FUTURE WASTE ARISINGS

Main Report

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Report for Defra

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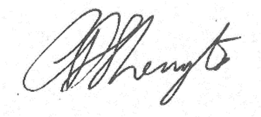

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Version	Date	Author	Description
V0.8	31/03/21	Tanzir Chowdhury	First draft (internal)
V1.0	06/04/21	Tanzir Chowdhury	Second draft (sent to client)
V1.1	23/04/21	Tanzir Chowdhury	Client comments address (sent to client)
V2.0	25/06/21	Tanzir Chowdhury	Final version
V3.1	01/09/21	Tanzir Chowdhury	Final version (resubmitted with some edits)

Contents

1.0 Introduction

Defra has commissioned Eunomia to review Defra's existing methods for forecasting waste arisings in England, and to develop approaches for improving both short-term (<5 years) and long-term (>30 years) forecasts for future waste arisings for different waste streams.

1.1 Project Objectives

The main objectives of the project are as follows:

- **Objective 1:** To provide a review of current methods used by Defra to produce forecasts of waste arisings in light of the most up to date evidence on drivers, and available forecasting and projection techniques;
- **Objective 2:** To provide, to the extent possible, an analysis of historic and current drivers of waste arisings in England covering, at a minimum, waste from households (WfH), local authority collected waste (LACW), municipal waste (MSW), commercial and industrial (C&I) waste, and construction, demolition and excavation (CD&E) waste;
- **Objective 3:** To propose methods for predicting future waste arisings covering at a minimum the waste streams outlined above in objective 2; and
- **Objective 4:** To supply Defra with forecasting models developed under Objective 3.

1.2 Work Packages

Based on the above objectives, the project outputs were divided into the following work packages:

- **WP1 – Review Phase:** A written review of methods currently used by Defra for forecasting and projecting waste arisings across household and commercial and industrial sources;
- **WP2 – Research Phase:** A written analysis of historic and current drivers of waste arisings, covering WfH, LACW, MSW, C&I waste, and CD&E waste;
- **WP3 – Proposal Phase:** A written outline of the methodology for proposed improvements to existing forecasting methods, and where approaches are not already established, an outline of newly proposed methods; and
- **WP4 – Integration Phase:** The development of forecasting formulae and modelling tools (either in spreadsheet format or R code) enabling Defra to make use of proposed (improvements to) methods for forecasting and projecting waste arisings, alongside user documentation.

2.0 WP1 – Review Phase

The aim of the Review Phase is to review the methodology of the Local Authority Collected Waste (LACW) forecast and Commercial and Industrial waste (C&I) projection currently used by Defra to assess the ability of the models to accurately predict future waste arisings.

We will review both the data sources and methodology used. The data sources included will be reviewed to assess their relevance, availability, and reliability (data quality). The methodology will be reviewed to assess whether it is fit for purpose, follows best practice for econometric modelling and the extent to which it utilises the data in the best possible way. In combination, this will enable an assessment of the reliability the LACW and C&I forecasts to determine the overall quality of the tools to project arisings. Finally, where possible, we will assess the performance of the current models by quantitatively assessing the predictive power of the models to accurately predict waste arisings data.

2.1 Local Authority Collected Waste Forecast

2.1.1 Modelling LACW

2.1.1.1 Definition of LACW

LACW consists of all 'Waste from Households' (WfH) in addition to street sweepings, municipal parks and gardens waste, beach cleansing waste, and waste resulting from the clearance of fly-tipped materials plus some commercial and/or industrial waste.[1]

WfH is defined as:[2]

- Residual household waste from the following sources:
  - regular household collection;
  - civic amenity sites;
  - bulky waste and;
  - other household waste.
- Recycled household waste from the following sources:
  - households and other premises similar to households, CA sites, Bring banks;
  - metal recovered and recycled from incinerator bottom ash and;
  - other, from residual streams.

[1] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/918856/Methodology_summary_201819_accessible_.pdf

[2] ibid

The C&I waste included can be defined as non-household municipal waste (NHM) or household-like C&I waste such as that generated at offices.[3] Non-household municipal waste is generated through local authority activities including waste from local authority premises, parks and gardens, and waste collected from businesses by local authorities.

2.1.1.2 Defra LACW Model

A range of approaches have been used by Defra to predict LACW arisings and the categories of waste it includes such as WfH. Previous models have included the use of Auto-Regressive Integrated Moving Average (ARIMA) and Seasonal Auto-Regressive Integrated Moving Average (SARIMA) time series forecasting based on trends in historic data[4], input-output modelling that linked consumer expenditure to waste arisings and causal econometric models that use past consumption expenditure and GDP as explanatory variables.

Here, we will review the most recent method that is currently used by Defra, the consumption approach. The other approaches previously used by Defra are explored at a high level in Section **Error! Reference source not found.**.

2.1.1.3 LACW Model Use

This short run forecast is used for returns for the Treasury for Landfill Tax revenue projections.

As such, the LACW model used by Defra needs to provide both short term (3-5 years) and long term (up to 30 year) projections of LACW arisings.

2.1.2 Methodological Description

Here we describe the data, assumptions and method used in the current Defra LACW model in order to assess its ability to predict future LACW arisings.

2.1.2.1 Data

The data used in this model includes:

1) UK historic GDP sourced from ONS[5] with GDP deflator[6];
2) UK historical consumer expenditure from ONS[7] and OBR forecast[8] and;

[3] https://www.gov.uk/guidance/local-authority-collected-waste-definition-of-terms
[4] NERA Economic Consulting (2012) Review of Methodology for Forecasting Waste Infrastructure Requirements
[5] *Second estimate of GDP Statistical bulletins - Office for National Statistics*, accessed 21 December 2020, https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/secondestimateofgdp/previousReleases
[6] *GDP deflators at market prices, and money GDP*, accessed 21 December 2020, https://www.gov.uk/government/collections/gdp-deflators-at-market-prices-and-money-gdp
[7] *Consumer trends time series - Office for National Statistics*, accessed 21 December 2020, https://www.ons.gov.uk/economy/nationalaccounts/satelliteaccounts/datasets/consumertrends
[8] https://obr.uk/forecasts-in-depth/the-economy-forecast/

3) Historic waste arisings for England 2006-2017[9].

Each of these data sets are produced quarterly[10] and as a result are able to give a quarterly projection of LACW arisings.

A projection of consumer expenditure is used as a predictor of the future waste arisings. The forecast of UK consumer expenditure uses historic data from ONS and the percentage change based on the central, high and low OBR forecasts provided to Defra to give a central, high and low scenario for consumer expenditure.

2.1.2.2 Modelling Approach

The model uses past historic LACW arisings, in combination with a waste prevention measure for waste from non-household sources to give a quarterly projection of future LACW arisings. The method first calculates future values of a ratio of waste arisings to GDP minus household consumer expenditure. The ratio fits the following equation to observed data:

$$\left(\frac{LACW\ arisings}{GDP - hh\ cons.}\right)_t = a + \beta_1 ln(trend) + \beta_2 quarter1 + \beta_3 quarter2 + \beta_4 quarter3 + v_t$$

Subtracting household consumer expenditure from GDP leaves consumption in the government sector, investment and net exports included as the denominator. The numerator represents all LACW arisings. The ratio is used to represent a measure of waste prevention in sectors outside of household consumption and effectively gives a measure of “tonnes of waste generated per £ spent” for waste produced outside of the household. Larger values of this ratio reflect lower rates of waste prevention while smaller values representing higher rates. The forecast is generated using a simple time-series model with seasonal dummy variable for each quarter and a logarithmic trend, which is included to stabilise a strong growth trend in the data.

[9] *ENV19 - Quarterly local authority collected waste management statistics*, accessed 21 December 2020, https://www.gov.uk/government/statistical-data-sets/env19-local-authority-collected-waste-quarterly-tables

[10] It should be noted that the quarterly reported data on Local Authority collected waste (ENV19), has now been replaced with annually reported data (ENV18). However, quarterly data is still available in WasteDataFlow.

Producing the final waste arisings forecast then uses an Auto Regressive Integrated Moving Average model with external effects: ARIMAX(1,0,0). It uses an auto regression of the waste arisings from the previous quarter to predict future arisings, in addition to including external effects of the waste prevention ratio (as calculated above) from the previous year and consumer expenditure with a three and four period lag.

$$arisings_t = a + \beta_0 trend + \beta_1 \left(\frac{arisings}{GDP - C}\right)_{t-4} + \beta_2 arisings_{t-1} + \beta_3 consumer\ expenditure_{t-3} + \beta_4 consumer\ expenditure_{t-4} + v_t$$

2.1.3 Model Assessment

Here we review the advantages and disadvantages of the current LACW forecast approach used by Defra and the ability of the forecast to give accurate projections of waste arisings. We review the assumptions made by the model and whether they enable reliable predictions of LACW in relation to available outturn data.

2.1.3.1 Data

2.1.3.1.1 Historic LACW arisings

The arisings data specified in the model gives only LACW for England[11]. The other external variables incorporated into the model (GDP and consumer expenditure) are economic indicators for the whole of the UK. As these two economic indicators are used to give a projection for LACW, the mismatch in data is likely to have strong negative consequences for the fit of the waste prevention ratio and the overall ARIMA model. To account for this mismatch, the England LACW data is scaled up to account for waste produced in Wales, Scotland and Northern Ireland. This uses a standard scaling value for all previous years. This is unlikely to adequately account for the mismatch in data. Trends in GDP or consumer expenditure in the devolved nations that differ from England will impact the fit of the model in estimating the association between the economic indicators and LACW. This in turn will negatively affect the predictive capacity of the model and lead to projections being less accurate.

The LACW data is sourced from gov.uk, and has previously been published at a quarterly interval (January 2010 to March 2016). This data source is no longer maintained and LACW statistics are now published only on an annual basis[12]. This means the model specification for both the ratio and ARIMA model are incompatible with currently published data sources on LACW arisings and will have to be updated using unpublished data that is only available through the WasteDataFlow portal.

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[11] *ENV19 - Quarterly local authority collected waste management statistics*, accessed 21 December 2020, https://www.gov.uk/government/statistical-data-sets/env19-local-authority-collected-waste-quarterly-tables

[12] https://www.gov.uk/government/statistical-data-sets/env18-local-authority-collected-waste-annual-results-tables

The data set included in the LACW model gives the England-level summary of the total amount of LACW across all local authorities. This data set is collated through WasteDataFlow where LAs make quarterly submissions on waste collected[13]. As such, in addition to quarterly LACW for the whole of England, LA specific data is available for this period. Incorporating this LA level data would enable the model to account for LA specific tonnages and trends in waste generation enabling more accurate projections. There are regional differences in waste generation rates across the UK that are influenced by sociodemographic factors as well as the local waste collection infrastructure[14]. Including this readily available data into a forecast would enable a much larger dataset for analysis and would help produce a more robust forecast model.

In addition, the WasteDataFlow database gives a breakdown of the types of waste collected by LAs. It is feasible that there will be differences in both arisings and trends in the generation of waste from different sources, such as household versus non-household municipal waste. Specifically including waste origin as a factor would enable an econometric projection model to explicitly account for variation in waste generation by origin and account for this in projections of arisings.

2.1.3.1.2 Consumer Expenditure

In the current LACW model, a projection of consumer expenditure is used as a predictor of future waste arisings. The quality of this projection will directly influence the robustness of the LACW waste arisings forecast as it is included as an external variable in the final waste arisings model. The projection of consumer expenditure is based on an average historic rate of change between years, split between quarters to give the quarterly fluctuation in consumer expenditure. The rate of increase is based on the OBR official projection of consumer expenditure, which gives a sophisticated and informed short-term projection based on policy measures. However, the OBR forecast is available for 2015-2019 and then necessarily extrapolated to provide an estimate of growth for the extent of the projection to 2051. Although in place of a better approximation, a linear projection is the most justifiable, the approach used here is too simple to be representative of likely actual trends in consumer expenditure.

2.1.3.2 Method

2.1.3.2.1 Waste Prevention

A key component of the waste arisings model is the incorporation of a reasonable estimate of waste prevention to capture efficiency savings in relevant C&I operations and behaviour changes in household consumption.

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[13] https://www.wastedataflow.org/htm/datasets.aspx

[14] Lisa Dahlén, Helena Åberg, Anders Lagerkvist, Per E.O. Berg, 2009. *Inconsistent pathways of household waste*. Waste Management, Volume 29, Issue 6, 2009, Pages 1798-1806.

The ratio of LACW arisings to GDP minus consumer expenditure is used to estimate waste prevention and incorporated as an external variable in the final waste arisings model. There appears to be a mismatch between waste generated by households and the non-household sector in the data feeding into the waste prevention ratio. The LACW data included as the numerator for the waste prevention ratio includes both household and non-household municipal waste generated, but only non-household expenditure is included in the denominator. As such, the ratio gives a measure of the amount of waste prevented across *both* households and non-household municipal sources per £ spent outside the household sector. This incorrect specification will impact the forecast of the waste prevention ratio, meaning incorrect values feed into the final waste arisings model.

The ratio is intended to capture the waste prevention from non-household sources. The model does not account for waste prevention in the household in other ways. This may be incorporated through the trend in historic arisings from LACW which could capture a tendency for reduction in waste generation. However, with the model's current specification, any inclusion of waste prevention from historic data will also incorporate trends within non-household municipal waste, which is already accounted for in the waste prevention ratio. As a result, the model is unlikely to give an accurate estimation of waste prevention in the household over time.

2.1.3.2.2 Waste Forecast Model Specification

A strength of the modelling approach is the inclusion of consumer expenditure as an external factor in the forecast model. Much research has identified a close association between consumer expenditure and waste arisings.[15,16] However, the model does not include other external factors such as population, population density, social deprivation, etc., all of which are considered as key drivers of households waste arisings.[17,18]

To generate forecasts of the waste arisings, future projections of external factors are required. In the model, the future values of one of the external factors, consumer expenditure, are projected using a standard linear projection based on the OBR consumer expenditure forecast growth rate for the next three years, which is then extrapolated out to 2050. The projection scenarios are mainly driven by assumptions placed on the expected change in future consumer expenditure. However, in its current

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[15] Skovgaard, M., Moll, S., Møller Andersen, F., & Larsen, H. V. (2005). Outlook for waste and material flows. Baseline and alternative scenarios. European Topic Centre on Resource and Waste Management. ETC/RWM Working Paper 2005/1
https://orbit.dtu.dk/files/175851869/ETC_RWM_working_paper_2005_1.pdf

[16] https://link.springer.com/article/10.1007/s10661-015-4977-5

[17] https://www.researchgate.net/profile/Jii_Hebicek/publication/263425991_Case_study_Prognostic_model_of_Czech_municipal_waste_production_and_treatment/links/0a85e53acc09c5d147000000.pdf

[18] http://www.academia.edu/download/48712690/Inconsistent_pathways_of_household_waste20160909-25830-f4r986.pdf

form, there is insufficient support to justify the method used to project consumer expenditure.

The external factors specified in the waste arisings forecast model include the waste prevention ratio from four quarters ago, and consumer expenditure from three and four quarters ago. So the model excludes the waste prevention ratio from the current quarter and the preceding three quarters, and consumer expenditure for the current quarter and the preceding two quarters as external factors.

We believe that excluding the above external factors from the model was carried out as they were non-significant for explaining the variation in waste arisings. The approach used here to exclude variables is generally only employed on very large datasets. Due to the size of the current dataset, it is feasible that variables that are important for explaining the dependent variable are interpreted as non-significant through the fitting of the econometric model. However, excluding external factors purely based on statistical significance can result in biased and inconsistent estimates of the regression coefficients, and in turn diminish forecasting accuracy.

Moreover, the waste forecasting model used quarterly data, which is subject to strong seasonal trends. For example, waste arisings during the summer months will be significantly higher than the winter months due to increase in garden waste arisings during the summer months. Yet the forecasting model does not correct for the potential season trends that will be present in the data, which in turn reduces forecast accuracy.

The 2008 financial crisis and the subsequent years of austerity, as well as the ongoing pandemic have a significant impact on economic indicators and in turn waste generation. Incorporating historic waste arisings data into future projections must be carried out carefully as these anomalous results may impact the association between GDP and waste generation. A large disruption to waste production could affect the association between the dependent and independent variables and reduce the robustness of the forecasts. Failing to account for these anomalous years of waste generation such as through the use of dummy variables, may result in poor estimation of the association between consumer expenditure and waste generation which would reduce the accuracy of the model.

2.1.3.3 Predictive Power

To estimate the predictive power of the forecast model, we have compared the reported waste from households (WfH) for England with the forecasted values for the period between 2016 Q2 and 2019 Q1. The reported WfH for England was sourced from Defra's ENV18 - Local authority collected waste: annual results tables.[19] The model provides forecasts of LACW for England. However, quarterly figures for LACW are not officially reported since March 2016, and only WfH figures are reported quarterly.. So, to compare with the officially reported quarterly WfH figures, we have converted the LACW

19 https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/848689/WFH_England_Data_201819.xlsx

forecasts to WfH forecasts using the average ratio between the two measures over 2010-Q1 to 2016-Q1.

The results are presented in Table 2-1. It can be observed that the absolute deviation ranges from 25 to 577 thousand tonnes with the mean absolute deviation of 222 thousand tonnes. On the other hand, the percentage deviation ranges from 0.5% to 10.3% with is mean percentage deviation of 3.9%.

Table 2-1: Comparison between Reported and Forecasted WfH in England for 2016-Q2 to 2019-Q1 ('000 tonnes)

Quarter	WfH Reported	LACW Forecast	WfH Forecast	Absolute Deviation	Percentage Deviation
2016q2	5,235	5,889	5,068	408	**6.59%**
2016q3	6,185	6,713	5,777	190	**3.11%**
2016q4	6,116	6,886	5,926	76	**1.45%**
2017q1	5,234	5,994	5,158	54	**1.03%**
2017q2	5,204	6,109	5,258	187	**3.08%**
2017q3	6,069	6,835	5,882	124	**2.09%**
2017q4	5,959	7,069	6,083	25	**0.49%**
2018q1	5,205	6,019	5,180	346	**6.94%**
2018q2	4,992	6,203	5,338	311	**4.97%**
2018q3	6,252	6,904	5,941	577	**10.33%**
2018q4	5,584	7,159	6,161	31	**0.59%**
2019q1	5,205	6,084	5,236	330	**6.50%**
Mean Error				**222**	**3.93%**

2.1.4 Summary

In summary, although the LACW model has shown good predictive power, there were some clear weaknesses in the model. These are:

- Inconsistency in the waste minimisation definition;
- Lack of correct seasonal specification in the waste generation equation; and
- Not accounting for macroeconomic shock such as, the economic recession in 2008 and COVID-19.

Also, the model does not incorporate the rich information available at a local authority level captured in WasteDataFlow. Along with the variation across time, incorporating the variations across the local authorities using a panel data regression modelling approach should improve the model significantly.

2.2 Commercial and Industrial Waste Projection Model

2.2.1 Modelling C&I Waste

There is a high degree of uncertainty in the amount of C&I waste arising in England, largely due to C&I waste producers not having the same obligation as LAs to report these arisings. C&I sector surveys have been used in the past by Defra to provide snapshot-based estimates of C&I waste arisings, the most recent of which were conducted in 2003 and 2009[20]. Variation in the C&I sector definition in these surveys due to changes in the standard SIC classification scheme necessitates careful comparison of the results of these surveys[21]. Moreover, the results of the 2009 survey could have been affected by the 2008 financial crisis, and thus should be interpreted carefully.

Since 2010, C&I waste arisings have instead been based on regulatory waste management data and, as a result, the timeseries of comparable C&I estimates is limited. Due to the lack of regular survey data, a reliable method for estimating the current C&I waste arisings in England from the available regulatory data is needed in addition to a model to predict arisings into the future. Defra's 2014 'Reconcile' project presented a new methodology[22], which has been revised over time, with the most recent publication of revisions in 2018[23].

C&I waste is defined as waste arising from a specific collection of economic activities described by NACE ("statistical classification of economic activities in the European Community")[24]. NACE codes currently considered to be C&I include:

- C;
- D;
- E36;
- E37;
- E39 (excluding sewage sludge) and;
- G-U (excluding G46.7.7).

[20] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/400595/ci-statistics-release.pdf

[21] https://www.ons.gov.uk/file?uri=/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities/uksic2007/uksic2007web.pdf

[22] SKM Europe Ltd, WRc, Urban Mines (2014) *New Methodology to Estimate Waste Generation by the Commercial and Industrial Sector in England*, August 2014

[23] Department for Environment, Food and Rural Affairs (2018) *Commercial and Industrial Waste Arisings Methodology Revisions for England*, October 2018

[24] https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDFhttps://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

Due to the low resolution of data available on C&I waste arisings, predicting future C&I arisings has not been based on an econometric model to date but rather a simple projection model based on projected economic growth within the C&I sectors (as measured in gross value added (GVA)), calibrated to GDP projections and adjusted for assumed efficiency gains in waste intensity. This version of the C&I waste arisings model is reviewed in the following sections.

2.2.2 Methodological Description

The current method for predicting future arisings is as follows:

2.2.2.1 Forecast Data and Assumptions

1) UK Gross Domestic Product at market prices and growth rate from ONS[25];
2) UK Gross Value Added for separate commercial and industrial sectors by SIC07 category from ONS[26];
3) Commercial and Industrial waste arisings for England (2010-2017)[27];
4) Value for 2018 from Non-Household Municipal (NHM) waste arisings projection and;
5) Annual efficiency savings in C&I generated.

