.03, 3.89]	
2	5.58	[-20.61, 40.41]	
3	13.60	[-4.82, 35.57]	
4	24.22	[-3.42, 59.77]	
5	4.00	[-4.00, 12.67]	
6	22.87	[7.80, 40.06]	*
Overall	**9.68**	**[-0.78, 21.25]**	
Panel I: Paper and Cardboard			
-4	0.60	[-1.20, 2.43]	

Continued on next page

Table B.47 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-3	0.61	[-1.42, 2.68]	
-2	-2.90	[-7.80, 2.26]	
-1	1.02	[-3.70, 5.98]	
0	-1.24	[-10.83, 9.39]	
1	-1.01	[-6.75, 5.08]	
2	-1.36	[-8.68, 6.55]	
3	0.48	[-7.98, 9.71]	
4	1.67	[-11.79, 17.17]	
5	0.37	[-2.99, 3.83]	
6	-5.98	[-9.16, -2.68]	*
Overall	**-1.04**	**[-5.41, 3.54]**	
Panel J: Vegetable and Animal Oils/Fats			
-4	9.65	[6.69, 12.69]	*
-3	-4.50	[-8.05, -0.82]	*
-2	4.20	[-5.43, 14.81]	
-1	-2.03	[-10.18, 6.86]	
0	3.15	[-6.49, 13.78]	
1	0.07	[-12.81, 14.86]	
2	-3.74	[-19.59, 15.25]	
3	9.38	[-28.93, 68.34]	
4	0.42	[-18.85, 24.26]	
5	3.72	[-3.19, 11.13]	
6	8.66	[4.38, 13.13]	*
Overall	**3.00**	**[-8.01, 15.33]**	
Panel K: PMC			
-4	2.14	[-0.52, 4.88]	
-3	-5.21	[-8.75, -1.53]	*
-2	-5.98	[-14.04, 2.85]	
-1	10.07	[-14.22, 41.25]	
0	8.46	[-5.05, 23.90]	
1	11.22	[0.01, 23.69]	*

Continued on next page

Table B.47 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
2	13.43	[-3.76, 33.70]	
3	13.39	[-10.97, 44.41]	
4	11.35	[-11.88, 40.70]	
5	22.92	[18.20, 27.83]	*
6	8.54	[3.95, 13.34]	*
Overall	**12.67**	**[3.13, 23.10]**	*
Panel L: Residual Waste			
-4	0.88	[-1.12, 2.91]	
-3	4.74	[2.38, 7.15]	*
-2	-1.16	[-2.51, 0.20]	
-1	-3.88	[-19.35, 14.56]	
0	-16.57	[-22.94, -9.67]	*
1	-23.95	[-35.36, -10.51]	*
2	-22.90	[-31.07, -13.77]	*
3	-23.60	[-48.36, 13.02]	
4	-22.97	[-37.67, -4.79]	*
5	-18.88	[-21.43, -16.25]	*
6	-17.71	[-21.60, -13.62]	*
Overall	**-20.99**	**[-27.88, -13.45]**	*
Panel M: Textiles			
-4	-10.24	[-16.74, -3.22]	*
-3	2.39	[-3.99, 9.18]	
-2	-9.02	[-24.50, 9.63]	
-1	12.41	[-9.69, 39.92]	
0	3.32	[-15.78, 26.76]	
1	42.38	[-17.87, 146.85]	
2	3.41	[-12.54, 22.28]	
3	-6.41	[-44.80, 58.68]	
4	4.12	[-27.68, 49.89]	
5	16.89	[3.04, 32.59]	*

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Table B.47 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
6	0.63	[-10.92, 13.69]	
Overall	**8.27**	**[-10.50, 30.97]**	
Panel N: Packaging Glass			
-4	-9.76	[-14.66, -4.57]	*
-3	-3.68	[-7.75, 0.56]	
-2	-20.70	[-41.04, 6.67]	
-1	14.12	[5.21, 23.79]	*
0	-5.98	[-12.12, 0.60]	
1	-1.60	[-6.34, 3.38]	
2	-5.77	[-13.80, 3.02]	
3	-3.82	[-10.99, 3.93]	
4	-10.65	[-17.19, -3.59]	*
5	1.03	[-4.64, 7.04]	
6	-12.14	[-18.05, -5.81]	*
Overall	**-5.66**	**[-9.34, -1.84]**	*
Panel O: Flat Glass			
-4	8.24	[1.88, 15.00]	*
-3	-21.76	[-27.03, -16.12]	*
-2	1.16	[-17.09, 23.44]	
-1	-0.45	[-11.16, 11.55]	
0	5.28	[-16.41, 32.60]	
1	-0.92	[-18.00, 19.72]	
2	-0.79	[-10.54, 10.03]	
3	-4.12	[-20.36, 15.42]	
4	-2.36	[-16.59, 14.30]	
5	2.58	[-6.50, 12.53]	
6	-6.04	[-15.64, 4.65]	
Overall	**-0.97**	**[-10.12, 9.10]**	

Urbanized Municipalities

Table B.48: Exact Percentage Change for All Fractions (Urbanized Municipalities)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-4	0.81	[-1.41, 3.09]	
-3	1.66	[-2.35, 5.83]	
-2	1.18	[-6.88, 9.94]	
-1	-3.99	[-14.70, 8.06]	
0	1.04	[-2.92, 5.16]	
1	4.60	[-9.48, 20.88]	
2	11.19	[-25.38, 65.68]	
3	9.61	[-31.58, 75.61]	
4	26.98	[-14.37, 88.30]	
Overall	**10.34**	**[-13.93, 41.46]**	
Panel B: Construction and Demolition Waste			
-4	22.24	[2.83, 45.33]	*
-3	11.40	[-10.74, 39.03]	
-2	-4.75	[-19.85, 13.21]	
-1	3.46	[-12.17, 21.87]	
0	-3.15	[-17.68, 13.94]	
1	7.22	[-21.81, 47.03]	
2	22.75	[-35.64, 134.09]	
3	14.07	[-45.00, 136.56]	
4	5.73	[-41.67, 91.65]	
Overall	**8.98**	**[-27.83, 64.55]**	
Panel C: Organic Waste (VFG)			
-4	-10.60	[-13.88, -7.19]	*
-3	-2.42	[-9.37, 5.07]	
-2	5.53	[0.12, 11.23]	*
-1	-1.76	[-9.14, 6.22]	
0	7.92	[-13.87, 35.22]	
1	2.96	[-20.93, 34.08]	
2	6.67	[-18.16, 39.04]	

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Table B.48 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
3	6.73	[-25.92, 53.78]	
4	53.85	[27.12, 86.20]	*
Overall	**14.25**	**[-8.75, 43.04]**	
Panel D: Green Waste			
-4	11.66	[-5.98, 32.59]	
-3	7.24	[-3.99, 19.77]	
-2	-1.82	[-9.55, 6.57]	
-1	-4.94	[-18.36, 10.69]	
0	-2.15	[-16.15, 14.18]	
1	4.27	[-6.95, 16.84]	
2	1.95	[-12.03, 18.15]	
3	10.40	[-3.90, 26.84]	
4	-7.96	[-24.63, 12.39]	
Overall	**1.11**	**[-9.91, 13.49]**	
Panel E: Wood Waste			
-4	4.82	[-2.23, 12.38]	
-3	-1.92	[-9.85, 6.70]	
-2	-7.50	[-16.52, 2.50]	
-1	2.97	[-7.94, 15.17]	
0	-6.32	[-21.52, 11.82]	
1	3.41	[-21.22, 35.75]	
2	10.56	[-31.17, 77.57]	
3	9.17	[-34.77, 82.71]	
4	-17.83	[-46.61, 26.47]	
Overall	**-0.80**	**[-27.38, 35.52]**	
Panel F: Small Hazardous Waste			
-4	1.24	[-6.59, 9.73]	
-3	0.37	[-4.35, 5.33]	
-2	1.78	[-6.85, 11.22]	
-1	6.56	[-4.26, 18.60]	

