



Review of Methodology for Forecasting Waste Infrastructure Requirements

Prepared for Defra

20 December 2012

Project Team

Richard Druce
Matthew Mair

NERA Economic Consulting
15 Stratford Place
London W1C 1BE
United Kingdom
Tel: +44 20 7659 8500
Fax: +44 20 7659 8501
www.nera.com

Disclaimer

Extracts of this report may not be reproduced or redistributed without the written permission of NERA, and NERA accepts no liability whatsoever for the actions of third parties in this respect. This report may not be sold without the written consent of NERA. This report is intended to be read and used as a whole and not in parts. Separation or alteration of any section or page from the main body of this report is expressly forbidden and invalidates this report.

All opinions, advice and materials provided by NERA are included, reflected or summarized herein as the “NERA Content”. There are no third party beneficiaries with respect to the NERA Content, and NERA disclaims any and all liability to any third party. In particular, NERA shall not have any liability to any third party in respect of the NERA Content or any actions taken or decisions made as a consequence of the results, advice or recommendations set forth herein.

The NERA Content does not represent investment advice or provide an opinion regarding the fairness of any transaction to any and all parties. The opinions expressed in the NERA Content are valid only for the purpose stated herein and as of the date hereof. Information furnished by others, upon which all or portions of the NERA Content are based, is believed to be reliable but has not been verified. No warranty is given as to the accuracy of such information. Public information and industry and statistical data are from sources NERA deems to be reliable; however, NERA makes no representation as to the accuracy or completeness of such information and has accepted the information without further verification. No responsibility is taken for changes in market conditions or laws or regulations and no obligation is assumed to revise NERA Content to reflect changes, events or conditions, which occur subsequent to the date hereof.

Contents

Executive Summary	i
1. Introduction	1
2. Defra’s Current Approach	2
2.1. Waste Arisings (Demand) Forecasts	2
2.2. Forecasting Diversion Capacity	2
2.3. Assessing Infrastructure Requirements	3
3. Forecasting Household Waste Arisings	5
3.1. Appraisal of the Central Forecast	5
3.2. Alternative Model Specifications	6
3.3. Alternative Approach: Input-Output Modelling	12
3.4. Recommendations	14
4. Forecasting Commercial and Industrial Waste Arisings	15
4.1. Central Forecast Based on Survey Data	15
4.2. Alternative Forecast: Input-Output “REEIO” Model	21
4.3. Recommendations	22
5. Forecasting Additional Infrastructure	23
5.1. Drivers of Infrastructure Completion Rates	23
5.2. Defra’s Current Treatment	23
5.3. Evidence from Power Generation	24
5.4. Recommendation	25
6. Appraisal of Defra’s Overall Approach	27
6.1. Contingencies	27
6.2. Stochastic Modelling	27
6.3. Recommendation	31
7. Conclusions	32
Appendix A. (S)ARIMA Estimation Results	33
Appendix B. Model Audit	34

**Appendix C. Modelling Approach Using Latest
Landfill Returns Data**

35

Executive Summary

Defra has commissioned NERA Economic Consulting to provide an independent review of the modelling approach used to assess whether England will contribute the necessary diversion from landfill for the UK to meet the targets imposed under the Landfill Directive by 2020. The Directive requires that no more than 10.2 megatonnes of biodegradable municipal waste (BMW) be sent to landfill by 2020. Ensuring that England has sufficient infrastructure to divert the necessary quantity of BMW from landfill is a policy challenge addressed by the Waste Infrastructure Delivery Programme (WIDP).

Defra's current modelling approach consists of forecasting demand for diversion capacity (i.e. the volume of waste arisings), the supply of diversion capacity, and comparing the two. If there is a sufficiently large gap (or "residual") between expected capacity and expected demand, after applying a series of contingencies, the model concludes that there is sufficient capacity to meet the Landfill Directive target by 2020. If demand exceeds supply (plus contingencies), the model would conclude that further action, either to provide additional capacity or reduce demand, would be required to meet targets with an adequate degree of certainty.

Through this assignment, we have conducted a detailed review of the methods used by Defra to assess whether England has sufficient waste diversion capacity to meet the Landfill Directive targets that requires that no more than 10.2 megatonnes of BMW be sent to landfill in 2020. We have made recommendations to help improve the robustness of the waste arisings forecasts, and have provided an independent assessment of the delivery adjustment rates used to define the diversion capacity Defra expects to be made available. In particular, our analysis shows that:

- The ARIMA model currently used to forecast residential waste arisings is probably not the optimal specification in light of currently available data, due to the presence of structural breaks in the time series, and we recommended an alternative SARIMA model;
- We conclude that the "input-output" model has certain advantages compared to the (S)ARIMA approach for forecasting residential waste arisings, because it accounts explicitly for the fundamental drivers of waste generation (i.e. consumption expenditure). However, the model inputs (particularly forecasts of consumption expenditure) are now rather out of date;
- We concluded that GVA is a more meaningful driver of C&I waste arisings than employment, although we note that all methods used to forecast C&I waste arisings are somewhat uncertain due to the paucity of historic data. The robustness of the forecasts could be enhanced by obtaining more data, e.g. by surveying evidence from other EU markets; and
- The "delivery adjustment rates" are close to the historically observed success rates for power generation projects proposed in the UK. However, Defra's current approach assumes that projects that have not been proposed yet will not contribute to meeting the 2020 landfill diversion targets, and may therefore understate the amount of capacity that will be delivered if some diversion capacity can be delivered over a timeframe shorter than the period to 2020. Also, assuming delivery adjustment rates based on historic

experience does not account for the possibility that the underlying economic drivers of waste diversion capacity projects will change over time.

Finally, in terms of the overall framework, our main conclusion is that Defra's approach should be refined to better reflect the uncertainty inherent in forecasting demand and capacity. Based on our experience in other sectors, we believe a more robust treatment of such uncertainty is a stochastic modelling approach, which accounts explicitly for the range of uncertainty around all of the key input assumptions.

1. Introduction

Defra has commissioned NERA Economic Consulting to provide an independent review of the modelling approach used to assess England will contribute the necessary diversion from landfill for the UK to meet the targets imposed under the Landfill Directive by 2020. The Directive requires that no more than 10.2 megatonnes of biodegradable municipal waste (BMW) be sent to landfill by 2020. Ensuring that England has sufficient infrastructure to divert the necessary quantity of BMW from landfill is a policy challenge addressed by the Waste Infrastructure Delivery Programme (WIDP).

The remainder of this report is structured as follows:

- Chapter 2 summarises Defra’s current modelling approach;
- Chapter 3 reviews the methods used to forecast residential waste arisings;
- Chapter 4 reviews the methods used to forecast commercial and industrial waste arisings;
- Chapter 5 appraises Defra’s assumptions on delivery adjustment rates;
- Chapter 6 provides our comments on the overall framework; and
- Chapter 7 concludes.

2. Defra's Current Approach

In this chapter we set out Defra's current approach to assessing the likelihood of meeting the Landfill Directive target. This approach consists of forecasting demand for diversion capacity (i.e. the volume of waste arisings), the supply of diversion capacity, and comparing the two. If there is a sufficiently large gap (or "residual") between expected capacity and expected demand, after applying a series of contingencies, the model concludes that there is sufficient capacity to meet the Landfill Directive target by 2020. If demand exceeds supply (plus contingencies), the model would conclude that further action, either to provide additional capacity or reduce demand, would be required to meet targets with an adequate degree of certainty. We describe the components of this calculation in the sections below.

2.1. Waste Arisings (Demand) Forecasts

To understand how the need for diversion capacity will evolve, the model uses a forecast of Municipal Solid Waste (MSW) arisings each year from 2012 to 2020. MSW has two sources: household waste collected by Local Authorities, and waste arisings from commercial and industrial (C&I) sources that is similar in composition and nature to household waste.

These two streams of waste arisings are forecast in different ways:

- For household waste, where annual data is available from 1986, Defra uses a time-series "ARIMA" modelling approach.¹ This approach uses historic data on household waste arisings to generate predictions of future growth; and
- For C&I waste, where data is far more restricted, Defra forecasts waste arisings by indexing it to forecast changes in employment numbers across different business sectors. Defra also assumes an efficiency improvement, which reduces waste per employee over time, when deriving its estimate of total C&I waste in each year.

These methods predict total MSW arising in 2020. These two streams of MSW are then adjusted by a contingency level that represents the uncertainty surrounding these forecasts. The contingencies increase household waste volumes by a given percentage (currently, 6.6%), and C&I waste volumes by a larger amount (currently, 13.3%). Defra applies a higher contingency to the forecast of C&I waste arisings due to the greater underlying uncertainty regarding this component of the forecast.

The forecasts of MSW arisings are then reduced to reflect forecast recycling rates in 2020, which are 50% for households and 60% for C&I. Finally, Defra assumes that 68% of MSW is composed of BMW.

2.2. Forecasting Diversion Capacity

Different types of infrastructure are available that have the capacity to divert BMW from landfill. To assess whether this capacity is sufficient to meet forecast demand, Defra compiles a list of projects that are currently proposed by local authorities or merchant

¹ An "Autoregressive, Integrated, Moving Average" (ARIMA) process uses historical data on the dependent variable (in this case household waste) to predict future values of the same variable.

developers, which are all at various stages in the planning and development pipeline. Defra then assumes that the utilisation rate of all plants will be 80% of their nominal capacity (in tonnes per annum), except for energy from waste projects which are assumed to have 100% utilisation rates.

Two major sorts of plants are included in the model:

- Energy from Waste (EfW) plants are assumed to divert 100% of BMW processed from landfill; and
- Bio-treatment Mechanical Biological Treatment (MBT) plants are assumed to divert 50% of MSW to EfW plants, and an additional 85% of BMW from landfill.

Combining the diversion capacities provided by this range of plants gives a total capacity for MSW diverted from landfill, of which 68% is assumed to be BMW.

Defra accounts for the uncertainty in future capacity additions by applying “Delivery Adjustment Rates” to the capacities of each plant. Plants that are “Fully Operational” are derated to 95% of their diversion capacity (calculated as set out above) to account for the possibility of unforeseen interruptions. Capacity that is not yet built is adjusted to reflect the stage of its development, and the chance that the project will be abandoned before it comes online. These “Delivery Adjustment Rates”, shown in Table 2.1, differ depending on whether the project is in the commissioning stage, has achieved financial close, whether it has planning permission, and so forth. Different “Delivery Adjustment Rates” also apply depending on the source of projects’ funding. If the project is covered by a PPP or PFI scheme, Defra assumes it is more likely to come online than if it is a “merchant” plant.

**Table 2.1
WIDP Delivery Adjustment Rates**

Delivery Adjustment Rate					
WIC/G or PPP	RAG	%	Merchant	RAG	%
Fully Operational	B	95	Fully Operational	B	95
Commissioning	G	90	Commissioning	G	90
Financial close, with planning	AG	80	Financial close, with planning	AG	80
Financial close, no planning	A	70	Planning, no financial close	A	40
In porcurement, no planning	AR	60	No planning	AR	20
Unlikely to go live	R	20	Unlikely to go live	R	0

Source: (1) Defra, WIDP Flow Chart. N.b. “B” means blue, “G” green, “AG” amber-green and so forth, and (2) Email from Defra dated 20 December 2012.