Gross Value Added: GVA, as a measure of volume of outputs, is more relevant to waste arisings than the volume of inputs for many industries. In some cases, the volume of inputs, such as employee number is likely to give a better reflection of waste production, especially for office-based industries. Within the current Defra model, it has been assumed that GVA is a more important determinant of waste generation as it represents a complete picture of economic outputs.

Efficiency savings: The model makes the assumption that waste arisings are associated with GVA, but takes account that this relationship is unlikely to be static. Instead, over time it is likely that waste intensity for the sector overall--i.e. the relationship between waste arisings and economic output--will change, , using fewer inputs per unit of output, and as a result, produce less waste. Therefore, the amount of waste produced per unit of output (GVA) was assumed to fall with time. An estimate of the efficiency savings based on the 2003 and 2009 waste survey results was available. However, given the impacts of the recession during that period, combined with the likelihood of diminishing opportunities for waste reduction over time, this estimate of efficiency saving was not used. Instead, the model uses a long-term estimate of a 1% waste efficiency savings per

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[25] *Second estimate of GDP Statistical bulletins - Office for National Statistics*, accessed 21 December 2020, https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/secondestimateofgdp/previousReleases

[26] *Regional gross value added (balanced) by industry: all NUTS level regions - Office for National Statistics*, accessed 22 December 2020, https://www.ons.gov.uk/economy/grossvalueaddedgva/datasets/nominalandrealregionalgrossvalueaddedbalancedbyindustry

[27] *ENV23 - UK statistics on waste*, accessed 24 July 2019, https://www.gov.uk/government/statistical-data-sets/env23-uk-waste-data-and-management

year into the future for UK commerce and industry[28,29]. The model also used high, central, and low scenarios with varying waste efficiency savings, all of which converge to the long-term efficiency savings of 1% as implied by the literature.

2.2.2.2 Model

The model calibrates between the Oxford Economics GVA projection and the Office of Budget Responsibility (OBR) GDP projection. The calibration uses the elasticity of GVA with respect to GDP for the commercial and industrial sectors. This is then used as a growth rate to provide a linear projection for the tonnage of C&I waste produced into the future, adjusted using the waste efficiency savings value.

2.2.3 Model Assessment

2.2.3.1 Data

Both the overall projection of C&I waste arisings and the waste efficiency gains assumption are calculated using the association of waste generated to GVA. However, numerous sectors in C&I show a stronger association between inputs and waste generation, such as office-based industries. As a result, using a standard waste efficiency calculation for all C&I activities is unlikely to give an accurate reflection of the true waste arisings and savings, which can vary, for example, by waste composition and technological development of the sector.

2.2.3.2 Method

This approach to projecting C&I waste arisings applies the same growth rate to the entire C&I sector. This doesn't have sensitivity to changes within specific C&I industries and their variable growth rates.

2.2.3.3 Predictive Power

We have compared the 2018 forecasts of the commercial and the industrial waste arisings in England with the actual data for 2018[30]. This is presented in Table 2-2. It can be observed that the model under-predicted the commercial waste arisings by 4.4% while it over-predicted the industrial waste by 2.3%. Overall, the total C&I forecast was 2.6% lower than the actual arisings for England in 2018. However, it should be noted that it is a comparison using only 1 data point, and it is not possible to estimate the true predictive power with such limited data.

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28 https://www.iea.org/data-and-statistics/data-tables?country=WORLD

29 https://www.academia.edu/190057/Resource_efficiency_for_sustainable_growth_global_trends_and_European_policy_scenarios

30 https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/918270/UK_Statistics_on_Waste_statistical_notice_March_2020_accessible_FINAL_updated_size_12.pdf

Table 2-2: Comparison between Actual and Forecasted C&I Waste Arisings for England in 2018 (million tonnes)

Category	Forecast	Actual	Percentage Difference
Commercial	25.9	27.1	**-4.4%**
Industrial	10.3	10.1	**2.3%**
Total C&I	**36.2**	**37.2**	**-2.6%**

2.2.4 Summary

In summary, there were some key weaknesses in Defra’s current C&I waste forecasting model. These are:

- Use of arbitrary efficiency saving assumption;
- Same efficiency saving assumption for both commercial and industrial sector;
- Not accounting for impact of growth in number of businesses on waste arisings; and
- Not accounting for macroeconomic shock such as, the economic recession in 2008 and COVID-19.

Incorporating the above in the C&I waste forecasting model should improve the accuracy and robustness of the forecasts.

3.0 WP2 – Research phase

The Research Phase consists of a written analysis of historic and current drivers of waste arisings, covering Waste from Households (WfH), Local Authority Collected Waste (LACW), municipal, C&I and C, D & E waste. This review of the literature has been conducted to assess the historic and current drivers of waste arisings and identify best practice methods for producing waste arisings projections.

3.1 Methodology

Here we assess academic literature and other national waste projection methods to develop a guide of best practice for waste arisings projections. We review comparable international models, where available, to inform the key drivers and methods for estimating this data.

This review will create a set of best practice guidelines for developing waste arisings models. Below are listed the key issues that were assessed through the review of each driver, which help enable an evaluation of the validity of the driver based on its nature and influence on waste generation, in addition to data quality and applicability to making predictions. These drivers are presented in summary here but reviewed in full in the matrix in the appendices. They have been split into two categories: nature of driver and data sourcing and modelling. These categories are designed to encompass an assessment of the effect on volume of waste produced; the magnitude of effect; and likely timings of implementation in addition to the quality and practicability of including the variable in a waste arisings forecast.

Nature of driver:

1) **Driver and explanation:** Justification for how the driver influences the waste stream, and uncertainties for this association. This is of particular importance for policy drivers which can be targeted to impact overall waste generation or waste stream (WfH vs C&I), or be targeted to impact waste treatment (residual vs. recycling) and result in a reduction of overall waste arisings indirectly.
2) **Timescale:** Extent of impact over time. For drivers such as policy measures, time scale is of particular importance to account for timing of impact.
3) **Intensity of impact:** Strength of impact over time. This is particularly relevant for the impact that economic indicators have on waste arisings as the impact is likely to be delayed depending on the product in question.
4) **Influencing factors:** Additional external factors likely to influence the driver in question, whether this can be accounted for/ controlled for in the model and characterisation of the impact.

Data sourcing and modelling:

1) **Data source and resolution:** Reviewing the data source available, the extent of time series and level of disaggregation (e.g. country or LA level reporting) in the data to feed into the model development.
2) **Methods of estimation:** For drivers without existing projections, methods of estimation and their strengths and weaknesses.

3) **Quality of projection:** For drivers with existing projections, the source, quality, resolution and duration of projection.
4) **Methodological uncertainty:** Uncertainties associated with the use of driver in forecasting.

The review was conducted by searching academic and grey literature that assessed factors influencing arisings across each waste streams of interest in other developed nations where the drivers of waste generation were considered to be similar to that of England.

The outcome of this review and matrix will provide the basis for identifying the key drivers to include in the proposal phase for new models and the context needed for the Review phase for past models used by Defra.

3.1.1 Waste Streams

The waste streams modelled on behalf of Defra have very specific definitions in the context of Local Authority waste collection. Academic research and modelling approaches from other countries rarely use comparable definitions of waste. As such, a generalised approach is used here to assess factors that influence waste arisings, and findings are caveated by discrepancies between definitions.

The assumption is made for all streams of waste explored here that the amount collected is equivalent to all waste generated from that waste stream. This does not account for waste that is not processed through legal routes, (i.e. waste crime), or waste processed through avenues that are not directly accounted for the reporting methodology, for example, waste collected by sources not included in the WasteDataFlow returns.

3.2 Waste from Households and Local Authority Collected Waste

The ‘waste from households’ measure was introduced by the UK in 2014 to provide a harmonised UK indicator for reporting recycling rates at a UK-level, complying with the Waste Framework Directive (2008/98/EC). It excludes local authority collected waste (LACW) not considered to have come directly from households, i.e. street bins, street sweepings, parks and grounds waste, and compost-like output. It includes IBA metals. Specifically, waste from households includes:

- Recycling:
    - from households and other premises similar to households, CA sites, Bring banks
    - from household-related parks and grounds (from community skips only)
    - Metal recovered and recycled from incinerator bottom ash
- Residual waste:
    - Regular household collection
    - From civic amenity sites
    - From bulky waste
    - From other household waste

Local authority collected waste consists of all ‘waste from households’, street sweepings, municipal parks and gardens waste, beach cleansing waste, and waste resulting from the clearance of fly-tipped materials plus some commercial and/or industrial waste.

3.2.1 Historic Waste Arisings

English Local Authorities provide quarterly submissions to WasteDataFlow[31] which has served as the main source for LACW data since 2006, and WfH data since 2014. The data is made available online at yearly intervals with a one-year lag. It provides high resolution data on recycling and residual waste collected by local authorities, and from 2014, also provides details of waste treatment destinations through Qu100.

3.2.2 Socio-economic Drivers

3.2.2.1 Population Density and Deprivation

Population, population density and level of deprivation have been identified as key drivers of waste generation from several sources. WRAP uses a classification method for identifying comparable local authorities (LAs) in order to understand the likely impacts of proposed service changes for residual and recycling collections. The LA Portal uses an index of rurality and deprivation to classify authorities’ waste characteristics, suggesting these variables are maybe indicative of waste generated from households[32]. The tool uses a 6-part rurality classification that represents the typical operating conditions of LAs according to their predominant geographical and demographic contexts. The classification consisted of three geographical contexts (Predominantly Urban, Mixed Urban and Rural, and Predominantly Rural) and two levels of social deprivation (higher deprivation, lower deprivation) [33]. A caveat to this research is that the WRAP generated waste collection methods are also based on this index. LA waste collection methods are known to impact upon the composition of waste collected from households and may also impact the total amount of waste collected.

Rurality in this case is used as a proxy for population density, which has been found to influence household waste generation negatively in other countries. Research of the drivers of Czech municipal waste production found that the municipal status (whether a town or a city), in addition to other socio-demographic variables such as number of inhabitants per house and share of unemployed were socio-demographic variables were associated with the amount of waste generated[34]. A further study of Swedish household

[31] https://www.wastedataflow.org/htm/datasets.aspx

[32] https://laportal.wrap.org.uk/Documents/ICP%20online%20tool%20assumptions.pdf

[33] WRAP (2015) ICP2 - Online Tool Modelling Assumptions Technical Annex

[34] https://www.researchgate.net/profile/Jii_Hebicek/publication/263425991_Case_study_Prognostic_model_of_Czech_municipal_waste_production_and_treatment/links/0a85e53acc09c5d147000000.pdf

waste generation found waste generation per person is higher in more populous municipalities, and those with a high population density[35].

3.2.2.2 GDP & Consumer Expenditure

For some waste streams, the amount of waste produced is linked to the consumption of categories of goods, such as the link between municipal waste and the consumption of food, beverage and clothing. This is captured in consumer expenditure or through GDP as a proxy (see Section 3.3.2 for greater discussion of GDP). Forecasts of waste flows for residential and C&I sectors by the European Topic Centre on Resource and Waste Management used an assessment of waste per inhabitant or per household, using household consumption expenditure as an external variable for forecasting[36]. GDP is more commonly used as a predictor of waste arisings than consumer expenditure due to more readily available estimates and forecasts.

A study predicting municipal solid waste generation that tested a range of demographic and economic variables such as population number, GDP, electricity demand per capita and employment numbers found that the optimum model with an R2 of 0.97 had three inputs: GDP, population and employment.[37] However, it should be noted that though these drivers generated a high model fit in this study, the results may not be generalisable and the same model applied to different data may not perform as well.

3.2.2.3 Municipality-Specific Trends

A study of household waste generation in Sweden identified that site-specific factors are a key influence on waste generation[38]. The proximity to waste disposal infrastructure such as recycling centres, drop off points and the location of collection of recyclables all showed a strong correlation with the amount of waste generated. This underpins the importance of including Local Authority level data in forecasts of waste arisings data to account for LA specific regional trends that are likely to affect waste collection practices.

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35 http://www.academia.edu/download/48712690/Inconsistent_pathways_of_household_waste20160909-25830-f4r986.pdf

36 Skovgaard, M., Moll, S., Møller Andersen, F., & Larsen, H. V. (2005). Outlook for waste and material flows. Baseline and alternative scenarios. European Topic Centre on Resource and Waste Management. ETC/RWM Working Paper 2005/1 https://orbit.dtu.dk/files/175851869/ETC_RWM_working_paper_2005_1.pdf

37 https://link.springer.com/article/10.1007/s10661-015-4977-5

38 http://www.academia.edu/download/48712690/Inconsistent_pathways_of_household_waste20160909-25830-f4r986.pdf

3.2.3 Policy Drivers

The UK's waste regulations are designed mostly for diversion of waste from landfill and increasing recycling rates. Here we review some of these historic and future policy drivers that may also impact waste arisings in WfH and LACW.

3.2.3.1 European Commission: Waste Framework Directive (2008)

The European Waste Framework Directive (WFD) provides the overarching legislative framework for the collection, transport, recovery, and disposal of waste across Europe. Through the WFD, the UK is subject to legally binding recycling targets, among other requirements adopted into UK legislation. The WFD introduced into policy the concept of the waste hierarchy which makes prevention the top waste management priority, followed by preparation for reuse, recycling and recovery and landfill being the least desirable option.

3.2.3.2 Plastic Bag Charge

A 5p charge on single use carrier bags was introduced in October 2015. As of 2019/20, there has been a 95% reduction in the number of single use carrier bags sold by the main retailers (Asda, The Co-Operative Group, Marks and Spencer, Morrisons, Sainsbury's, Tesco and Waitrose) since 2014, before the carrier bag charge was introduced. This is equivalent to over 7.4 billion single use carrier bags fewer sold by the main retailers in 2019/20 than in 2014[39]. The single use carrier bag fee is due to double to 10p and extended to all shops, including those employing 250 people of fewer from April 2021. Based on the success of the tax for large retailers, the introduction to smaller retailers could result in a substantial reduction in waste generation. However, the behaviour change introduced by the charge may have already reduced the use of carrier bags in smaller stores. As carrier bags will be disposed by the household after use, this will impact household waste generation.

3.2.3.3 Defra's Resources and Waste Strategy

Defra's Resources and Waste Strategy (RWS)[40] indicates future policy direction and the extent to which, and how, the Circular Economy Package will be implemented in England. Implementation of the RWS is likely to impact both recycling and residual waste arisings from households, which are reviewed here.

Policy for these measures under the RWS is not due to be implemented anytime soon and are subject to further consultation. In the current political climate, there is uncertainty around the extent to which policy changes will be implemented. As such, making predictions around the range of impacts that would result from policy changes is challenging. As part of the Resources and Waste Strategy, three main policy avenues are being explored, with the second phase of public consultation having completed mid-2021:

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[39] https://www.gov.uk/government/publications/carrier-bag-charge-summary-of-data-in-england/single-use-plastic-carrier-bags-charge-data-in-england-for-2019-to-2020

[40] https://www.gov.uk/government/publications/resources-and-waste-strategy-for-england

3.2.3.3.1 Consistency in collection standards

LAs will be required to provide a minimum service of collections of a core set of recycling materials by 2023, including separate food waste collection. Businesses will also have to segregate their recycling and food waste for separate collection. This is likely to change the tonnages of waste from household sources reported in recycling and residual streams, but is unlikely to impact the overall volume of waste generated by households.

3.2.3.3.2 Deposit Return Schemes (DRS)

DRS systems are highly effective at achieving both high quality (due to segregation) and high collection rates of plastics (reportedly as high as 95-98%[41]), which is under consideration from the Government to introduce from 2023. The introduction of a DRS system is likely to reduce the overall amount of waste recorded from household sources as this waste is transferred to the C&I waste stream where it is processed. Approximately 947 thousand tonnes of plastic bottles were placed on the market in the UK in 2017,[42] much of this tonnage is disposed of through household waste routes currently but under a DRS system would become the responsibility of C&I waste stream.

3.2.3.3.3 Extended Producer Responsibility (EPR)

EPR is a policy approach wherein producers are given a significant responsibility – financial and/or physical – for the treatment or disposal of post-consumer products (e.g. packaging). Under the EPR proposals, producers of packaging will bear the full net costs of collecting, sorting and disposing of packaging. The costs of managing waste are currently borne by LAs, but could be transferred to producers, whose costs could then include those associated with collecting, transporting, sorting, treatment and disposal of waste, and also the costs of littering.

Placing costs on producers gives them an incentive to reduce those costs by:

- eliminating unnecessary packaging;
- ensuring packaging is readily recyclable; and
- using recycled material (assuming supporting policies and economics are right).

The proposed changes to EPR, including the introduction of a DRS, seek to increase the amount of packaging that is recycled, thereby reducing the packaging content present in residual waste and increasing the financial value within the recycling system.

Around 1.7 million tonnes of plastic packaging waste is generated from households every year in the UK[43]. Under EPR and DRS there is likely to be a large shift from waste generated from households as responsibility for waste progressing is transferred to producers.

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[41] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/694916/voluntary-economic-incentives-working-group-report-drinks-containers-final.pdf
[42] https://www.wrap.org.uk/sites/files/wrap/WRAP_Plastics_market_situation_report.pdf
[43] https://www.preventedoceanplastic.com/how-europes-plastic-waste-exports-contribute-to-ocean-plastic-pollution-elsewhere/

3.2.3.4 Consumer Awareness

Brands selling products in plastic packaging are recognising heightened consumer awareness with plastic (the Blue Planet II effect[44]). In addition, food waste awareness (using media coverage of food waste as a proxy) has been identified by WRAP to have a significant impact of food purchasing behaviour and food waste.[45] This means consumers find ways to avoid waste and change their purchasing behaviour to buy smaller quantities of more expensive food. This change in consumer awareness is likely to impact the consumer expenditure to waste ratio for organics and plastics.

3.2.3.5 Climate Emergency Declarations

As of February 2021, a total of 300 out of 404 (74%) District, County, Unitary & Metropolitan Councils—including 8 Combined Authorities/ City Regions—have made Climate Emergency declarations and will be drafting action plans focussed on carbon reduction[46]. As a key element of climate emergencies, local authorities will be focusing on waste prevention from household and non-household municipal waste sources. Focus on minimising waste generation, increasing recycling rates and reducing residual waste are likely to be consequences of this.

3.2.3.6 Waste Prevention Programme for England

The 2013 Waste Prevention Programme for England[47] outlined how government and industry should work together to help achieve a more sustainable and resource efficient economy with less waste. The programme recommended ways that all parts of society could contribute to waste reduction and laid out ways the Government planned to improve resource efficiency, such as supporting voluntary agreements with business on food and clothing with waste reduction at their core, raising awareness of resource efficient-business models, and developing schemes to support communities to take forward waste prevention actions. A review of the Waste Prevention Programme by WRAP[48] (2020) assessed the impact and effectiveness of individual measures and reviewed overall performance of the programme on waste prevention. It found that waste arisings are at a similar level in 2017 to 2013, and waste arisings per unit GVA has decreased. A similar trend has been observed in the economy's total raw material consumption, indicating that the UK economy is continuing to grow faster than material consumption and waste arisings. The study found that about 400,000 tonnes of waste had been prevented, the majority of which were food and packaging waste as a result of the Courtauld Commitments. Government consulted on a new 'Waste Prevention

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[44] The change in consumer behaviour as a result of the Blue Planet series that highlighted the negative consequences of plastic packaging on wildlife.

[45] https://wrap.org.uk/sites/files/wrap/Econometrics%20Report.pdf

[46] https://www.climateemergency.uk/blog/list-of-councils/

[47] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/265022/pb14091-waste-prevention-20131211.pdf

[48] https://wrap.org.uk/sites/files/wrap/Final%20WPP%20Summary%20Evaluation%20Report.pdf

Programme for England: Towards a Resource Efficient Economy' between March and June 2021. This builds on the 2018 Resources and Waste Strategy, and seeks to agree a programme which helps with the Government's strategic goals of reducing greenhouse gas emissions and achieving Net Zero, protecting natural capital, addressing resource security, and creating jobs and growth, as well as increasing resource productivity and minimising waste.

The consultation document outlines the potential for, and benefits of, action on waste prevention and sets out the actions that the government intends to take. It recognises that action is required across society – by government, businesses, local authorities, consumers and others - for progress to be made. It proposes action across seven key sectors – construction; textiles; furniture; electrical and electronics products; road vehicles; packaging, plastics and single-use items; and food - to minimise waste and work towards a more resource efficient economy. This includes steps to use resources more efficiently, design and manufacture products for optimum life and repair and reuse more items. The Government expects to publish a new Waste Prevention Programme in Autumn 2021.