Continued on next page

Table B.48 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
0	2.74	[-2.29, 8.04]	
1	7.16	[-0.83, 15.79]	
2	7.04	[-3.21, 18.38]	
3	3.47	[-6.95, 15.06]	
4	-0.84	[-10.96, 10.42]	
Overall	**3.87**	**[-2.26, 10.39]**	
Panel G: Hard Plastics			
-4	1.75	[-13.38, 19.53]	
-3	-1.62	[-13.19, 11.50]	
-2	-13.34	[-23.50, -1.83]	*
-1	-5.46	[-13.23, 3.00]	
0	8.82	[-3.37, 22.55]	
1	18.06	[-4.74, 46.33]	
2	18.66	[-7.37, 52.01]	
3	20.29	[-7.92, 57.14]	
4	21.40	[-5.76, 56.39]	
Overall	**17.36**	**[-2.11, 40.70]**	
Panel H: Scrap Metal			
-4	5.73	[-0.11, 11.91]	
-3	0.64	[-4.76, 6.34]	
-2	-4.19	[-10.77, 2.87]	
-1	-2.76	[-10.34, 5.46]	
0	-0.83	[-7.50, 6.32]	
1	4.14	[-8.47, 18.48]	
2	4.32	[-16.80, 30.80]	
3	7.75	[-14.44, 35.69]	
4	2.82	[-16.48, 26.59]	
Overall	**3.60**	**[-9.29, 18.33]**	
Panel I: Paper and Cardboard			
-4	-2.21	[-4.06, -0.32]	*

Continued on next page

Table B.48 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-3	-0.68	[-4.13, 2.90]	
-2	-1.39	[-6.29, 3.76]	
-1	0.52	[-2.13, 3.24]	
0	2.76	[-0.86, 6.51]	
1	2.03	[-1.74, 5.95]	
2	-0.96	[-6.75, 5.19]	
3	3.72	[-5.71, 14.08]	
4	-4.52	[-9.88, 1.16]	
Overall	**0.56**	**[-2.40, 3.61]**	
Panel J: Vegetable and Animal Oils/Fats			
-4	2.93	[-0.96, 6.97]	
-3	0.06	[-5.59, 6.06]	
-2	-2.22	[-7.14, 2.96]	
-1	-3.82	[-9.72, 2.46]	
0	5.05	[-4.72, 15.83]	
1	-1.93	[-13.75, 11.51]	
2	2.10	[-11.40, 17.67]	
3	13.27	[5.08, 22.09]	*
4	-9.97	[-14.38, -5.32]	*
Overall	**1.41**	**[-4.51, 7.71]**	
Panel K: PMC			
-4	5.33	[3.54, 7.15]	*
-3	3.06	[-4.24, 10.92]	
-2	8.66	[2.18, 15.56]	*
-1	3.60	[-5.74, 13.87]	
0	0.98	[-18.15, 24.59]	
1	-2.46	[-15.75, 12.93]	
2	-5.84	[-14.61, 3.83]	
3	-9.29	[-20.00, 2.86]	
4	1.46	[-6.39, 9.97]	

Continued on next page

Table B.48 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
Overall	**-3.12**	**[-13.25, 8.20]**	
Panel L: Residual Waste			
-4	-0.04	[-1.76, 1.71]	
-3	-0.17	[-2.70, 2.42]	
-2	-1.27	[-5.47, 3.12]	
-1	-4.72	[-15.12, 6.94]	
0	-16.80	[-25.81, -6.69]	*
1	-15.63	[-31.96, 4.61]	
2	-12.18	[-29.27, 9.03]	
3	-15.02	[-27.40, -0.52]	*
4	-26.87	[-33.08, -20.09]	*
Overall	**-17.46**	**[-25.71, -8.29]**	*
Panel M: Textiles			
-4	1.05	[-3.86, 6.21]	
-3	1.76	[-5.99, 10.15]	
-2	7.51	[-12.96, 32.80]	
-1	-17.62	[-40.30, 13.66]	
0	-8.68	[-32.69, 23.90]	
1	-4.50	[-41.65, 56.28]	
2	2.24	[-21.62, 33.36]	
3	-13.79	[-27.44, 2.43]	
4	-23.60	[-39.52, -3.50]	*
Overall	**-10.10**	**[-26.40, 9.81]**	
Panel N: Packaging Glass			
-4	-4.46	[-8.87, 0.17]	
-3	1.06	[-4.00, 6.38]	
-2	-3.23	[-7.99, 1.78]	
-1	8.66	[2.65, 15.01]	*
0	-7.61	[-10.48, -4.64]	*
1	-4.76	[-14.56, 6.18]	

Continued on next page

Table B.48 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
2	-10.53	[-19.91, -0.04]	*
3	-9.69	[-19.04, 0.73]	
4	-16.31	[-26.00, -5.35]	*
Overall	**-9.86**	**[-15.17, -4.22]**	*****
Panel O: Flat Glass			
-4	-5.04	[-24.18, 18.93]	
-3	-5.28	[-19.79, 11.85]	
-2	-6.38	[-15.44, 3.65]	
-1	-0.35	[-6.14, 5.81]	
0	-1.20	[-6.11, 3.97]	
1	0.86	[-9.98, 13.00]	
2	3.84	[-10.06, 19.88]	
3	-4.00	[-17.91, 12.27]	
4	3.03	[-11.18, 19.50]	
Overall	**0.46**	**[-8.13, 9.87]**	

Large and Regional Cities

Table B.49: Exact Percentage Change for All Fractions (Large and Regional Cities)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-6	3.50	[-0.23, 7.36]	
-5	0.97	[-1.99, 4.03]	
-4	-0.65	[-3.83, 2.64]	
-3	-2.40	[-10.83, 6.83]	
-2	3.40	[-2.23, 9.36]	
-1	-3.77	[-6.51, -0.96]	*
0	4.46	[-3.59, 13.18]	
1	7.87	[-2.96, 19.91]	
2	8.59	[-4.17, 23.05]	

Continued on next page

Table B.49 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
3	17.20	[6.49, 28.99]	*
4	-21.31	[-30.69, -10.65]	*
Overall	**2.45**	**[-5.59, 11.17]**	
Panel B: Construction and Demolition Waste			
-6	7.70	[-2.88, 19.42]	
-5	2.00	[-22.84, 34.84]	
-4	22.74	[8.39, 38.98]	*
-3	9.47	[-8.69, 31.24]	
-2	-2.29	[-15.39, 12.84]	
-1	7.60	[-7.56, 25.25]	
0	-0.68	[-20.35, 23.85]	
1	4.40	[-23.33, 42.17]	
2	1.21	[-23.90, 34.60]	
3	-3.07	[-26.43, 27.69]	
4	-11.22	[-32.80, 17.30]	
Overall	**-2.02**	**[-17.92, 16.96]**	
Panel C: Organic Waste (VFG)			
-6	0.66	[-0.07, 1.41]	
-5	-3.07	[-6.04, 0.00]	*
-4	-2.57	[-4.56, -0.54]	*
-3	-0.24	[-2.34, 1.91]	
-2	12.46	[-13.33, 45.92]	
-1	7.93	[-14.30, 35.93]	
0	1.07	[-27.93, 41.74]	
1	37.12	[-8.03, 104.44]	
2	62.94	[-22.11, 240.86]	
3	42.05	[-17.48, 144.51]	
4	42.33	[11.58, 81.54]	*
Overall	**35.49**	**[-0.46, 84.41]**	
Panel D: Green Waste			

