Quantifying Uncertainty in Baseline Emissions Projections

Final report for the Committee on Climate Change

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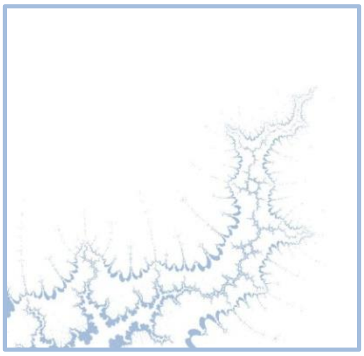

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Executive Summary

- The Committee on Climate Change (CCC) commissioned Cambridge Econometrics (CE) to assess sources of uncertainty with regard to carbon emissions projections, in order to inform their approach to recommending carbon budgets. The CCC had three objectives for the research:

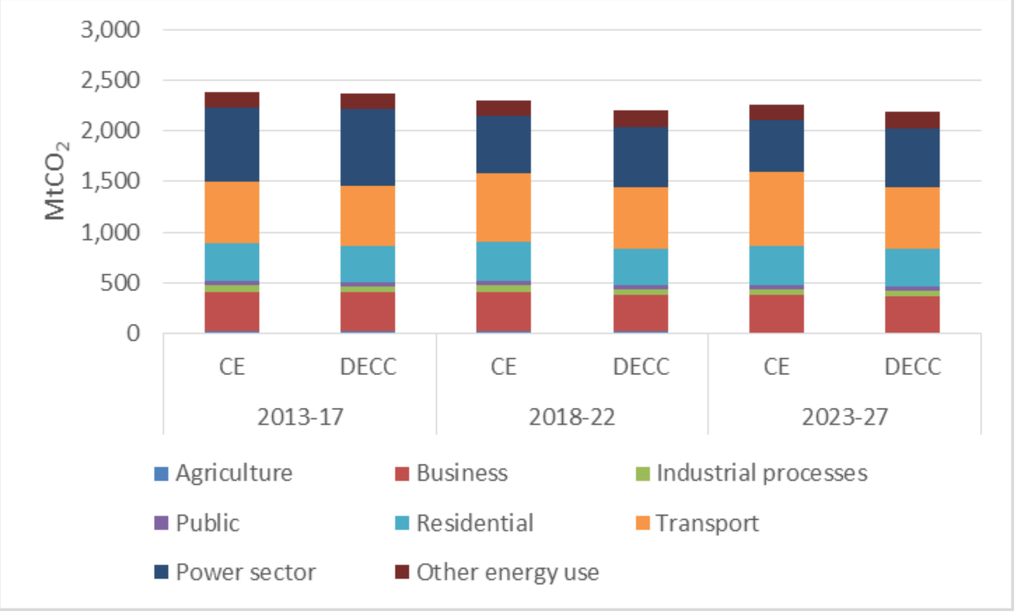
The main objectives of the analysis

  - to provide baseline energy demand and emissions projections to compare with the central Baseline Policies emissions projection of the Department of Energy and Climate Change (DECC)
  - to identify and quantify the potential effects of recent trends and expected future trends that may not be adequately reflected in econometrically estimated equation parameters
  - to quantify the degree of known parameter and input uncertainty inherent within estimated CO_2 emissions projections

Energy demand and emissions projections

- Energy related CO_2 emissions projections were developed using the approach defined in CE's MDM-E3 model. For 22 final energy sectors and 8 fuels, energy demand was estimated as a function of economic activity in the sector, energy prices, investment and air temperature. These drivers of energy demand were then projected forward based on the central assumptions used by DECC in the 2014 'Updated Energy and Emissions Projections' (UEP).

Figure E.1: Carbon emissions projections (excl LULUFC)



- Figure E.1 shows that, in aggregate, the CO_2 projections developed are broadly consistent with DECC's projections. The CE baseline for total CO_2 emissions is slightly higher than DECC's, with the implication that there is a greater policy effort required to meet the carbon budgets. However, there are variations across sub-sectors. The CE baseline projection has more emissions arising from road transport and the residential sector, while the DECC projection has more emissions arising from the power sector. Importantly, power sector emissions are capped in carbon budget terms, whereas an underestimation of road transport and residential emissions could lead to carbon budgets being missed.

- As the input data for the CE projections was aligned with DECC's input assumptions, the difference can be ascribed to the design and specification of each model. The implication for setting carbon budgets is a recognition that, as models are developed and improved, projections are also likely to change. This does not necessarily mean that the projections are not robust, but rather that changes in information and analytical approaches means that each new set of projections should be an improvement on the previous set.
- Comparing more models, with aligned assumptions, would provide more evidence on the robustness of DECC's approach and the consistency of alternative modelling specifications.