3.2.3.7 Courtauld Commitment 2025

The Courtauld Commitments are a series of voluntary agreements that have improved resource efficiency and reduced the carbon and wider environmental impacts of the UK grocery sector. The agreements are funded by the UK governments and delivered by WRAP.[49] Efforts being made by industry and manufactures to reduce food waste as part of the Courtauld Commitment 2025.[50] Over the four-year period of Phase 1 of the Commitments, 1.2 million tonnes of food and packaging waste was prevented. As a result of actions by signatories, Love Food Hate Waste, local authorities and charity partners, 670,000 tonnes of food waste and 520,000 tonnes of packaging waste was avoided across the UK.[51]

3.3 C&I Waste Arisings

C&I waste is defined as waste arising from a specific collection of economic activities described by NACE ("statistical classification of economic activities in the European Community")[52]. NACE codes currently considered to be C&I include:

- C;
- D;
- E36;
- E37;

[49] https://www.wrap.org.uk/food-drink/business-food-waste/history-courtauld
[50] https://www.wrap.org.uk/food-drink/business-food-waste/courtauld-2025
[51] https://www.wrap.org.uk/food-drink/business-food-waste/courtauld-2025
[52] https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDFhttps://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

- E39 (excluding sewage sludge) and;
- G-U (excluding G46.7.7).

3.3.1 Historic Waste Arisings

3.3.1.1 Data Availability

The 'Reconcile' methodology for estimating C&I waste generation in the UK was developed in 2014[53] and used to estimate waste arisings in 2010 and 2012. The method has been reviewed and updated to improve the assumptions made in reporting waste generated and incorporated considerable input from industry experts.[54] This method was used to revise the C&I waste generation figures from 2010 to provide a complete time series. The most recent statistics on waste published by Defra provided revised estimates for 2017 and new values for 2018, giving a yearly aggregate figure for the tonnage of commercial and industrial streams reported separately.[55]

3.3.1.2 C&I Surveys

There have been several studies that have gathered C&I arising information for England:

1) The Environment Agency conducted a survey of C&I waste arisings in 1998/9.
2) The Environment Agency conducted a smaller survey in 2002/3. The survey collected data from 4,500 commercial and industrial businesses which included information on the type of waste, quantity of waste, and waste disposal or recovery method.[56] The results of the 2002/3 survey were used in the proceeding years to estimate C&I waste arisings.
3) ADAS undertook a study[57] based on primary source data in 2006/7 which surveyed commercial and industrial businesses in the North West. This dataset was used to estimate the waste produced per employee for each sector which was then applied to business demographic data for the other regions in England.
4) The most recent estimate of C&I waste arisings conducted in 2009 collected data from just over 6,000 businesses combined with a similar survey for the North West and augmented with data from published datasets.[58]

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[53] http://randd.defra.gov.uk/Document.aspx?Document=12262_FinalProjectReport120814.pdf
[54] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/873328/Commercial_and_Industrial_Waste_Arisings_Methodology_Revisions_Oct_2018_contact_details_update_v0.2.pdf
[55] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/918270/UK_Statistics_on_Waste_statistical_notice_March_2020_accessible_FINAL_updated_size_12.pdf
[56] http://archive.defra.gov.uk/evidence/statistics/environment/waste/wrindustry.htm
[57] https://api.warwickshire.gov.uk/documents/WCCC-680-172
[58] Commercial & Industrial Waste Survey 2009, Defra(Jacobs), May 2011

There are several key issues with the quality of the estimates of C&I waste arisings from these sources[59], as explored in the 2013 CIWM Commercial and Industrial waste in the UK and Republic of Ireland. These issues include:

- Differences in sampling strategy and size in each survey gives a representation bias of the businesses included. As the surveys reviewed 4,500 to 6,000 businesses, which were used to represent the waste generation of over 2 million businesses in the UK, the samples had to be highly representative.
- Each study has focussed on a slightly different definition of C&I sectors. This means that deriving historical trends from this data requires making assumptions about the definition of C&I to estimate waste arisings from.
- Past surveys have been conducted at a time of economic recession and are likely to produce underestimated waste arisings which are not applicable to any current association between productivity and waste generation.
- The 2009 study focussed only on businesses in the North West and then generalised this to the whole of the UK.

A further study reviewed the types, quantities, origins and fate of C&I waste generated by businesses in the public sector in Wales in 2018.[60] The study reviewed 1,755 business sites of different sectors and sizes through Wales in 2019. This data is comparable with previous C&I surveys carried out in Wales, the most recent of which was conducted in 2012.

3.3.2 Socio-economic Drivers

3.3.2.1 GDP

GDP can be used as a metric of economic performance to measure resource efficiency, the resource use in delivering output. For a given producer resource efficiency could be considered at the level of process by making the same amount of product with fewer resource inputs. From a macro-perspective, resource efficiency might not be a function solely of process efficiencies: what and how businesses and households consume also influences how productively resources are used.

Waste flows relate to economic activity, and thus waste is generated through inputs used at the production stage and outputs in households' use of commodities. Over the past few decades, the amount of solid waste has grown alongside GDP, indicating that waste generation is closely coupled to economic growth. Waste prevention is a top priority for the EU[61], and research has found that waste quantities are expected to

[59] https://www.ciwm.co.uk/Custom/BSIDocumentSelector/Pages/DocumentViewer.aspx?id=QoR7FzWBtisamYEcWSfL6SxAJRLAPT9vf9UOxY7TX%252bRvV%252ffsIKIsqU2EtUq%252bj7oCo87WOf%252fbs9PqCytSgZ5tfRfy2%252bBshoiDu7f882AjZtqLLztRjeHBL8ywUdWyhRgk

[60] https://cdn.cyfoethnaturiol.cymru/media/691993/survey-of-commerical-and-industrial-waste-generated-in-wales-2018.pdf

[61] https://ec.europa.eu/environment/integration/research/newsalert/pdf/203na2_en.pdf

increase then decouple from GDP by 2020[62], with the intention of achieving an absolute decoupling of waste production and GDP, meaning that waste quantities would stabilise or decrease while GDP still increases. Despite this, it is expected that GDP will still have some influence on waste generation through income effect.
Due to differences in waste intensity in products, the association between economic growth and waste production is not equivalent. Equally, different types of waste are likely to be affected differently by changes in economic growth, with some waste types related to declining economic activities and some related to growing economic activities.[63] This decoupling association may be sector and waste stream specific. Regional level data from the UK revealed bidirectional causal relationship between GDP and gross capital formation to waste[64]. The result provides both unidirectional and bidirectional granger causality running from gross capital formation, GDP and employment to waste in the UK[65].

At the EU level, the headline indicator used is the ratio of GDP to domestic material consumption, expressed in euros per tonne. These show indexed values (based on year 2000 levels) of GDP itself, as well as:

- **Domestic material consumption (DMC):** This measures the amount of materials directly used in the economy i.e. apparent material consumption. It is measured as domestic extraction used minus exports plus imports. It is measured in tonnes and for the traded products it does not differentiate between whether materials consumed are the primary raw materials, or a finished product.
- **Raw material consumption (RMC):** RMC measures used extraction within a country as well as the full upstream used material extraction associated with the production of imports, while excluding materials associated with exports and hidden flows throughout.[66]

Measures of GDP in relation to DMC and RMC are often used to calculate resource productivity indicators (units of GDP per unit of DMC, for example, for the '*Resource Productivity (GDP / DMC)*' index)[67]. As an effective measure of gross output after accounting for intermediate inputs, GDP does not reflect the full consequences of economic activity and excludes the environmental consequences of resource use.

Resource productivity is of interest in the context of the low rate of productivity growth in the UK economy. The weakness of manufacturing productivity (measured as GVA per unit of labour input) since 2011 has been a defining feature of the UK's apparently stagnant labour productivity growth: in manufacturing in particular, ONS data indicate that in Q1 2016, manufacturing productivity stood only 1.8% higher than in Q1 2008. The

[62] https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.558.6277&rep=rep1&type=pdf
[63] https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.558.6277&rep=rep1&type=pdf
[64] https://dl.acm.org/doi/abs/10.1145/3157754.3157761
[65] https://dl.acm.org/doi/abs/10.1145/3157754.3157761
[66] For example, consumption of a processed product would imply the use of more raw material, on a tonne for tonne basis, than consumption of the raw ore.
[67] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Resource_productivity

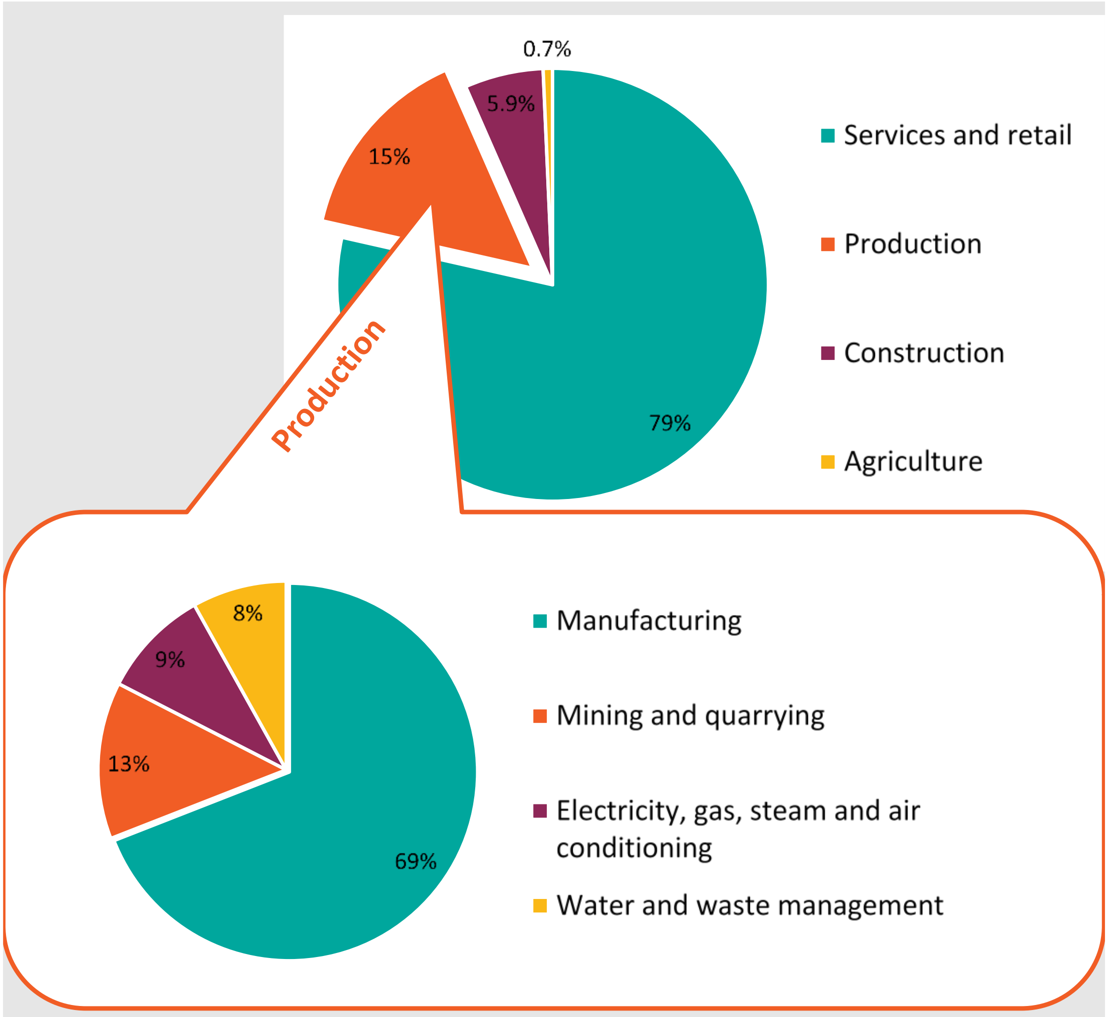
apparent divergence in the resource productivity trends in the economy, and the labour productivity trends, raises a number of points regarding the effect of different influences on the different measures. In principle, however, they can work in the same direction, so that resource productivity in a given industry can contribute positively to GVA. Whilst some such changes may also increase labour inputs (remuneration of which is effectively a component of GVA), labour productivity may also increase (though this might not always be true). It matters also – at an economy wide level – that multipliers do not stimulate only those sectors which are stagnant in terms of productivity.

A reason for the increase in the resource productivity of the UK economy is the reduced significance of production industries (i.e. manufacturing, mining & quarrying, energy supply and water supply & waste management) in the economy. This is because more GDP is generated per unit of resource use as the structure of the economy shifts to less resource intensive forms of wealth generation. The UK economy is dominated by the service and retail sectors, which accounted for 78.6% of the country's GDP in April 2016.[68] As shown in Figure 3-1, production industries accounted for 14.9% of GDP, whilst construction and agriculture accounted for 5.9% and 0.7% of GDP, respectively.

The combined index of production remained more or less constant between 1997 and the onset of the financial crisis in 2009. As shown in Figure 3-2, the financial crisis resulted in a marked decrease in production, which has not yet recovered to pre-recession levels.[i] The sub-components of production exhibit rather different trends: mining and quarrying has shown a steady long-term decline (reflecting, amongst other things, the decline of coal), whilst outputs from electricity, gas, steam and air-conditioning, as well as water and waste management, have increased; the performance of the water and waste management sector has been the strongest in relative terms. The majority of the index (69%) is accounted for by manufacturing, with water and waste management contributing 7.5%.

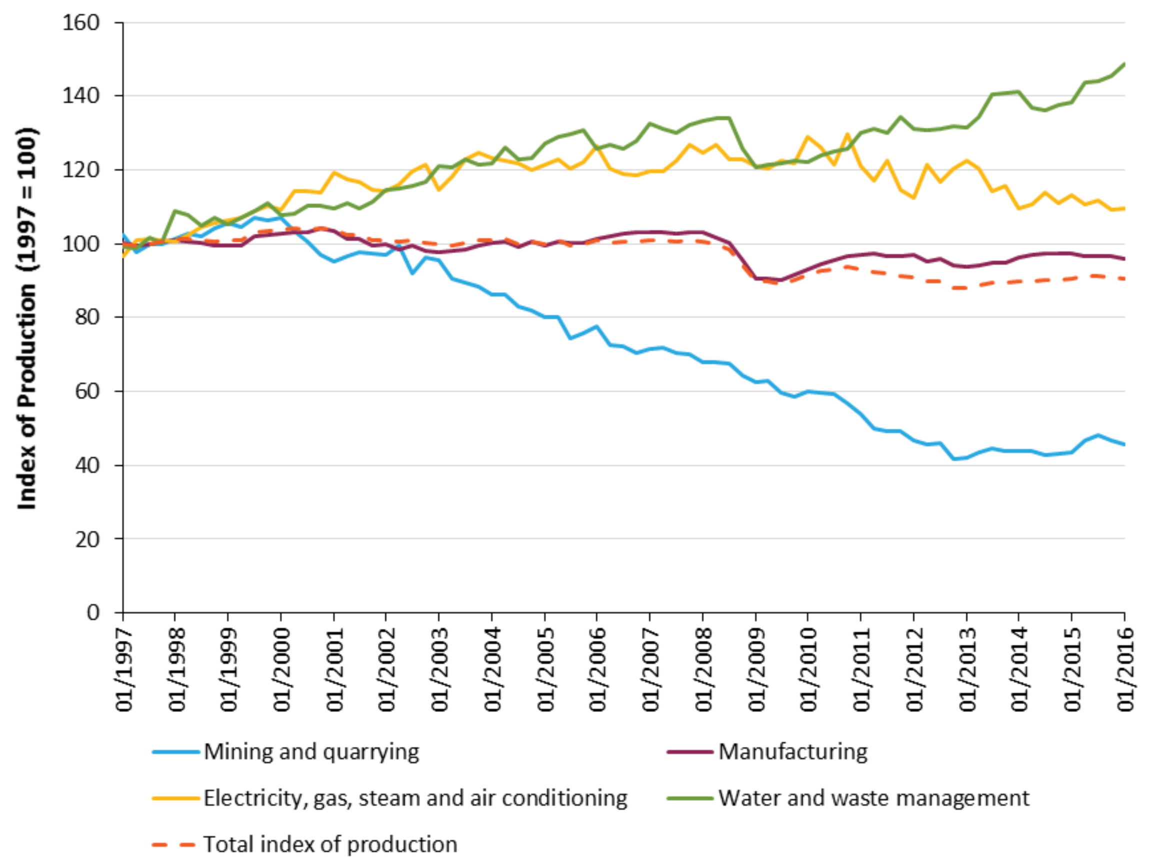
[68] Office for National Statistics (2016) *UK Index of Production: April 2016*, Date Accessed: 21st June 2016, Available at: www.ons.gov.uk/economy/economicoutputandproductivity/output/bulletins/indexofproduction/april2016

Figure 3-1: Components of the UK's GDP (April 2016)



Source: Office for National Statistics, 2016

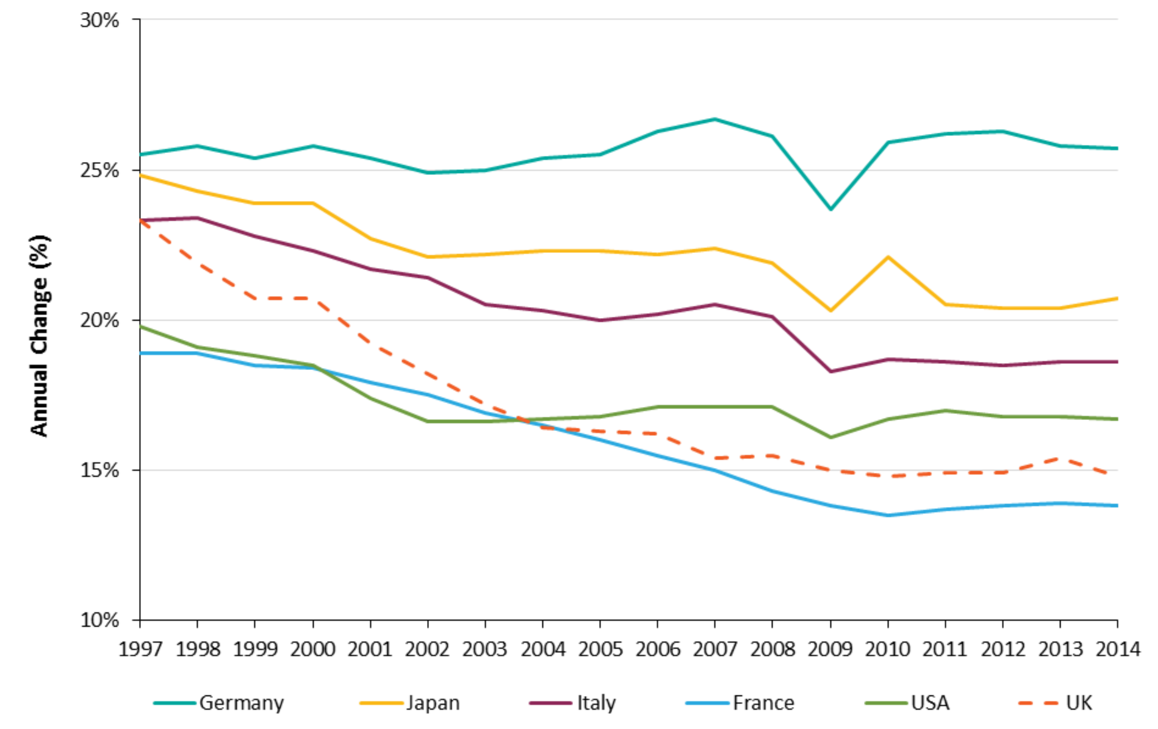
Figure 3-2: Index of Production and Sub-Components, UK, 1997-2016



Note: The Index of production measures the volume of production at base year prices for the manufacturing, mining & quarrying, energy supply and water & waste management industries
Source: Office for National Statistics, 2016

Although total production output has started to grow over recent years, the rate of growth has been outstripped by better performance in other areas of the economy. This has meant that, as a proportion of nominal GVA, production has been in decline for many years. Indeed, as shown in Figure 3-3, the UK's production output has been declining more rapidly than in other advanced economies and has stabilised at around 15% of nominal GVA since 2009. It is partly this decline in the relative (and to a lesser extent, the absolute) prominence of production activities in the economy that underpins a renewed interest in articulating an industrial strategy which can help to maintain diversity (both sectoral and spatial) in the sources of employment and earnings within the UK.

Figure 3-3: Production as a Percentage of Nominal Gross Value Added in Comparable Economies to the UK, 1997 to 2014



Source: Office for National Statistics 2016

3.3.2.2 Gross Value Added (GVA)

GVA is a measure of the increase in the value of the economy due to the production of goods and the delivery of services. GVA measured using the 'income' approach is used by the Office for National Statistics (ONS) to estimate regional GVA figures for the UK.[69] This approach to calculating GVA adds up all of the income earned by individuals or businesses involved in the production of goods and services. The main components of income-based GVA are:

- Compensation of employees.
- Gross operating surplus (includes gross trading profit and surplus, mixed income, non-market capital consumption, rental income, less holding gains).
- Taxes (less subsidies) on production. These are included, whereas unit taxes on products are not. This means that in the waste and resource management sector, landfill tax – considered as a unit tax on a 'product' – does not fall within GVA calculations.