Continued on next page

Table B.49 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-6	22.73	[17.11, 28.63]	*
-5	3.75	[-10.34, 20.06]	
-4	36.55	[29.02, 44.52]	*
-3	1.80	[-9.77, 14.86]	
-2	-12.60	[-45.61, 40.45]	
-1	7.19	[-1.64, 16.81]	
0	11.51	[-36.33, 95.31]	
1	-16.42	[-28.86, -1.79]	*
2	-20.46	[-38.86, 3.49]	
3	-19.60	[-50.94, 31.76]	
4	-43.88	[-50.78, -36.02]	*
Overall	**-19.67**	**[-36.29, 1.28]**	
Panel E: Wood Waste			
-6	-3.80	[-9.90, 2.71]	
-5	1.71	[-10.89, 16.10]	
-4	7.08	[-3.32, 18.60]	
-3	11.77	[-13.24, 44.00]	
-2	-1.73	[-13.14, 11.18]	
-1	11.41	[6.65, 16.38]	*
0	-12.53	[-28.45, 6.94]	
1	-16.77	[-33.01, 3.40]	
2	-16.52	[-34.55, 6.48]	
3	-16.49	[-35.57, 8.24]	
4	-26.93	[-41.75, -8.35]	*
Overall	**-18.00**	**[-30.97, -2.58]**	*
Panel F: Small Hazardous Waste			
-6	5.87	[1.31, 10.64]	*
-5	-1.47	[-5.09, 2.28]	
-4	-0.19	[-6.71, 6.78]	
-3	3.28	[-3.73, 10.79]	
-2	4.56	[1.18, 8.04]	*

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Table B.49 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-1	3.47	[-8.58, 17.12]	
0	-0.93	[-6.51, 4.99]	
1	3.46	[-6.37, 14.32]	
2	4.51	[-7.21, 17.70]	
3	2.42	[-7.34, 13.21]	
4	0.86	[-10.48, 13.64]	
Overall	**2.05**	**[-5.75, 10.49]**	
Panel G: Hard Plastics			
-6	6.31	[-35.91, 76.34]	
-5	2.00	[-6.37, 11.11]	
-4	16.00	[7.36, 25.34]	*
-3	-30.52	[-58.54, 16.46]	
-2	-16.95	[-36.15, 8.02]	
-1	0.77	[-6.71, 8.86]	
0	8.53	[-18.13, 43.87]	
1	43.42	[-5.78, 118.32]	
2	45.29	[-8.15, 129.82]	
3	38.37	[-16.82, 130.18]	
4	39.52	[-14.29, 127.12]	
Overall	**34.28**	**[-3.70, 87.24]**	
Panel H: Scrap Metal			
-6	1.69	[-2.26, 5.80]	
-5	2.18	[-3.99, 8.75]	
-4	13.60	[1.35, 27.34]	*
-3	4.47	[-8.07, 18.72]	
-2	3.59	[-2.36, 9.90]	
-1	4.08	[0.07, 8.26]	*
0	-1.66	[-17.37, 17.03]	
1	-0.33	[-15.96, 18.22]	
2	-3.05	[-15.38, 11.07]	
3	2.44	[-10.26, 16.93]	

Continued on next page

Table B.49 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
4	1.41	[-16.16, 22.66]	
Overall	**-0.26**	**[-11.81, 12.80]**	
Panel I: Paper and Cardboard			
-6	-0.18	[-1.32, 0.97]	
-5	-2.96	[-3.89, -2.01]	*
-4	0.69	[-2.10, 3.55]	
-3	0.41	[-2.52, 3.42]	
-2	0.22	[-0.84, 1.28]	
-1	3.08	[-2.13, 8.57]	
0	0.99	[-0.28, 2.27]	
1	1.26	[-1.47, 4.06]	
2	3.57	[0.30, 6.95]	*
3	2.62	[-2.32, 7.81]	
4	-3.53	[-6.90, -0.04]	*
Overall	**0.95**	**[-1.68, 3.65]**	
Panel J: Vegetable and Animal Oils/Fats			
-6	2.62	[-8.11, 14.61]	
-5	-5.10	[-15.71, 6.85]	
-4	21.15	[9.74, 33.74]	*
-3	0.49	[-6.22, 7.67]	
-2	-1.75	[-7.82, 4.72]	
-1	-0.66	[-6.64, 5.70]	
0	-4.41	[-14.06, 6.32]	
1	-2.19	[-10.85, 7.32]	
2	-5.39	[-14.51, 4.70]	
3	6.79	[-4.03, 18.83]	
4	-9.12	[-15.38, -2.39]	*
Overall	**-3.00**	**[-7.82, 2.06]**	
Panel K: PMC			
-6	-1.74	[-3.74, 0.30]	

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Table B.49 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-5	-6.16	[-12.15, 0.24]	
-4	-6.26	[-14.55, 2.83]	
-3	7.67	[-21.09, 46.91]	
-2	7.23	[-8.99, 26.34]	
-1	16.12	[-9.52, 49.03]	
0	4.74	[-25.86, 47.97]	
1	-2.74	[-26.55, 28.80]	
2	-7.46	[-29.88, 22.13]	
3	-8.75	[-28.51, 16.48]	
4	-5.78	[-21.49, 13.08]	
Overall	**-4.12**	**[-16.82, 10.52]**	
Panel L: Residual Waste			
-6	-1.28	[-3.40, 0.89]	
-5	0.72	[-0.70, 2.17]	
-4	0.80	[-2.65, 4.38]	
-3	0.12	[-2.92, 3.26]	
-2	-0.33	[-3.03, 2.44]	
-1	-8.22	[-22.45, 8.61]	
0	-11.69	[-27.04, 6.88]	
1	-16.69	[-20.57, -12.62]	*
2	-14.08	[-19.36, -8.45]	*
3	-10.37	[-16.55, -3.73]	*
4	-1.96	[-7.76, 4.21]	
Overall	**-11.09**	**[-14.69, -7.35]**	*
Panel M: Textiles			
-6	-1.40	[-7.07, 4.61]	
-5	-7.89	[-15.03, -0.14]	*
-4	-1.43	[-7.95, 5.55]	
-3	-9.78	[-24.61, 7.97]	
-2	9.61	[-4.07, 25.23]	
-1	-3.80	[-20.21, 16.00]	

Continued on next page

Table B.49 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
0	2.24	[-11.95, 18.70]	
1	-17.39	[-62.86, 83.72]	
2	16.22	[2.30, 32.03]	*
3	9.86	[-5.25, 27.37]	
4	3.55	[-6.62, 14.82]	
Overall	**2.23**	**[-11.57, 18.18]**	
Panel N: Packaging Glass			
-6	-2.63	[-3.83, -1.42]	*
-5	0.82	[0.18, 1.46]	*
-4	2.27	[-1.22, 5.88]	
-3	1.55	[-3.35, 6.69]	
-2	7.70	[-11.06, 30.42]	
-1	0.26	[-9.21, 10.73]	
0	6.99	[-7.38, 23.60]	
1	9.58	[-11.61, 35.85]	
2	11.93	[-6.77, 34.39]	
3	5.39	[-21.99, 42.38]	
4	15.36	[12.28, 18.53]	*
Overall	**9.79**	**[-4.21, 25.85]**	
Panel O: Flat Glass			
-6	-0.60	[-5.39, 4.42]	
-5	-3.15	[-13.21, 8.07]	
-4	5.34	[-4.34, 16.00]	
-3	4.70	[-2.13, 12.00]	
-2	-3.14	[-15.07, 10.47]	
-1	8.22	[-9.18, 28.97]	
0	0.21	[-5.46, 6.22]	
1	9.59	[-12.68, 37.53]	
2	7.55	[-9.69, 28.09]	
3	-1.82	[-17.86, 17.35]	