Summing the diversion capacity across all projects in Defra’s database, and derating it as described above, gives a total forecast diversion capacity of 7.5 megatonnes per annum in 2020. This is also reduced by an assumed contingency, in this case 10%, to give a forecast diversion capacity of 6.7 megatonnes.

2.3. Assessing Infrastructure Requirements

As described above, Defra’s model forecasts BMW waste arisings (in megatons per annum) in 2020, the amount of diversion capacity expected to be online in 2020 (in megatons per

annum) and calculates the difference between the two. It then compares this difference to the Landfill Cap of 10.2 megatons to assess whether there is sufficient diversion capacity to meet the target.

3. Forecasting Household Waste Arisings

The first major source of uncertainty in the Defra methodology is the forecast of future waste arisings from households. Defra has considered two alternative methods to provide this forecast:

- The “central forecast”, which is derived using an econometric model called an autoregressive integrated moving average (“ARIMA”) model that uses statistical methods to predict future waste arisings based solely on historical waste arisings data; and
- An input-output model that links a forecast of waste arisings to data on historic and forecast consumption expenditure across different categories of goods.

In this chapter, we review and appraise both of these methods, and suggest possible improvements to them.

3.1. Appraisal of the Central Forecast

Defra uses an annual dataset on waste arisings from 1986-2010 to fit an autoregressive integrated moving average (“ARIMA”) model. The projections from this model are used to derive Defra’s central forecast of residential waste arisings.

In general, ARIMA models are fitted to time series data either to better understand the data or to forecast future observations of the data series. Defra’s model is an ARIMA(1,1,1) model.² This means that it has the following structure.

$$\Delta_1 y_t = \beta_0 + \beta_1 \Delta_1 y_{t-1} + \beta_2 \Delta_1 x_t + \beta_3 \varepsilon_{t-1} + \varepsilon_t$$

In other words, it assumes that changes in the natural logarithm of waste arisings (Δy_t) depend on changes in itself in the preceding year (Δy_{t-1}) and on changes in an exogenous variable (Δx_t), which indicates years of recession.³ This recession indicator takes a value of zero or one, i.e. it is a “dummy variable”. Changes in waste arisings also depend on ε_t , which is a “white noise” error term, representing random variation in the data that the model itself cannot explain.

Fitting this “ARIMA” structure to time-series data requires that a number of statistical assumptions are satisfied, each of which we assess below.

3.1.1. Stationarity

Fitting an ARIMA model requires that the data is “stationary”, which means the mean and variance of the data does not change over time. Typically, the use of “differences” on the left hand side of the model, i.e. using changes in y_t , rather than y_t itself, is intended to ensure the series is stationary. However, in this case, we find that even the differenced series (Δy_t) is

² <http://www.stata.com/features/time-series/ts-arima.pdf>, p.15.

³ By incorporating an independent variable the model is also known as an “ARMAX” model, where the X stands for “exogenous”.

non-stationary over the period from 1986 to 2010, which suggests the ARIMA model described above is not the optimal forecast model with currently available data. To overcome this problem, Defra excludes the years after 2007 to produce a stationary series. However, applying an ARIMA model to a non-stationary variable risks estimating a “spurious” regression, and removing data points does not overcome the problem of non-stationarity.⁴

3.1.2. Model selection

Defra’s approach also assumes that the data, the change in the natural logarithm of waste arisings, follows a particular statistical process. Specifically, it assumes that it depends on one lagged observation of itself (Δy_{t-1}), i.e. that the process has a first-order autoregressive, or AR(1), component. It also assumes that the white noise error term, which represents the random “shocks” to the data series over time, affects waste arisings both in the year when the shock occurs and also in the following year. In other words, the model follows a first order moving average, or MA(1), process.

We have assessed whether the regression diagnostics support these assumptions. We cannot reject the hypothesis that β_1 (the AR(1) component) is equal to zero at the 5% significant level, which suggests the data may not really follow an AR(1) process. Also, we cannot reject the null hypothesis that β_3 (the MA(1) component) is equal to zero at the 5% significance level or above.

The model structure also requires that the recession dummy variable is a true driver of waste arisings. In fact, the coefficient β_2 is statistically insignificant, which suggests its inclusion in the model may reduce the reliability of the forecasts produced.⁵

From the above, we believe there is sufficient evidence to conclude that the current ARIMA(1,1,1) is not the optimal choice of forecast model with currently available data, and other similar models may produce more reliable predictions of waste arisings.

3.2. Alternative Model Specifications

3.2.1. Alternative annual ARIMA model

In an attempt to identify an optimal ARIMA model using the annual data provided by Defra on historic waste arisings, we have applied the “Box-Jenkins” methodology for model selection.⁶ First, this procedure requires that we identify the correct model structure. In other words, we need to select the correct number of lags with which the AR and MA components feed into the model, as well as the number of times the series needs to be “differenced” to ensure stationarity (the variable y_t is “differenced” once in Defra’s model to give Δy_t).

In performing this analysis, we decided to drop all observations between 1986 and 1990, since our examination of the data shows that these are linear interpolations between two data

⁴ See Granger, C. and Newbold, P. *Spurious Regressions In Econometrics* Journal of Econometrics (1974), pp.111-120.

⁵ Moreover, from our review of Defra’s forecast, it appears that this recession dummy variable is set equal to one for all years after 2010, so its exact purpose in the analysis remains unclear.

⁶ Kennedy, Peter *A Guide To Econometrics - 5th ed.* (2003, Blackwell Publishing), p.320.

points, so this window of data does not provide enough information on the underlying process that the data follows from year-to-year to estimate an ARIMA model.

The next step was to take differences in the remaining data to remove non-stationarity. We needed to difference the series twice to obtain a stationary series.⁷ We then examined “autocorrelation plots” to determine the order of AR and MA lags needed for the model. There was some weak evidence (accepted at the 10% significance level) that the time series had an AR(1) component, so we assume that the data follows an AR(1) process. There was not sufficient evidence to suggest the data has an MA component.

The Box-Jenkins model selection procedure therefore leads to the ARIMA(1,2,0) model, which has the following structure.

$$\Delta_2 y_t = \beta_0 + \beta_1 \Delta_2 y_{t-1} + \varepsilon_t$$

Using the statistical software STATA, we fitted parameters to this equation. The results are presented graphically in Figure 3.1, with the estimated coefficients recorded in Appendix A. This alternative model specification leads to a very steep reduction in predicted waste arisings. Although this projection of falling waste arisings may seem implausible, we conducted some tests to compare the fit of this model to the ARIMA(1,1,1) model estimated by Defra,⁸ and found that the ARIMA(1,2,0) model provides a slightly better fit to the underlying data than the ARIMA(1,1,1) model.⁹

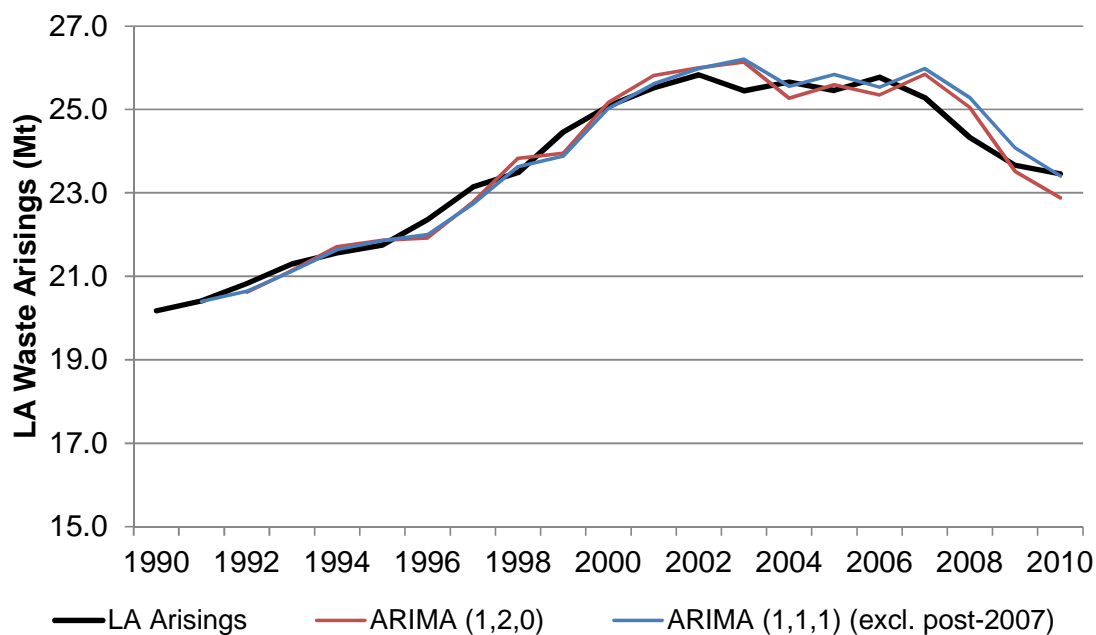
Hence, our statistical tests suggest the ARIMA(1,1,1) model can be improved upon in light of our various statistical tests and using more recent arisings data. However, the potentially superior ARIMA(1,2,0) model produces counterintuitive results, as shown in Figure 3.2. This analysis therefore suggests that the currently available annual data on waste arisings does not provide a clear prediction of future waste arisings.

⁷ A Dickey-Fuller test on “ $\Delta_1 \ln(\text{waste})$ ” reports a MacKinnon approximate p-value of 0.3680, whereas the same test on “ $\Delta_2 \ln(\text{waste})$ ” reports a p-value of 0.000.

⁸ We re-estimated the Defra model, following the procedure of censoring data from 2008 onwards, but excluding the time-series “rece” to which we do not have access.