[69] ONS also produces balanced GVA estimates (balanced by industry or by local/combined/regional authority) based on income approach and production approach. https://www.ons.gov.uk/economy/grossvalueaddedgva/datasets/nominalandrealregionalgrossvalueaddedbalancedbyindustry/current

An increase in demand for a product will result in an increase in the production of that product, as producers react to meet the increased demand. This is known as the 'direct' effect. As producers increase output there will be a corresponding increase in demand on their suppliers along the entire supply chain. This is known as the 'indirect' effect. Because of the direct and indirect effects, the level of household income throughout the economy will increase as a result of higher aggregate compensation to employees. A proportion of this increased income will be spent on final goods and services and thereby generate additional economic activity. This is known as the 'induced' effect. By accounting for the various effects across the economy, it is possible to obtain a more accurate picture of the likely impact that changes to specific sectors such as waste and resource management, will have on the broader economy.

3.3.2.3 Waste Prevention

Estimating the economic impact of waste prevention is challenging as one has to consider a number of possible upstream and downstream impacts. The prevention / avoidance of waste through reduced consumption in various sectors is associated with a fall in the GVA in the relevant sectors. On the other hand, if the activities that lead to waste prevention are not incurring significant costs, householders will save money and businesses' profits will increase. These avoided costs may be spent by households or used in various ways by businesses. This can offset (or even exceed) any direct reduction in GVA.

Figures published by WRAP suggest that by reducing avoidable food waste, households could save around £2,604 per tonne (or about £500 per household).[70] These savings from households can be reflected in lost GVA associated with retail. It can also be assumed that a proportion of these savings will be spent, thereby offsetting the reduction in GVA from reduced retailer expenditure.

3.3.3 Policy Drivers

3.3.3.1 Landfill Tax

The Landfill Tax was first introduced in the UK as a Statutory Instrument in 1996 for active waste (waste other than inert construction and demolition waste). Landfill Tax rose rapidly, especially between 2008 and 2014, and has successfully disincentivised landfill-- the amount of waste sent to landfill has reduced by over 80% since 2000.[71] The

[70] Research undertaken by WRAP suggests that total preventable food waste from households is between 4.2 and 5.4 million tonnes per annum and this is reported to be worth a total of £12.5 billion. This is equal to £2,604 per tonne of preventable food waste if one takes the average of the range suggested by WRAP (i.e. 4.8 million tonnes). The estimated number of households in 2016 was based on data presented in the Technical Appendix (www.sita.co.uk/downloads) that accompanies this report. For further details on the value of avoidable food waste see: WRAP (2016) *Estimates of Food Surplus and Waste Arisings in the UK*, May 2016, www.wrap.org.uk/sites/files/wrap/UK%20Estimates%20May%2016%20%28FINAL%20V2%29.pdf

[71] https://ieep.eu/uploads/articles/attachments/e48ad1c2-dfe4-42a9-b51c-8fa8f6c30b1e/UK%20Landfill%20Tax%20final.pdf?v=63680923242

Landfill Tax was also intended to stimulate recycling and has had a meaningful effect in this regard. However, the high rate of landfill tax in recent years also increased the amount of waste sent to energy-from-waste (EfW) as well as an increase in export of waste as refuse derived fuel (RDF).[72] The Landfill Tax is likely to also have had an indirect effect on overall waste generation, as increasing waste treatment prices will incentivise waste minimisation schemes from LAs.

3.3.3.2 UK Climate Change Act

The UK Climate Change Act 2008 legally binds the UK to net-zero greenhouse gas emissions by 2050. Net-zero refers to balancing the amount of emitted greenhouse gases with the equivalent emissions that are either offset or sequestered. This should primarily be achieved through a rapid reduction in carbon emissions, but where zero carbon cannot be achieved, offsetting through carbon credits or sequestration through rewilding or carbon capture and storage needs to be utilised. It is not clear how net-zero greenhouse gas emissions by 2050 will be achieved from the waste sector, as the full range of policies that will be needed to deliver this are not yet on the government's drawing board. Under the net-zero policy, we expect to see a renewed focus on reducing carbon dioxide (CO_2) emissions from incineration in the future. The overall impact of waste generation will depend on the policies adopted by the government to reach the net-zero target by 2050.

3.3.3.3 Plastic Packaging Tax

The proposed tax on plastic packaging with less than 30% recycled plastic content will apply to the production and importation of plastic packaging. The policy tax design is currently under consultation[73], with draft legislation expected in 2020, and the tax is likely to apply from April 2022.[74] It has been estimated that it is more likely that producers will increase their use of recycled content rather than transfer the cost to households.[75] Currently, not enough plastic is being recycled in the UK to fuel the anticipated increase in demand for recycled material. The expectation is that once the tax is introduced, demand will increase, thereby encouraging supply. This may incentivise residual waste pre-treatment to extract more plastic, as well as stimulating further UK plastics recycling facility capacity. The tax might also incentivise producers to shift to alternative packaging materials, such as cardboard. However, overall impact of the plastic packaging tax on waste generation is unclear.

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[72] https://ieep.eu/uploads/articles/attachments/e48ad1c2-dfe4-42a9-b51c-8fa8f6c30b1e/UK%20Landfill%20Tax%20final.pdf?v=63680923242

[73] HM Revenue and Customs (2020) *Plastic Packaging Tax - Consultation*, March 2020

[74] Note that these timeframes may well be impacted by the ongoing COVID-19 pandemic.

[75] https://www.veolia.co.uk/sites/g/files/dvc1681/files/document/2019/07/Plastic%20packaging%20tax%20in%20the%20UK%20Whitepaper.pdf

3.3.3.4 The UK Plastics Pact

The UK Plastics Pact (the Pact) is a voluntary agreement with brands and retailers that sets a range of targets for 2025 relating to the use of plastic packaging:

- 100% of plastic packaging to be reusable, recyclable or compostable;
- 70% of plastic packaging to be effectively recycled or composted;
- Plastic packaging is to have at least 30% recycled content; and
- Eliminating problematic or unnecessary single-use packaging.

In advance of policy changes like extended producer responsibility and the Plastic Packaging Tax, it is currently the most influential factor driving change and improvement in reducing plastic packaging waste. The commitment to the Pact both from government and producers indicates that active efforts to change plastic production are underway, which will affect the waste stream through the emergence of increased recycled and recyclable plastic content. As with the plastic packaging tax, the Pact might incentivise producers to shift to away from plastic packaging towards cardboard. However, overall impact on waste generation is ambiguous.

3.3.3.5 Defra's Resources and Waste Strategy

As reviewed in Section 3.2.3, Defra's Resources and Waste Strategy (RWS, 2018) indicates how the Circular Economy Package will be implemented in England. Implementation of the RWS is likely to impact the C&I waste arisings through the three main policy avenues:

- Separate Collection Standards: Under the RWS, businesses will have to segregate their recycling and food waste for separate collection. This will result in a reduction of residual waste and increased organics and recycling collection. It is unclear whether this policy will have the indirect effect of reducing overall waste arisings, however greater scrutiny on C&I waste arisings may result in improvements in waste monitoring and reporting from the sector.
- DRS and EPR: As explored in section 3.2.3.3 the introduction of EPR and DRS regulation will mean a shift in the stream where waste is recorded from household waste to C&I waste.

3.4 Construction, Demolition and Excavation (C,D&E) Waste

3.4.1 Definitions

C,D&E waste is defined as unwanted material from demolition, soil excavation or any other waste material produced at the construction site. C,D&E waste is one of the heaviest and most voluminous waste streams generated in the EU. It accounts for approximately 35% of all waste generated in the EU and consists of numerous materials, including concrete, bricks, gypsum, wood, glass, metals, plastic, solvents, asbestos and excavated soil.[76,77] In addition to soils, CD&E waste also includes dredging spoils generated as a result of marine dredging and marine aggregate extraction. In 2016, UK generated 136.2 million tonnes CD&E waste, out of which 120.3 million tonnes were from England.

3.4.2 Historical Arisings

CD&E waste is reported annually through Defra waste statistics for the UK and England[78]. A proportion is collected by LAs through LACW from housing renovations. A study identified the quality of C&D waste data in the UK as average quality in comparison to other European countries[79].

3.4.3 Socio-Economic Drivers

3.4.3.1 Dwelling Characteristics

An assessment of C&D waste generation in Beijing, that includes excavated soil, demolition waste and furnishing waste found that the lifetime of dwellings was the most important variable influencing future C&D waste generation. Per capita floor area was also associated with higher C&D waste generation.[80]

3.4.3.2 GDP

C,D&E waste generation is strongly related to construction activities. An assessment of generation and recovery practice in the European Union identified that C&D waste production is influenced by GDP, construction turnover and capita.[81]

3.4.4 Policy Drivers

3.4.4.1 Waste Framework Directive

The EU Waste Framework Directive set a minimum of 70% recovery target for C&D waste (by weight) by 2020 to boost C&D recovery and management.[82]

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[76] https://ec.europa.eu/environment/waste/construction_demolition.htm

[77] https://repository.lboro.ac.uk/articles/journal_contribution/A_diagnosis_of_construction_and_demolition_waste_generation_and_recovery_practice_in_the_European_Union/9825446/files/17621783.pdf

[78] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/918270/UK_Statistics_on_Waste_statistical_notice_March_2020_accessible_FINAL_updated_size_12.pdf

[79] https://repository.lboro.ac.uk/articles/journal_contribution/A_diagnosis_of_construction_and_demolition_waste_generation_and_recovery_practice_in_the_European_Union/9825446/files/17621783.pdf

[80] https://www.academia.edu/download/49344962/j.1530-9290.2010.00245.x20161004-28819-1le11m0.pdf

[81] https://repository.lboro.ac.uk/articles/journal_contribution/A_diagnosis_of_construction_and_demolition_waste_generation_and_recovery_practice_in_the_European_Union/9825446/files/17621783.pdf

[82] https://repository.lboro.ac.uk/articles/journal_contribution/A_diagnosis_of_construction_and_demolition_waste_generation_and_recovery_practice_in_the_European_Union/9825446/files/17621783.pdf

3.4.4.2 UK Aggregates Levy

The aggregates levy in the UK was implemented in order to reduce the negative environmental impacts of aggregates extraction and to incentivise production of recycled aggregates. It was introduced in 2002 and is currently levied at a rate of £2 per tonne of aggregates. The levy is applied at the point at which it is commercially exploited in the UK. The levy is applied to all rock, sand and gravel that has either been dug from the ground, dredged from the sea in UK waters or imported. The levy is applied at the point at which the aggregates are first commercially exploited[83] in the UK. Exemptions are in place for certain materials, e.g. clay, soil, vegetable or other organic matter. Export of aggregates and their use in certain agricultural and industrial process are also exempted from the levy.

Since the levy was announced in 2000, the use of primary aggregates per unit of construction output has reduced by around 40% to the years 2010-2014.[84] However, these figures cannot be solely attributed to the aggregates levy and may be influenced by the other policy drivers reviewed in this section.

Given that the cost of primary aggregates tends to be only a small proportion of the overall cost of construction projects, it is unlikely that the aggregates levy has had any significant impact on the construction industry.[85] There might have been some minor competitiveness impacts, particularly on smaller companies in the construction sector, but these impacts are likely to be small as the levy is expected to have been passed on to consumers due to the inelastic demand of the product.[86] Moreover, the design of the levy have eliminated any potential comparative disadvantage for the domestic producers, as aggregates imports are levied at the same rate as domestic extraction, while exports are exempted from the levy. Although, there has been some concerns about illegal cross-border movement of aggregates across the Republic of Ireland and Northern Ireland border, the issue relates more to monitoring and enforcement of the levy rather than its design.

3.4.4.3 Landfill Tax

The UK Landfill Tax, as explored in Section 3.3.3, is also thought to have had a significant impact on reducing C&D waste by incentivising recycling.[87] However, the impact of landfill tax on C&D waste generation is likely to be small, as the generation of C&D waste

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[83] Commercial exploitation is defined as when it is removed from the aggregate's originating site (e.g. quarry); when subject to a written agreement to supply; or when mixed with anything other than water.
[84] IEEP et al., 2017. Capacity building, programmatic development and communication in the field of environmental taxation and budgetary reform. Report for the DG Environment of the European Commission.
[85] ECOTEC et al. (2001) Study on the economic and environmental implications of the use of environmental taxes and charges in the European Union and its Member States, Report for DG Environment, European Commission. https://ec.europa.eu/environment/enveco/taxation/environmental_taxes.htm
[86] ibid.
[87] Eunomia Research & Consulting et al. (2009) International review of waste management policy: Summary report, report for Department of Environment Heritage and Local Government (Ireland).

will primarily be driven by the amount of demolition activity that is taking place in the economy.

3.5 Modelling Approaches

From reviewing the literature of models predicting WfH, LACW, MSW, C&I and C,D&E waste arisings, some general trends in the approach have emerged.

3.5.1 Waste Prevention Measure

Developments in production processes, such as through technological changes, can result in less waste-intensive activities. Behavioural changes in the household, which are becoming increasingly common as awareness of the impact of waste becomes to the consumer, can also make household activities less waste intensive. This is accounted for in models of waste generation through a waste reduction, efficiency savings or waste prevention measure. These are commonly employed in models of waste production such as WRAP estimates of food waste generation[88], estimates of US C&D waste[89], projects of residential and C&I sectors in the EU[90] and studies of municipal waste intensity factors in Romania, Bulgaria, Slovenia and Greece[91].

3.6 Factors Likely to Influence All Waste Streams

3.6.1 Economic Recession

The 2008 financial crisis and ongoing pandemic mean relying on historic data is going to be difficult into the future. Specification of models may need to be changed based on this to place greater emphasis on previous year's data rather than moving average. A large disruption to waste production could affect the association between the dependent and independent variables and reduce the robustness of the forecasts.

3.6.2 COVID-19

The lockdown has caused, and will continue to create, massive disruption to businesses and also to typical waste generation behaviours, in addition to the impacts on individuals.

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[88] https://wrap.org.uk/sites/files/wrap/Econometrics%20Report.pdf

[89] https://www.researchgate.net/profile/Xiao-Li-2/publication/344382634_Estimating_non-hazardous_industrial_waste_generation_by_sector_location_and_year_in_the_United_States_A_methodological_framework_and_case_example_of_spent_foundry_sand/links/5f6ed3cf92851c14bc972f24/Estimating-non-hazardous-industrial-waste-generation-by-sector-location-and-year-in-the-United-States-A-methodological-framework-and-case-example-of-spent-foundry-sand.pdf

[90] https://orbit.dtu.dk/files/175851869/ETC_RWM_working_paper_2005_1.pdf

[91] https://www.researchgate.net/profile/Vassilis_Inglezakis/publication/261365729_Municipal_Solid_Waste_Generation_and_Economic_Growth_Analysis_for_the_years_2000-2013_in_Romania_Bulgaria_Slovenia_and_Greece/links/59b4f1d4458515a5b493388f/Municipal-Solid-Waste-Generation-and-Economic-Growth-Analysis-for-the-years-2000-2013-in-Romania-Bulgaria-Slovenia-and-Greece.pdf

Due to the forced shutdown of many businesses and people following the requirement to remain at home during the outbreak, waste generation for 2020 has already shown an increase in household waste generation and an extreme decrease in commercial and (to a lesser extent) industrial waste.

It is, however, challenging to meaningfully comment on the actual impact and implications beyond 2020 for the following reasons:

- A public health threat this extreme has not occurred in living memory;
- The situation – and guidance around COVID-19 – is developing and changing rapidly, as well as varying between localised areas within the UK;
- The full effect is yet to be realised; and
- The full impacts across societies, business, and the economy are yet to be understood.

Nevertheless, we draw out a few signals here in an attempt to discern how the virus may affect waste feedstocks in the longer term. Of relevance are the following:

1) Waste generation has long been tied closely to economic growth. For instance, the European Commission noted in 2010 that *"Over the past few decades the amount of solid waste has grown alongside growth in Gross Domestic Product (GDP)"*.[92] The UK economy shrunk by ~20% from April to June due to the COVID-19 pandemic[93], and overall waste generation will therefore decrease accordingly in sectors such as C&I and construction. However, it is also likely that the rapid fall in the generation of commercial waste will, to an extent, be offset by the relative rise in household waste arisings. Reports on residual waste arisings throughout the lockdown indicate that tonnages (from C&I and household combined) are expected to be ~5% lower by the end of 2021 than pre-COVID-19 projections.[94]
2) The UK has entered into an economic recession after two quarters of negative GDP growth. A reduction in overall economic output, higher unemployment, and a reduction in the number of operating businesses will all act to suppress waste generation in the general case.
3) Both supply and demand sides of the economy are affected by the virus. Supply of goods and services is impaired because factories and offices are shut, and output falls accordingly. Demand also falls because consumers stay at home and spend significantly less. The modest rise in e-commerce and the subsequent growth in packaging will contribute to an increase in household waste, but this

[92] European Commission (2010) *Breaking the Link Between Economic Growth And Waste Generation*, 2010, https://ec.europa.eu/environment/integration/research/newsalert/pdf/203na2_en.pdf
[93] World Economic Forum *Global Economic Prospects*, accessed 17 August 2020, https://www.worldbank.org/en/publication/global-economic-prospects
[94] Tolvik Consulting (2020) *Covid19 and the UK Waste Sector*, accessed 3 September 2020, https://www.tolvik.com/wp-content/uploads/2020/05/Covid-19-and-UK-Waste-Sector-v3_published-29-May.pdf

will likely not be of a comparable volume to expected quantities of commercial waste.

4) The pandemic will in time run its course and controls on the movement of people and business functions will ultimately be lifted. Household and C&I waste generation should then balance out once again. It is anticipated that the sudden decline in waste generation resulting from the lockdown will not instantly rebound, and instead the trough will gradually rise back to pre-pandemic levels. In addition, it is expected that municipal waste arisings will increase at a faster rate than commercial waste, which will be adversely affected by low footfall through the upcoming winter months.
5) In the longer term, perhaps within a few years, the negative impact on the economy (and thus waste generation) should pass. A relatively high-level European Commission report from 2006 considered the macroeconomic impact of a pandemic in Europe, concluding that *"although a pandemic would take a huge toll in human suffering, it would most likely not be a severe threat to the European macroeconomy."*[95] Indeed, this report points towards government and central bank economic stimulus measures (such as those already being put forward in the UK, across Europe and in the US) as a factor reducing the economic impacts.
6) Looking forwards, it is unclear whether future lockdowns (or at least continued restrictions in the hospitality and commercial sectors) will be implemented on a national scale. We assume that similar trends in waste generation would be seen again if such restrictions are reinstated in the future.

Concluding from these indicators, we can certainly expect that overall waste generation will be reduced in the short term as a result of the shock to the global economy. The magnitude of the pandemic is yet to be realised, so we cannot properly estimate the scale and duration of the economic fallout yet to occur. Nevertheless, the macroeconomic literature indicates that economic output and associated waste generation ought to recover in the longer term.

Furthermore, although individual businesses will suffer losses or closure, waste generation in the general sense will continue. This means that the waste industry tends to be more resilient than many other parts of the economy. As a result, waste supply chains are less likely to be unduly disrupted.

[95] Jonung, L., and Röger, W. (2006) The Macroeconomic Effects of a Pandemic in Europe - A Model-Based Assessment. Directorate-General for Economic and Financial Affairs, European Commission, *SSRN Electronic Journal*

4.0 WP3 – Proposal Phase

In this work package, we have developed forecasting models for the following waste streams:

- Waste from Households;
- Local Authority Collected Waste;
- Municipal Solid Waste;
- Commercial and Industrial Waste; and
- Construction, Demolition and Excavation Waste.

The forecasting methods and results for each of the above waste streams are discussed in the following subsections.

4.1 Waste from Households (WfH)

4.1.1 Methodological Approach

As discussed in WP1, a panel data regression model for forecasting WfH will allow us to incorporate both time-series and cross-sectional data to capture variation over time as well as the variation across local authorities. Specifically, it will allow us to model local authority specific unobservable characteristics that affects household waste arisings (e.g., attitude towards waste minimisation) using the random-effects modelling approach.

In addition, the number of observations in a panel data model is far greater compared to a time-series model, which will allow us to include more independent variables without losing the predictive power of the model. Finally, we would also be able to include time-series specific modelling techniques (ARIMA errors, lagged dependent variable, etc.), through a dynamic panel data modelling approach which can add additional predictive power to the forecast model. So, based on the above considerations, a panel data regression modelling approach was chosen to model WfH instead of using a time-series forecasting approach.

4.1.2 Data Preparation

Data on Local Authority Collected Waste were downloaded from WasteDataFlow[96], the web-based system for waste reporting by UK local authorities to government. Local authorities in England report to Defra via WasteDataFlow on a quarterly basis, by answering a range of questions that encompass different aspects of local authority collected waste. Multiple steps are required to filter and collate this data to obtain the total tonnage of WfH collected by each local authority. Data preparation and cleaning was undertaken in R, as described below.

[96] https://www.wastedataflow.org/

4.1.2.1 Calculating WfH

There are 10 questions relevant to calculating the waste tonnages collected by each local authority in England that are reported on a quarterly basis from 2006 – 2019[97] (Table 4-1). Within questions relating to recycling/reuse, local authorities are required to report on total tonnages, tonnages collected for recycling that are actually rejected/disposed as well as provide further breakdowns of tonnages by material (e.g., paper, glass, co-mingled materials). Within questions related to residual waste (Q023), local authorities are required to report the tonnage of waste collected from categories that would fall under WfH (e.g., residual waste from regular household collections) and categories that would not fall under WfH (e.g., residual waste from street cleaning).

