Enabling circularity: Analysis of factors influencing MSW sorting behaviour in Central Norway

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Abstract

A comprehensive waste composition analysis was undertaken in 2021, covering ten municipal waste companies in Central Norway. The results are used in a multiple linear regression model to explore factors influencing the municipal solid waste sorting behaviour. The aim of the study is to better understand what affects waste sorting, to aid in the progress of achieving circular economy targets. The share of food waste and mixed waste in the mixed waste bin is analysed considering three variables: Food waste collection system, glass and metal packaging waste collection system and type of settlement. The waste collection systems are found to have a significant effect on the sorting behaviour, where the *possibility* for sorting and the *user-friendliness* and *transparency* of the sorting system are important factors. Type of settlement is not found to have a significant effect on the sorting behaviour. We recommend further in-depth studies to confirm and expand on the findings in this study, and to better utilise the potential of waste composition analyses to enhance understanding of waste sorting behaviour. This understanding is crucial to reach a more circular waste system.

Keywords: Municipal solid waste, sorting behaviour, waste management, regression analysis, circular economy.

1. Introduction

To achieve a more circular future, municipal solid waste (MSW) management plays a key role, as large quantities of materials with great potential for reuse and recycling are handled. The 2021 Norwegian material recovery rate for MSW was 43 % (Statistics Norway 2022), far from the 2025 target in line with the EU of 55 % (Directive (EU) 2018/851 2018). Effective sorting at source is vital to increase material recovery, and there is room for improvement as more than 60 % of the waste in the mixed waste bin is recyclable materials (Fagerheim et al 2021). Effective waste strategy planning relies on good data (Thomas 2004), and this paper aims to contribute by studying the effects of various factors on the sorting behaviour.

This work was initiated to test an assumption that there is a difference in MSW sorting behaviour between different size settlements, i.e., cities versus more sparsely populated areas. To test this assumption, consistent and comparable data was needed. In 2021 the largest waste composition analysis in Norway to date was carried out, for the circular waste cluster CIVAC (Fagerheim et al 2021). The analysis was carried out for eight MSW companies in Central Norway, further including results from waste composition analyses performed in the same time period by two other MSW companies in the region. The resulting analysis covers an area of more than 750 000 inhabitants, and more than ten tonnes of waste was analysed. This data set made it possible to compare variations between cities and villages/towns, as well as variations between different sorting systems, on a sample area basis.

2. Methodology

Using the results from the waste composition analysis, a multiple linear regression analysis was carried out, to study what significantly affects waste sorting.

The waste composition analysis investigated the contents of the mixed waste (MW) bin, identifying the share (weight percentage) of the 11 fractions shown in Table 1. The share of the fraction was used as dependent variable, and the regression was run for each fraction. Using a 5 % significance level, significant results were found for five fractions (in italic in Table 1). The focus of this study is the two largest fractions: Food waste including paper towel (FW) and MW which comprises the correctly sorted MW.

Twenty distinct sample areas were analysed, nine in cities and 11 in smaller settlements. 15 of the areas have separate collection of FW, and nine have kerbside collection of glass and metal packaging waste (G&M). One of the two additional MSW companies included reported only the totals, which cover eight sample areas, but in our analysis only counts as one sample area: a city without separate FW and kerbside G&M collection. See Table 2 for an overview of the MSW companies' solutions for sorting at source. This Table 1 Overview of dependent variables: waste fractions in the mixed waste bin.

Waste fractions
Paper and cardboard
Food waste incl. paper towel
Garden waste
Bags for waste
Plastic packaging
Glass packaging
Metal packaging
Other metal
Recyclable textiles
Hazardous waste and WEEE
Mixed waste

Table 3	Overview of MSW companies' source	
	and the first of the standard st	

orting solutions: basis for independent variables.										
	MSW 1	MSW 2	MSW 3	MSW 4	MSW 5	MSW 6	MSW 7	MSW 8	MSW 9	MSW 10
Mixed waste										
Food waste		×							\times	\times
Paper/cardboard										
Plastic										
Glass/metal										
Kerbside collection Central coll./recycling point										
Optibag			se ⁻	par	ate	col	lec	tior	n: ×	

methodology made it possible to isolate three independent variables for the regression analysis, shown in Table 3. As the independent variables are categorical, they were all initially coded as dummy variables (Wooldridge 2009).

Table 2 Overview of independent variables and their coding in the model.

Independent	Short name	Values					
variables	Short hanne	-1	0	1			
Separate FW	sepEW	No separate	Ontibag	Separate FW			
collection	sepriv	collection	Optionag	bin			
Kerbside G&M	Ironh C %M		Central recycling point	Kerbside G&M			
collection	KerbGam		or civic amenity site	collection			
Settlement			Town/village	City			

For separate FW collection, two systems were represented in the sample areas: A separate bin, and the optibag system. In the optibag system, several waste fractions are sorted in colour-coded bags and collected in the same bin, to be machine sorted centrally. Using a scatter plot, in Figure 1, we found that the results from the optibag system lie between no

separate collection and a separate FW bin. To corroborate this finding, the share of FW in the MW bin for a city which also uses the optibag system, is included in the figure as *Alt. optibag*. The coding of the dummy variable was changed to linear, increasing the explanatory power of the model (R^2) by 10 percentage points.