Continued on next page

Table B.49 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
4	-1.23	[-17.80, 18.68]	
Overall	**2.75**	**[-7.84, 14.56]**	

Econometric Output Method of Collection: Conditional Log-Linear Staggered DiD: Subsitution Effects on Collected Fractions

Weight and Frequency (WF) Pricing

Table B.50: Exact Percentage Change for All Fractions (Weight and Frequency (WF) Pricing - Conditional Model)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-6	-1.25	[-4.81, 2.45]	
-5	-0.10	[-2.44, 2.30]	
-4	7.16	[-12.97, 31.95]	
-3	0.94	[-2.90, 4.92]	
-2	-0.85	[-5.09, 3.59]	
-1	0.63	[-3.35, 4.76]	
0	-3.84	[-7.70, 0.19]	
1	-5.35	[-13.03, 3.01]	
2	-4.16	[-14.91, 7.95]	
3	-2.47	[-10.85, 6.69]	
4	-4.90	[-15.39, 6.90]	
5	-6.92	[-25.13, 15.70]	
6	-4.37	[-9.47, 1.01]	
Overall	**-4.58**	**[-9.08, 0.14]**	
Panel B: Construction and Demolition Waste			
-6	-0.78	[-11.00, 10.61]	
-5	3.13	[-4.09, 10.90]	
-4	10.47	[-3.55, 26.52]	

Continued on next page

Table B.50 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-3	5.58	[-1.75, 13.46]	
-2	0.38	[-8.03, 9.56]	
-1	1.48	[-12.79, 18.10]	
0	-8.25	[-16.25, 0.52]	
1	-7.53	[-20.43, 7.46]	
2	-0.74	[-15.67, 16.84]	
3	-5.46	[-20.88, 12.96]	
4	-3.19	[-54.85, 107.57]	
5	13.55	[-24.78, 71.39]	
6	11.30	[-23.26, 61.41]	
Overall	**-0.38**	**[-15.38, 17.29]**	
Panel C: Organic Waste (VFG)			
-6	-0.92	[-3.31, 1.54]	
-5	-5.65	[-9.41, -1.73]	*
-4	-2.58	[-8.70, 3.94]	
-3	-1.67	[-4.62, 1.38]	
-2	-1.26	[-4.79, 2.40]	
-1	0.87	[-2.89, 4.78]	
0	-6.54	[-12.06, -0.67]	*
1	-8.92	[-19.51, 3.06]	
2	-10.38	[-21.45, 2.25]	
3	-14.68	[-25.51, -2.28]	*
4	-13.92	[-25.45, -0.61]	*
5	-13.62	[-25.35, -0.04]	*
6	-15.81	[-26.54, -3.51]	*
Overall	**-12.04**	**[-18.85, -4.65]**	*
Panel D: Green Waste			
-6	-2.02	[-6.43, 2.60]	
-5	-2.57	[-11.01, 6.66]	
-4	6.20	[-11.04, 26.78]	
-3	4.57	[-0.85, 10.29]	

Continued on next page

Table B.50 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-2	8.85	[-4.34, 23.85]	
-1	-5.37	[-18.17, 9.42]	
0	-0.70	[-6.69, 5.66]	
1	-2.93	[-11.17, 6.08]	
2	5.89	[-6.79, 20.30]	
3	2.61	[-11.93, 19.55]	
4	-6.39	[-51.21, 79.62]	
5	-15.51	[-38.69, 16.43]	
6	21.00	[-2.54, 50.22]	
Overall	**0.03**	**[-10.58, 11.90]**	
Panel E: Wood Waste			
-6	-2.51	[-11.27, 7.13]	
-5	5.30	[-3.82, 15.28]	
-4	-0.05	[-8.14, 8.76]	
-3	-1.80	[-7.51, 4.27]	
-2	-0.08	[-7.32, 7.73]	
-1	-4.02	[-15.16, 8.59]	
0	-13.95	[-21.14, -6.11]	*
1	-15.99	[-25.40, -5.39]	*
2	-15.02	[-26.24, -2.11]	*
3	-20.38	[-31.14, -7.94]	*
4	-12.39	[-48.86, 50.09]	
5	3.89	[-14.01, 25.51]	
6	4.80	[-13.62, 27.13]	
Overall	**-10.32**	**[-19.73, 0.19]**	
Panel F: Small Hazardous Waste			
-6	-7.06	[-10.46, -3.53]	*
-5	8.44	[3.92, 13.16]	*
-4	0.80	[-6.02, 8.11]	
-3	-0.76	[-4.09, 2.69]	
-2	1.28	[-4.63, 7.56]	

Continued on next page

Table B.50 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-1	1.93	[-3.11, 7.24]	
0	1.23	[-2.93, 5.56]	
1	2.72	[-2.66, 8.40]	
2	2.24	[-3.07, 7.84]	
3	-0.76	[-7.08, 5.99]	
4	5.52	[-23.95, 46.42]	
5	16.73	[8.64, 25.43]	*
6	18.86	[-1.07, 42.80]	
Overall	**6.41**	**[0.54, 12.62]**	*
Panel G: Hard Plastics			
-6	-4.51	[-19.43, 13.18]	
-5	-6.37	[-15.87, 4.20]	
-4	13.98	[-4.75, 36.40]	
-3	-0.72	[-9.68, 9.12]	
-2	-7.67	[-14.23, -0.62]	*
-1	-10.08	[-17.24, -2.30]	*
0	11.95	[-1.40, 27.11]	
1	18.35	[-2.87, 44.21]	
2	18.40	[-4.88, 47.39]	
3	19.31	[-3.86, 48.06]	
4	-20.67	[-48.29, 21.69]	
5	-7.64	[-20.55, 7.39]	
6	-11.78	[-29.00, 9.61]	
Overall	**2.76**	**[-8.74, 15.71]**	
Panel H: Scrap Metal			
-6	-6.89	[-9.99, -3.69]	*
-5	0.14	[-5.20, 5.78]	
-4	2.54	[-4.24, 9.80]	
-3	0.26	[-3.57, 4.25]	
-2	0.57	[-5.03, 6.49]	
-1	-3.80	[-9.30, 2.04]	