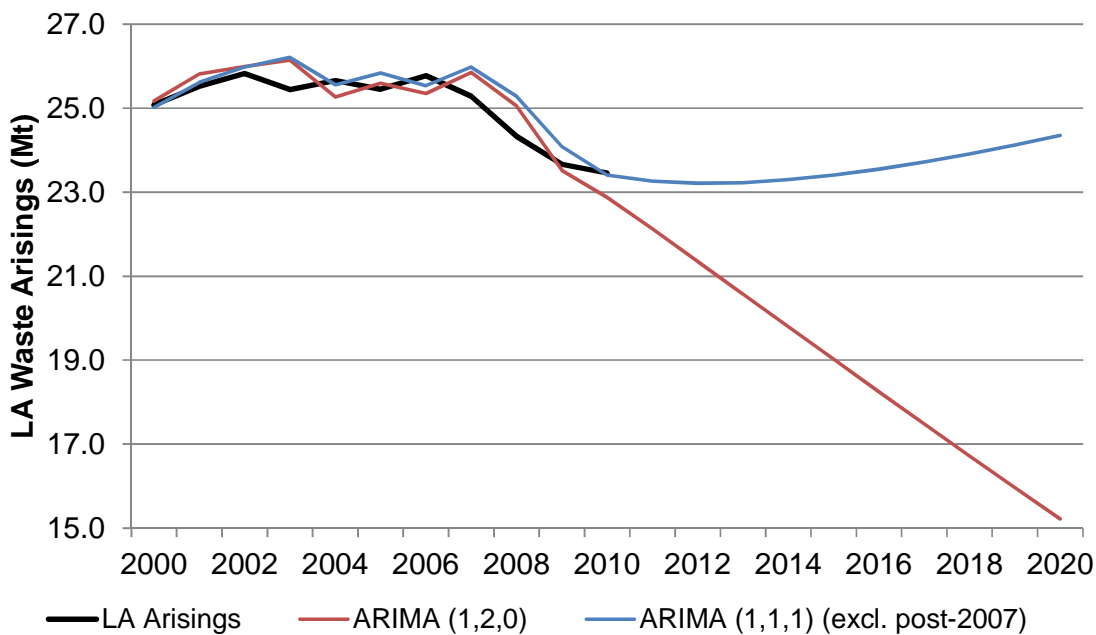
⁹ We used “information criteria” tests to compare which of the two models minimised information loss. However, as all these tests are “asymptotic” i.e. valid in large samples, when applied to models estimated from limited data it is not possible to unambiguously select an “optimal” model. We therefore cannot rule out the possibility that the ARIMA(1,2,0) is not an improvement on the original model at all.

Figure 3.1
ARIMA Forecasts Both Fit Historic Data ...



Source: NERA Analysis of Defra data.

Figure 3.2
... But Different Models Lead To Very Different Predictions



Source: NERA Analysis of Defra data.

One possible explanation for this problem is the change in the data that appears to have taken place around 2003, when the consistent upward trend in waste arisings observed in previous years came to an end. Although we cannot be sure of the causes for this structural change, in 2007 the “Waste Strategy for England”¹⁰ outlined incentives to “decouple waste growth from economic activity”¹¹. For this reason, we might expect to see a materially slower growth rate in household waste after 2007, so forecasts calibrated to growth in the preceding period may predict waste arisings that revert to an out-dated trend.

Overall, having performed a range of statistical tests after including the most recently available data, we conclude that it appears forecasts generated from annual ARIMA models may not give a truly reliable forecast of waste arisings with current data.

3.2.2. Quarterly ARIMA models

An alternative data source is quarterly data on waste collected from 2006. Unlike the annual data series, this more recent series does not obviously suffer from the “structural break” problem identified above, as it was all collected more recently. Moreover, since the data is quarterly, forecasts made using this data source can be updated far more regularly, allowing the model’s performance to be reassessed more frequently.

In this case, the underlying seasonal pattern in waste arisings means that a Seasonal ARIMA (or SARIMA) model is appropriate.¹² We apply the same Box-Jenkins methodology used in Section 3.2 to derive the following structure for a SARIMA model:

- The data is quarterly, so we impose a quarterly pattern of seasonality on the model;
- We also apply one annual difference to the data to obtain a stationary series;
- The data does not show any seasonal autocorrelation, which means the seasonal effect observed in year t does not depend on the seasonal effect observed in year $t-1$;
- Post-estimation testing suggests that constant terms should be suppressed, so we have not included these in our candidate models; and
- Because we could not clearly identify the correct AR and MA components from “autocorrelation plots”, we estimated three SARIMA models with different AR and MA components in order to compare the extent to which they fit the underlying historic data. “Model A” has an AR(1) component, but no MA component. “Model B” has an AR(2) and no MA components. “Model C” has both an AR(1) and MA(1) component.

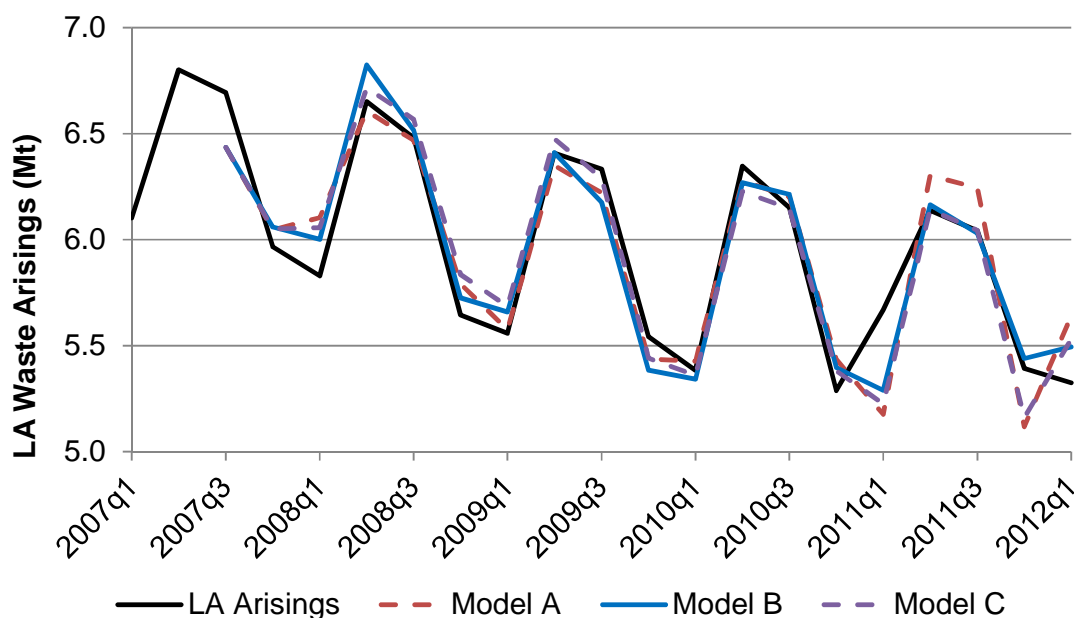
Figure 3.3 presents the historic fit of these three models. The forecast of waste arisings in 2020 produced by each model is: 24.0Mt (Model A), 21.1Mt (Model B), 19.7Mt (Model C).

¹⁰ <http://archive.defra.gov.uk/environment/waste/strategy/strategy07/documents/waste07-strategy.pdf>

¹¹ Defra *Waste Strategy for England* (2007), p.11.

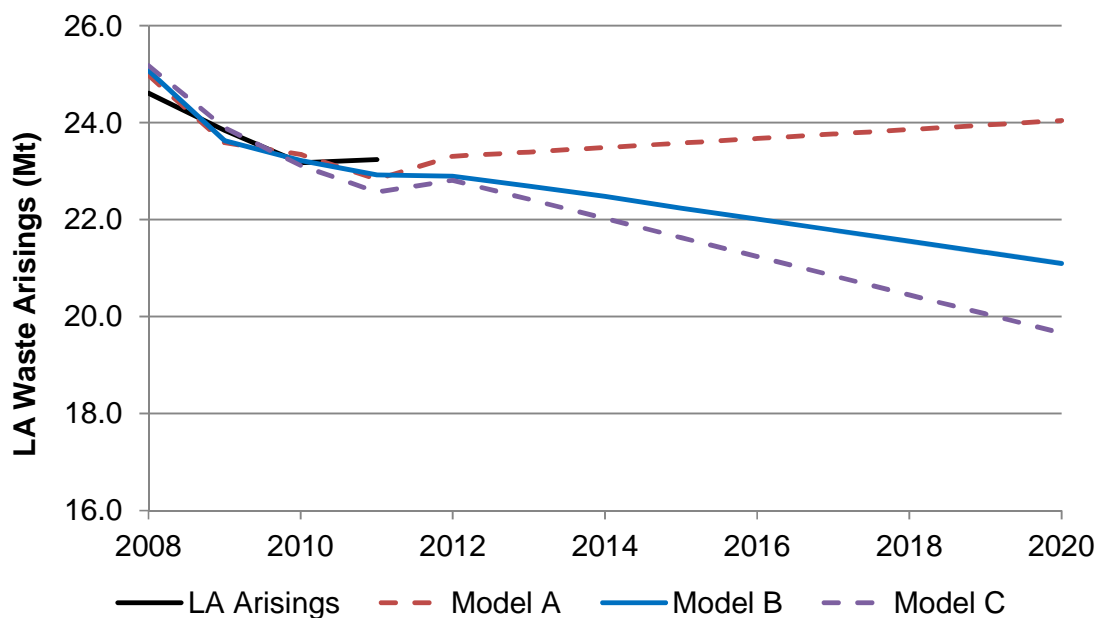
¹² SARIMA models are denoted $SARIMA(p,d,q) \times (P,D,Q)$, The parameters (p,d,q) have the same meaning as in Section 3.2. The parameters (P,D,Q) , refer to the seasonal autoregressive component, order of difference, moving average component and period of seasonality respectively.

Figure 3.3
SARIMA Models Fit Quarterly Data on Household Waste



Source: NERA Analysis of Defra data. "Model A" is a SARIMA(1,1,0)x(0,1,0), "Model B" is a SARIMA(2,1,0)x(0,1,0), "Model C" is a SARIMA(1,1,1)x(0,1,0).

Figure 3.4
Range of Predictions From SARIMA Models



Source: NERA Analysis of Defra data.

Selecting between these models involves an element of judgement because a range of statistical tests do not unambiguously favour one model over the others. However Model B, the SARIMA(2,1,0)x(0,1,0) model, probably provides the most theoretically consistent approach within the ARIMA framework to forecasting future waste arisings:

- The coefficients in Model C, which includes an MA component, are highly insignificant, which suggests that an MA component should not be included. The AR coefficients in Model A and Model B, by contrast, are significant at the 1% level. This test favours Models A and B;
- A plot of residuals against the quantiles of the normal distribution shows a closer fit from the SARIMA(1,1,0)x(0,1,0) model. This test favours Model A;¹³ and
- Comparing the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) suggests that Model B, the SARIMA(2,1,0)x(0,1,0), fits the underlying data marginally better than Model A, which is marginally better than Model C. This test favours Model B.

3.2.3. Conclusions

In the sections above, we have provided a detailed review of alternative ARIMA and SARIMA models that aim to forecast residential waste arisings. Our analysis suggests that Defra's previous ARIMA model could be improved in light of more recent waste arising data. We attempted to derive an alternative ARIMA model using annual data, but the results seemed to be affected by a structural break. Having performed a range of statistical tests after including the most recently available data, we conclude that it appears forecasts generated from annual ARIMA models may not give a truly reliable forecast of waste arisings with current data.

Given this finding, we calibrated a seasonal ARIMA process using quarterly data from a more recent period, which we consider is the most reliable forecast achievable using the ARIMA approach. However, this model was calibrated using a relatively short data series, so the forecast it produces may change as more data becomes available. New data may alter both the parameters of the SARIMA model we estimated, and the results of the statistical tests we used to derive it. Hence, the validity of this model should be re-examined periodically to ensure its robustness as more data becomes available.