Recent trends

- Econometric time-series models, such as those used for this analysis and by DECC, have the advantage that they fit (and hopefully, explain) the data over the whole historical data set. However, a potential disadvantage is that recent trends are missed or implicitly considered temporary rather than assumed to persist (the recent trend is considered "random noise"). The implication for emissions projections is therefore that new and relevant information is not being considered leading to over or under prediction of future emissions. Of the recent trends identified, seven were considered quantifiable over three domains:
- Residential energy demand
  - changes to the composition of the future housing stock
  - changes to the use and purchase of appliances
  - stabilisation of desired room temperatures
  - demographic factors
- Industrial energy demand
  - changes in energy intensity as a result of changing structural composition of industries
- Road transport energy demand
  - changes in car ownership and trip demand
  - improved logistics in the heavy goods vehicles sector
- There was evidence to suggest that these recent trends were not wholly included in the central emissions projections but, if assumed to be wholly excluded, could have an impact on the central emissions projections of between +19.9 $MtCO_2$ pa (+4.5%) and -59.1 $MtCO_2$ pa (-13.5%) by 2035 (see Table E.1).

Table E.1: Emissions uncertainty arising from the potential effects of recent trends

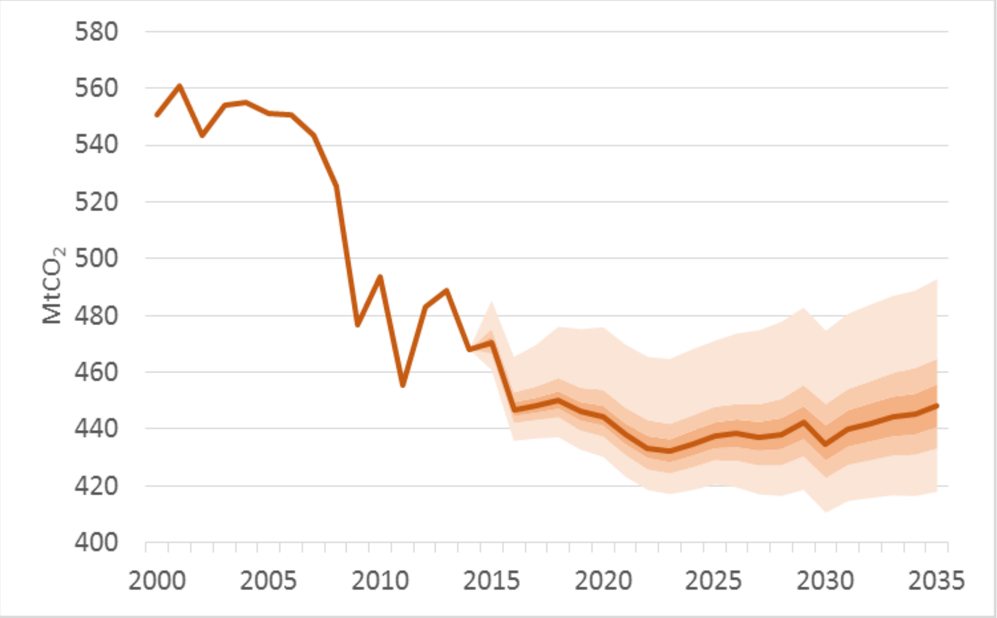
	Potential effect on emissions projections for 2035
Trends in the residential sector	-6.6 $MtCO_2$ to +0.4 $MtCO_2$ adjustment to power sector emissions arising from the effect on residential electricity demand -10.4 $MtCO_2$ to +0.9 $MtCO_2$ adjustment to residential emissions **Effect on total emissions uncertainty:** **-3.9% to +0.2%**
Trends in the industry sector	+/-14.5 $MtCO_2$ adjustment total emissions **Effect on total emissions uncertainty:** **+/- 3.3%**
Trends in the transport sector	-27.6 $MtCO_2$ to +4.1 $MtCO_2$ adjustment to road transport emissions **Effect on total emissions uncertainty:** **-6.3% to +0.9%**
Total uncertainty range of CO_2 emissions in 2035	-59.1 $MtCO_2$ to +19.9 $MtCO_2$ adjustment to total CO_2 emissions **Effect on total emissions uncertainty:** **-13.5% to +4.5%**

Statistical uncertainty analysis

- Monte Carlo simulations of the econometric model of energy demand were undertaken to quantify several sources of uncertainty that could affect the central baseline projection:
  - the time-invariant error stemming from the imperfect fit of each equation to the historical data (unexplained random noise)
  - input uncertainty that arises from the inherent uncertainty around the exogenous assumptions of future economic activity in each sector, energy prices, and air temperature
  - parameter uncertainty, as specified by the statistical significance of each long-term elasticity in the model
- The analysis of the error shows that for any given individual year the total CO_2 projection could be out by between +/-6%, simply because of the unexplained random noise not captured by the equations. However, the error in any single given year is not correlated to the error in the previous period. This is the reason that the outturn data fluctuates around a trend, whereas projections are smooth trends. Over the long term, the unexplained random noise (the error) should average zero and not affect the uncertainty bound, but this might not necessarily happen in a carbon budget period of just five years.
- The combined parameter and input uncertainty suggested that, within the 95% confidence interval, baseline emissions would lie between +6.8% and -4.6% for traded sector CO_2 emissions and between +13.5% and -9.7% for non-traded sector CO_2 emissions. For total CO_2 emissions the range is between +10.0% and -6.7%, (see Figure E.2).