For each local authority, WfH can be calculated on a quarterly basis by summing the aspects of each question that fall under the WfH definition. For WfH from recycling, this includes all tonnage from households, as well as recycling extracted from residual waste streams and the metals recovered from incinerator bottom ash. WfH recycling includes total tonnage from Q010, Q012, Q014, Q016, QO17, Q018 and Q033 minus the corresponding tonnage rejected for recycling or reuse reported for each question, while excluding any tonnages reported as soil, plasterboard or rubble.

Residual WfH takes total tonnage from Q023 and subtracts the categories not covered by WfH residual that are also reported with Q023 (e.g., asbestos waste that is separately collected is reported in Q023). Residual waste reported as collected by Waste Collection Authorities (WCAs) is removed from the total tonnage to remove duplication as the same tonnage is reported by Waste Disposal Authorities (WDAs) that geographically cover the same area.

[97]https://www.wastedataflow.org/Documents/GuidanceNotes/WastefromHouseholds/WfH_recycling_guidance_2020-02-21.pdf

Table 4-1 Waste classification for key questions in WDF

Question	Question Text	WfH	WnfH
Q010	Tonnes of material collected through kerbside schemes from household sources by LA or its contractors	All materials are classified as WfH except plasterboard, rubble, and soil.	Plasterboard, rubble, and soil classified as WnfH
Q012	Tonnes of material collected through kerbside schemes by non-contracted voluntary/community sector from household sources		
Q014	Tonnes of material collected for recycling/reuse at CA Sites operated by LA or its contractors		
Q016	Tonnes of material collected for recycling/reuse at CA Sites operated by LA or its contractors		
Q017	Tonnes of material collected at bring sites operated by LA or its contractors		
Q033	Tonnes of materials collected at bring sites operated by voluntary / community sector		
Q011	Tonnes of material collected from commercial, industrial or other non-household sources by LA or its contractors	N/A	All materials as WnfH
Q034	Tonnes of material collected for recycling at street recycling bins		
Q018	Composting / Recycling tonnage collected through any other recycling schemes.	"Waste collected in community skips" as WfH	"Municipal parks/grounds waste collected through 'other' means for composting" &" Other method of waste / material capture" as WnfH
Q023	Please provide details of other waste collected for disposal.	"Civic amenity sites waste: Household", "Collected household waste: Bulky Waste", "Collected household waste: Other", "Collected household waste: Regular Collection"	"Asbestos Waste separately collected", "Beach cleansing", "Civic amenity sites waste: Non-household", "Collected gully emptyings", "Collected household waste: Street Cleaning", "Collected non-household waste: Commercial and Industrial", "Collected non-household waste: Construction and Demolition", "Collected non-household waste: Grounds waste", "Collected non-household waste: Highways waste", "Collected non-household waste: Other Other collected waste", "Separately collected healthcare waste", "Waste Arising from clearance of fly-tipped materials"

4.1.2.2 Creating units for panel data modelling

We planned to use panel data models to create forecasts for WfH, which meant that the data needed to be combined into balanced spatial units. Panel data refers to multidimensional cross-sectional data through time, in our example, this would be WfH produced by multiple local authorities across multiple years. To create an accurate forecast, panel data should meet some key assumptions:

- Grouping units must be spatially independent (i.e., waste from local authorities should only be counted once)
- Ideally panel data is balanced with the same number of observations for each group through time (i.e., each local authority has observations from each year from 06/7 to 18/19).

Raw data from WDF violates both assumptions. Recall that WDF data is reported by local authorities, which can be one of three types: Waste Collection Authorities (WCAs), Waste Disposal Authorities (WDAs) or Unitary Authorities (UAs). Between 2006 and 2019, multiple changes to local authority's waste governance have been made, such as mergers to form larger WCAs or UAs and name changes. As historic data in WDF is not updated to reflect changes in waste responsibility or governance, data had to be reassigned to create spatially independent units for time-series modelling. To do this, authorities were assigned to the groups based on their waste governance structure in 2020.

For example, the area covered by Alnwick District Council WCA in 2006 now forms part of the Northumberland UA and as such data from this time series in 2006 was used to create a time-series for the area covered by Northumberland UA from 2006 to 2019. If we did not do this, we would have two time series unsuitable for panel data modelling, (Alnwick District Council from 2006 to 2009 and Northumberland 2009 to 2018) that would be spatially co-dependent and unbalanced. This process of reassigning waste based on 2020 boundaries resulted in 122 independent local authority units for modelling representing the boundaries of either WDAs or UAs.

This could not be done at the level of WCAs. Also, we could not model WfH from WCAs and WDAs in the same model as this would violate the assumption of spatial independence, while modelling them separately would result in an unnecessarily complex final model. Finally, excluding the WDA tonnages from modelling would cause an underestimate of England-wide WfH figures of approximately 10%.

4.1.3 Modelling WfH

WfH was modelled using a dynamic panel data specification using the external variables described in WP2, which are listed below. A dynamic panel data specification assumes that WfH is dependent on past values of WfH as well as other external variables and their lagged values. The variables considered in the final model were as follows:

$$\log(WfH) = \log(WfH)_{t-1} + \log(pop) + \log(GDHI) + \log(pop)_{t-1} + \log(GDHI)_{t-1} + \text{shock} + \log(\text{trend}) + \log(\text{IMD})$$

Where:

- WfH= Waste from Households
- pop = Population (Office of National Statistics, ONS[98])
- GDHI = Regional Gross Disposable Household Income at current market prices, [99]
- shock = A categorical variable modelling shock to the economic system (0= no shock, 1 =shock, for the impacts of 2008 to 2013 global economic downturn)
- IMD = Index of Multiple Deprivation (ONS)[100]
- trend = A numerical variable equal to time (2005=1, 2006=2 etc.). log(trend) captures the effect of waste minimization through time.

Dynamic panel data models were constructed in R using the package *plm.*[101] The model was estimated in log form as it displayed a better fit of the data.

Models were constructed based on financial year. As the starting point of the available data in WDF was the first quarter of 2006-07 financial year (i.e., April – June 2006), using waste arisings data by calendar year would result in a smaller dataset starting from 2007. Given that there is only a limited number of datapoints across the time dimension, the model based on financial year had higher predictive power due to the additional observation across time. A conversion factor has been provided to permit the transformation of financial year WfH to calendar year WfH instead of providing a separate forecast based on calendar year (Section 4.1.5).

The estimated regression coefficients are presented in Table 4-2. Lagged WfH had a strong positive and significant effect on WfH and was the strongest determinant of WfH. The combined effects of population, GDHI, and their respective lagged values had a weakly positive effect on WfH (although not significant). *Log_trend* and *shock* both had significant and negative effects on WfH. WfH was not predicted to decline over time as waste minimisation (*log_trend)* was offset by increases in GDHI. The fitted values of the model were very similar to historic values of the model, suggesting good fit.

Table 4-2 WfH model coefficients

Variable	Estimate	Std error	Z value	p value
log pop	0.21	0.24	0.90	0.37
log GDHI	0.00	0.06	-0.05	0.96
lag(log wfh, 1)	0.29	0.06	4.53	0.00*

[98]https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/mid2018
[99]https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/datasets/regionalgrossdisposablehouseholdincomebylocalauthoritiesbynuts1region
[100] https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019
[101] https://cran.r-project.org/web/packages/plm/index.html

lag(log pop, 1)	-0.13	0.29	-0.46	0.65
lag(log gdhi, 1)	0.14	0.09	1.57	0.12
log IMD	0.11	0.09	1.28	0.20
log trend	-0.06	0.01	-4.41	0.00*
shock	-0.02	0.01	-3.01	0.00*

**p<0.00001*

4.1.4 Predicting WfH

Future projections of England-wide WfH were then calculated from projections of external variables. Individual projections were calculated for each of the 122 local authorities and then summed to calculate England-wide WfH.

Projections for external variables were calculated as follows:

- Population follows ONS predictions to 2043, then a linear projection from 2043 to 2050 in the absence of any official projections for these periods.[102]
- GDHI is calculated based on Office of Budget Responsibility (OBR) growth rates up to 2025.[103] After that, a 10-year moving average of growth rates was assumed from 2026 to 2050 as no other official forecasts are available.
- Index of Multiple Deprivation is projected following a 5-year moving average of IMD, as it matched well with the historical trend.

Sensitivity analyses were performed to understand how external variable projections influenced the predicted WfH. To do this, 3 different future scenarios were constructed as follows:

- A Central scenario where forecasted real GDHI is calculated using the central forecast rates from the March 2021 OBR Forecast (no upside or downside scenarios available for this forecast)
- A scenario where forecasted real GDHI is calculated using the 'upside' growth rates from the November 2020 OBR Forecast
- A scenario where forecasted real GDHI is calculated using the 'downside' growth rates from the November 2020 OBR Forecast

The central WfH projection (Figure 4-1) predicted a small decrease in WfH for a couple of years after 2020 and a slight upward trend afterwards reaching ~22,500 kt in 2050. The

[102]https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationprojections/datasets/localauthoritiesinenglandtable2
[103] https://obr.uk/efo/economic-and-fiscal-outlook-november-2020/

alternative scenarios of GDHI had small impacts on WfH produced, with the upside scenario resulting in an increase in WfH to ~25,000 kt by 2050, compared with the central and downside scenarios (Figure 4-2,Figure 4-3).

Figure 4-1 WfH Central projection, March 2021 OBR Forecast (Dashed lines show 95% CIs)

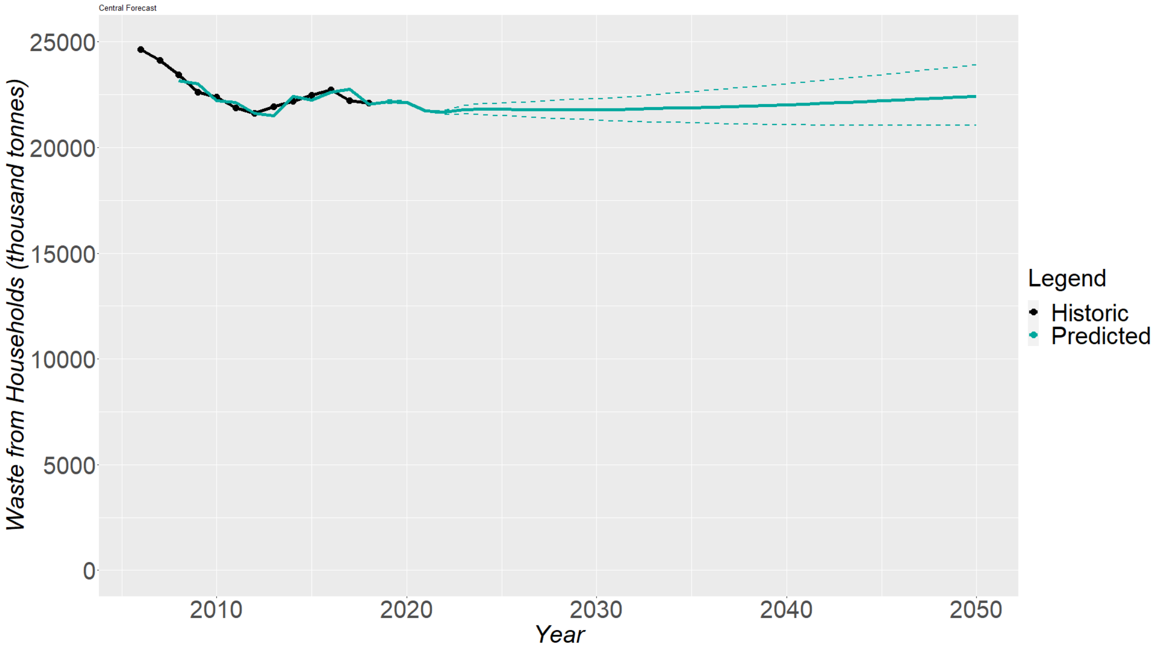


Figure 4-2 WfH Nov 2020 OBR Forecast Downside (Dashed lines show 95% CIs)

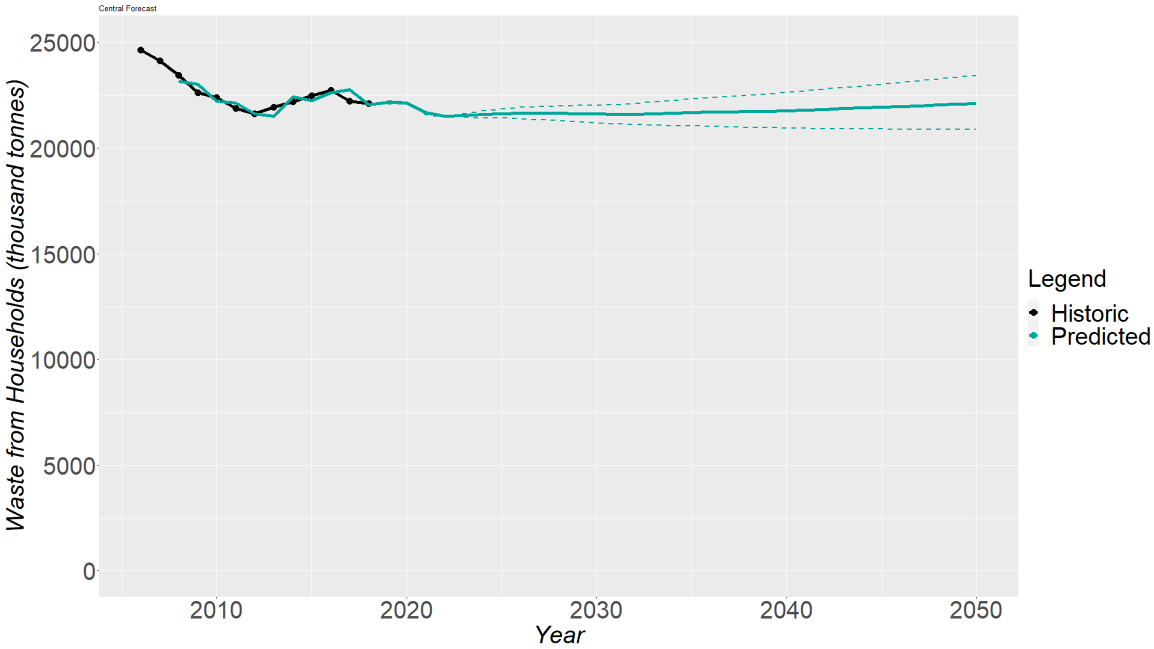
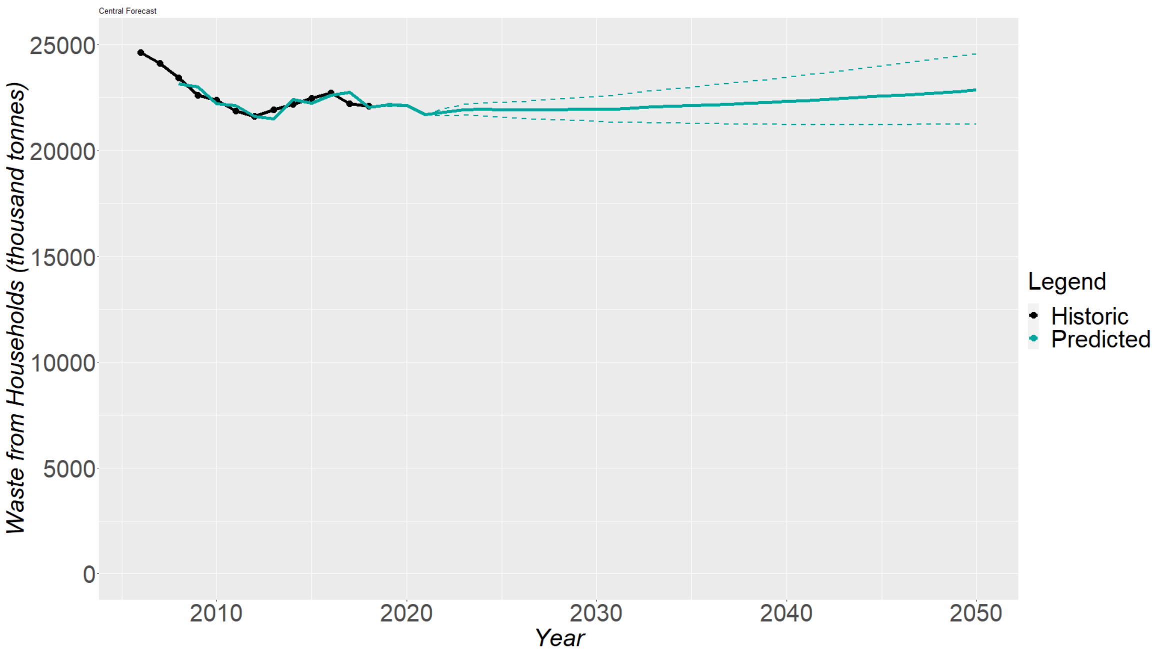


Figure 4-3 WfH Nov 2020 OBR Forecast Upside (Dashed lines show 95% CIs)



4.1.5 Conversion Factors

To prevent the need for multiple forecasts for calendar year and financial year, a conversion factor was created to convert financial year modelled predictions into calendar year predictions based on the proportion of total WfH produced in each financial quarter.

For a given calendar year, the total WfH is equal to the sum of the WfH produced in financial Q1, Q2 and Q3 plus the WfH produced in Q4 from the previous financial year.

$$WfH[Calendar]_t = WfH[Financial, Q1]_t + WfH[Financial, Q2]_t + WfH[Financial, Q3]_t + WfH[Financial, Q4]_{t-1}$$

Therefore, to convert a financial year prediction into a calendar year prediction we simply need the proportion of annual waste produced in each financial quarter, and we can use these proportions as a conversion factor.

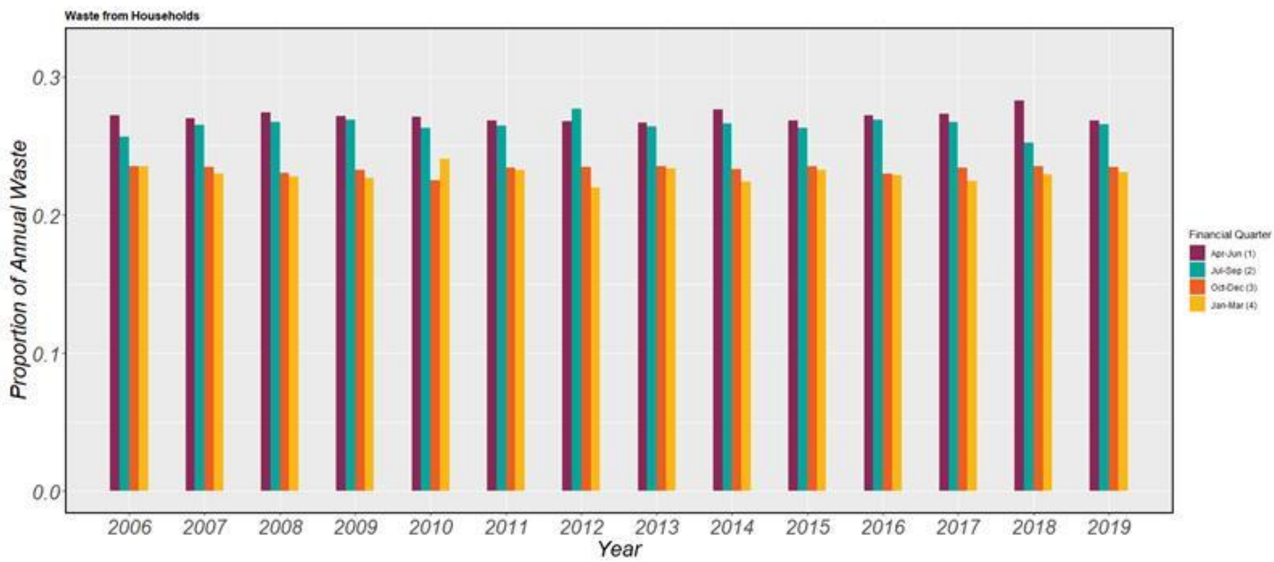
For each financial year, the proportion of total yearly WfH was calculated by quarter, and the mean of each of these proportions was calculated to give a conversion factor (Table 4-3). To check the robustness of these conversion factors, standard errors and 95% confidence intervals were also calculated (Table 4-3). Confidence intervals were narrow and there was little variance in the proportions between 06/7 and 18/19 (Table 4-3, Figure 4-4).

$$
\begin{aligned}
WfH[Calendar]_t \\
&= 0.272.WfH[Financial]_t + 0.265.WfH[Financial]_t \\
&+ 0.233.WfH[Financial]_t + 0.230.WfH[Financial]_{t-1}
\end{aligned}
$$

Table 4-3 WfH conversion Factor

Financial Quarter	Proportion of Annual Waste	SE	n	variance	Upper CI	Lower CI	Period
Q1	0.272	0.0012	13	0.00002	0.274	0.270	Apr to Jun
Q2	0.265	0.0017	13	0.00004	0.268	0.262	Jul to Sep
Q3	0.233	0.0008	13	0.00001	0.235	0.232	Oct to Dec
Q4	0.230	0.0015	13	0.00003	0.233	0.227	Jan to Mar

Figure 4-4 Proportion of Annual Waste by Financial Quarter



4.2 Local Authority Collected Waste (LACW)

4.2.1 Methodological Approach

Given that a large portion of Local Authority Collected Waste (LACW) is WfH, the same dynamic panel data modelling approach should be suitable for forecasting LACW. Moreover, as discussed in Section 4.1.1, a dynamic panel data model will have a number of advantages over a pure time-series forecasting approach. So, we have chosen the dynamic panel data regression modelling approach for forecasting LACW instead of using a time-series forecasting approach that is used in the current LACW forecasting model of Defra.