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Table B.50 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
0	-2.16	[-7.12, 3.07]	
1	-3.43	[-8.96, 2.44]	
2	-4.31	[-11.40, 3.36]	
3	-6.79	[-16.30, 3.80]	
4	-7.11	[-46.33, 60.78]	
5	7.76	[-0.86, 17.12]	
6	20.37	[10.85, 30.72]	*
Overall	**0.22**	**[-7.88, 9.03]**	
Panel I: Paper and Cardboard			
-6	1.05	[-0.18, 2.30]	
-5	-1.89	[-3.49, -0.26]	*
-4	-1.20	[-6.68, 4.60]	
-3	0.19	[-3.04, 3.52]	
-2	-2.15	[-4.70, 0.47]	
-1	-0.15	[-4.44, 4.33]	
0	-2.11	[-5.66, 1.57]	
1	-0.92	[-4.08, 2.35]	
2	-0.44	[-3.61, 2.82]	
3	-2.25	[-5.38, 0.98]	
4	-5.03	[-10.34, 0.60]	
5	-1.18	[-4.53, 2.28]	
6	-5.16	[-7.60, -2.66]	*
Overall	**-2.46**	**[-4.00, -0.89]**	*
Panel J: Vegetable and Animal Oils/Fats			
-6	-0.12	[-5.26, 5.30]	
-5	2.95	[-1.92, 8.06]	
-4	-2.87	[-13.55, 9.14]	
-3	-0.94	[-3.91, 2.12]	
-2	2.13	[-3.70, 8.32]	
-1	-9.02	[-14.94, -2.68]	*
0	5.75	[-0.51, 12.40]	

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Table B.50 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
1	7.33	[-1.50, 16.96]	
2	10.87	[2.45, 19.99]	*
3	11.63	[4.67, 19.05]	*
4	4.29	[-14.92, 27.84]	
5	16.44	[-12.22, 54.46]	
6	2.08	[-9.15, 14.69]	
Overall	**8.25**	**[3.70, 12.99]**	*
Panel K: PMC			
-6	3.84	[2.53, 5.17]	*
-5	-6.73	[-10.40, -2.92]	*
-4	3.51	[-4.81, 12.55]	
-3	-0.97	[-4.90, 3.11]	
-2	5.84	[-1.25, 13.43]	
-1	4.66	[-0.16, 9.72]	
0	-3.42	[-11.12, 4.95]	
1	-3.75	[-12.96, 6.43]	
2	-4.46	[-13.69, 5.76]	
3	-8.06	[-19.15, 4.56]	
4	10.43	[-4.66, 27.90]	
5	14.26	[4.77, 24.61]	*
6	7.38	[3.92, 10.95]	*
Overall	**1.45**	**[-4.41, 7.68]**	
Panel L: Residual Waste			
-6	5.39	[3.22, 7.60]	*
-5	1.73	[-3.06, 6.77]	
-4	2.36	[-0.51, 5.31]	
-3	0.18	[-1.44, 1.84]	
-2	0.17	[-2.39, 2.79]	
-1	-1.21	[-4.65, 2.34]	
0	-14.61	[-18.66, -10.35]	*
1	-15.98	[-22.22, -9.22]	*

Continued on next page

Table B.50 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
2	-14.26	[-21.75, -6.05]	*
3	-13.95	[-22.30, -4.69]	*
4	-4.87	[-29.47, 28.31]	
5	-3.84	[-45.68, 70.25]	
6	-1.72	[-43.96, 72.38]	
Overall	**-10.06**	**[-19.08, -0.03]**	*
Panel M: Textiles			
-6	6.31	[0.30, 12.68]	*
-5	0.86	[-4.32, 6.31]	
-4	1.29	[-9.27, 13.08]	
-3	5.75	[-3.73, 16.17]	
-2	1.77	[-8.21, 12.83]	
-1	-8.07	[-16.12, 0.75]	
0	-1.82	[-21.83, 23.33]	
1	8.65	[-4.16, 23.18]	
2	9.65	[-5.51, 27.24]	
3	-9.28	[-26.73, 12.31]	
4	-7.69	[-23.32, 11.13]	
5	-2.53	[-36.13, 48.75]	
6	-9.66	[-28.25, 13.74]	
Overall	**-2.09**	**[-11.79, 8.68]**	
Panel N: Packaging Glass			
-6	7.82	[5.36, 10.33]	*
-5	-4.87	[-6.91, -2.78]	*
-4	-2.59	[-10.33, 5.82]	
-3	0.09	[-2.58, 2.83]	
-2	-2.22	[-5.45, 1.12]	
-1	2.24	[-1.16, 5.76]	
0	-0.28	[-3.94, 3.51]	
1	-0.90	[-3.72, 2.00]	
2	-4.12	[-7.66, -0.45]	*

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Table B.50 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
3	-5.96	[-10.91, -0.74]	*
4	-3.80	[-8.29, 0.91]	
5	-7.18	[-27.83, 19.38]	
6	-8.31	[-16.30, 0.45]	
Overall	**-4.41**	**[-6.39, -2.38]**	*
Panel O: Flat Glass			
-6	61.07	[50.64, 72.23]	*
-5	-12.60	[-25.22, 2.16]	
-4	2.17	[-14.47, 22.06]	
-3	4.03	[-4.00, 12.73]	
-2	0.62	[-7.04, 8.90]	
-1	-1.26	[-8.98, 7.12]	
0	-7.33	[-15.15, 1.21]	
1	-10.21	[-17.70, -2.03]	*
2	-6.32	[-14.99, 3.23]	
3	-12.29	[-20.77, -2.90]	*
4	-16.97	[-43.67, 22.38]	
5	3.94	[-3.54, 12.00]	
6	-5.40	[-13.07, 2.95]	
Overall	**-7.99**	**[-13.41, -2.24]**	*

Non-Linear Weight and Frequency (WF NL) Pricing

Table B.51: Exact Percentage Change for All Fractions (Non-Linear Weight and Frequency (WF NL) Pricing - Conditional Model)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-2	2.69	[-2.21, 7.84]	
-1	-8.80	[-14.41, -2.82]	*
0	6.33	[-1.89, 15.25]	

Continued on next page

Table B.51 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
1	5.57	[-2.22, 13.99]	
2	3.29	[-4.28, 11.46]	
3	10.42	[1.43, 20.21]	*
4	6.26	[-8.78, 23.78]	
Overall	**6.35**	**[1.78, 11.13]**	*
Panel B: Construction and Demolition Waste			
-2	1.29	[-11.44, 15.85]	
-1	10.37	[-0.76, 22.75]	
0	4.89	[-8.24, 19.89]	
1	7.08	[-4.25, 19.76]	
2	12.60	[-5.02, 33.48]	
3	2.47	[-16.61, 25.93]	
4	-14.70	[-28.99, 2.45]	
Overall	**2.02**	**[-6.76, 11.64]**	
Panel C: Organic Waste (VFG)			
-2	1.99	[-0.51, 4.57]	
-1	20.48	[9.48, 32.58]	*
0	37.83	[26.08, 50.69]	*
1	35.49	[20.38, 52.51]	*
2	44.02	[12.74, 83.97]	*
3	42.77	[14.14, 78.58]	*
4	28.32	[11.09, 48.21]	*
Overall	**37.57**	**[21.36, 55.95]**	*
Panel D: Green Waste			
-2	13.38	[-29.74, 82.97]	
-1	-10.04	[-20.94, 2.35]	
0	-1.40	[-18.78, 19.69]	
1	-5.08	[-27.42, 24.14]	
2	-14.79	[-25.99, -1.88]	*
3	-15.21	[-33.25, 7.71]	