- The uncertainty range would have been larger if the modelling had included the power sector explicitly. However, the approach taken was to assume a constant carbon intensity of electricity generation projected in DECC's baseline, such that power sector emissions responded only to changes in electricity demand.
- Assuming that the uncertainty attributed to the recent trends not being captured in the model is independent of the parameter and input uncertainty, the combined range of uncertainty in our projections could be between +15.0% and -19.3% by 2035 (a range of 34.3%, 153MtCO_2 pa).
- Beyond the quantifiable uncertainty considered in this report, there is clearly also an inexhaustible list of unpredictable and unquantifiable uncertainty that would have an unknown impact. This could include:
  - disruptive technological breakthrough
  - societal-scale behavioural change
  - geo-political shocks with long-lived consequences
  - persistent economic crises
- A common mis-interpretation of quantified uncertainty analysis is that it is deemed to represent the entire range of uncertainty, rather than a conditional range of uncertainty defined by the modelling and analytical inputs.

Figure E.2: Combined parameter and input uncertainty



1 Introduction

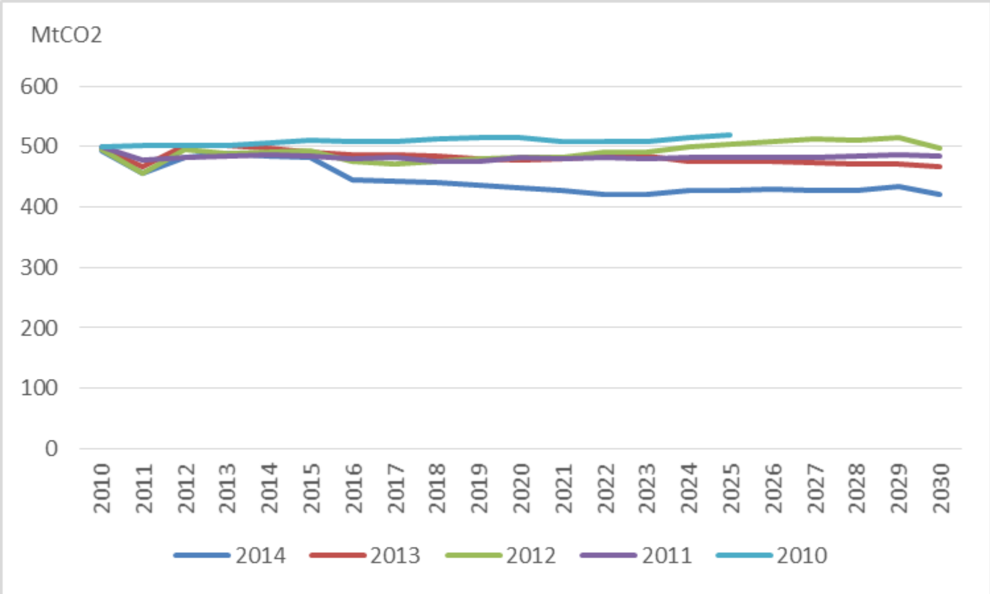
1.1 Background

The CCC is required to recommend to government the level of ambition for carbon emissions reduction in the UK, in the form of five-yearly carbon budgets. In December 2015, the CCC will set out its recommendation for the fifth carbon budget covering the period 2028-2032.

The CCC use DECC's 'Baseline Policies' emissions projections (which include the effects of policies pre-dating the 2009 Low Carbon Transition Plan) as the starting point for their analysis underpinning the carbon budgets. From this, a detailed, bottom-up assessment of potential abatement measures (including expected take-up of these measures and associated energy efficiency savings) is applied to inform the level at which the carbon budget should be set.

The DECC 'Baseline Policies' emissions projections are based on DECC's Energy Demand Model (EDM) and published on a regular basis, but the projections can vary quite dramatically from year to year (see Figure 1.1).

Figure 1.1: DECC 'Baseline Policy' emissions projections, from recent vintages of DECC's annual 'Updated Energy and Emissions Projections' 2010-2014



Source: DECC Updated Energy and Emissions Projections, 2010-2014

Differences between the various vintages of the DECC Updated Energy Projections (UEP) can occur for a number of plausible reasons, including:

- revisions to the historical data
- changes to the model specification
- changes to the model's central input assumptions (such as economic growth and energy prices)

The table below shows how different factors, such as changes to model specification and updates to input assumptions, have affected the emissions projections for the fourth carbon budget period (2023-2027), as published by DECC in the 'Updated Energy and Emissions Projections' for 2012, 2013 and 2014.