Table 3.1
Comparison of Time Series Predictions

Model:	Predicted Household Waste (Mt)		
	ARIMA(1,1,1)	ARIMA(1,2,0)	SARIMA(2,1,0)x(0,1,0)
2012	23.2	21.4	22.9
2015	23.4	19.0	22.2
2020	24.3	15.2	21.1

Source: NERA Analysis of Defra data.

¹³ In this context "fit" refers to the residuals lying on the 45° line of the q-q plot, indicating they are approximately normally distributed.

Finally, in applying the ARIMA framework, Defra should note the limitations of this approach. Most notably, time series models of this sort do not account for changes in the underlying drivers of waste arisings, such as population growth, consumption expenditure, and so on. It may be possible to control for some of these changes in fundamental drivers of waste arisings by including them as explanatory factors in a regression equation, and Defra may wish to examine such models in the future to obtain an alternative forecast of waste arisings. However, the success of any such exercise is likely to be constrained by limitations on data availability.

3.3. Alternative Approach: Input-Output Modelling

As an alternative to its central ARIMA forecast, Defra also uses an “input-output” model that attempts to predict waste arisings using data on historic consumption expenditure by category, and the life cycle of household items. The model is produced by Trajectory Partnerships (TP), and we have only reviewed the outputs of their study.

3.3.1. Model structure

The model appears to work as follows:¹⁴

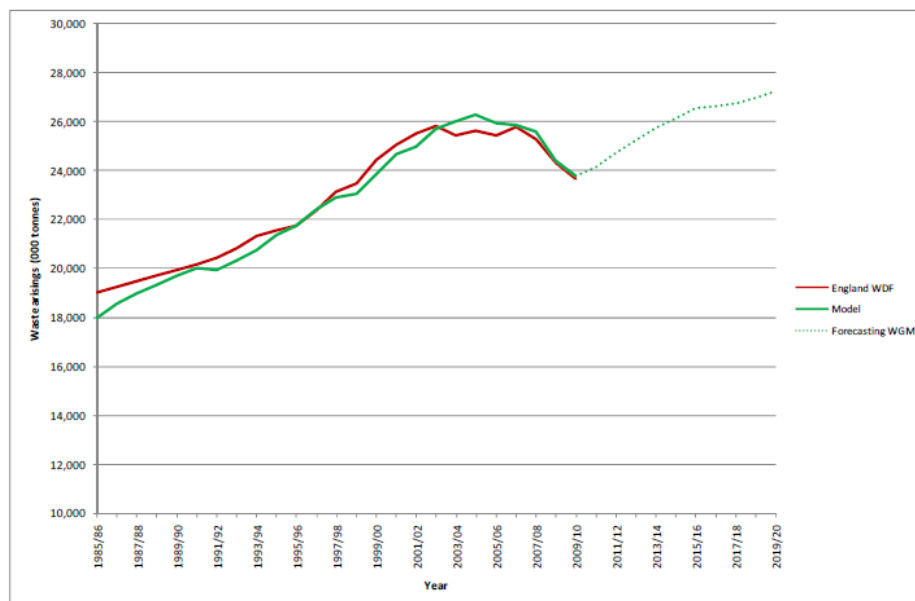
- Expenditure across different product categories is predicted, using growth forecasts from Oxford Economics. This is the input to the model;
- Each product category has some £/kg metric to convert expenditure into weight of produce;
- Assumptions are made about the percentage of product wasted and packaging waste. This gives a kg figure for waste. Some of these parameters are derived from historical data, but we have no information on how this was done; and
- Finally, each category has a life cycle associated with it. So all food waste is assumed to appear as waste arisings in the year of purchase, whereas durable goods such as electronics are assumed to last longer. This gives the output of the model, which is waste arisings per year.

3.3.2. Appraisal

Figure 3.5 illustrates the model’s performance when used to back-cast waste arisings, and shows its forecast waste arisings for the period from 2010.

¹⁴ Defra *The Economics of Waste and Waste Policy* (2011).

Figure 3.5
Input-Output Model



Source: Defra (2011), p.29.

Between 2003 and 2006, the model slightly overstates waste arisings by 0.5 megatonnes, which is a 2% divergence from the actual figure. In this respect it is not markedly worse than the central forecast generated using the ARIMA model. For the period between 2006 and 2010 when waste arisings have fallen, the model predicts waste arisings very close to the actuals.

From 2010 onwards, the model predicts that the upward trend in waste arisings that occurred before 2003 will continue. In practice, growth in waste arisings has been slower than this forecast since 2010. However, rather than highlighting a problem with the model, this divergence between actuals and TP's forecast is likely to result (at least in part) from the worsening macroeconomic conditions over this period.

Table 3.2 makes this point by comparing consumer expenditure forecasts from when the model was originally run in 2010 with the most recently available consumption forecasts. In 2010, consumer expenditure was expected to grow at 0.8% in 2011, whereas in reality it fell by 0.8%. The outlook for consumption growth during 2012 and 2013 is also much weaker now than in 2010.

Table 3.2
Evolution of Consumer Expenditure Forecasts

Forecast Date	2009 (% change y.o.y.)	2010 (% change y.o.y.)	2011 (% change y.o.y.)	2012 (% change y.o.y.)	2013 (% change y.o.y.)
July 2010	-3.4	0.6	0.8	1.8	2.5
July 2011		0.9	-0.3	1.2	2.0
September 2012			-0.8	0.5	1.3

Source: Oxford Economics "Economic Outlook", July 2010, p.2; July 2011, p.2; Office of Budget Responsibility via Datastream, September 2012.

We therefore conclude that updating the input-output modelling to reflect recent macroeconomic developments is likely to provide a useful additional forecast, as it is able to account for changes to fundamental drivers of waste arisings. However, it may be necessary to update other parameters in the model to produce a fully up-to-date projection of waste arisings to 2020.

3.4. Recommendations

Of the two forecasting methods available, the input-output modelling approach has certain advantages compared to the time series methodology, as it accounts for the fundamental drivers of waste arisings. However, we understand that many of the assumptions embedded within this model are now somewhat out of date, and any future changes in the fundamental drivers of waste arisings may increase forecast error.

In light of this, the time series (ARIMA) modelling approach provides a useful alternative, because it can be updated regularly and at relatively low cost as new data becomes available. The shortcoming of the ARIMA approach is that it does not account for fundamentals; it assumes that the patterns in the data evident today will continue into the future. Changes in the fundamental drivers of waste arisings may show up as "structural breaks" in the ARIMA model, resulting in potentially increasing margins of forecast error.

Finally, our analysis suggests that Defra's current ARIMA model has the potential to be improved in light of the statistical tests we have conducted and by using more recent arisings data, so we have produced an alternative SARIMA model that uses quarterly waste arisings data. However, we recommend that the process of identifying the "optimal" model should be repeated as more data becomes available.

4. Forecasting Commercial and Industrial Waste Arisings

The second major source of uncertainty in the Defra methodology is the forecast of future waste arisings from commercial and industrial (C&I) sources. Again, there are two methods used to provide this forecast that Defra's modelling has considered:

- The central forecast, which uses regional data on different business sectors to extrapolate to national aggregates; and
- An input-output model that links growth in different industrial sectors with waste arisings.

We review both of these methods, and suggest possible improvements to them, in the following sections.

4.1. Central Forecast Based on Survey Data

Forecasting C&I waste arisings is complicated by the lack of data: there are only three annual data points available from 1999, 2003, and 2009. Therefore, any sort of formal econometric time series analysis is impossible.¹⁵

Defra's central forecast is based on a study completed by ADAS in 2009.¹⁶ This study uses data obtained from a survey of waste arisings by sector that took place in the North West region in 2006/7. The central forecasts combine this survey data with detailed data on employment by sector in a different region, the East of England. Defra's forecast is then based on forecasts of employment.

4.1.1. Existing model structure

The central forecast of C&I waste arisings was developed as follows:

- A survey of 1,000 businesses was undertaken in the North West region. This data is used to infer total waste arisings across different segments of the business sector in the NW, for example retail and wholesale, power and utilities, and public administration, etc;
- The data is then used to estimate waste arisings by business sector in other English regions, using regional data on business and employee numbers. This gives an annual estimate of waste arisings across all regions for 2006/7;
- To forecast future waste arisings, ADAS makes a "rudimentary" forecast of sector growth across regions.¹⁷ To do this, they use employment forecasts by sector for a different English region, the East of England, and apply these forecasts to all regions; and
- Defra makes its own adjustments to this model, by adding in exogenous changes in "waste per employee".¹⁸ This is forecast to fall by 20% by 2031, with large changes due to the landfill tax increase in 2014.

¹⁵ Other data points from 2004, 2006, and 2008 are interpolated and are often quoted, but it should be borne in mind these are not empirical data.

¹⁶ ADAS *Study into Commercial and Industrial Waste Arisings* (2011).

¹⁷ ADAS (2011), p.i.

ADAS follows a rigorous survey methodology, given the scarce data they have to work with. For example, they address the issue of confidence bands around estimated total waste, and conclude that there is an interval of +/- 3% at the 95% level when scaling up their sample of 981 companies.¹⁹ However, this confidence level only applies to the region from which the sample is drawn, the North West. Extrapolating this to other regions introduces far more uncertainty.

Further uncertainty is then introduced by combining waste estimates from one region (North West) with growth estimates for another (East of England). We understand from our discussions with Defra that this model predicted the fall in waste arisings that took place between 2006 and 2009. However, the model's ability to forecast this observed fall in waste arisings does not necessarily mean it will continue to robustly capture the effects of changes in the underlying drivers of waste arisings going forward. Since patterns of waste arisings (as observed in the residential data) have behaved so unusually over this period, without further C&I data we cannot say whether this agreement between forecast and actual data is due to the model's validity or random chance.

4.1.2. Possible revisions to the model

Since data from 2009 has become available since the last time C&I forecasts were made, revisions to the model are now possible. The first possible revision we consider is a change in the variable used as the key driver of C&I waste growth, from employment to Gross Value Added (GVA).

To assess whether employment or GVA growth is likely to be the most relevant driver of changes in waste arisings, we searched for published articles and studies on waste arisings growth, and found a 2005 report by the European Topic Centre on Resource and Waste Management (ETC/RWM) which addressed a very similar forecasting problem at the EU level.²⁰ In this report, ETC/RWM states its method for calculating waste flows for different residential and C&I sectors. The dependent variables in the analysis are waste/GDP and waste/capita, and the two key explanatory variables in this analysis are;²¹

1. Household Consumption Expenditure, and
2. Gross Value Added.

ETC/RWM then weights these variables according to an *a priori* judgement it makes about their relative importance in explaining a particular waste stream.²² In industrial sectors GVA is given a weighting of 1, and hence this study uses GVA as the input variable for industrial waste arisings. Moreover, this is also supported by economic theory. As productivity in industrial processes increases, less total employment is required to produce the same quantity of output, and hence the same GVA. This reduced employment does not necessarily suggest

¹⁸ Defra (2011), p.33.

¹⁹ Subject to errors in the data being normally distributed, which may be in doubt.

²⁰ http://www.risoe.dk/rispubl/SYS/syspdf/ETC-RWM_working_paper_2005-1.pdf.

²¹ ETC/RWM (2005), p.14.