Continued on next page

Table B.51 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
4	-12.26	[-30.69, 11.09]	
Overall	**-9.91**	**[-23.73, 6.40]**	
Panel E: Wood Waste			
-2	-3.76	[-8.74, 1.49]	
-1	6.18	[-1.78, 14.79]	
0	-25.77	[-39.07, -9.57]	*
1	-23.61	[-34.37, -11.08]	*
2	-24.98	[-35.68, -12.51]	*
3	-23.83	[-40.41, -2.64]	*
4	-32.96	[-47.27, -14.76]	*
Overall	**-26.31**	**[-36.61, -14.35]**	*
Panel F: Small Hazardous Waste			
-2	-9.18	[-29.10, 16.35]	
-1	-0.21	[-7.13, 7.22]	
0	8.30	[-2.90, 20.79]	
1	3.38	[-2.08, 9.14]	
2	14.69	[3.88, 26.63]	*
3	2.35	[-3.90, 9.00]	
4	3.39	[-5.30, 12.88]	
Overall	**6.32**	**[0.40, 12.59]**	*
Panel G: Hard Plastics			
-2	0.49	[-8.97, 10.94]	
-1	2.83	[-7.73, 14.60]	
0	-2.63	[-12.15, 7.93]	
1	19.70	[3.92, 37.88]	*
2	28.79	[4.41, 58.86]	*
3	35.38	[17.81, 55.57]	*
4	28.40	[12.64, 46.38]	*
Overall	**21.15**	**[10.40, 32.94]**	*

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Table B.51 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
Panel H: Scrap Metal			
-2	2.01	[-2.66, 6.90]	
-1	1.35	[-2.92, 5.81]	
0	-1.36	[-11.44, 9.87]	
1	-2.43	[-8.82, 4.41]	
2	4.85	[-12.47, 25.59]	
3	5.25	[-8.83, 21.50]	
4	3.12	[-18.22, 30.04]	
Overall	**1.84**	**[-10.00, 15.22]**	
Panel I: Paper and Cardboard			
-2	-1.88	[-4.54, 0.85]	
-1	1.69	[-0.49, 3.92]	
0	2.40	[-1.07, 5.99]	
1	-1.47	[-7.41, 4.86]	
2	-0.75	[-7.92, 6.97]	
3	0.69	[-5.43, 7.20]	
4	-0.46	[-6.29, 5.73]	
Overall	**0.07**	**[-4.14, 4.47]**	
Panel J: Vegetable and Animal Oils/Fats			
-2	1.15	[-4.74, 7.39]	
-1	1.88	[-8.01, 12.83]	
0	-5.53	[-15.91, 6.14]	
1	-3.15	[-13.24, 8.11]	
2	-10.21	[-19.93, 0.69]	
3	12.25	[-8.40, 37.55]	
4	-6.25	[-18.25, 7.51]	
Overall	**-2.87**	**[-13.24, 8.75]**	
Panel K: PMC			
-2	-0.55	[-2.76, 1.72]	

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Table B.51 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-1	20.03	[3.21, 39.59]	*
0	20.77	[5.76, 37.92]	*
1	4.11	[-2.85, 11.57]	
2	-3.34	[-12.49, 6.76]	
3	-3.98	[-14.06, 7.28]	
4	-5.34	[-17.09, 8.07]	
Overall	**2.01**	**[-4.48, 8.94]**	
Panel L: Residual Waste			
-2	-0.63	[-1.69, 0.44]	
-1	-12.13	[-20.22, -3.21]	*
0	-20.99	[-28.67, -12.47]	*
1	-21.39	[-31.42, -9.90]	*
2	-18.87	[-31.12, -4.44]	*
3	-18.20	[-30.02, -4.38]	*
4	-17.09	[-28.63, -3.67]	*
Overall	**-19.32**	**[-27.79, -9.86]**	*
Panel M: Textiles			
-2	-2.21	[-13.35, 10.38]	
-1	14.10	[3.83, 25.38]	*
0	-5.05	[-20.02, 12.72]	
1	-12.71	[-49.88, 52.04]	
2	-13.67	[-31.45, 8.72]	
3	-5.94	[-25.48, 18.72]	
4	-6.41	[-25.22, 17.13]	
Overall	**-8.83**	**[-27.14, 14.07]**	
Panel N: Packaging Glass			
-2	-14.14	[-31.07, 6.95]	
-1	7.74	[-1.94, 18.37]	
0	1.87	[-7.34, 11.98]	
1	-2.17	[-11.23, 7.81]	

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Table B.51 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
2	-1.46	[-14.57, 13.67]	
3	-1.75	[-12.41, 10.20]	
4	-4.94	[-14.16, 5.26]	
Overall	**-1.72**	**[-12.85, 10.84]**	
Panel O: Flat Glass			
-2	-11.25	[-25.38, 5.56]	
-1	12.03	[-3.20, 29.66]	
0	7.47	[-6.09, 22.99]	
1	3.99	[-10.12, 20.31]	
2	0.69	[-11.09, 14.03]	
3	0.57	[-7.83, 9.74]	
4	-7.91	[-24.70, 12.61]	
Overall	**0.83**	**[-8.73, 11.39]**	

Weight and Volume (WV) Pricing

Table B.52: Exact Percentage Change for All Fractions (Weight and Volume (WV) Pricing)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-6	3.50	[-1.29, 8.52]	
-5	0.97	[-2.42, 4.48]	
-4	-0.17	[-2.79, 2.52]	
-3	-2.27	[-7.63, 3.39]	
-2	4.00	[-3.12, 11.64]	
-1	0.09	[-6.75, 7.44]	
0	0.01	[-10.04, 11.18]	
1	8.38	[-7.52, 27.01]	
2	9.37	[2.40, 16.82]	*
3	7.15	[3.30, 11.14]	*

Continued on next page

Table B.52 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
Overall	**6.16**	**[-0.13, 12.85]**	
Panel B: Construction and Demolition Waste			
-6	7.70	[-2.16, 18.55]	
-5	2.00	[-23.77, 36.48]	
-4	17.87	[6.49, 30.47]	*
-3	6.24	[-7.95, 22.61]	
-2	1.92	[-4.49, 8.76]	
-1	15.84	[-5.95, 42.68]	
0	7.55	[-3.61, 20.00]	
1	21.72	[10.41, 34.18]	*
2	21.87	[1.41, 46.46]	*
3	24.96	[9.57, 42.51]	*
Overall	**18.83**	**[9.67, 28.75]**	*
Panel C: Organic Waste (VFG)			
-6	0.66	[-0.98, 2.34]	
-5	-3.07	[-4.13, -1.99]	*
-4	1.55	[-5.29, 8.89]	
-3	6.57	[0.01, 13.57]	*
-2	6.73	[-16.06, 35.71]	
-1	3.17	[-6.28, 13.56]	
0	6.17	[-18.57, 38.42]	
1	21.91	[10.32, 34.72]	*
2	24.70	[9.85, 41.56]	*
3	29.07	[12.25, 48.41]	*
Overall	**20.14**	**[7.36, 34.45]**	*
Panel D: Green Waste			
-6	22.73	[16.25, 29.58]	*
-5	3.75	[-10.33, 20.04]	
-4	34.14	[28.09, 40.47]	*
-3	-2.45	[-8.44, 3.92]	