Table 1.1 Different reasons for revisions to Reference emissions projections for the fourth carbon budget (2023-2027) in subsequent editions of DECC's 'Updated Energy and Emissions Projections'

	2011-2012	2012-2013	2013-2014
Model development	-63 MtCO2, (-3.0%)	-35 MtCO2, (-1.6%)	-27 MtCO2, (-1.2%)
Growth assumptions	-42 MtCO2, (-2.0%)	-11 MtCO2, (-0.5%)	9 MtCO2, (0.4%)
Population assumptions	13 MtCO2, (0.6%)	0 MtCO2, (0.0%)	-36 MtCO2, (-1.7%)
Price assumptions	0 MtCO2, (0.0%)	4 MtCO2, (0.2%)	27 MtCO2, (1.2%)
Data revisions	1 MtCO2, (0.0%)	18 MtCO2, (0.8%)	-1 MtCO2, (0.0%)
New policy, policy changes	-15 MtCO2, (-0.7%)	28 MtCO2, (1.3%)	-80 MtCO2, (-3.7%)
CHP treatment	-5 MtCO2, (-0.2%)	2 MtCO2, (0.1%)	-4 MtCO2, (-0.2%)
Other	-2 MtCO2, (-0.1%)	-13 MtCO2, (-0.6%)	-69 MtCO2, (-3.2%)
Total	**-113 MtCO2 (-5.3%)**	**-7 MtCO2 (-0.3%)**	**-181 MtCO2 (-8.4%)**

Source: DECC Updated Energy and Emissions Projections, 2010-2014

Since revisions to the DECC emissions projections have implications for setting carbon budgets, it is important to understand the uncertainty around forward looking emissions projections. This uncertainty includes the factors listed above, but also includes

- error in estimation (the random noise associated with any econometric relationship)
- uncertainty in input assumptions
- uncertainty in the performance of the model to capture the relationship between emissions and their drivers

1.2 Objectives of this analysis

Given that uncertainty is inherent in emissions projections, the over-arching objective of this study is to attempt to quantify uncertainty in emissions projections, so that the range of uncertainty can be taken into consideration by the CCC when setting carbon budgets. In particular, three interdependent analyses have been undertaken:

- we developed an alternative set of baseline emissions projections for comparison with DECC (presented in Chapter 2)
- we considered model specification and the extent to which top-down econometric models (such as the DECC EDM, and CE's MDM-E3) capture recent trends and structural breaks; we also analysed recent and future trends that may not be captured in the estimated equations (presented in Chapter 3)
- we undertook an assessment of uncertainty in the projections with regard to data revisions, point forecast errors, assumptions of the drivers and model parameters; uncertainty in the drivers and parameters was assessed using Monte Carlo analysis (as presented in Chapter 4)

In Chapter 5, we offer our conclusions on the analysis, draw together the findings and consider the wider implications for setting carbon budgets.

2 Baseline GHG Emissions Projections in the UK over the period to 2035

The first task for this project involved developing a series of baseline energy demand and emissions projections for the UK. These emissions projections are consistent with the DECC Baseline Policies emissions projections in the sense that they only include policies that existed before the Low Carbon Transition Plan (2009). We assume that the CO_2 intensity of the power sector is the same as that implied by the DECC 2014 emissions projections. However, there are some key differences in the specification of CE's and DECC's energy demand equations, which lead to differences in our energy demand and emissions projections. This section of the report presents our central energy demand and emissions projections and considers uncertainty in model specification, by comparing different model results.

2.1 Approach to estimating energy demand and emissions

Our methodological approach involves empirically estimating energy demand equations for each fuel and final user. This forms a series of 176 individual energy demand projections[1], to which we apply emissions coefficients and a calibration residual to align with the most recent historical emissions data. The emissions results by 8 fuels and 22 sectors are then aggregated to form our emissions projections for the traded and non-traded sectors. For some sectors, in particular those in which fuel consumption is low, individual equations do not fit the data very well. This is particularly evident, for example, in the refining and own use of energy sectors and, in these cases, we do not use empirically estimate equations but instead keep annual emissions from those sectors fixed at 2014 levels.

The approach to estimate emissions related to electricity generation combines our estimated electricity demand equations and DECC projections for the carbon intensity of electricity generation. We econometrically estimate total electricity demand for each final user and then convert electricity demand projections to CO_2 equivalents using DECC's estimates of the CO_2 intensity of electricity generation under their 'Baseline Policies' scenario. Therefore the generation mix (and related carbon intensity) of the power sector is not modelled but is calibrated to DECCs baseline.

Our energy demand projections are consistent with historical energy demand data published in DUKES after the effects of post-2008 policies have been removed. To eliminate the effects of recent policies, an adjustment factor is applied to 2014 data, which then forms the starting point for the emissions projections. The adjustment factor is based on the difference between DECC Baseline Policies and DECC Reference energy demand scenarios in 2014.

[1] Some of these 176 equations are redundant as not all fuel users use all fuels (as defined by our classification). For example, only the road transport sector consumes motor spirit and DERV. Excluding instances of zero energy use, there are 74 individual equations that are estimated.

Our emissions projections differ slightly to published data because we do not estimate process emissions or other non-energy related CO_2 emissions. There are also small differences in the carbon intensity of fuels used for different purposes that are not reflected in our eight broad fuel-type classification. Therefore, we apply a multiplicative residual to calibrate our emissions projections to published data.