4.2.2 Data Preparation

Data was obtained from WasteDataFlow and processed following the same sequence used to reassign waste to spatially independent units for WfH (Section 4.1.2.2). LACW was defined as all waste collected by a local authority reported to WDF including municipal and non-municipal fractions, such as construction and demolition waste[104]. This would include all waste streams previously covered in Table 4-1.

4.2.3 Modelling LACW

Given that LACW comprises of mostly WfH, we used the same external variables to construct the LACW model as for the WfH model.

$$\log(LACW) \sim \log(LACW)_{t-1} + \log(pop) + \log(GDHI) + \log(pop)_{t-1} + \log(GDHI)_{t-1} + \text{shock} + \log(\text{trend}) + \log(\text{IMD})$$

Where:

- LACW = Local Authority collected Waste
- pop = Population (Office of National Statistics, ONS[105])
- GDHI = Regional Gross Disposable Household Income at current market prices, [106]
- shock = A categorical variable modelling shock to the economic system (0= no shock, 1 =shock, for the impacts of 2008 to 2013 global economic downturn)
- IMD = Index of Multiple Deprivation (ONS)[107]
- trend = A numerical variable equal to time (2005=1, 2006=2 etc.). log(trend) captures the effect of waste minimization through time.

Table 4-4 LACW Model coefficients

Variable	Estimate	Std error	Z value	p value
log pop	1.57	0.35	4.52	0.00**
log GDHI	-0.05	0.06	-0.86	0.39

[104] https://www.gov.uk/guidance/local-authority-collected-waste-definition-of-terms#:~:text=Local%20Authority%20Collected%20Waste%20(LACW,as%20construction%20and%20demolition%20waste.

[105]https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/mid2018

[106]https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/datasets/regionalgrossdisposablehouseholdincomebylocalauthoritiesbynuts1region

[107] https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019

Variable	Estimate	Std error	Z value	p value
lag(log LACW, 1)	0.60	0.07	9.02	0.00**
lag(log pop, 1)	-1.34	0.48	-2.79	0.01*
lag(log GDHI, 1)	0.07	0.11	0.63	0.53
log IMD	0.08	0.11	0.73	0.47
log trend	-0.03	0.01	-3.02	0.00*
shock	-0.01	0.00	-2.90	0.00*

*p<0.01 **p<0.00001

4.2.4 Predicting LACW

Future predictions of LACW were calculated using projections of external variables, as described in Section 4.1.4. Individual LA-level projections were calculated for each of the 122 local authorities and then summed to calculate England-wide LACW.

Similar to WfH, sensitivity analyses were performed to understand how external variable projections influenced the predicted LACW. To do this, 5 different future scenarios were constructed as follows:

- A Central scenario where forecasted real GDHI is calculated using the central forecast rates from the March 2021 OBR Forecast (no upside or downside scenarios available for this forecast)
- A scenario where forecasted real GDHI is calculated using the 'upside' growth rates from the November 2020 OBR Forecast
- A scenario where forecasted real GDHI is calculated using the 'downside' growth rates from the November 2020 OBR Forecast

In the central scenario, LACW is predicted to increase slightly between 2019 and 2021 and then remain constant around ~25,000 kilotonnes between 2022 in 2050 (Figure 4-5). For the downside scenario (Figure 4-6), the LACW shows slight upward trend from 2022, reaching ~22,500 kt in 2050. There was little difference between the central scenario and the upside scenario (Figure 4-7), where LACW is predicted to remain around ~25,500 kt for the entire period between 2020 and 2050.

Figure 4-5 LACW – Central Scenario based on March 2021 Forecast (Dashed lines show 95% CIs)

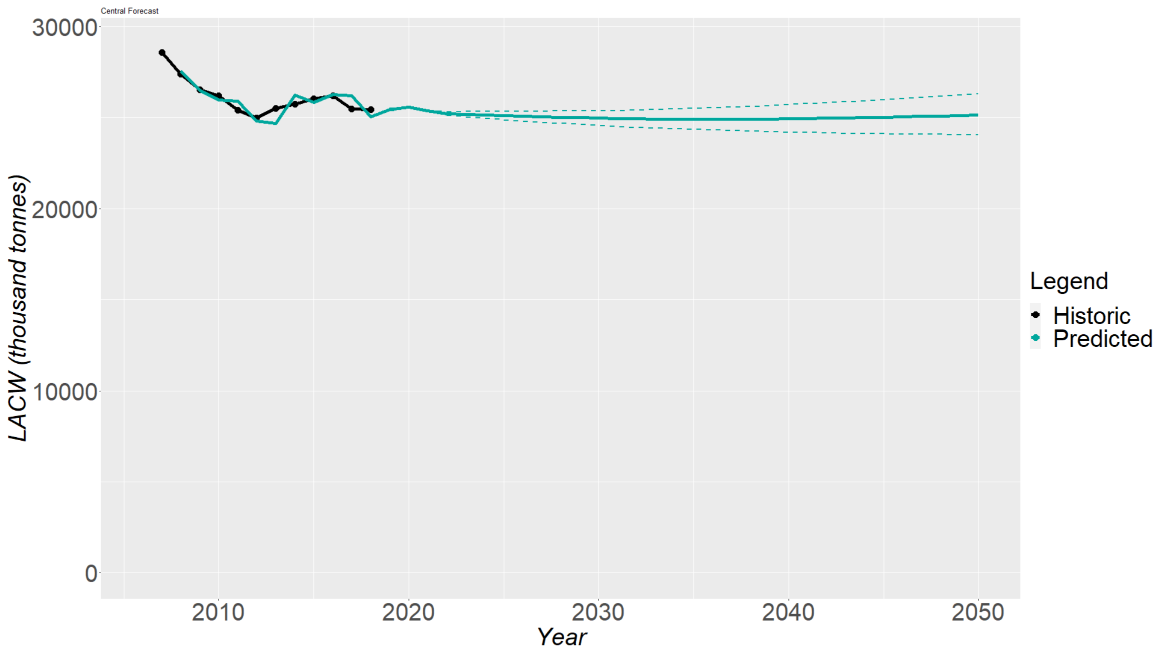


Figure 4-6 LACW – Nov 2020 Downside Forecast (Dashed lines show 95% CIs)

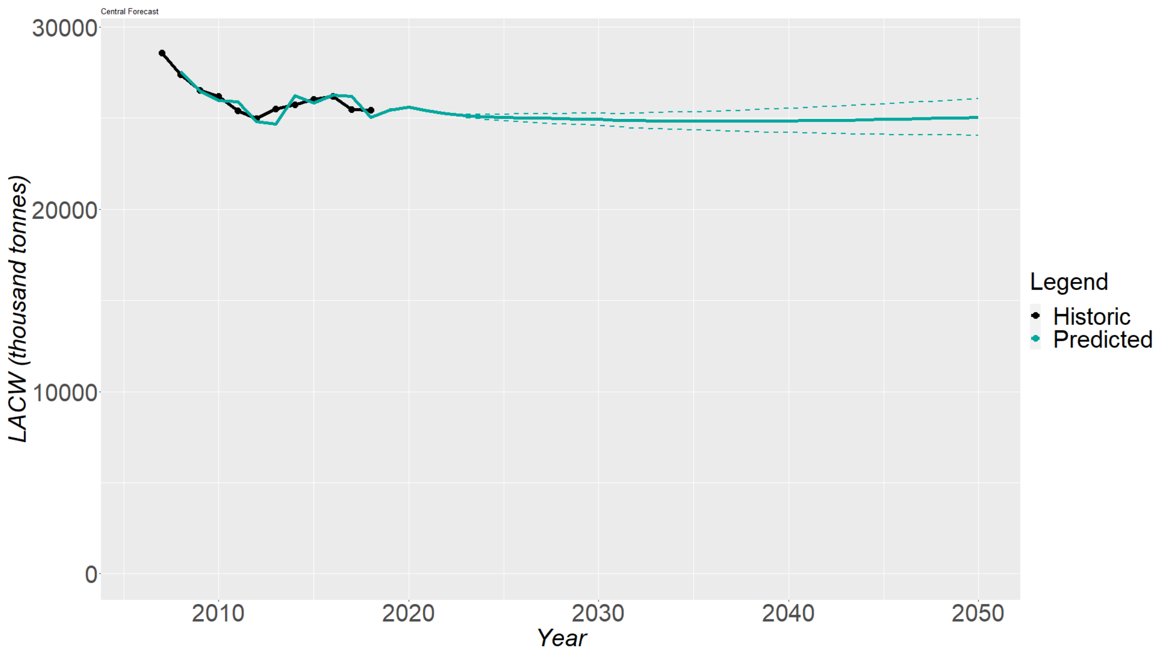
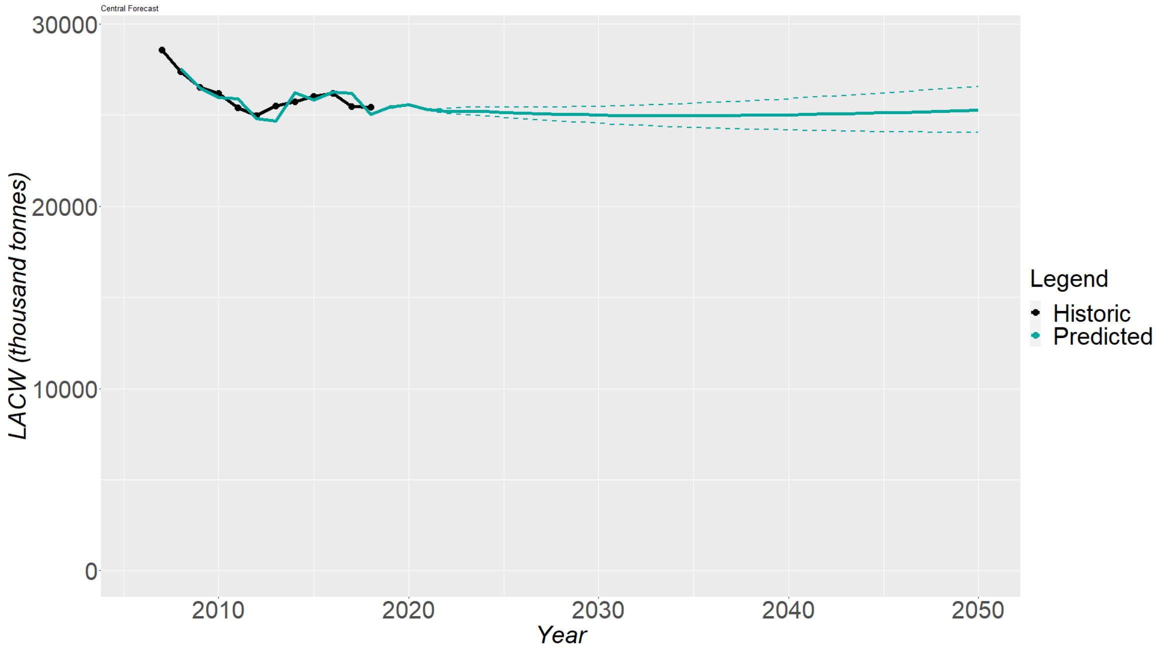


Figure 4-7 LACW – Nov 2020 Upside Forecast (Dashed lines show 95% CIs)



4.2.5 Conversion Factors

As with WfH, conversion factors were also produced to allow financial year predictions to be converted into calendar year predictions (Table 4-5). This followed the same method as WfH.

$$
\begin{aligned}
LACW[Calendar]_t &\\
&= LACW[Financial, Q1]_t + LACW[Financial, Q2]_t \\
&+ LACW[Financial, Q3]_t + LACW[Financial, Q4]_{t-1}
\end{aligned}
$$

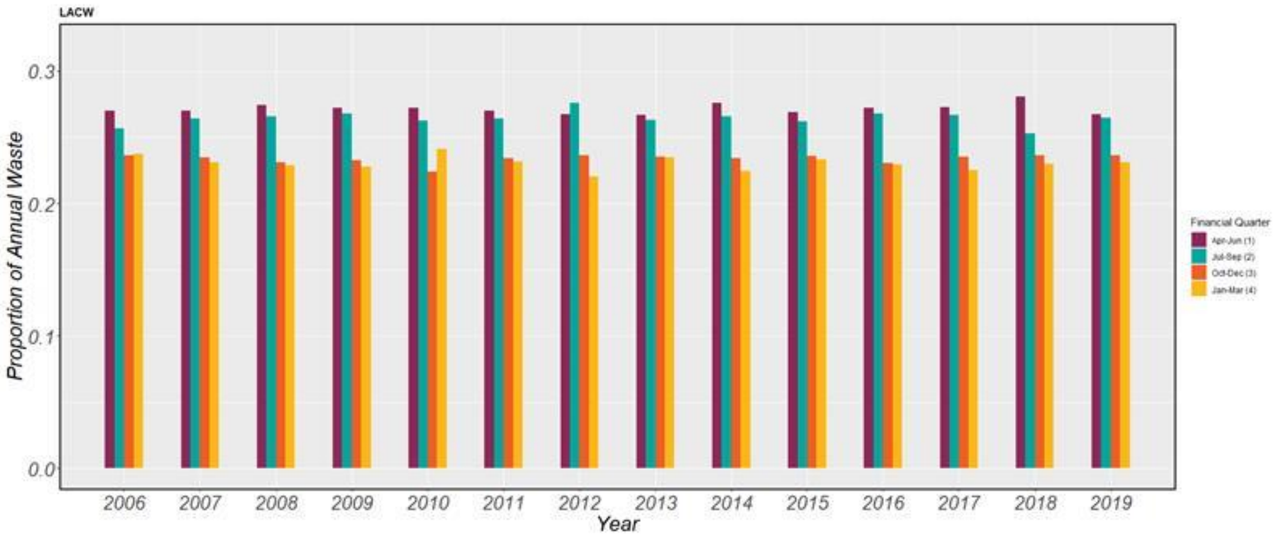
Table 4-5 LACW financial to calendar year conversion factors

Financial Quarter	Proportion of Annual Waste	SE	n	variance	Upper CI	Lower CI	Period
Q1	0.272	0.001	13	0.00001	0.274	0.269	Apr to Jun
Q2	0.264	0.002	13	0.00003	0.267	0.261	Jul to Sep
Q3	0.234	0.001	13	0.00001	0.236	0.232	Oct to Dec
Q4	0.231	0.002	13	0.00003	0.234	0.228	Jan to Mar

$$LACW[Calendar]_t = 0.272. LACW[Financial]_t + 0.264. LACW[Financial]_t + 0.234. LACW[Financial]_t + 0.231. LACW[Financial]_{t-1}$$

As LACW is largely comprised of WfH, it is unsurprising that very similar conversion factors are applied for both waste streams. Like WfH, confidence intervals for conversion factors were narrow and there was little variance in the proportions between financial year 06/7 and 18/19 (Table 4-5, Figure 4-8).

Figure 4-8 Proportion of Annual Waste by Financial Quarter



4.2.6 Strengths of WfH and LACW Models

The strength of the WfH and LACW models lie in their incorporation of LA level variation. This greatly increases sample size, indeed the model incorporated 121 WDAs, UAs and London Boroughs. This mitigates the risk of outliers influencing the modelled relationships between WfH/LACW and the external variables. In doing so the likelihood of misspecification of the model is also reduced, because we are able to include multiple external variables without the risk of overfitting the model. This is the key benefit of using a panel data model, where the large number of local authorities included greatly increases predictive power while reducing omitted variable bias.

4.2.7 Model Limitations

The key weakness of WfH and LACW models is the uncertainty around projections of external variables, as projecting any variable out to 2050 is inherently difficult. The model does not account for uncertainty in the projections of external variables, often this is due to a lack of a data availability. For example, the ONS population projections do not contain upper and lower bounds. Moreover, given that there is no data on future projection of GHDI, we have assumed GHDI for all local authorities will follow the UK

GDP growth projections from OBR. Nonetheless, sensitivity analyses were conducted to mitigate the risk of uncertainty of projections of external variables (e.g., for GHDI).

Moreover, the impact of COVID on the WfH and LACW waste arisings has not been incorporated in the forecasting models as it is still unclear what impact COVID will have on future waste arisings and how long these effects will last.

4.3 Municipal Waste (MSW)

4.3.1 Methodological Approach

There is no published data available on MSW arisings in England. By definition, MSW arisings should sum to waste from households (WfH) and non-household municipal (NHM) waste. As we have already developed an econometric forecasting model for WfH, we needed to develop a forecasting model for NHM for forecasting MSW arisings.

Data on NHM can be constructed from the C&I arisings data reported by EWC codes. However, C&I data for England by EWC codes are only available from 2010 to 2018. Given such a short time-series dataset, it is not possible to develop a time-series forecasting model for NHM waste. So, the annual NHM arisings data were split over the 9 regions in England, and a panel dataset with 81 observations was created for estimating a panel data econometric forecasting model.

Besides the increase in number of observations for a more robust model estimation, a panel data econometric model would also account for unobservable region-specific effects (e.g., people's attitude towards waste minimisation in a region) on waste generation that would not be captured by the external factors included in the model.

The main drivers for NHM arisings should be similar to the drivers for the C&I waste, as NHM are household-like waste generated from businesses. Therefore, GVA in the NHM sector should be able to explain the variations in NHM arisings. In addition, inclusion of a time-trend should be able to capture any underlying trend in waste minimisation. Finally, NHM arisings might have been affected by the economic recession in 2008.

4.3.2 Data Preparation

The data on NHM arisings by English regions were constructed by combining the NHM arisings in England and transfer station MSW waste by English regions from the Waste Data Interrogator.[108] The NHM arisings for England was estimated from the C&I waste arisings using the EWC codes that are classified as MSW under the EU definition.[109] To maintain consistency with the definition of 'Municipal waste' used by WRAP, waste with

[108] https://data.gov.uk/dataset/d409b2ba-796c-4436-82c7-eb1831a9ef25/2019-waste-data-interrogator
[109] https://ec.europa.eu/eurostat/documents/342366/351811/Municipal+Waste+guidance/bd38a449-7d30-44b6-a39f-8a20a9e67af2

EWC codes 15 01 10* and 15 01 11* were excluded from NHM arisings. The list of EWC codes used for constructing the NHM arisings from the C&I waste are provided in Appendix A.2.0.

The data on regional GVA[110] was collected from the ONS. To construct the GVA for the NHM sector, the GVA for food manufacturing sector was added to the GVA of the service sector (excluding activities of households).

To create future projections of NHM sector GVA, GDP growth projections from the OBR were used.[111] It should be noted that the OBR forecasts are for real GDP growth, and they are not available for the regions in England separately. So, it was assumed that all the regions in England will have the same GVA growth as the UK GDP growth. Also, the OBR forecast for GDP growth was available only till 2025. For 2026-2050, it was assumed that the GVA growth is the same as the growth in 2025.

4.3.3 Model Estimation

A panel random-effects model was estimated for NHM arisings for the 9 regions in England over 2010-2018. The model was estimated in logarithmic form (log), as it displayed a better fit to the historic NHM arisings. The independent variables used in the model are:

- Log of GVA for the NHM sector;
- Dummy variable for macroeconomic shock (capturing the economic recession in 2008); and
- Log of time-trend.

We have checked for the presence of unobservable individual effects by comparing the random-effects panel data regression model against an ordinary least squares regression model using the Lagrange Multiplier test, which suggested a strong presence of region-specific unobservable effects.

We also compared random-effects model with fixed-effects models (where error terms are correlated with the independent variables) using the Hausman Specification test, which suggested that the random-effects model specification is more efficient compared to the fixed-effects model.

We also checked for the presence of unobservable time-specific effects. However, the included time-trend variable already captured the time-specific effects, and therefore time-specific random-effects were not included in the model.

The idiosyncratic errors in the random-effects model were tested for serial correlation using Baltagi and Li serial dependence test for random-effects models, where the errors

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[110] https://www.ons.gov.uk/economy/grossvalueaddedgva/datasets/nominalandrealregionalgrossvalueaddedbalancedbyindustry

[111] https://obr.uk/forecasts-in-depth/the-economy-forecast/

displayed presence of serial-correlation. To correct for the serial-correlation in the idiosyncratic errors, a linear mixed effects (LME) model with MA(1) error specification was estimated.

The final model estimated is presented in the following equation:

$$\ln(\mathrm{NHM}_{it}) = \beta_1 + \beta_2 \ln(\mathrm{GVA}_{it}) + \beta_3 \,\mathrm{Shock}_{it} + \beta_4 \ln(t) + u_i + \varepsilon_{it}$$

Where:

- NHM_{it}= NHM arisings for region i at year t
- GVA_{it}= GVA for NHM sector for region i at year t
- Shock_{it}= Indicator variable for region i at year t taking the value greater than 0 and up to 1 during a shock, and 0 otherwise
- u_i= Unobservable individual (random) effect for region i
- ε_{it}= Idiosyncratic error term for region i at year t

4.3.4 Results

Table 4-6 presents the estimated regression coefficients.