This study has a small number of observations for a multiple regression analysis, which can increase uncertainty. This is because it was carried out at a sample area level rather than a household level. A sample area is however aggregated waste from typically 30-40 households, and we expect that the analysis represents around 600-800 households. Each bin collected is a snapshot in time, which may not be representative of the households' average waste composition. Aggregating into sample areas may



Figure 1 Actual shares of FW in the MW bin, by source sorting solution.

thus make a more representative waste composition, but for an area rather than a household. As we do not have any information about each household, the additional resolution would give limited value, as variations cannot be explained. On the other hand, using data from only one analysis will ensure consistent data collection, reducing other sources of uncertainty. Differences between waste composition analyses can include analysis methods, such as sample size and location, or types and number of waste components (Dahlén & Lagerkvist 2008). In conclusion, the consistent data collection was considered to compensate for the small number of observations, and the study deemed a good contribution to advance the understanding of how external factors can affect MSW source-sorting results. To strengthen the findings and increase generalisability, similar studies should be carried out.

3. Results and discussion

The results from the linear regression model for FW are shown in Table 4. The model explains (\mathbb{R}^2) 85 % of the variation in the fraction, but only separate FW collection has a significant impact (p<0.01) on the amount of FW in the MW

Table 4 Results for food waste fraction regression model.

Dependent variable: Food waste								
\mathbb{R}^2	85 %	6		95 % confidence				
Obs.	20	Coeff.	P-value	intervals				
(Intercept)		35 %	< 0.01	32 %	39 %			
sepFW		-9.7 %	< 0.01	-12.5 %	-7.0 %			
kerbG&M		-3.3 %	0.13	-7.6 %	1.1 %			
Settlement		1.7 %	0.45	-3.0 %	6.5 %			

bin. With each increment in the separate FW collection variable, i.e. from no collection to optibag, or from optibag to dedicated FW bin, the share of FW in the MW bin is reduced by almost 10 percentage points. Due to how the sepFW variable is coded, this means the FW share goes from 45 % with no collection, to 35 % with optibag, to 25 % with dedicated bin, which amounts to an average 25 % reduction per step. The confidence intervals indicate a 95 % likelihood that the real reduction is between 7 and 12.5 percentage points. Kerbside collection of glass and metal packaging waste and the settlement type do not show any significant effects on the amount of FW in the MW bin.

The results from the linear regression model for correctly sorted MW are shown in Table 5. The model explains 82 % of the variation in the fraction, both and separate FW collection and kerbside G&M collection have significant effects (p<0.01) on the

Table 5	Results	for mixed	l waste	fraction	regression	model.
Deper	ndent v	ariable: N	Mixed	waste		

Dependent variable. Mixed waste								
R ²	82 %	6		95 % confidence				
Obs.	20	Coeff.	P-value	intervals				
(Intercept)		31 %	< 0.01	27 %	34 %			
sepFW		6.7 %	< 0.01	3.9 %	9.4 %			
kerbG&M		7.5 %	< 0.01	3.1 %	11.8 %			
Settlement		-4.4 %	0.07	-9.1 %	0.3 %			

dependent variable. With each increment in the separate FW collection variable, the share of correctly sorted MW increases by almost 7 percentage points, going from 24 % with no collection, to 31 % with optibag, to 37 % with dedicated FW bin. This amounts to an increase of about 25 % per step on average. The confidence intervals indicate an increase between 4 and 9.5 percentage points. For kerbside collection of G&M, the share of correctly sorted MW increases by 7.5 percentage points, from 31 % to 38.5 %, which amounts to a 24 % increase. There is a 95 % probability that the increase is between 3 and 12 percentage points.

The increase in the share of correctly sorted MW from kerbside collection of G&M is larger than can be explained by a reduction in G&M alone, as G&M are small weight fractions. This suggests that other factors may be at play, and indeed we found a significant effect on the share of plastic packaging waste in the MW bin: When there is kerbside G&M collection there is less plastic packaging waste in the MW bin. This interrelation cannot be explained by our dataset, but Mikkelborg (2017) also found a connection between sorting of different waste fractions, where better sorting in one fraction coincides with better sorting in other fractions. He points at communication and information as important factors behind this, further discussed below for other variables.