General energy demand equation specification

Energy demand equations are estimated as a function of economic activity, fuel prices, real accumulated investment and air temperature. The original equation is based on work by Barker, Ekins and Johnstone (1995)[2] and Hunt and Manning (1989)[3]. The basic specification is as follows:

Fuel demand = f(economic activity, fuel price, real accumulated investment, air temperature)

For industry sectors, the economic activity indicator is real gross sector output and it reflects the changes to energy requirements when there is a change in the level of industrial production. For the residential sector, real household incomes is used as an indicator of economic activity. In both cases, we would expect a positive relationship when all other factors are kept constant. For industry sectors, it is clear that increases in real output will require an increase in inputs to production (including energy inputs) and for the residential sector, it is also expected that, as incomes rise and the UK population increases, demand for energy by the households will also increase. This positive relationship between economic activity and energy demand is imposed in the estimation process by restricting the estimated parameter for economic activity to a positive value.

The price elasticity is important to reflect the trade-off between energy inputs and other inputs to production (in the case of industries) or alternative goods/services that money could instead be spent on (in the case of households). Consistent with economic theory, we impose the restriction for a negative relationship between energy demand and real energy prices.

The investment term is calculated as discounted cumulative investment and R&D expenditure. The term takes account of replacement of the existing energy-using capital stock and is a proxy for technological change.

The air temperature variable is defined as the deviation from historical mean air temperatures. The rationale for inclusion in the model is to reflect the change in demand for heating and cooling as temperatures deviate from the long-run average (particularly in the residential and service sectors).

Econometric specification

The econometric specification of the energy demand equations is of cointegrating form:

$$\Delta y_t = \beta_0 + \underbrace{\beta_1 \Delta x_t + \beta_2 \Delta y_{t-1}}_{\text{Short-run first differences regression}} + \beta_3 \underbrace{(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1})}_{\text{Long-run levels equation}}$$

[2] Barker, T S, Ekins, P and N Johnstone (1995), ‘Global Warming and Energy Demand’, Routledge, London

[3] Hunt, L and N Manning (1989), 'Energy price- and income-elasticities of demand: some estimates for the UK using the cointegration procedure', Scottish Journal of Political Economy, 36(2) pp183-193

The estimation process involves two stages. The first stage is to estimate a long-run levels relationship, whereby we test whether a cointegrating relationship exists, such that the dependent variable (energy demand) and the explanatory variables in the equation trend together in the long-run. To test for cointegration, we test that the residual form the long-run levels equation is stationary (i.e. that its mean and variance of is constant over time). Stationarity of the residual from the levels regression would imply that there is a true long-run cointegrating relationship between the variables.

If a cointegrating relationship exists, then the equation can be expressed in error-correction form. The error correction representation involves a dynamic, first-difference, regression of all the variables from the first stage, along with lags of the dependent variable, lagged differences of the exogenous variables, and the error-correction term (the lagged residual from the first stage regression).

Expressed in this form, the first-differences part of the equation measures the short-run response to a change in any of the explanatory factors. The levels equation shows how the variables are related in a long-run steady state, and the error correction term is an estimate of the rate at which an exogenous shock to energy demand dissipates. In the equation above, β_3 is the error correction term. It is estimated for each equation and its value is restricted to be between -0.95 and -0.05. The closer the value is to -1, the quicker that energy demand relationships return to the estimated long-run relationships following a short-term shock or deviation from trend.

Model selection is based on the Akaike Information Criterion (AIC). For each equation, we impose restrictions on the various parameters to reflect the plausible range of causal relationships. Bounded by these parameter restrictions, the AIC then determines the specification of the equation and the value of the parameter estimates that best explain the historical data. All explanatory variables in the equation are expressed in logarithmic form and so the parameter estimates can be interpreted as elasticities.

Data

The data sample used for the econometric estimation covers the period 1970-2008. We have purposefully excluded data from 2009-2014, as we do not wish to take into account the effect of policies that were introduced since the Low Carbon Transition Plan. The benefit of using a long time series is that it increases the sample size and, when using a consistent estimator, the precision of the estimate improves as the sample size increases.

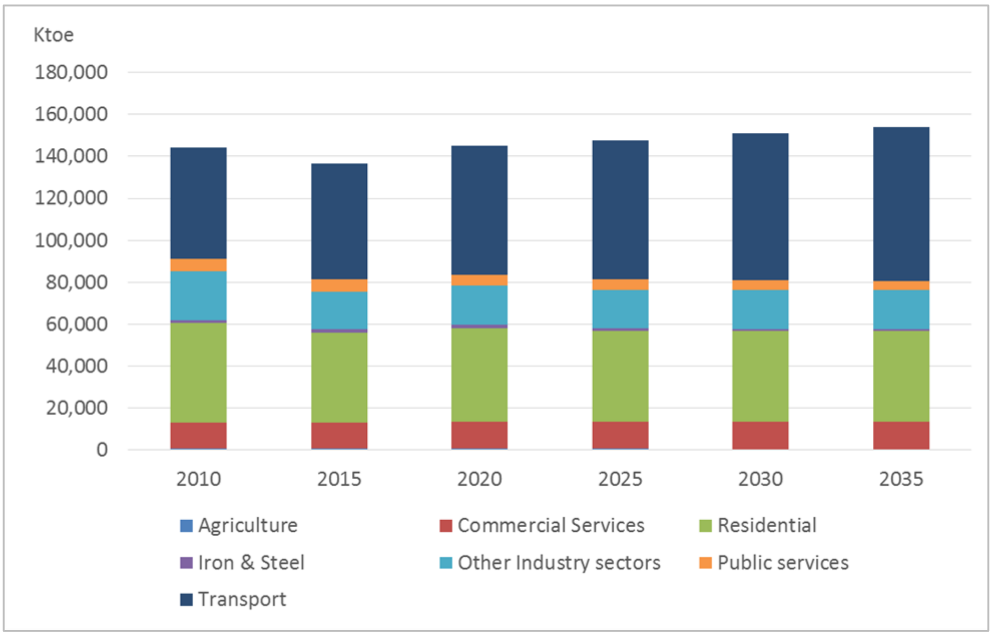
However, the drawback of using this data sample is that the estimated coefficients will reflect average trends over the period 1970-2008 and the sample does not attribute more weight to the most recent data. Recent trends or structural breaks therefore might not be fully reflected in the estimated parameters and would instead be treated as random noise in the most recent years of data. To take account of potential uncertainty associated with recent changes to energy demand trends, we undertook an analysis to put an upper and lower bound on emissions, after considering different trends which are unlikely to be reflected in our top-down econometric equations (as presented in Chapter 3). Furthermore, we calculate a multiplicative residual based on the difference between the actual data and the predicted value in the last year.