Table 4-6: Regression Coefficient Estimated for MSW Arisings

Variable	Coefficient	Standard Error	p-value	Significance Level
Intercept	9.2025	1.2865	0.0000	***
log(NHM Sector GVA)	0.4611	0.1110	0.0001	***
log(Trend)	0.0560	0.0280	0.0490	**
Shock	-0.0267	0.0330	0.4203	
Random-Effects (Std. Deviation of Regression Errors)				
Individual: 0.1943				
Idiosyncratic: 0.1186				
Fraction of error variance due to individual specific effects: 0.729				
MA(1) coefficient for serial-correlation in idiosyncratic errors: 0.8063				

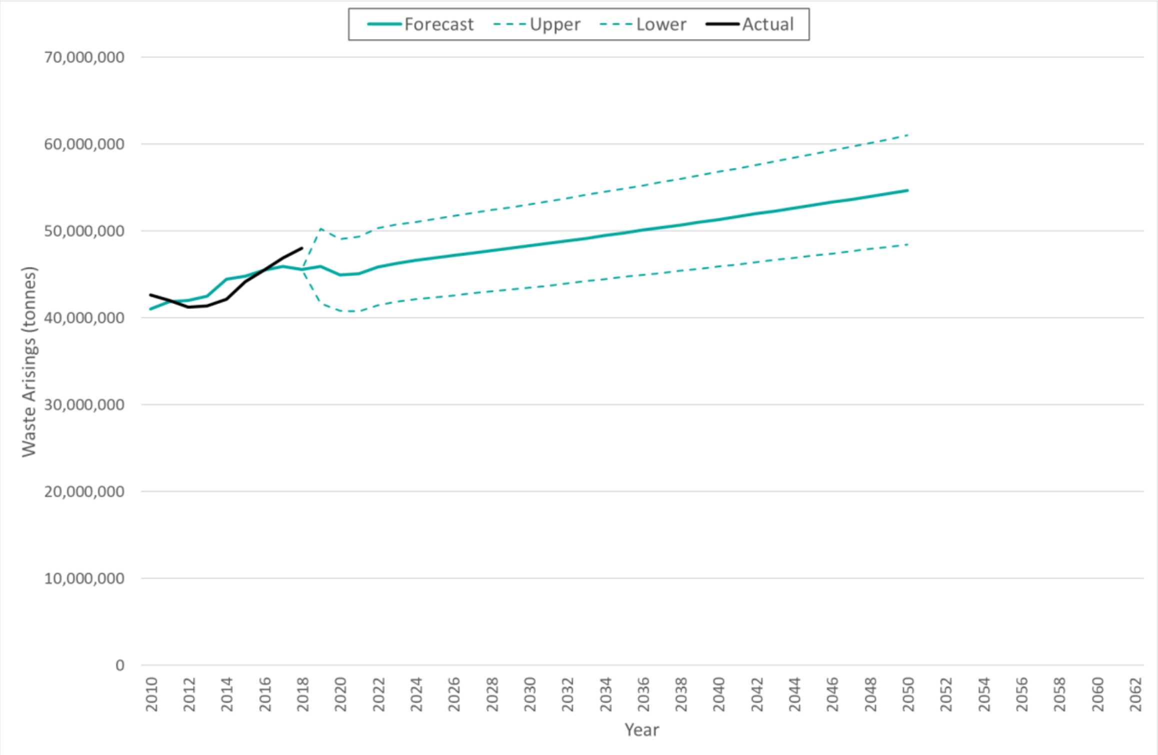
*Significance Level: *** 1%, ** 5%, * 10%.*

It can be observed that GVA affects NHM arisings positively while the shock affects NHM arisings negatively. The coefficient for time-trend is also positive, which implies an increasing trend in NHM generation over time. Coefficients of all the independent variables in the model are statistically significant at 5% or lower, except for the shock dummy variable, which was not statistically significant. Also 73% of the error variance are explained by the individual specific effects, which suggests presence of unobservable region-specific effects. Based on the estimated regression model, the forecast for NHM arisings for 2019-2050 were generated for each region in England. The regional NHM arisings were summed together to generate forecast for NHM arising in England for

2019-2050. Then the forecasts for WfH in England was added to the NHM forecasts for generating the forecasts for MSW in England for 2019-2050.

Figure 4-9 presents the actual and forecasted MSW arisings in England for 2010-2050. The forecasts of MSW arisings, on the other hand, displays a sharp decline in 2020, which is due to the impact of COVID-19 on OBR GDP growth forecasts. The forecasted MSW arisings starts to increase slowly from 2021 and displays a slight increasing trend afterwards. By 2050, it is forecasted that circa 54 million tonnes of MSW will be generated.

Figure 4-9: MSW Arisings Forecasts for England (2020-2050)



4.3.5 Model Limitations

Key limitations of the MSW forecasting model are listed below:

- The panel dataset for NHM arisings consists of only 81 observations (9 datapoint over time for 9 regions). Prediction based on such a small panel dataset will be subject to high degree of uncertainty.
- Data on NHM arisings was not available by English regions. It was constructed based on transfer station MSW waste. This introduces an additional uncertainty in the MSW forecasts.
- There is no data on projections of the NHM GVA by English regions. The GVA projection in the model is based on the UK GDP projections from OBR. This makes the MSW forecasts sensitive to factors affecting UK GDP rather than factors GVA for individual English regions.

- The impact of COVID on the MSW waste arisings has not been incorporated in the forecasting model as it is still unclear what impact COVID will have on future waste arisings and how long these effects will last.

4.4 Commercial and Industrial waste (C&I)

4.4.1 Methodological Approach

C&I waste arisings in England are estimated by Defra using data from Waste Data Interrogator, supplemented by national estimates for dry recyclates from the National Packaging Waste Database (NPWD) and trade association data.[112] These C&I waste arisings figures are then published through UK waste statistics and are available for 2010 to 2018. With just 9 data points in time, it was not possible to develop forecasts for C&I waste arisings using time-series econometric modelling.

An alternative approach for developing the forecasts for C&I waste arisings was to develop a time-series forecasting model for GVA for the commercial and the industrial sectors and then use the waste to GVA ratio to convert the GVA forecasts to waste arisings forecasts. The main driver of GVA for both commercial and industrial sector GVA is likely to be real GDP, which needs to be incorporated when developing the time series forecasting models for commercial and industrial sector GVAs. Both commercial and industrial sector GVA will also be affected by macroeconomic shocks, such as the 2008 economic recession, or COVID-19.

In addition to the above factors, C&I waste arisings will also depend on growth in the number of businesses over time, which will not be captured by the forecasting model based on the GVA of the commercial and industrial sector. So, to incorporate the impact of growth in a number of businesses on C&I waste arisings, we will need to combine the data on waste generated by business size and business sector with the trend in number of local business units by size and business sector. This will enable us to estimate the growth in C&I waste arisings due to the change in number of businesses over time. Finally, the waste to GVA ratios for the commercial and the industrial sector will then be adjusted using the waste growth rates in these sectors, respectively.

It should be noted that, the existing C&I waste forecasting model of Defra, discussed in WP1, also uses a similar approach. The model uses waste to GVA ratio to forecast waste arisings based on GVA forecasts for the commercial and the industrial sector. The existing model also adjusts the waste to GVA ratios for the commercial and the industrial sector using a waste minimisation rate (negative waste growth rate). However, while the

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112 https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/873328/Commercial_and_Industrial_Waste_Arisings_Methodology_Revisions_Oct_2018_contact_details_update_v0.2.pdf

existing model assumes an arbitrary rate of waste minimisation, this model estimates the waste minimisation / growth rate based on the change in number of businesses over time.

4.4.2 Data Preparation

Historic data on waste arisings for the commercial and industrial sectors in England between 2010 and 2018 were provided by Defra.

Historic data on UK real GDP[113] and GVA of the commercial and industrial sectors[114] were collected from the ONS. GDP growth projections were obtained from the OBR.[115] As the OBR forecasts for GDP growth was available only till 2025, for 2026-2050, we have assumed a 10-year moving average rate of growth.

To estimate the C&I waste growth due to growth in number of businesses over time, firstly, data from the 2009 Defra survey of Commercial and Industrial waste were collected for the data on waste arisings by business size and sectors.[116] The second set of data were collected from NOMIS. This data provided the number of local units within each size category by sector.[117]

The data collected from the 2009 waste survey and NOMIS did not utilise the same business categories, leading to the need to recategorize the NOMIS data from two digit SIC code data into 12 distinct business categories (6 from Commercial and 6 from Industrial). These data were recategorized, which allowed for the NOMIS and 2009 waste survey data to be compared effectively. This reclassification also provided an easier way to split the sectors between commercial and industrial waste clearly.

Following the preparation of the NOMIS data, the collated 2009 waste survey and NOMIS data were combined to create an average waste generation per local unit (business) for the 2010 year, as this was the closest available data to the 2009 survey. This average was then utilised for each year of NOMIS data for local units between 2010 and 2019, to calculate total waste generated per sector per business size. A weighted average was then calculated, using the (published) data from 2010 onwards, to ensure that the data was representative of the different business size bands, as well as the sectors. This weighted average was then utilised to create a time series of commercial and industrial sector waste growth, which in turn can be utilised for the future projection of waste up to 2030, after which the projection is estimated to be a flat rate up to 2050.

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[113] https://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/abmi/qna

[114] https://www.ons.gov.uk/economy/grossvalueaddedgva/datasets/nominalandrealregionalgrossvalueaddedbalancedbyindustry

[115] https://obr.uk/forecasts-in-depth/the-economy-forecast/

[116] http://www.defra.gov.uk/statistics/environment/waste/wrfg03-indcom/

[117] https://www.nomisweb.co.uk/

4.4.3 Model Estimation

For forecasting commercial sector GVA, we used an ARMA (Autoregressive Moving Average) model with external factors. We tested for stationarity of the dependent variable using the Augmented Dicky-Fuller (ADF) test. The null hypothesis for the ADF test was not rejected, implying that the dependent variable is non-stationary. However, a closer observation of the data-series and the autocorrelation function (ACF) suggested that the dependent variable followed a trend stationary process, rather than a difference stationary process. So, inclusion of a time-trend in the model should make the model stationary. Finally, the order of AR and MA terms were determined based on autocorrelation function (ACF) and partial autocorrelation function (PACF) for the dependent variable. The final estimated model included AR term of order 1.

The external variables included in the final model are:

- Real GDP; and
- Dummy variable for macroeconomic shock (capturing the economic recession in 2008).

The estimate model is presented in the following equation:

$$\mathrm{GVA}_t = \beta_1 \mathrm{GDP}_t + \beta_2 \mathrm{Shock}_t + \delta t + \rho_1 \mathrm{GVA}_{t-1} + \varepsilon_t$$

Where:

- GVA_t= GVA of commercial sector at year t
- GDP_t= Real Gross Domestic Product (2016 prices) at year t
- Shock_t= Indicator variable taking the value greater than 0 and up to 1 during a shock, and 0 otherwise
- ε_t= Random error at year t

The Shock dummy variable was assigned the value 1 between 2009 and 2013 to capture the impact of 2008 economic recession on the GVA of commercial sector. The value of the shock was assumed to be zero for the entire forecasting period.

The GVA for the commercial sector was forecasted for 2020 to 2050 using the estimated model. Waste to GVA ratio in the commercial sector was projected forward for 2019 to 2050 using the waste minimisation rate for the commercial sector which was estimated based on the growth in number of businesses in the commercial sector. Finally, the waste arisings forecast for the commercial sector for 2019 to 2050 was generated using the waste to GVA ratio in the commercial sector for the same period.

The model for forecasting the GVA for industrial sector was developed similarly using an ARMA model with the same external factors as the commercial sector GVA forecasting model. We also tested for stationarity of the dependent variable using the ADF test, which displayed presence of mild non-stationarity. However, based on Akaike Information Criterion (AIC) and Bayes Information Criterion (BIC) the undifferenced model performed better compared to the differenced stationary model. Finally, the order of AR and MA terms were determined based on ACF and PACF as before. The final estimated model included MA term of order 1 and presented in the following equation:

$$\mathrm{GVA}_t = \mu + \beta_1 \mathrm{GDP}_t + \beta_2 \mathrm{Shock}_t + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

Where:

- GVA_t= GVA of industrial sector at year t
- GDP_t= Real Gross Domestic Product (2016 prices) at year t
- Shock_t= Dummy variable taking the value 1 during a shock and 0 otherwise
- ε_t= Random error at year t

The Shock dummy variable was constructed in the same way as above to capture the impacts of 2008 economic recession on industrial sector GVA. The value of the shock was assumed to be zero for the entire forecasting period.

After estimating the above model, industrial sector GVA was forecasted for 2019 to 2050 using the estimated model. The growth rate of the forecasted GVA for the industrial sector was then adjusted by the waste growth of the industrial sector due to growth in number of businesses. Finally, the forecasts for the industrial sector waste arisings were generated by converting the adjusted industrial sector GVA using an average waste to GVA ratio of 0.057.

4.4.4 Results

The estimated coefficients of the commercial sector GVA model are presented in Table 4-7. It can be observed that, both real GDP and the shock dummy variable affects commercial sector GVA positively. Examining the historic trend in the GVA of commercial sector during the 2008 economic recession period, it was observed that the commercial sector GVA grew steadily since 2009, which explains the estimated positive impact of shock dummy on the GVA of the commercial sector. It can also be observed that all the estimated coefficients are significant at 1% except the shock dummy variable, which is significant at 12%.

Table 4-7: Regression Coefficients for the Commercial Sector GVA Model

	Coefficient	Standard Error	p-value	Significance Level
Trend	8005.7	442.67	0.0000	***
Real GDP	0.54	0.0032	0.0000	***
Shock Dummy	5933.6	3615.2	0.1191	
ARMA				
AR1	0.6304	0.1732	0.0020	***

*Significance Level: *** 1%, ** 5%, * 10%.*

Similarly, the estimated coefficients for the industrial sector GVA model are presented in Table 4-8, which shows that all of the estimated coefficients are significant at 1% except the real GDP, which is significant at 12%. It can be observed that the coefficient of real GDP is positive while the coefficient of the Shock dummy is negative.

Table 4-8: Regression Coefficients for the Industrial Sector GVA Model

	Coefficient	Standard Error	p-value	Significance Level
Intercept	184140	8003.1	0.0000	***
Real GDP	0.0071	0.0043	0.1168	
Shock Dummy	-9363.9	1988.5	0.0002	***
ARMA				
MA1	0.7465	0.1821	0.0007	***

*Significance Level: *** 1%, ** 5%, * 10%.*

Figure 4-10 presents the estimated forecasts for commercial waste arisings in England for 2019 to 2050 along with 95% confidence intervals. The forecasted waste arisings for the commercial sector display a sharp decline in 2020 to ~25 million tonnes. Then the waste arisings increase to 2018 level by 2022, and afterwards gradually increase to ~32 million tonnes by 2050.

Figure 4-10: Commercial Waste Arisings Forecasts for England (2019-2050)

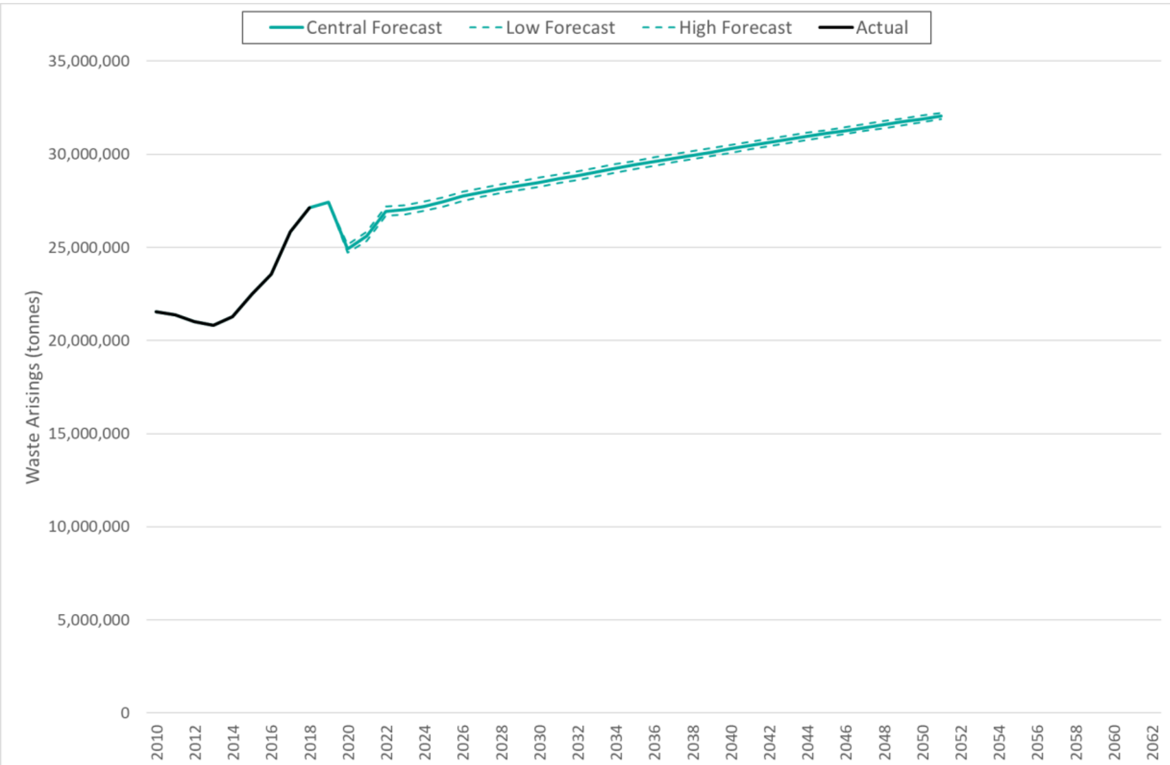
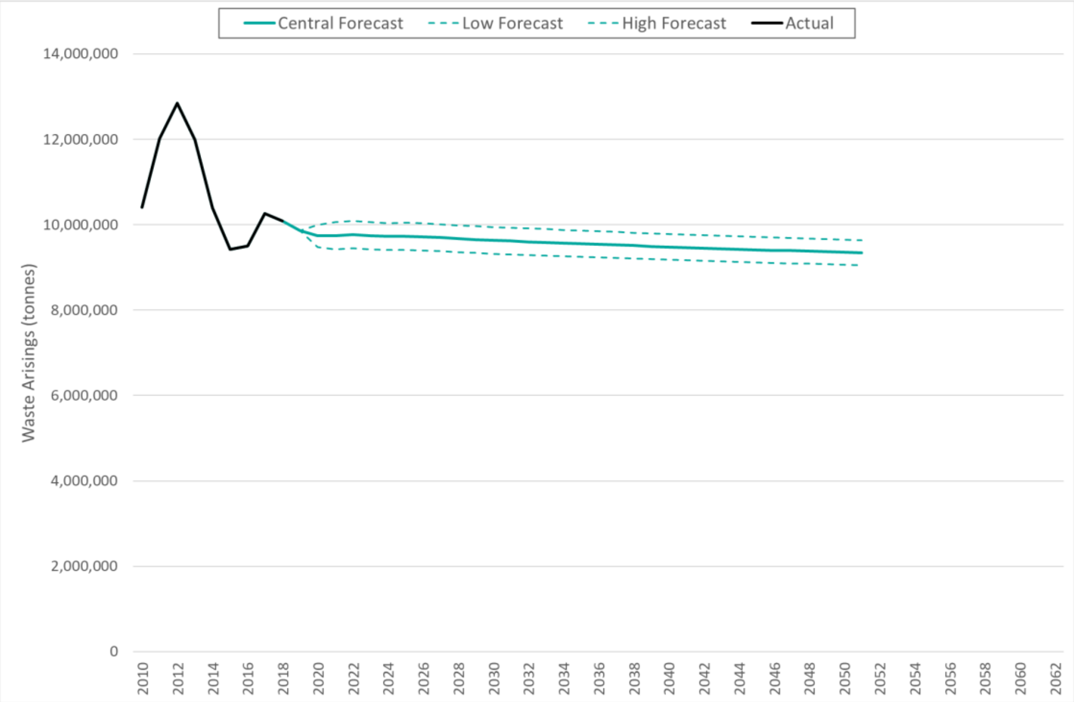


Figure 4-11 presents the estimated forecasts for industrial waste arisings in England for 2019 to 2050 along with 95% confidence intervals. The forecasted waste arisings for the industrial sector declines in 2019 and 2020, then display an increasing trend for the next few years, and afterwards slowly decline to ~9.5 million tonnes in 2050.

Figure 4-11: Industrial Waste Arisings Forecasts for England (2019-2050)



4.4.5 Model Limitations

Key limitations of the C&I forecasting model are listed below:

- Due to limited historic data on C&I waste arisings in England, a time-series econometric model for directly forecasting C&I waste arisings could not be developed. Rather the forecasting model was developed based on GVA of the commercial sector and the industrial sector in England. So, the C&I forecasting model will be sensitive to any external factors that will affect the GVA of the commercial and/or industrial sector.
- Although the C&I waste arisings model estimates the waste minimisation rate using the change in number of businesses over time, the estimation is based on the average waste generated by businesses of different sizes in different sectors from the 2009 C&I Waste Survey. However, the average waste generated by businesses in different sectors might have changed since 2009, which cold not be incorporated in the calculation of waste minimisation rate due to the unavailability of more recent estimates of average waste arisings per business.