²² ETC/RWM (2005), pp.18-21.

a reduction in waste, since this may be related to the production process itself. Therefore, using GVA as the key metric for waste arisings also seems theoretically attractive.

This argument is less applicable in commercial sectors such as retail, and it is not apparent that one metric will be necessarily better than another. In this case, the pragmatic approach would be to treat equally uncertain drivers of waste as equally likely, and produce a weighted 50:50 forecast.²³

4.1.3. Incorporating “efficiency savings”

A second possible revision to the model is to incorporate observed “efficiency savings” in waste/GVA into the central forecast of C&I waste arisings. As set out below, while it is important to account for potential efficiency savings, we believe that any future approach using this method should proceed by:

- Assuming that the potential for efficiency savings diminishes over time;
- Calculating efficiency savings for the two high-level commercial and industrial industry classifications, rather than for each sector of the economy separately.

Data is available from 2003 and 2009, from which “efficiency savings” in each sector can be calculated as:

- $GVA \text{ Efficiency Savings (\%)} = (2003 \text{ waste/GVA} - 2009 \text{ waste/GVA}) / 2003 \text{ waste/GVA}$
- $Employment \text{ Efficiency Savings (\%)} = (2003 \text{ waste/employee} - 2009 \text{ waste/employee}) / 2003 \text{ waste/employee}$

We note that it seems unlikely that “efficiency savings” will remain constant over time, as this ignores the effect of “low-hanging fruit”. That is, in a drive to eliminate unnecessary waste, businesses may have already achieved large and relatively inexpensive reductions in waste volumes. It seems likely that each further increment will prove more costly, thus reducing the rate of efficiency savings over time.

Secondly, we note that care must be taken when calculating annual efficiency savings, to account for the effect of compounded growth. The annual efficiency saving rate may be stated as:

- $Annual \text{ Savings (\%)} = (2009 \text{ Value} \div 2003 \text{ Value})^{(1/6)} - 1.$

In Table 4.1 we present sectoral estimates of efficiency savings using the GVA method. We also demonstrate the effect of assuming that these efficiency savings remain constant from 2009 to 2020 in terms of tonnes of waste arising.

²³ Assigning equal prior probabilities to uncertain outcomes is sometimes referred to as assigning “Laplacian” priors, after probability theorist Pierre-Simon Laplace.

Table 4.1
Estimated Efficiency Savings and 2020 C&I Waste

Business Sector	Observed Efficiency Saving (GVA)	Annual Efficiency Rate	2020 Arisings ('000s tonnes)
Food, drink & tobacco	35.0%	6.93%	2,881
Textiles / wood / paper / publishing	31.1%	6.02%	2,224
Power & utilities	-0.9%	-0.15%	6,132
Chemicals / non-metallic minerals manufacture	35.4%	7.03%	2,007
Metal manufacturing	34.0%	6.68%	2,102
Machinery & equipment (other manufacture)	35.3%	7.01%	1,221
Retail & wholesale	30.4%	5.85%	6,171
Hotels & catering	10.8%	1.89%	3,374
Public administration & social work	-62.5%	-8.43%	6,903
Education	28.6%	5.45%	791
Transport & storage	-17.8%	-2.76%	4,176
Other services	51.3%	11.29%	1,895

Source: NERA Analysis of Defra workbook.

The sectoral efficiency savings shown in the tables above raise questions over the validity of this method. A case in point is forecast waste arisings from “Public administration & social work”. As Table 4.1 shows, “Public administration” waste/GVA *grew* by 8.43% per annum between 2003 and 2009.

One way to address this problem is to assume that the estimated efficiency saving is the result of a mis-measurement, and to use an alternative rate of efficiency savings for “Public administration”. We experimented with assuming that efficiency savings in this sector remain at 0% from now until 2020. The difference between this and the original 2020 estimate was 4.1 million tonnes of waste arising, 11.1% of the total from all sectors, which we illustrate in Figure 4.1 and Figure 4.2. Clearly, sector level measurements have the potential to make an extremely large difference to the resulting forecast.

Figure 4.1
Scenario 1 – Public Administration Waste Growth of 10.3%

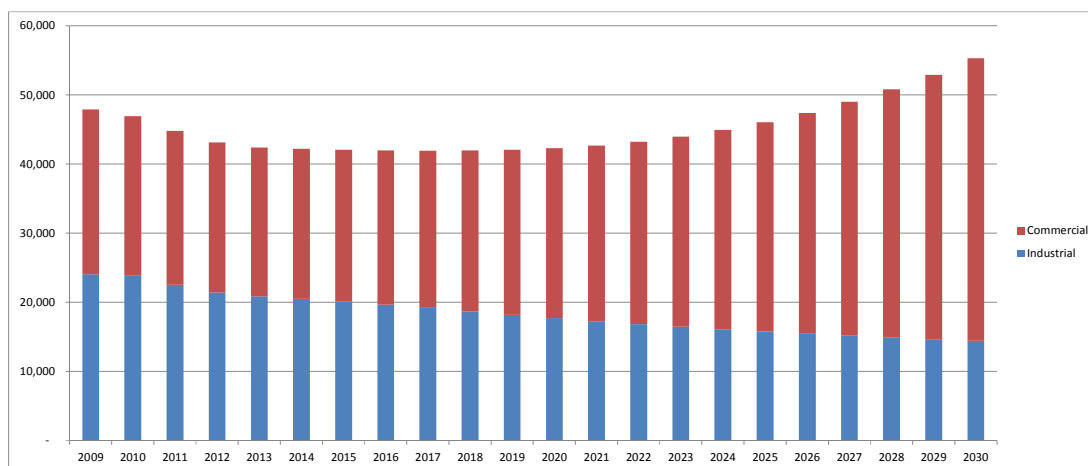
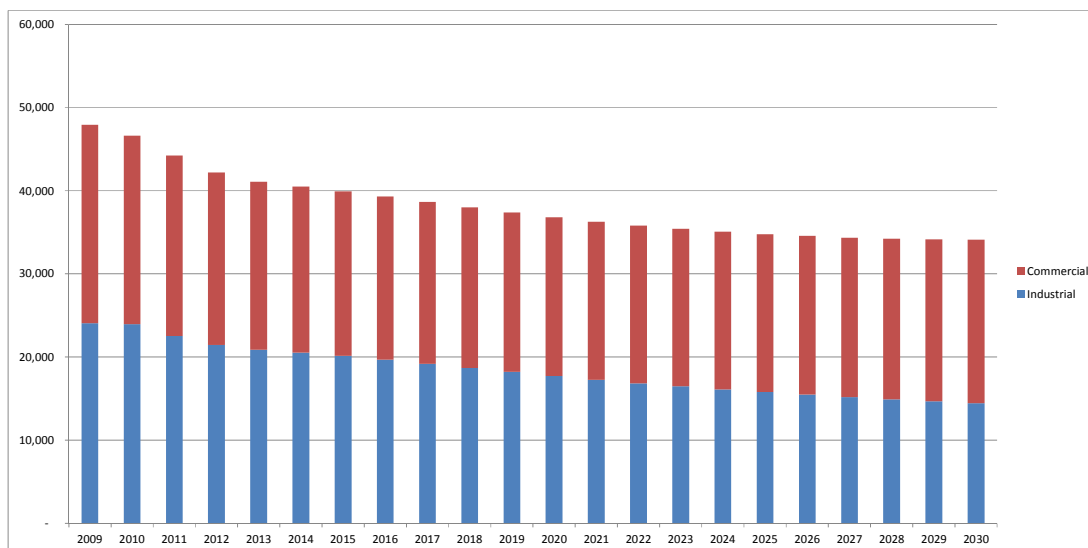


Figure 4.2
Scenario 2 - Public Administration Waste Growth of 0%



Source: Defra workbook.

It seems likely that the very large growth in waste/GVA or waste/employee in “Public administration” is due to some sort of business reclassification. Whilst reclassification may have occurred within the commercial and industrial sectors, reclassification is less likely to have occurred *between* them. We therefore recommend forecasting non-domestic waste arisings using data aggregated to the level of commercial and industrial businesses to reduce the effect of the reclassifications. In Table 4.2 we compare the two estimates of efficiency savings using both the GVA and employment metrics, aggregating at the level of the commercial and industrial business sectors.

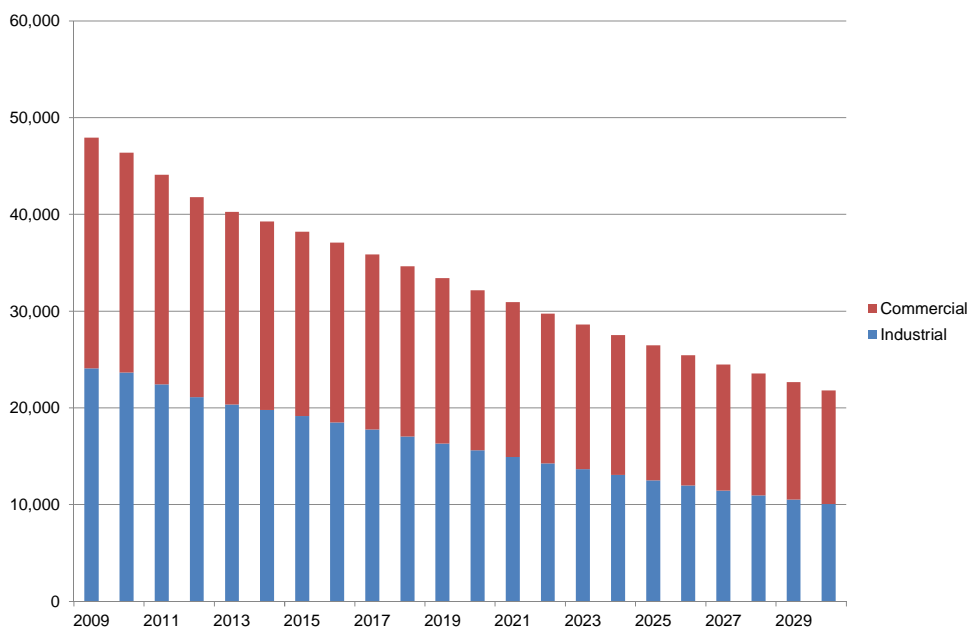
Table 4.2
Aggregate Efficiency Comparisons

Business Sector	Efficiency Saving (Waste/Employment)	Efficiency Saving (Waste/GVA)
TOTAL (I)	3.18%	5.45%
TOTAL (C)	4.85%	5.61%

Source: NERA Analysis of Defra workbook.

We use this method to project the waste arisings 32.2 megatonnes in 2020, as Figure 4.3 shows. Since “efficiency savings” exceed forecast average growth in GVA (2.32% from 2010-2030), this method predicts waste arisings falling. However, as noted above, this projection does not reflect the possibility that efficiency savings will fall over time.