This multiplicative residual is applied to all future projections on the assumption that there is a structural break in the last year(s) of data and that, without this multiplicative residual, our equations would continue to systematically over-predict or under-predict energy demand over the projection period.

2.2 Energy demand and emissions projections

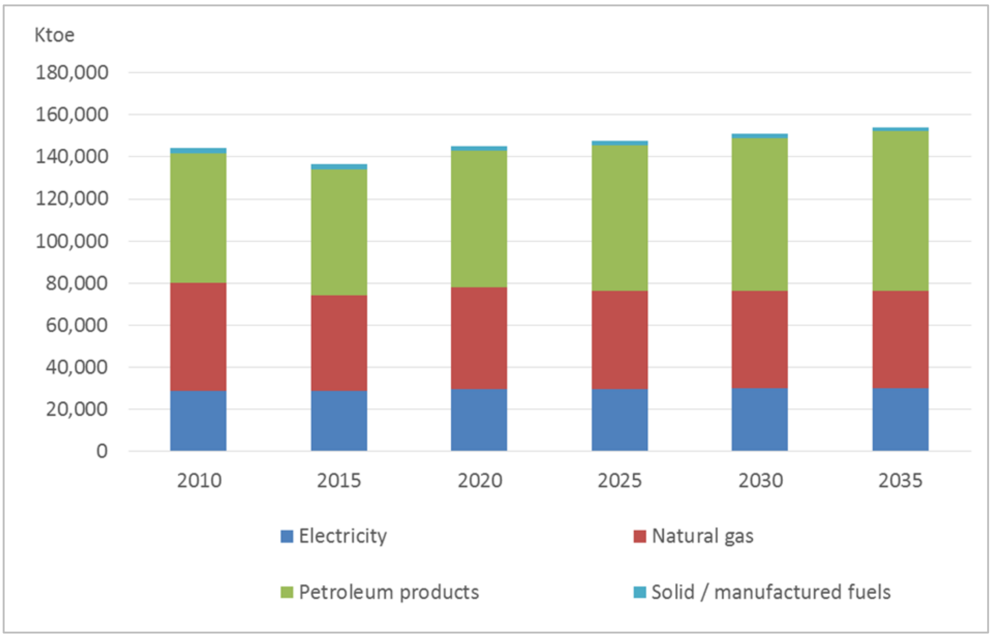
The charts below shows our central energy demand projections by fuel user and by fuel.

Figure 2.1: Central final energy demand projections



Source: Cambridge Econometrics, MDM-E3

Figure 2.2: Central final energy demand projections by fuel



Source: Cambridge Econometrics, MDM-E3

Our Baseline Policy energy demand projections predict a gradual increase in total energy demand over the period to 2035. This is mainly attributable to a small increase in energy demand in the residential and service sectors (equivalent to around 0.5% year-on-year increase in demand over the period to 2035), as well as around 1.5% pa growth in demand for petrol and diesel by the road transport sector. The projections show a decline in energy demand from public services, the iron and steel sector and other industry sectors.

Our equations are estimated using data to for the period 1970-2008. To test how well the energy demand equations predict the outturn data, we re-estimated the energy demand equations using a sample of data from 1970-2004. We used the parameter estimates from this restricted sample estimation, combined with historical data for the input variables (economic activity, price, temperature), to estimate energy demand by sector and fuel over the period 2005-2014. We compared our 'predicted' energy demand results to outturn data and found that, while some equations were good predictors of energy demand and fitted the recent data well (eg the residential equations), in other cases, there was evidence of systematic over or under prediction. This was particularly evident in the transport energy demand equations, which over-estimated demand for petrol and under-estimated demand for diesel. Although these errors cancel out to some degree at an aggregate level, it indicates that our top-down econometric equations are not picking up recent increases in sales of diesel cars relative to petrol cars. This prediction error justified a closer analysis of recent trends in the vehicle stock (as outlined in Chapter 3).