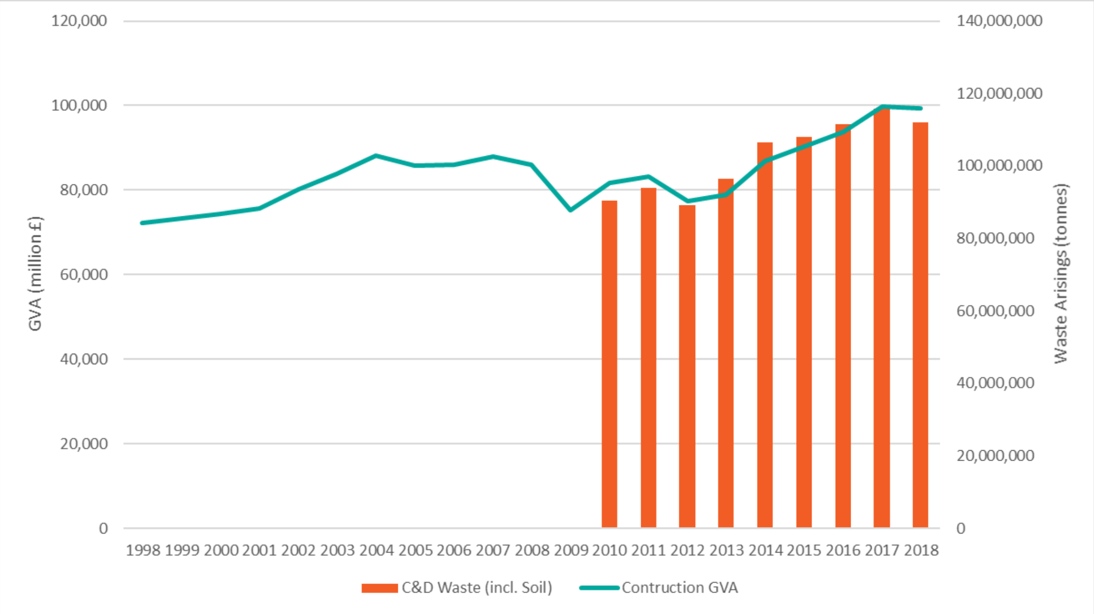
The impact of COVID on the C&I waste arisings has not been incorporated in the forecasting model as it is still unclear what impact COVID will have on future waste arisings and how long these effects will last.

4.5 Construction, Demolition and Excavation (CD&E) Waste

4.5.1 Methodological Approach

The available data on CD&E Waste Arisings are very limited, and thus it was not possible to develop a time-series econometric forecasting model for the CD&E waste stream. After separating the dredging spoils from the CD&E waste stream, a closer observation of specifically the C&D waste (including soil excavation) revealed that it follows a similar trend as the GVA for the construction sector (Figure 4-12). On the other hand, it was observed that the trend in dredging spoils closely matched the trend in dredging area.

Figure 4-12: Comparison of Trends in GVA for the Construction Sector and C&D Waste (including Soil Excavation)



Given the above relationships, an alternative approach to forecasting CD&E waste arisings is to develop separate time-series forecasting models for Construction GVA and dredging spoils and then use waste to GVA ratio and waste to dredging area ratio to forecast the C&D waste arisings and dredging spoils, respectively.

The main driver for construction sector GVA is the real GDP. In addition, a time-trend variable could be useful to include in the regression model to capture any underlying trends in waste minimisation. Finally, a dummy variable for the 2008 recession should be able to capture the impact of 2008 regression on the construction sector.

The above drivers were also included for the forecasting model for dredging area. However, only the time-trend was found to have any significant impact on the dredging area.

4.5.2 Data Preparation

Historic data on CD&E waste arisings were collected from Defra publications.[118] The data on only C&D waste arisings (excluding soil excavation and dredging spoils) was available for 2010-2016. Data on soil excavation and dredging spoils were only available for 2010, 2012, 2014 and 2016. Defra also provided us with the updated data on CD&E waste arisings for England for 2010-2018 and dredging spoils for England in 2018.

Historic data on UK real GDP[119] and GVA of the construction sector[120] were collected from the ONS. The data on dredging area was collected from the British Marine Aggregate Producers Association (BMAPA).[121]

GDP growth projections were obtained from the OBR.[122] As the OBR forecasts for GDP growth was available only till 2025, for 2026-2050, we have assumed a constant rate of growth equal to the rate of growth in 2025.

4.5.3 Model Estimation

For forecasting construction sector GVA, we used an ARMA (Autoregressive Moving Average) model with external factors. The dependent variable was log of GVA of the construction sector. We also tested for stationarity of the dependent variable using the ADF test, which displayed presence of mild non-stationarity. However, based on Akaike Information Criterion (AIC) and Bayes Information Criterion (BIC) the undifferenced model performed better compared to the differenced stationary model.

The order of AR and MA terms were determined based on ACF and partial autocorrelation function (PACF) for the dependent variable. The final estimated model included MA term of order 1. The external variables included in the model are:

- Real GDP; and
- Dummy variable for macroeconomic shock (capturing the economic recession in 2008).

The estimate model is presented in the following equation:

$$\ln(\mathrm{GVA}_t) = \beta_1 \ln(\mathrm{GDP}_t) + \beta_2 \mathrm{Shock}_t + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

Where:

- GVA_t= GVA of construction sector at year t
- GDP_t= Real Gross Domestic Product (2016 prices) at year t

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118 https://www.gov.uk/government/statistical-data-sets/env23-uk-waste-data-and-management

119 https://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/abmi/qna

120 https://www.ons.gov.uk/economy/grossvalueaddedgva/datasets/nominalandrealregionalgrossvalueaddedbalancedbyindustry

121 https://bmapa.org/downloads/reference.php

122 https://obr.uk/forecasts-in-depth/the-economy-forecast/

- Shock_t= Dummy variable taking the value 1 during a shock and 0 otherwise
- ε_t= Random error at year t

The Shock dummy variable was assigned the value 1 between 2009 and 2013 to capture the impact of 2008 economic recession on the GVA of construction sector. The value of the shock was assumed to be zero for the entire forecasting period.

After estimating the above model, the GVA for the construction sector was forecasted for 2020 to 2050 using the estimated model. The forecast for construction sector GVA was then converted to forecast for C&D waste arisings (including soil excavation), using an average waste to GVA ratio of 1.088.

Similarly, for forecasting dredging area, we also used an ARMA model. We also tested for stationarity of the dependent variable using the ADF test, which showed presence of mild non-stationarity in the dependent variable. However, a closer observation of the data-series and the autocorrelation function (ACF) suggested that the dependent variable followed a trend stationary process, rather than a difference stationary process. So, inclusion of a time-trend in the model should make the model stationary. As before, the order of AR and MA terms were determined based on ACF and PACF for the dependent variable. The final estimated model included AR term of order 1. The estimated model also included a time-trend (in log form) to capture any underlying trend in area dredged over time.

The estimate model is presented in the following equation:

$$\mathrm{D}_t = \mu + \rho_1 \mathrm{D}_{t-1} + \delta \ln(t) + \varepsilon_t$$

Where:

- D_t= Area dredged at year t
- ε_t= Random error at year t

The area dredged was forecasted for 2020 to 2050 using the above model. The forecast for area dredged was then converted to forecast for dredging spoils, using an average dredging spoil to dredging area ratio of 0.103.

4.5.4 Results

The estimated coefficients of the construction sector GVA model are presented in Table 4-9. As expected, real GDP affects construction sector GVA positively, while the shock dummy affects construction GVA negatively. The coefficient of time-trend is positive, which reflects the presence on an increasing trend in construction sector GVA over time. It can also be observed that all the estimated coefficients are significant at 10% or less.

Table 4-9: Regression Coefficients for the Construction Sector GVA Model

	Coefficient	Standard Error	p-value	Significance Level
Log(Real GDP)	0.7929	0.0007	0.0000	***
Shock Dummy	-0.0929	0.0180	0.0000	***

	Coefficient	Standard Error	p-value	Significance Level
ARMA				
MA1	-0.5614	0.1586	0.0023	***

*Significance Level: *** 1%, ** 5%, * 10%.*

Similarly, the estimated coefficients for the area dredged model are presented in Table 4-10, which shows that all the estimated coefficients are significant at 1%. The coefficient of time-trend is negative, denoting a declining trend in area dredged over time.

Table 4-10: Regression Coefficients for the Area Dredged Model

Variable	Coefficient	Standard Error	p-value	Significance Level
intercept	253.1590	9.1954	0.0000	***
log(Trend)	-54.4082	3.9338	0.0000	***
ARMA				
ar1	0.3888	0.2113	0.0822	*

*Significance Level: *** 1%, ** 5%, * 10%.*

Figure 4-13 presents the estimated forecasts for C&D waste arisings (including soil excavation) for 2019 to 2050, along with the 95% confidence intervals. The waste is forecasted to decline sharply in 2020 due to the predicted impact of COVID-19 on the real GDP, but it increases back to the previous level over the next few years. In 2050, the forecasted C&D waste arisings (including soil excavated) in England is circa 170 million tonnes.

Figure 4-13: C&D Waste Arisings (including Soil Excavation) Forecasts for England (2019-2050)

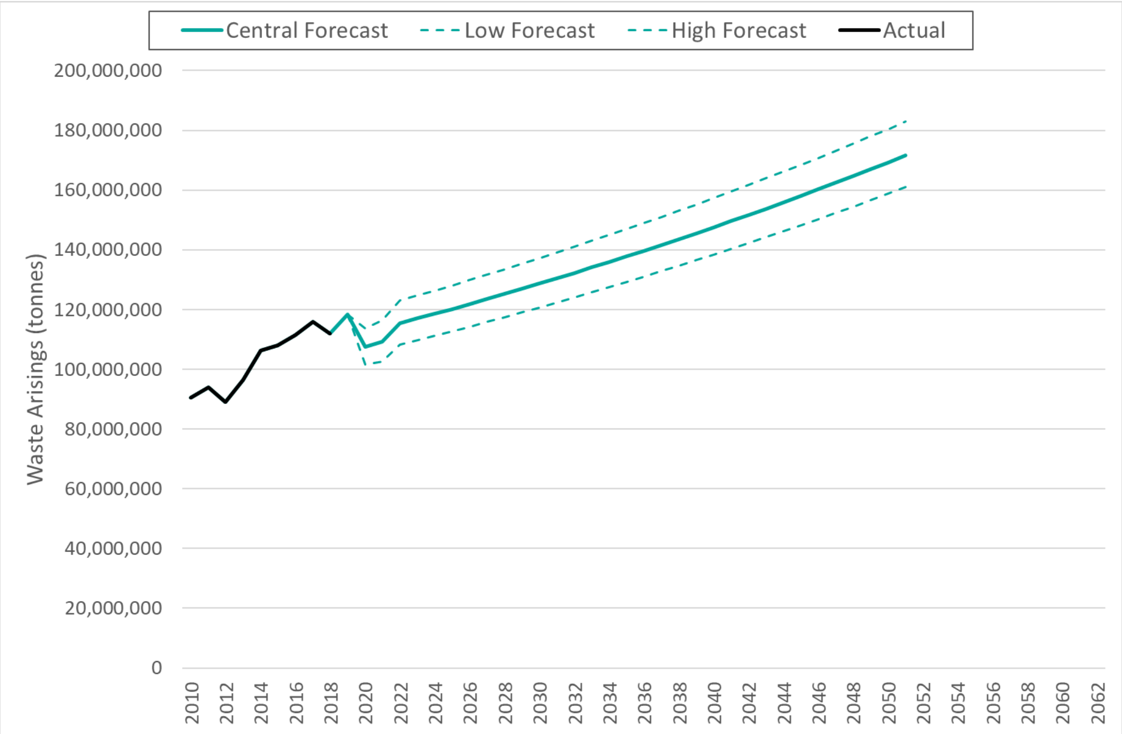
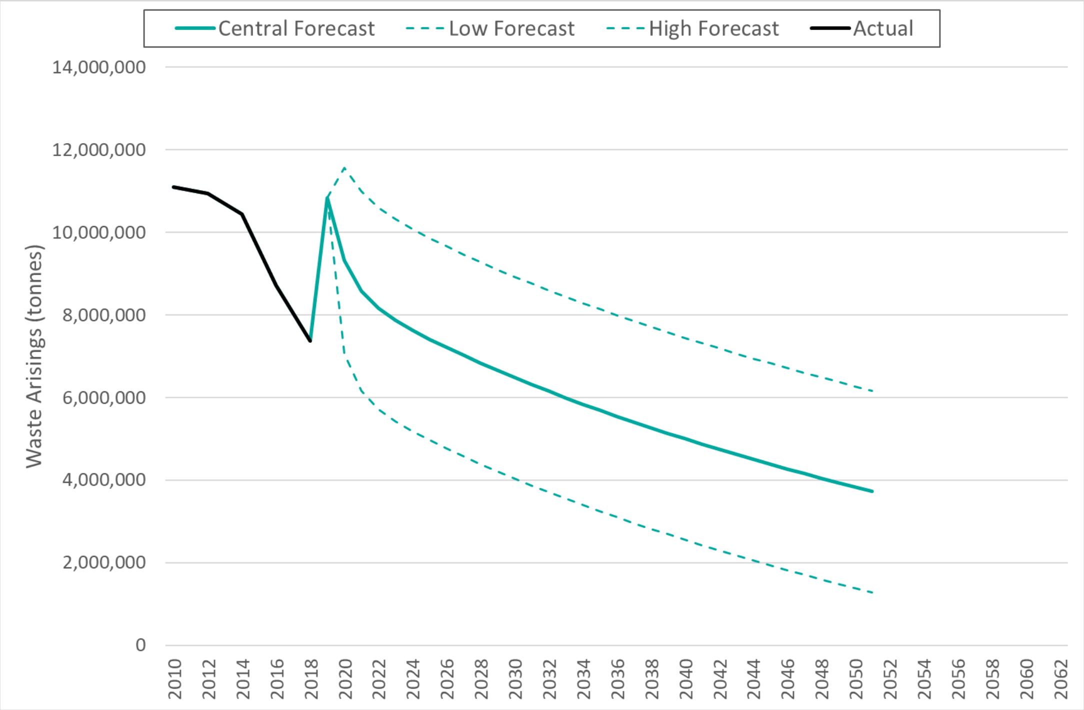


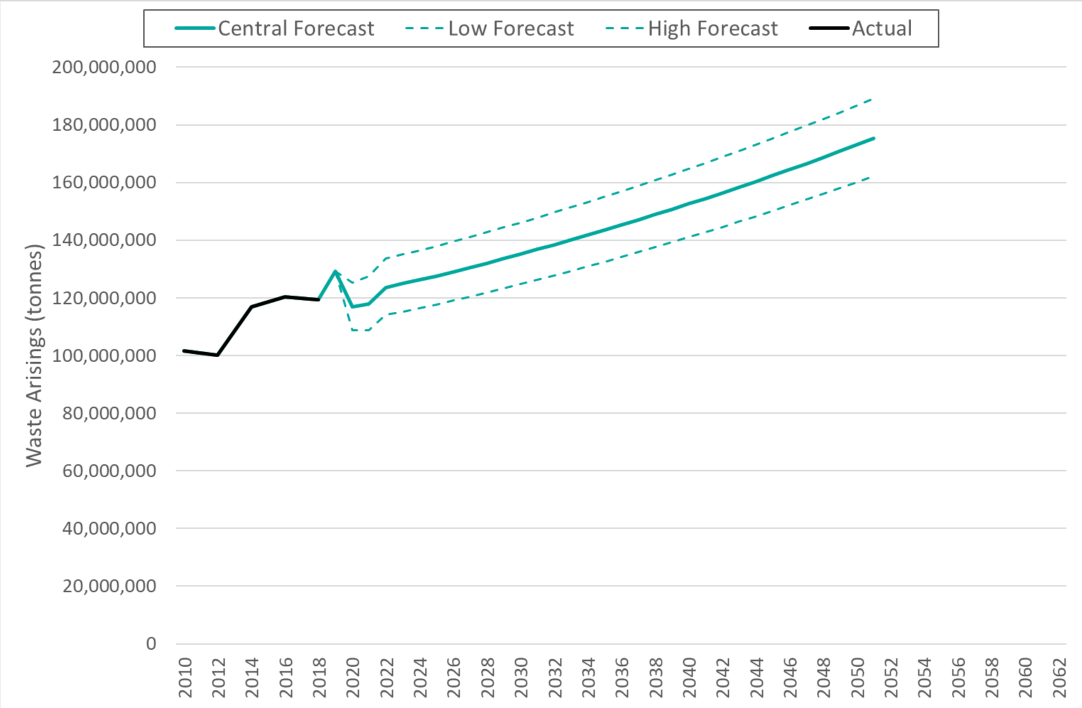
Figure 4-14 presents the forecasts for dredging spoils for 2019 to 2050, along with the 95% confidence interval for the forecasted values. Dredging spoils are forecasted to decline gradually over time from 11 million tonnes in 2020 to about 4 million tonnes in 2050.

Figure 4-14: Dredging Spoils Forecasts for England (2019-2050)



Combining the forecasts for C&D waste arisings (including excavated soils) and the dredging spoils, the forecasts for total CD&E waste arisings in England for 2019 to 2050 was generated, which is presented in Figure 4-15.

Figure 4-15: Total CD&E Wate Arisings Forecasts for England (2019-2050)



4.5.5 Model Limitations

Key limitations of the CD&E forecasting model are listed below:

- Due to limited historic data on CD&E waste arisings (including dredging spoils) in England, a time-series econometric model for directly forecasting CD&E waste arisings could not be developed. Rather the forecasting model was developed based on GVA of the construction sector in England and dredging area in England and Wales. So, the CD&E forecasting model will be sensitive to any external factors that will affect construction sector GVA and/or dredging area.
- Moreover, the ratio between dredging area and dredging spoils were estimated based on limited number of data points, which can make the forecasting of dredging spoils more uncertain.
- The impact of COVID on the CD&E waste arisings has not been incorporated in the forecasting model as it is still unclear what impact COVID will have on future waste arisings and how long these effects will last.

APPENDICES

A.1.0 Glossary

List of acronyms

Acronym	Definition
ACF	autocorrelation function
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Autoregressive Moving Average
C&D	Construction and Demolition
C&I	Commercial and Industrial
CD&E	Construction, Demolition and Excavation
DMC	Domestic Material Consumption
DRS	Deposit Return Scheme
EPR	Extended Producer Responsibility
GDP	Gross Domestic Product
GVA	Gross Value Added
LA	Local Authority
LACW	Local Authority Collected Waste
MSW	Municipal Solid Waste
NACE	Nomenclature of Economic Activities
NHM	non-household municipal
PACF	partial autocorrelation function
OBR	Office of Budget Responsibility
ONS	Office of National Statistics
RMC	Raw Material Consumption

RWS	Resources and Waste Strategy
SARIMA	Seasonal Auto-Regressive Integrated Moving Average
WFD	Waste Framework Directive
WfH	Waste from Households
WRAP	Waste and Resources Action Programme

A.2.0 EWC Codes for MSW

EWC Codes	Description
20 01 01	Paper and cardboard
20 01 02	Glass
20 01 08	Biodegradable kitchen and canteen waste
20 01 10	Clothes
20 01 11	Textiles
20 01 13*	Solvents
20 01 14*	Acids
20 01 15*	Alkalines
20 01 17*	Photo-chemicals
20 01 19*	Pesticides
20 01 21*	Fluorescent tubes and other mercury-containing waste
20 01 23*	Discarded equipment containing chlorofluorocarbons
20 01 25	Edible oil and fat
20 01 26*	Oil and fat other than those mentioned in 20 01 25
20 01 27*	Paint, inks, adhesives and resins containing dangerous substances
20 01 28	Paint, inks, adhesives and resins other than those mentioned in 20127
20 01 29*	Detergents containing dangerous substances
20 01 30	Detergents other than those mentioned in 20 01 29
20 01 31*	Cytotoxic and cytostatic medicines
20 01 32	Medicines other than those mentioned in 20 01 31
20 01 33*	Batteries and accumulators included in 16 06 01, 16 06 02 or16 06 03 and unsorted batteries and accumulators containing these batteries
20 01 34	Batteries and accumulators other than those mentioned in 20 0133
20 01 35*	Discarded electrical and electronic equipment other than those mentioned in 20 01 21 and 20 01 23 containing hazardous components

20 01 36	Discarded electrical and electronic equipment other than those mentioned in 20 01 21, 20 01 23 and 20 01 35
20 01 37*	Wood containing dangerous substances
20 01 38	Wood other than that mentioned in 20 01 37
20 01 39	Plastics
20 01 40	Metals
20 01 41	Wastes from chimney sweeping
20 01 99	Other fractions not otherwise specified
20 02 01	Biodegradable waste
20 02 03	Other non-biodegradable wastes
20 03 01	Mixed municipal waste
20 03 02	Waste from markets
20 03 03	Street-cleaning residues
20 03 07	Bulky waste
20 03 99	Municipal wastes not otherwise specified
15 01 01	Paper and cardboard packaging
15 01 02	Plastic packaging
15 01 03	Wooden packaging
15 01 04	Metallic packaging
15 01 05	Composite packaging
15 01 06	Mixed packaging
15 01 07	Glass packaging
15 01 09	Textile packaging