Continued on next page

Table B.52 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-2	-19.18	[-53.76, 41.27]	
-1	38.38	[-1.28, 93.96]	
0	21.17	[-17.82, 78.64]	
1	7.61	[-2.27, 18.49]	
2	11.55	[2.84, 21.00]	*
3	16.47	[2.30, 32.60]	*
Overall	**14.08**	**[3.94, 25.21]**	*
Panel E: Wood Waste			
-6	-3.80	[-9.56, 2.33]	
-5	1.71	[-9.39, 14.17]	
-4	5.28	[-0.25, 11.11]	
-3	6.32	[-8.61, 23.69]	
-2	-0.01	[-15.61, 18.47]	
-1	-8.59	[-40.03, 39.36]	
0	27.35	[-30.92, 134.76]	
1	70.46	[-28.64, 307.16]	
2	66.25	[-40.62, 365.49]	
3	115.80	[-12.08, 429.66]	
Overall	**67.05**	**[-24.07, 267.53]**	
Panel F: Small Hazardous Waste			
-6	5.87	[1.21, 10.75]	*
-5	-1.47	[-5.58, 2.81]	
-4	-0.40	[-3.85, 3.18]	
-3	8.00	[4.15, 11.98]	*
-2	0.34	[-9.21, 10.90]	
-1	5.28	[-4.43, 15.99]	
0	5.37	[-0.80, 11.93]	
1	5.14	[0.44, 10.05]	*
2	7.78	[-2.94, 19.67]	
3	16.92	[-10.92, 53.45]	

Continued on next page

Table B.52 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
Overall	**8.70**	**[-1.53, 19.99]**	
Panel G: Hard Plastics			
-6	6.31	[-31.08, 63.99]	
-5	2.00	[-5.82, 10.47]	
-4	34.59	[-4.74, 90.16]	
-3	-27.25	[-48.66, 3.07]	
-2	-2.73	[-26.64, 28.98]	
-1	-8.11	[-36.94, 33.91]	
0	32.29	[2.33, 71.03]	*
1	66.93	[17.66, 136.83]	*
2	61.13	[14.61, 126.54]	*
3	82.41	[53.62, 116.60]	*
Overall	**59.62**	**[30.31, 95.51]**	*
Panel H: Scrap Metal			
-6	1.69	[-1.86, 5.37]	
-5	2.18	[-3.62, 8.33]	
-4	6.28	[-4.84, 18.71]	
-3	4.92	[-1.48, 11.73]	
-2	-4.92	[-10.69, 1.22]	
-1	-3.06	[-7.64, 1.75]	
0	6.83	[-2.74, 17.35]	
1	17.99	[-12.52, 59.15]	
2	11.09	[3.68, 19.03]	*
3	9.55	[3.92, 15.48]	*
Overall	**11.29**	**[5.43, 17.48]**	*
Panel I: Paper and Cardboard			
-6	-0.18	[-1.39, 1.04]	
-5	-2.96	[-4.03, -1.87]	*
-4	0.34	[-1.09, 1.79]	
-3	3.09	[1.03, 5.19]	*

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Table B.52 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-2	-0.76	[-3.18, 1.72]	
-1	-2.78	[-6.79, 1.40]	
0	1.37	[-1.75, 4.59]	
1	7.08	[1.66, 12.80]	*
2	6.13	[1.27, 11.22]	*
3	1.26	[-4.35, 7.21]	
Overall	**3.93**	**[-0.97, 9.06]**	
Panel J: Vegetable and Animal Oils/Fats			
-6	2.62	[-6.95, 13.18]	
-5	-5.10	[-14.94, 5.88]	
-4	7.13	[-11.43, 29.57]	
-3	-1.17	[-9.01, 7.33]	
-2	2.15	[-4.95, 9.78]	
-1	5.36	[-7.63, 20.17]	
0	-7.39	[-20.06, 7.30]	
1	-5.29	[-12.01, 1.94]	
2	0.60	[-13.13, 16.51]	
3	6.63	[-8.86, 24.74]	
Overall	**-1.51**	**[-10.17, 7.98]**	
Panel K: PMC			
-6	-1.74	[-3.46, 0.02]	
-5	-6.16	[-10.55, -1.54]	*
-4	-5.32	[-8.75, -1.76]	*
-3	2.94	[-11.24, 19.40]	
-2	-2.86	[-7.39, 1.89]	
-1	1.03	[-6.29, 8.92]	
0	3.15	[-5.04, 12.05]	
1	15.51	[8.22, 23.28]	*
2	16.18	[10.28, 22.40]	*
3	11.22	[3.27, 19.78]	*

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Table B.52 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
Overall	**11.39**	**[6.63, 16.36]**	*
Panel L: Residual Waste			
-6	-1.28	[-3.57, 1.06]	
-5	0.72	[-0.74, 2.20]	
-4	2.10	[-0.95, 5.25]	
-3	0.54	[-1.62, 2.75]	
-2	0.91	[-2.17, 4.09]	
-1	0.09	[-1.77, 1.98]	
0	-8.61	[-16.43, -0.05]	*
1	-14.54	[-17.72, -11.24]	*
2	-9.66	[-16.60, -2.14]	*
3	-11.94	[-16.14, -7.53]	*
Overall	**-11.22**	**[-14.34, -7.98]**	*
Panel M: Textiles			
-6	-1.40	[-7.06, 4.60]	
-5	-7.89	[-15.44, 0.34]	
-4	-3.30	[-8.32, 1.98]	
-3	-9.87	[-21.49, 3.46]	
-2	8.66	[-4.74, 23.94]	
-1	-2.61	[-23.47, 23.93]	
0	15.34	[-10.89, 49.31]	
1	8.18	[-10.96, 31.43]	
2	11.91	[-8.66, 37.10]	
3	29.90	[9.64, 53.92]	*
Overall	**16.05**	**[-1.05, 36.11]**	
Panel N: Packaging Glass			
-6	-2.63	[-3.99, -1.25]	*
-5	0.82	[0.15, 1.49]	*
-4	-2.61	[-12.94, 8.94]	
-3	4.17	[-0.50, 9.07]	

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Table B.52 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-2	-3.37	[-13.72, 8.22]	
-1	-1.36	[-4.43, 1.81]	
0	2.15	[-1.67, 6.11]	
1	9.76	[6.94, 12.65]	*
2	11.05	[6.19, 16.13]	*
3	18.95	[14.77, 23.27]	*
Overall	**10.31**	**[8.95, 11.69]**	*
Panel O: Flat Glass			
-6	-0.60	[-7.22, 6.49]	
-5	-3.15	[-17.89, 14.22]	
-4	-11.02	[-42.60, 37.95]	
-3	14.19	[-29.48, 84.92]	
-2	6.92	[-7.87, 24.08]	
-1	-5.45	[-17.85, 8.82]	
0	13.48	[-5.26, 35.94]	
1	8.24	[-0.40, 17.62]	
2	2.22	[-22.20, 34.30]	
3	7.90	[-2.34, 19.22]	
Overall	**7.89**	**[2.27, 13.82]**	*

Weight (W) Pricing

Table B.53: Exact Percentage Change for All Fractions (Weight-Based (W) Pricing)

Event Time	Estimate (%)	95% CI	Significance
Panel A: Batteries			
-4	4.57	[2.95, 6.22]	*
-3	-1.00	[-3.06, 1.11]	
-2	-1.61	[-3.67, 0.50]	
-1	1.14	[-3.46, 5.95]	
0	-2.54	[-4.39, -0.65]	*