Figure 2.3: Comparison between predicted and actual energy demand in road transport

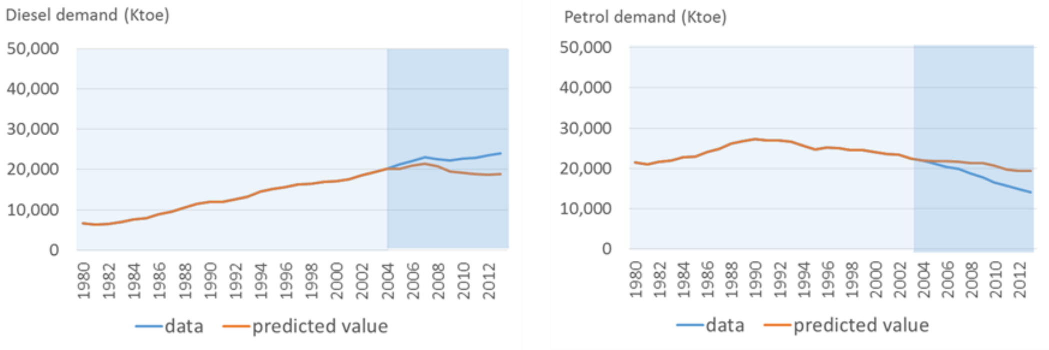
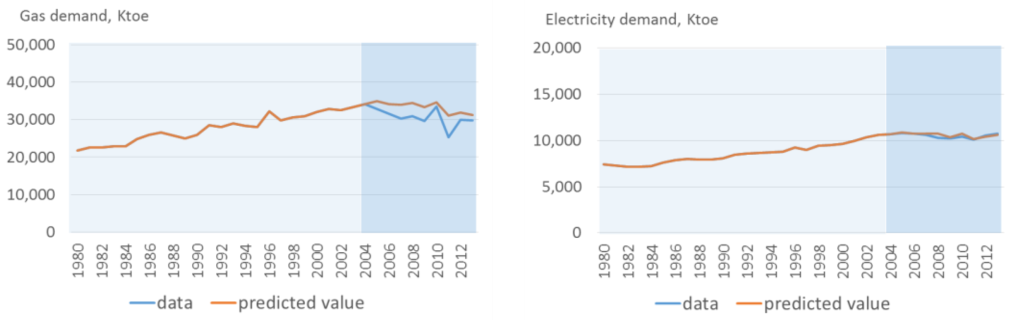


Figure 2.4: Comparison between predicted and actual energy demand in the residential sector



Source: Cambridge Econometrics

2.3 Comparison with DECC projections

The DECC Energy Demand Model (EDM) and Cambridge Econometrics' MDM-E3 model (which form the basis of our own energy demand projections) have been developed independently of each other and the econometric specification of these two sources of energy demand equations is very different. Therefore, by comparing our central emissions results with DECC's, we obtain some understanding of the potential degree of uncertainty attributable to choice of model specification.

DECC predominantly use Ordinary Least Squares (OLS) to estimate energy demand equations by final user. A general-to-specific modelling approach is applied, whereby variables in the energy demand equations are included if a statistically significant relationship is identified or if there is a strong theoretical rationale for inclusion (in some cases, despite econometric insignificance). For the road transport sector, vehicle efficiency is aligned to the Department for Transport's assumptions and an econometric equation for distance travelled is estimated, which is consistent with Department for Transport estimates at an aggregate level. To derive emissions projections for the 'Baseline Policies' scenario, DECC estimate current policy emissions and then, from these projections, they subtract an estimate of the impact on energy demand from the various policies introduced since the Low Carbon Transition Plan (2008). DECC's Energy Demand Model is also linked to the Dynamic Dispatch Model (DDM). Energy prices iterate between the DDM and the EDM until convergence is reached. DECC also uses slightly different sectoral activity projections than those used in MDM-E3. Whilst the GDP assumptions used by DECC are, in the short term, taken from OBR projections, DECC's industry growth model is used to project shares of GVA by sector.

In comparison to DECC's approach, and as described in Section 2.1 and Section 2.2, we use cointegrating equations and a structured framework, where a similar or identical equation specification is used for all individual energy demand equations that are estimated. In our central energy demand projections we do not include detailed bottom-up modelling of the road transport sector (although different road transport scenarios are tested in a stock model for the recent trends analysis, which is presented in Chapter 3). We use the AIC to determine the model parameter estimates that best fit the historical data and, to estimate Baseline Policy emissions, we restrict the data sample to exclude post-2008 data.

By comparing our energy demand projections to those from alternative modelling approaches, we can obtain a more robust assessment of the likely path for future CO_2 emissions. In theory, the robustness of our analysis could be improved further by including emissions projections from other models.