Figure 4.3
Aggregate Projection using Waste/GVA



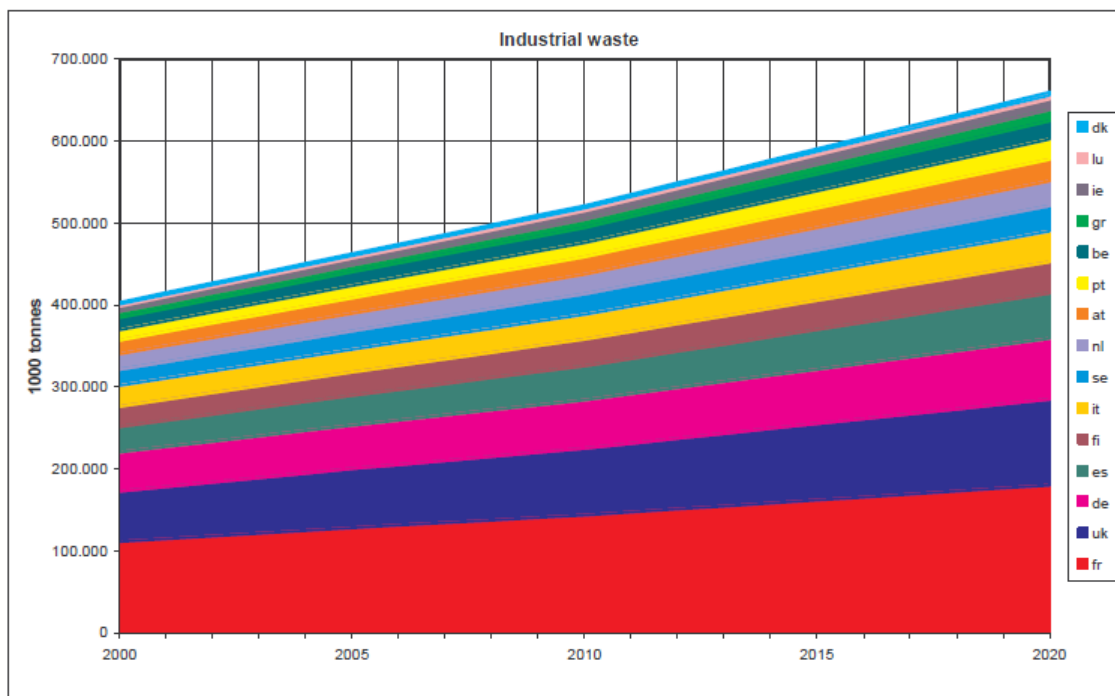
Source: NERA Analysis of Defra workbook.

4.1.4. International benchmarks

A key limitation in deriving reliable forecasts of C&I waste arisings is the lack of data. We understand from Defra that it will not be possible to repeat the 2009 national survey of C&I waste arisings due to the cost implications. An alternative source of more data on commercial and industrial waste arisings might be to study international comparators, especially those in other EU markets where the Landfill Directive will also apply. Such data might help Defra to better understand the fundamental drivers of C&I waste arisings. Additionally, third party forecasts might also contain information on future waste arisings.

For example, the ETC/RWM report contains forecasts for the UK alongside other EU-15 countries, which we reproduce in Figure 4.4. However, these forecasts date from 2005, and do not incorporate recent evidence.

Figure 4.4
ETC/RWM Forecasts of Industrial Waste



Source: ETC/RWM (2005) "Baseline scenario", p45.

4.2. Alternative Forecast: Input-Output "REEIO" Model

The alternative C&I forecast makes use of less data than the central forecast, since it is parameterised using only data from 2003. It is therefore subject to even greater uncertainty, and for this reason Defra does not propose using it as a forecast method

4.2.1. Model structure

Our understanding of the model is that it works as follows:²⁴

- Parameterised relationships are estimated (or assumed) between different industrial sectors and waste arisings using waste data from 2003; and
- Waste growth is inferred by using growth forecasts across 21 industrial sectors from Cambridge Econometrics, with no changes in waste efficiency or recycling practice assumed.

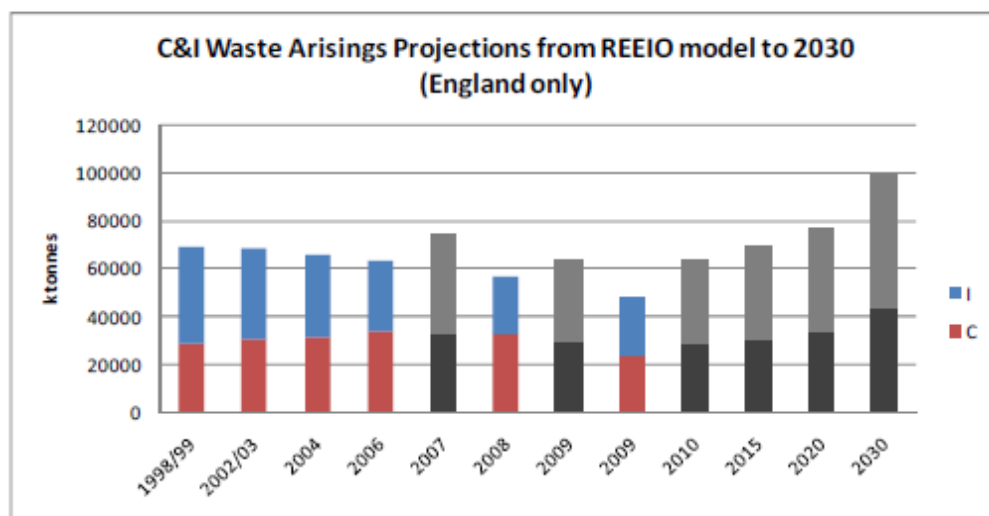
²⁴ See http://www.camecon.com/AnalysisTraining/suite_economic_models/Reeio/ReeioOverview.aspx.

4.2.2. Comment

Defra notes that the model does not perform very reliably, overestimating waste produced in 2009 by 15 megatonnes, which is close to 30% of total C&I waste. It comments that projections up to 2030, as presented in Figure 4.5, may also be large overestimations. For this reason, Defra has chosen not to use these “REEIO” forecasts.

We feel that this criticism of the model’s result is largely fair, but it is not surprising that it performs poorly as it was calibrated with so little data. Hence, the model’s forecast waste arisings growth out to 2030 is probably not reliable. In particular, one key feature of the model that undermines its reliability is the lack of any feedback effects of policy, or any change in the relationship between waste produced and business activity.

Figure 4.5
Defra Input-Output Model Forecast



Source: Defra (2011), p.32. Coloured bars are empirical data (or interpolations), black bars are forecasts.

4.3. Recommendations

After examining possible revisions to the current central forecast, we recommend the use of GVA as a more reliable driver of waste arisings than employment. We note that sectoral data is likely to suffer from considerable potential errors of reclassification, so recommend that forecasts of efficiency savings be based on data from the aggregated commercial and industrial sectors.

Finally, we conclude that the assumption of constant ongoing efficiency savings is probably not sustainable, but assessing the extent to which historic efficiency savings will slow down is not possible with the data available to us. We recommend that Defra surveys evidence from other EU markets to improve the robustness of its forecasts of C&I waste arisings forecasts if it is not practical to obtain new data using survey methods.

5. Forecasting Additional Infrastructure

The primary source of uncertainty on the capacity (supply) side of Defra’s modelling is the addition of future capacity. By accounting for the factors which influence project completion, Defra currently adjusts down the forecast additional infrastructure by a “delivery adjustment rate”.

5.1. Drivers of Infrastructure Completion Rates

The delivery of waste diversion infrastructure is driven by the following key factors:

- **Financing** – securing financing greatly improves a project’s chance of completion. If the project is supported through a PPP/PFI agreement, its chances of completion may be higher;
- **Underlying need** – developers must assess the demand for waste diversion within the area they are able to service before completing an infrastructure project. Insufficient demand may lead to stranded assets, and hence changes in the underlying need for capacity will materially affect a project’s chance of completion;
- **Competition between developers** – competition between developers to bring projects ‘to market’ and fulfil a given need for infrastructure means that more projects may be proposed than are ultimately developed; and
- **Planning constraints** – delays and costs caused by planning constraints can cause an investment in infrastructure to become unprofitable, or prevent development altogether. Securing planning permission therefore greatly increases the likelihood of completion.

5.2. Defra’s Current Treatment

Defra has compiled a list of all projects that have been proposed to become operational before 2020. As described above, it then adjust their forecast diversion capacity according to the perceived risk associated with them. These risks are represented by the “delivery adjustment rates” in Table 5.1 which we first presented in Table 2.1. The table shows that Defra uses two of the principal factors mentioned above, planning constraints and financing, in this weighting procedure.

Table 5.1
Defra's Delivery Adjustment Rates

Delivery Adjustment Rate					
WIC/G or PPP	RAG	%	Merchant	RAG	%
Fully Operational	B	95	Fully Operational	B	95
Commissioning	G	90	Commissioning	G	90
Financial close, with planning	AG	80	Financial close, with planning	AG	80
Financial close, no planning	A	70	Planning, no financial close	A	40
In porcurement, no planning	AR	60	No planning	AR	20
Unlikely to go live	R	20	Unlikely to go live	R	0

5.3. Evidence from Power Generation

Other sectors with large infrastructure needs face a similar problem of forecasting future capacity additions.

In the power sector, a large number of new power stations have been proposed for development in the last decade or so, and only a subset of those have ultimately been developed. As a comparator for the development of waste infrastructure projects, we used historic data from National Grid's "Seven Year Statement" (SYS) to calculate an empirical probability of delivery for power plants, according to their stage of development. To do this we examined the SYS issued in 2005 that forecast new capacity until 2011.²⁵ The SYS classified projects as "existing", "under construction" or "not constructed". Additionally, for those projects not yet under construction, the SYS notes whether they have obtained planning consent or not.

Table 5.2 shows the combined capacities of 74 generation projects listed in the 2005 SYS by stage of development.²⁶ We then calculated "Average Delivered Capacity" as the percentage of the additional generating capacity that was ultimately delivered, according to the most recent version of the SYS.²⁷

Table 5.2
Historical Rate on Capacity Addition in Electricity

E/UC	Consents	Average Delivered Capacity
Existing	Yes	91.8%
Under Construction	Yes	70.3%
No	Yes	68.8%
No	No	24.9%

Source: NERA Analysis of National Grid Seven Year Statements 2005, 2011.

The figures shown in Table 5.2 are broadly consistent with the current WIDP methodology. For example, existing plants delivered 91.8% of forecast additional capacity, close to the 95% projection for projects rated "B" under WIDP. Moreover, the assumption that merchant projects rated "R" will deliver only 20% of forecast additional capacity is supported by the data on power projects without planning consent, which deliver 24.9% of forecast capacity.

However, both the WIDP framework and the analysis in Table 5.2 take only a one-sided view of infrastructure uncertainty. In reality, over a seven year period, new projects may emerge that are currently unforeseen. Table 5.3 shows that this has occurred in the power sector, by comparing the additional generation capacity forecast in 2005 with the capacity actually delivered to market. Towards the end of the period (2009 and 2011), the additional capacity

²⁵ <http://www.nationalgrid.com/uk/library/documents/sys05/default.asp>

²⁶ National Grid *Seven Year Statement 2005*, Table 3.8.