Continued on next page

Table B.53 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
1	0.21	[-1.60, 2.05]	
2	5.54	[0.70, 10.61]	*
3	4.83	[1.63, 8.13]	*
4	12.01	[8.73, 15.39]	*
Overall	**3.89**	**[2.04, 5.78]**	*
Panel B: Construction and Demolition Waste			
-4	-14.44	[-18.58, -10.10]	*
-3	13.05	[5.76, 20.85]	*
-2	10.58	[-9.74, 35.48]	
-1	-0.97	[-28.76, 37.66]	
0	-0.03	[-8.58, 9.32]	
1	5.89	[-32.86, 67.00]	
2	-22.83	[-35.97, -6.98]	*
3	-14.88	[-25.68, -2.51]	*
4	-8.01	[-16.07, 0.82]	
Overall	**-8.55**	**[-16.68, 0.38]**	
Panel C: Organic Waste (VFG)			
-4	-2.59	[-3.81, -1.37]	*
-3	-0.58	[-2.00, 0.86]	
-2	-0.08	[-1.66, 1.53]	
-1	-4.96	[-8.31, -1.48]	*
0	-20.10	[-40.67, 7.60]	
1	-32.85	[-41.14, -23.40]	*
2	-35.47	[-46.00, -22.87]	*
3	-41.56	[-47.72, -34.67]	*
4	-41.53	[-46.03, -36.66]	*
Overall	**-34.75**	**[-40.49, -28.45]**	*
Panel D: Green Waste			
-4	63.54	[57.72, 69.57]	*
-3	9.53	[-9.67, 32.81]	

Continued on next page

Table B.53 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-2	-8.78	[-28.98, 17.17]	
-1	-2.34	[-23.83, 25.20]	
0	3.57	[-25.05, 43.12]	
1	4.12	[-5.08, 14.21]	
2	-1.85	[-26.32, 30.74]	
3	-0.15	[-26.57, 35.77]	
4	-13.19	[-18.58, -7.43]	*
Overall	**-1.71**	**[-17.23, 16.72]**	
Panel E: Wood Waste			
-4	6.73	[3.84, 9.70]	*
-3	4.61	[2.25, 7.03]	*
-2	0.27	[-8.97, 10.46]	
-1	-2.45	[-16.12, 13.45]	
0	-9.57	[-19.80, 1.97]	
1	-15.38	[-26.97, -1.95]	*
2	-19.35	[-42.15, 12.45]	
3	-12.25	[-34.87, 18.24]	
4	-21.61	[-27.55, -15.18]	*
Overall	**-15.74**	**[-29.29, 0.39]**	
Panel F: Small Hazardous Waste			
-4	-3.73	[-5.31, -2.13]	*
-3	2.07	[-0.67, 4.89]	
-2	-0.67	[-6.49, 5.51]	
-1	-3.34	[-9.88, 3.67]	
0	1.05	[-4.32, 6.72]	
1	8.01	[4.77, 11.36]	*
2	3.41	[-2.21, 9.36]	
3	0.30	[-1.71, 2.35]	
4	-3.74	[-6.36, -1.05]	*
Overall	**1.73**	**[-0.13, 3.63]**	

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Table B.53 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
Panel G: Hard Plastics			
-4	-4.17	[-9.65, 1.64]	
-3	1.10	[-10.52, 14.24]	
-2	-3.04	[-12.68, 7.67]	
-1	2.54	[-11.29, 18.51]	
0	-12.79	[-16.61, -8.79]	*
1	-17.21	[-42.90, 20.05]	
2	1.28	[-49.94, 104.88]	
3	52.83	[-63.65, 542.51]	
4	274.63	[239.12, 313.86]	*
Overall	**33.16**	**[-23.68, 132.33]**	
Panel H: Scrap Metal			
-4	3.40	[-1.28, 8.31]	
-3	0.32	[-2.25, 2.95]	
-2	5.26	[-11.32, 24.95]	
-1	4.92	[-31.45, 60.60]	
0	-11.66	[-48.79, 52.37]	
1	3.77	[-79.51, 425.47]	
2	-29.43	[-41.44, -14.96]	*
3	-18.27	[-40.44, 12.15]	
4	-1.85	[-9.18, 6.08]	
Overall	**-12.30**	**[-27.23, 5.70]**	
Panel I: Paper and Cardboard			
-4	0.65	[-0.02, 1.32]	
-3	-0.47	[-1.59, 0.67]	
-2	2.18	[-0.26, 4.69]	
-1	4.08	[2.79, 5.38]	*
0	-5.27	[-9.26, -1.11]	*
1	-4.86	[-5.61, -4.10]	*
2	-5.97	[-7.09, -4.84]	*

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Table B.53 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
3	-5.64	[-6.86, -4.40]	*
4	-0.80	[-2.51, 0.95]	
Overall	**-4.53**	**[-5.54, -3.50]**	*
Panel J: Vegetable and Animal Oils/Fats			
-4	8.57	[4.70, 12.58]	*
-3	0.68	[-13.27, 16.88]	
-2	-4.95	[-8.96, -0.76]	*
-1	-1.65	[-7.47, 4.54]	
0	1.93	[-2.44, 6.49]	
1	-3.00	[-13.32, 8.54]	
2	-2.69	[-13.96, 10.05]	
3	-1.04	[-14.92, 15.09]	
4	-15.39	[-19.10, -11.52]	*
Overall	**-4.23**	**[-8.50, 0.23]**	
Panel K: PMC			
-4	2.47	[1.64, 3.30]	*
-3	-1.12	[-2.73, 0.51]	
-2	-2.33	[-9.64, 5.57]	
-1	0.03	[-12.17, 13.93]	
0	5.19	[-18.66, 36.05]	
1	14.09	[2.29, 27.26]	*
2	15.54	[6.19, 25.72]	*
3	15.25	[6.67, 24.52]	*
4	11.90	[9.10, 14.76]	*
Overall	**12.33**	**[4.01, 21.31]**	*
Panel L: Residual Waste			
-4	1.59	[0.39, 2.79]	*
-3	3.06	[-2.12, 8.53]	
-2	2.29	[-4.09, 9.09]	
-1	1.40	[-9.45, 13.56]	

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Table B.53 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
0	-16.07	[-35.29, 8.85]	
1	-22.87	[-28.81, -16.44]	*
2	-20.43	[-29.57, -10.09]	*
3	-19.25	[-34.06, -1.13]	*
4	-21.58	[-23.99, -19.09]	*
Overall	**-20.07**	**[-21.77, -18.34]**	*
Panel M: Textiles			
-4	-10.97	[-13.71, -8.15]	*
-3	4.62	[2.46, 6.82]	*
-2	0.74	[-13.06, 16.74]	
-1	-1.42	[-26.52, 32.25]	
0	-4.11	[-33.41, 38.07]	
1	-12.36	[-17.03, -7.43]	*
2	-27.71	[-65.61, 51.95]	
3	-57.32	[-70.83, -37.55]	*
4	-59.37	[-61.40, -57.24]	*
Overall	**-36.25**	**[-44.31, -27.01]**	*
Panel N: Packaging Glass			
-4	-7.60	[-9.66, -5.49]	*
-3	-1.57	[-11.07, 8.94]	
-2	-7.78	[-19.17, 5.21]	
-1	3.60	[-8.46, 17.25]	
0	-0.05	[-12.31, 13.92]	
1	4.02	[0.10, 8.09]	*
2	0.86	[-16.78, 22.25]	
3	3.73	[1.56, 5.93]	*
4	0.92	[-1.69, 3.60]	
Overall	**1.88**	**[-1.99, 5.91]**	
Panel O: Flat Glass			
-4	10.31	[7.29, 13.42]	*

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Table B.53 – continued from previous page

Event Time	Estimate (%)	95% CI	Significance
-3	-12.71	[-25.04, 1.65]	
-2	3.48	[-2.82, 10.18]	
-1	0.63	[-9.79, 12.25]	
0	-3.14	[-16.68, 12.60]	
1	-15.35	[-27.97, -0.53]	*
2	-9.48	[-19.61, 1.92]	
3	-8.65	[-30.27, 19.66]	
4	-8.52	[-12.39, -4.48]	*
Overall	**-9.11**	**[-13.47, -4.54]**	*