Despite size of settlement not having a statistically significant effect on the share of correctly sorted MW, it is not far off, with a p-value of 0.07. Mikkelborg (2017) showed that typical city traits, such as limited indoor and outdoor space, more households likely to have small children (citizens in 20s and 30s age groups), more citizens with foreign background and more lower income households, are related to a lower degree of source sorting. The results from Mikkelborg (2017) were further analysed in Fagernæs (2018), and better communication differentiated by target group is presented as a key measure to improve poor source sorting. One could hypothesize that targeted communication is easier and social control stronger in a smaller community. The insignificant effect of settlement type on correctly sorted MW indicates better sorting in smaller communities.

Based on the results we see that two factors are important for improved MSW sorting at source: (1) The possibility to sort at source. For FW, we see that having separate FW collection reduces the amount of FW in the MW bin with both systems. This is in many ways obvious, as the only option if there is no separate FW sorting, is to dispose of FW in the MW bin (or home composting). (2) The convenience of the sorting system. We see that kerbside pickup of G&M reduces the amount of G&M in the MW bin, with significant reductions of the glass and metal packaging waste fractions, as well as a significant increase in correctly sorted MW. The easier it is for the consumer to sort at source, and the less transport required to use the correct waste bin, the more likely it is that they sort better at source.

However, while a more convenient sorting system means more of the fraction is collected separately, studies have shown that it also leads to more missorting in the case of glass and metal packaging. Syversen et al (2019) show that while the amount of sorted G&M waste collected with a kerbside system is more than 25 % higher, the share of waste that is missorted more than doubles, from 4 % to almost 10 %. This means that the quality of the sorted fraction is worse, and it will need more processing before recycling.

A third factor, which was outside the scope of this study, is the transparency of the waste system and the perceived fate of the waste. For FW, we see that the optibag system gives inferior results compared to a dedicated bin collected separately. Based on discussions with industry partners in the CircWtE project, we believe the main reason for this is that the inhabitants do not know enough about how the waste is further treated downstream. When several waste fractions are collected in one bin, they believe all the waste goes to the same place, most likely to incineration, hence perceiving it as less important to sort correctly. Industry partners reported that they see the same effect when several bins are collected with the same multi-compartment truck (CircWtE workshop, 31 May 2022, Trondheim, Norway). It is however worth noting that the optibag system is a space saving solution, requiring a single bin for four separate fractions. In densely populated areas where space is limited, this can enable source sorting of more fractions. This does not apply to indoor space limitations though, where multiple bins are still needed. The optibag system also enables collection of four fractions with one single-compartment truck, which can be beneficial in sparsely populated areas with long transport distances.

The type of settlement was not found to be a significant factor for the MSW sorting at source in this study. This may be rooted in how the type of settlement was determined. As we did not have detailed knowledge about where the waste was collected, sample areas were defined as city or town/village based on the name of the settlement. Most Norwegian cities are small and not densely populated, implying that the differences between a city and a town may be minor. Demographic traits also vary between neighbourhoods and different degrees of urbanization, meaning the sample areas from cities may not represent typical city traits. Without detailed knowledge about the locations, we were not able to analyse this further.

Despite interesting findings, a limited number of variables were available for analysis. Demographic variables are found to have significant effects on degrees of sorting at source (Mikkelborg 2017), but the dataset did not allow for such variables. With only two sample areas per MSW company, quantitative analysis of differences between companies was impossible, despite anecdotal indications that e.g. communication strategies can affect results significantly. In the presentation of the waste composition analysis, one MSW company was highlighted for outstanding FW sorting results, despite launching separate sorting only recently. This was explained by an active communication strategy, combined with a strict policy of not collecting wrongly sorted waste. Bad sorting is photodocumented, and the documentation including an explanation of why the waste is not collected is sent to the customer immediately. According to the MSW company, this active communication led to good sorting results as well as high customer satisfaction, which was validated in that they have the two highest shares of correctly sorted MW of all 20 sample areas (CIVAC: Presentation of results from waste composition analysis, 7 December 2021, Stjørdal, Norway). In summary, many variables other than sorting systems affect the results of MSW sorting, and these should be considered when designing systems to enable effective sorting at source. As for the effect of the sorting

systems, comparable results have been found in a similar study by the authors (Grytli & Birgen 2023), strengthening the findings of this study.

4. Conclusions

The results from our regression analyses show that the possibility to sort at source, as well as the user-friendliness and transparency of the waste system, are significant factors impacting MSW sorting behaviour. We recommend further in-depth studies of waste composition analyses to confirm and expand on these findings.

Despite no significant effects from type of settlement in this study, demographic variables have been found to have an effect in other studies. Targeted communication and sanction systems also appear to impact sorting results. These types of variables should be studied further, to aid MSW companies in developing strategies for increased sorting.

This study intends to better utilise the potential of waste composition analyses and the results obtained contribute to a deeper understanding of sorting behaviour and its drivers. The study can help MSW companies better design and select effective collection systems and policymakers in implementing measures to improve sorting and increase circularity.

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