²⁷ National Grid *Seven Year Statement 2011*, Annex F.2. Note, some of the variance shown in the table occurs because some projects' capacity is less than (or greater than) NG forecast in 2005.

from unforeseen projects is almost equal to the new capacity provided by projects that appeared in the 2005 forecast.

Although new power stations can be developed within less than a seven year planning horizon, it is possible that the planning and development phases of new waste management projects may take longer. If this is the case, then the potential for diversion projects that are currently unforeseen to come online by 2020 may be less than observed historically for power stations. However, even if most waste management projects take longer than seven years to be commissioned, it seems unlikely that absolutely no unforeseen capacity will come online by 2020, particularly given the possibility that the list of projects in Defra's database may not be entirely comprehensive.

Table 5.3
Capacity Additions from Unforeseen Sources

	Forecast Capacity Additions (MW)	Additions From Foreseen Projects (MW)	(%) Total Forecast	Additions From Unforeseen Projects (MW)	(%) Total Forecast
2005	2,474.0	474.0	19.2%	0.0	0.0%
2006	1,076.0	35.0	3.3%	83.0	7.7%
2007	6,160.0	507.9	8.2%	59.5	1.0%
2008	2,494.0	2,700.9	108.3%	149.8	6.0%
2009	840.0	2,157.6	256.9%	1,856.7	221.0%
2010	1,826.0	0.0	0.0%	0.0	0.0%
2011	1,600.0	1,680.0	105.0%	1,604.8	100.3%
Total	16,470.0	7,555.4	45.9%	3,753.8	22.8%

Source: NERA Analysis of National Grid Seven Year Statements.²⁸

5.4. Recommendation

Defra's current assumptions on delivery adjustment rates for existing projects appear to be largely supported by data on the past development of electricity generators in the UK. Electricity generators share a number of common characteristics with waste diversion projects. They entail large capital expenditure, and often suffer from planning delays.

However, the evidence presented above suggests that Defra's current approach may underestimate the supply of diversion capacity that will be developed over the coming eight years before the Landfill Cap comes into force. Historical evidence from the electricity sector suggests that additions to capacity can be unforeseen eight years ahead of delivery.

Additionally, the current approach does not take into account the reasons why projects may be cancelled. Clearly some will not come to fruition because they cannot obtain planning consents. However, many others may be cancelled because they are simply not needed. For example, if it turns out that the Landfill Cap is likely to be breached, this may occur because

²⁸ Table 5.3 also shows that construction delay is a very relevant consideration. For example, it can be seen that additions from foreseen projects in 2009 is 256.9% of forecast. This is due to the fact that infrastructure scheduled to deliver in 2005, 2006 and 2007 was delayed.

waste arisings are higher than expected. In this case, we might expect a higher number of the currently proposed projects to come online than would be the case if waste arisings turns out to be low. At present, the modelling framework does not account for the possible correlation between future waste arisings and capacity additions.

Finally, we note that deriving assumed delivery adjustment rates based on historic experience does not account for the possibility that the underlying economic drivers of waste diversion capacity projects will change over time. For example, the economic trade-off faced by local authorities when deciding whether to send waste to diversion projects or to landfill may change over time, which may affect the rate at which new diversion capacity is developed.

6. Appraisal of Defra's Overall Approach

In this section, we comment on Defra's overall approach to waste infrastructure planning.

6.1. Contingencies

As set out in the preceding chapters, we have identified a number of areas where uncertainty about the underlying drivers of waste arisings, or uncertainty of the appropriate model to use for forecasting, creates a wide range of plausible forecasts of waste arisings for 2020, especially for C&I waste. Moreover, although we make a number of recommendations for improving the methods Defra currently employs, this considerable uncertainty will remain. Similar uncertainties also apply to the forecasts of diversion capacity that feed into Defra's model.

Defra's modelling framework currently recognises such uncertainties through the application of contingencies to the underlying forecasts of demand or capacity, before the model calculates the shortfall in capacity:

- A contingency is applied to household waste arisings that increases forecast demand for diversion capacity by a given percentage;
- A contingency is applied to C&I waste arisings that increases forecast demand for diversion capacity by a given percentage; and
- A contingency is applied to forecast diversion capacity that reduces capacity by a given percentage.

Although the application of these contingencies provides some additional assurance that targets can be met, as compared to a run of the model where these contingencies are not applied, ultimately these contingencies are subjective. Moreover, this method is not able to identify the probability of meeting the Landfill Directive targets. In other words, such subjective contingency levels mean the modelling framework does not explicitly identify how much capacity is "enough" to guarantee meeting the Landfill Directive targets.

As Defra's WIDP modelling makes clear, the costs of overinvestment in diversion capacity are significant. It is therefore extremely important to ensure that these contingencies are calibrated robustly.

6.2. Stochastic Modelling

6.2.1. Role in forecasting

An alternative to making assumptions on contingencies is to model uncertainty explicitly within a "Monte Carlo" framework. Unlike the current approach, this approach is capable of providing a guide to the *probability* of meeting the Landfill Directive targets. In particular, it would also allow calculation of the probability of meeting the Landfill Cap targets, both without further action to increase capacity or reduce demand, and also the change in the probability of meeting the target following some intervention.

As well as probabilities of meeting the target, the Monte Carlo framework, like the current model, would also allow the calculation of a forecast surplus or deficit diversion capacity. However, this forecast would have the interpretation of an average²⁹ forecast.

The stochastic approach also avoids the need to impose potentially subjective assumptions on contingencies. On the other hand, a downside of the stochastic approach is the need to define distributional assumptions for key areas of uncertainty, which in some cases may entail a degree of subjectivity. However, the subjectivity associated with defining distributional assumptions can be mitigated somewhat by defining assumptions with reference to historic data, or to existing statistical models such as the ARIMA models described in Chapter 3.

6.2.2. Use in the water industry

Stochastic modelling is used widely in other infrastructure industries, such as water. The particular challenge faced here is to forecast the optimal level of “headroom”, which refers to the excess capacity to supply water over expected demand.³⁰ This, we believe, closely mirrors Defra’s problem of forecasting excess waste diversion capacity. Capacity should exceed expected demand to account for uncertainties about the future. However, capacity should not exceed the optimal level of “headroom” to avoid stranded, unnecessary investments.

One of the principal uncertainties faced by participants in this industry is the level of water resources available. To deal with this supply side uncertainty, probable future values are assigned to a range of different sources. For example, expert opinion is solicited on the likely yield of an additional water source, and different probabilities are assigned to future levels of supply. For a given project this could take the form: 10MI/d with 50% probability, 15MI/d with 30% probability, 20MI/d with 10% probability and zero yield with 10% probability.³¹

The second principal uncertainty is future levels of water demand in different areas. Like forecasts of waste arisings, this is affected by exogenous factors which give rise to a range of plausible scenarios. For example, using the estimated standard errors from a forecast model, different probabilities are also assigned to future demand levels. In a given area this could take the form: with 95% confidence, future demand will fall within +/-2 estimated standard errors of 10 MI/d, etc.

Finally, other uncertainties such as the probability of lost supply due to leakages, interruptions due to flooding, and other factors affecting the balance of supply and demand such as weather conditions are assigned similar probability weightings.

“Headroom” can then be forecast using probabilistic simulation methods. This procedure typically involves the following steps:

- All the inputs above are used in a “Monte Carlo” simulation. Using the assumed parameters, “headroom” is estimated several thousand times to simulate outturn across all

²⁹ Possibly a mean, median or mode forecast.

³⁰ UK Water Industry Research *An Improved Methodology For Assessing Headroom* (2002), p.119.

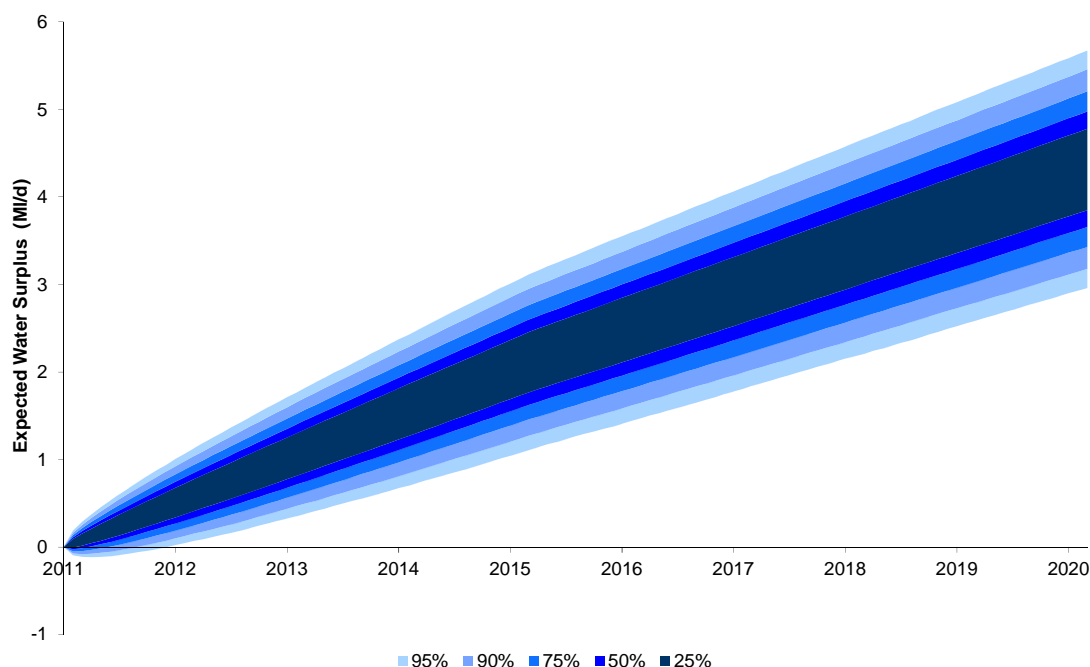
³¹ MI/d = “Megalitres per day”.

eventualities, by choosing values of supply and demand from within the probable distribution;

- From this, a mean level of “headroom” is calculated, with confidence bands at different percentiles surrounding this projection; and
- Additional capacity can be provided if the expected account of headroom is too low.

In Figure 6.1 we provide an example of the output of such a forecast. In this example, forecast “headroom” in 2020 is positive with a high level of confidence (greater than 95%). The appropriate course of action based on this modelling is therefore not to add further infrastructure.

Figure 6.1
Example Headroom Forecast



Source: NERA Analysis.

6.2.3. Practical implementation

In the case of Defra’s waste infrastructure modelling, implementing a stochastic Monte Carlo simulation model would require that Defra forms distributional assumptions on future waste arisings growth:

- For household waste arisings, these assumptions could be calibrated using the volatility in waste arisings recorded historically, and the confidence intervals forecast by the SARIMA modelling described in Chapter 3. The approach could also be developed to incorporate ‘model risk’ by assigning probabilities to forecasts from each modelling approach; and
- For C&I waste arisings, the lack of historic data makes it harder to robustly define a probability distribution, so we would recommend a simplistic assumption, such as

assuming a uniform distribution of 2020 waste arisings defined by the range of Defra's forecasts.

It would also be possible to randomise the delivery of diversion infrastructure, defining probability distributions with reference to the delivery adjustment rates already applied in the model, instead of applying simple deterministic derates to forecast capacity. If appropriate, Defra could also assume some correlation between the delivery rates for new infrastructure and waste arisings growth. This could be used, for example, to assume that more infrastructure is likely to be developed if waste arisings grow more quickly.

Finally, all values that are currently used as assumptions in the model, such as growth in recycling rates, diversion efficiencies of different infrastructure types, and utilisation rates of different plants, could also be incorporated into this framework to represent the range of uncertainty around them.

Defra's current sensitivity analysis is performed to examine the result of varying these assumptions. By using stochastic modelling, the uncertainty around these key parameters is integrated into the overall model. It would also allow Defra to estimate the probabilities associated with particular scenarios.

In practice, a Monte Carlo simulation model could be as an extension to Defra's existing Excel-based model. The additional steps required are:

- Turn some of the input assumptions (e.g. future waste arisings) into random variables;
- Remove the contingencies that the model currently applies to forecast waste arisings and available diversion capacity;
- Use add-ins to Excel such as "Crystal Ball" or "At Risk" to generate many random draws of the defined variables;³² and
- Use the outputs from these simulations to examine the probability distributions of the gap between waste arisings and delivered capacity.

6.2.4. Interpretation of results from stochastic modelling

The stochastic modelling framework set out above would assess the probability that England will have sufficient diversion capacity to contribute to meeting the 2020 Landfill Cap target. However, some care will be required in interpreting this result, e.g. when taking policy decisions. In particular, it is important to recognise that this calculation assumes that no more intervention can take place between now and 2020 to help meet the Landfill Cap targets, e.g. if waste arisings turn out to be relatively high.

To illustrate this point, consider an extreme example where the government has effectively unlimited flexibility to respond to changing circumstances. Specifically, suppose diversion capacity can be delivered instantaneously without any planning delays whatsoever. In this case, the probability of meeting the target in 2020 is always 100%, because in 2019 government would build precisely the capacity required for the following year. However, a

³² See <http://www.palisade.com/risk/> and <http://www.oracle.com/us/products/applications/crystalball/index.html>.

stochastic model run in 2012 would estimate that the probability of meeting the target that is below 100%.

Hence, it will be important to recognise that the probabilities emerging from the model will be *conditional* probabilities. They are conditional on the information available today, and they are calculated in a way that assumes government has no flexibility to react to new information in the future. If the minimum planning horizon for new waste management infrastructure is eight years or more, then this assumption is valid, but if lead times are shorter then it may be important to recognise this when interpreting the results of the model.

Analytical techniques recognising the effects of uncertainty, learning and flexibility are available, primarily emerging from the literature on “real options”, and typically work by valuing an “option” to defer decisions. However, a detailed analysis of real options is beyond the scope of this report.

6.3. Recommendation

As set out above, our main conclusion is that Defra’s approach could be refined to better account for the uncertainty inherent in forecasting demand and capacity. Based on our experience in other sectors, we recommend that Defra’s model be enhanced to represent this uncertainty explicitly through a stochastic modelling approach, which accounts for the range of uncertainty around all of the key input assumptions.

7. Conclusions

Through this assignment, we have conducted a detailed review of the methods used by Defra to assess whether England has sufficient waste diversion capacity to ensure no more than 10.2 megatonnes of BMW is sent to landfill in 2020. We have made recommendations to help improve the robustness of the waste arisings forecasts, and have provided an independent assessment of the delivery adjustment rates used to define the diversion capacity Defra expects to be made available. In particular, our analysis shows that:

- The ARIMA model currently used to forecast residential waste arisings is probably not the optimal specification in light of currently available data, due to the presence of structural breaks in the time series, and we recommended an alternative SARIMA model;
- We conclude that the “input-output” model has certain advantages compared to the (S)ARIMA approach for forecasting residential waste arisings, because it accounts explicitly for the fundamental drivers of waste generation (i.e. consumption expenditure). However, the model inputs (particularly forecasts of consumption expenditure) are now rather out of date;
- We concluded that GVA is a more meaningful driver of C&I waste arisings than employment, although we note that all methods used to forecast C&I waste arisings are somewhat uncertain due to the paucity of historic data. The robustness of the forecasts could be enhanced by obtaining more data, e.g. by surveying evidence from other EU markets; and
- The “delivery adjustment rates” are close to the historically observed success rates for power generation projects proposed in the UK. However, Defra’s current approach assumes that projects that have not been proposed yet will not contribute to meeting the 2020 landfill diversion targets, and may therefore understate the amount of capacity that will be delivered if some diversion capacity can be delivered over a timeframe shorter than the period to 2020. Also, assuming delivery adjustment rates based on historic experience does not account for the possibility that the underlying economic drivers of waste diversion capacity projects will change over time.

Finally, in terms of the overall framework, our main conclusion is that Defra’s approach should be refined to better reflect the uncertainty inherent in forecasting demand and capacity. Based on our experience in other sectors, we believe a more robust treatment of such uncertainty is a stochastic modelling approach, which accounts explicitly for the range of uncertainty around all of the key input assumptions.

Appendix A. (S)ARIMA Estimation Results

NERA carried out time-series estimation using annual and quarterly local authority data on household waste arisings. We briefly present the results of the different regression specifications, as carried out in the statistical software STATA.

In the ARIMA specifications, “ln_waste” is the natural logarithm of the annual series of waste arisings. “D.” is a difference operator. In the SARIMA specification “total_household” is the series of quarterly local authority data. “DS4” is a seasonal difference operator with period 4.

ARIMA(1,1,1)							
Sample: 1991 - 2007				Number of obs		17	
				Wald chi2(2)		5.21	
Log likelihood = 48.32576				Prob > chi2		0.0738	
OPG							
D.ln_waste	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]	
ln_waste							
	_cons	0.0110028	0.0102743	1.07	0.284	-0.0091345	0.0311401
ARMA							
	ar						
	L1.	0.7780069	0.3487988	2.23	0.026	0.0943737	1.46164
	ma						
	L1.	-.4577281	0.5729886	-0.80	0.424	-1.580765	0.665309
/sigma		0.0139822	0.0032519	4.30	0.000	0.0076085	0.0203559
ARIMA(1,2,0)							
Sample: 1992 - 2010				Number of obs		19	
				Wald chi2(1)		2.8	
Log likelihood = 51.3953				Prob > chi2		0.0944	
OPG							
D2.ln_waste	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]	
ln_waste							
	_cons	-0.0015102	0.0028248	-0.53	0.593	-0.0070467	0.0040263
ARMA							
	ar						
	L1.	-0.3708102	0.221725	-1.67	0.094	-0.8053831	0.0637627
/sigma		0.0161179	0.0041796	3.86	0.000	0.0079261	0.0243097
SARIMA(2,1,0)x(0,1,0)							
Sample: 2007q3 - 2012q1				Number of obs		19	
				Wald chi2(1)		19.66	
Log likelihood = -121.2555				Prob > chi2		0.0001	
DS4.							
total_household	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]	
ARMA							
	ar						
	L1.	-0.9670743	0.2658297	-3.64	0.000	-1.488091	-0.4460578
	L2.	-0.7236124	0.2581145	-2.8	0.005	-1.229508	-0.2177172
/sigma		136.1764000	23.04007	5.91	0.000	91.01875	181.3341

Appendix B. Model Audit

Defra asked NERA to audit the spreadsheet model “Super Model v00_025 (NERA).xlsx” that implements the modelling approach set out in Chapter 2. This task involved carefully examining the assumptions and calculations contained in the spreadsheet, to see if they matched the process outlined in the flow chart “Capacity Modelling Flowchart v00_09 (2011-11-08).pdf”, which was also sent to us.

During the audit, we identified a number of areas for potential improvement, including:

- Correcting some specific modelling errors we identified;
- Increasing the automated component of the model to avoid human error;
- Making assumptions in the model transparent, and keeping them consistent at every stage of calculation; and
- Fixing broken links, and sorting the data and assumptions so that future formulae are easier to audit.

We provided our findings to Defra in an Excel spreadsheet, separate from this report. Through our subsequent work to develop a stochastic waste infrastructure modelling tool,³³ we verified that the issues we raised during the model audit were addressed.³⁴

³³ Stochastic Modelling of Landfill Directive Targets: Prepared for Defra, NERA Economic Consulting, 20 December 2012.

³⁴ We verified that the corrections we recommended had been implemented in the version of the model we delivered by email to Defra on 20 November 2012.

Appendix C. Modelling Approach Using Latest Landfill Returns Data

In addition to providing high-level commentary on its overall modelling approach, Defra has asked us to comment specifically on a revision it is considering to the way it forecasts the surplus or deficit in diversion capacity, as compared to the amount required to meet the target.

The approach described in the main section of this report essentially forecasts available diversion capacity and waste arisings in 2020, and compares the two figures after accounting for contingencies.

The alternative approach starts from data on how much waste is sent to landfill in a reference year, as provided by the latest Landfill Return. This figure can be thought of current waste arisings, less the volume currently diverted from landfill using existing diversion capacity. Then, this alternative approach adds expected changes in waste arisings between now and 2020 to this amount, and subtracts expected growth in diversion capacity (including contingencies). The model then calculates the difference between this figure and the Landfill Cap, in the same way as the existing model.

From our discussions with Defra and our review of the model, our view of these alternative approaches is that they are fundamentally very similar, but the key differences between them are as follows.

Firstly, for existing diversion capacity, this approach does not require explicit assumptions about the capacity, availability and utilisation rates for existing diversion projects. These factors are already baked into the Landfill Return data. This approach may therefore provide more reliable assumptions on these parameters than the existing approach, which applies Defra's capacity, utilisation and availability assumptions to both existing and new projects.

The proposed alternative approach still requires capacity, utilisation and availability assumptions, but only applies them to new projects, thus reducing the influence on modelling outcomes of assumptions that could turn out to be inaccurate. However, it does implicitly assume that the capacity and utilisation and availability rates for diversion capacity achieved in the reference year are typical, and will be maintained throughout the period to 2020, which may turn out not to be the case.

Secondly, although the trajectory of waste arisings will be the same each year under this method, every time the forecast is updated this trajectory is rebased from a different starting point. If the Landfill Return data provides a more up-to-date view of outturn waste arisings, then this alternative approach might improve the accuracy of the demand forecast going forward.

Therefore, the alternative approach may bring some benefits by improving the accuracy of the assumptions used for modelling. However, it does place reliance on a single year of data, and bakes in assumptions relating to existing diversion capacity based on its performance in a single year, which may not be representative. However, it does not address the concerns we raise in Chapter 6 of this report regarding the treatment of uncertainty and the use of contingencies.

NERA

ECONOMIC CONSULTING

NERA Economic Consulting
15 Stratford Place
London W1C 1BE
United Kingdom
Tel: +44 20 7659 8500
Fax: +44 20 7659 8501
www.nera.com