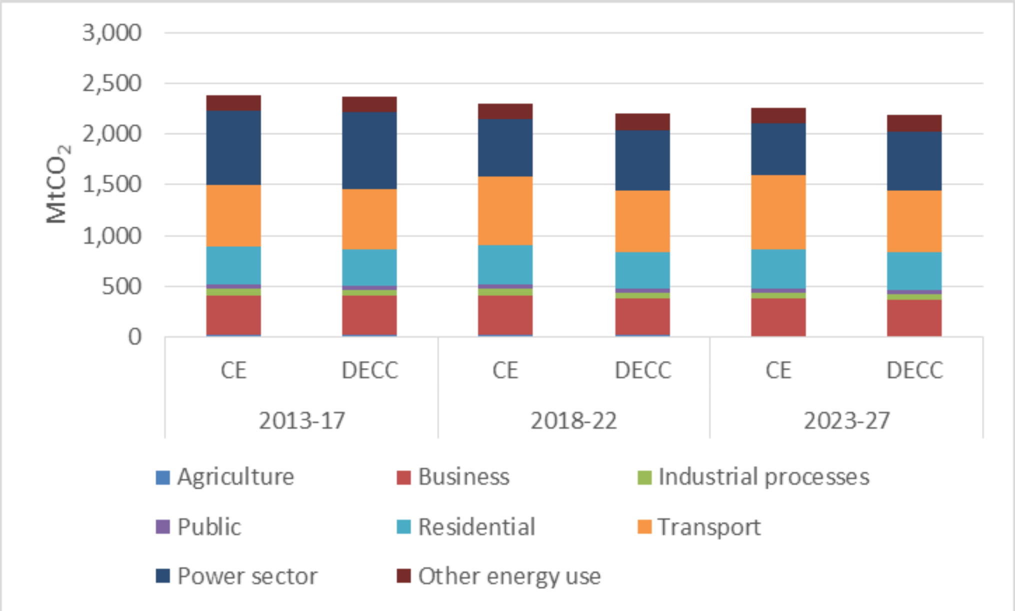
Table 2.2 shows how our energy demand projections compare to DECC's over the whole projection period. Figure 2.5 shows differences in emissions projections over the 3rd, 4th and 5th carbon budget periods.

Table 2.1 DECC and CE energy demand projections by final user (annual growth over the period 2014-2035)

	CE	DECC
Agriculture	-3.2%	0.0%
Commercial Services	0.5%	0.7%
Residential	0.6%	0.7%
Iron & Steel	-1.8%	-1.8%
Other Industry sectors	-0.7%	-0.5%
Public services	-0.9%	-0.2%
Transport	1.4%	0.7%
Final Energy Consumption	0.8%	0.5%

Source: Cambridge Econometrics; DECC (2014), 'Updated Energy and Emissions Projections'

Figure 2.5: Comparison between DECC and CE emissions projections over the four carbon budget periods



Source: Cambridge Econometrics; DECC (2014), 'Updated Energy and Emissions Projections'

3 Analysis of recent trends, expected future trends and structural breaks

Whilst there are many advantages of using a top-down econometric approach to forecast energy demand and emissions, one of the main limitations of this analytical approach is that it crucially relies on the assumption that economic agents (households, industries, government) (i) continue to use the same energy-using equipment as they have used in the past and (ii) continue to adjust their demand for energy in response to key economic drivers in a similar way as they have historically done. Recent and future expected technological and behavioural trends indicate that these assumptions could be unrealistic and, as a result, that the estimated parameters in the energy demand equation may be biased.

This section of the report considers recent trends and possible future trends that may affect energy consumption and which we do not believe would be adequately captured in our top-down econometric equations, particularly given that our equation parameters are estimated using data going back to the 1970s.

3.1 Estimating the effect of future trends

To quantify the potential effect of expected future trends, it is important to firstly consider the trends that our econometric equations already do capture. The time-series cointegrating equations that are used include the lagged dependent variable as an explanatory parameter and, to forecast the expected growth or change in energy demand, the equations include parameters that pick up a demand response in relation to other key explanatory factors (such as income, gross output, energy prices). When there is a temporary deviation from the trend due to an external factor that is not captured within the equation, the equations use an error correction term to estimate the rate at which a long-run steady state relationship between energy demand and its explanatory factors will be restored[4]. Under assumptions of stable future growth in real incomes, gross output and energy prices, the equations effectively reflect a continuation of the current trend in energy demand. For example, the equations assume a stable, logarithmic relationship between household income and household demand for electricity over the projection period. In their current form, the equations would not pick up the effects of a future structural break where this relationship between income and energy demand might break down (due to, for example, the use of more efficient appliances or a saturation in demand for the energy-using stock).

To test how well our equations predict trends in energy demand, we compared our short term energy demand projections for 2005-2014 (estimated using historical data over the period 1970 to 2004) with the true out-turn energy demand data in the years since 2004 (as shown in Section 2.2). Although this

[4] For more information on the Error Correction Term and the specification of our energy demand equations, refer to Chapter 2.

method only tests the short term prediction properties of the equations, systematic over or under prediction would strongly suggest that there are some underlying trends that the equations are not capturing effectively. Our results show that whilst the equations for some sectors (including residential) appear to fit the recent data well, other sector equations (including road transport) are less effective in capturing recent variations in energy demand. For equations with poor predication properties, in particular, analysis of recent and future trends could vastly improve the robustness of our estimated energy demand projections.

Due to data limitations, imperfect foresight and an inherent uncertainty about how people will change and adapt their behaviour in the future, it is impossible to accurately predict how future behavioural changes will affect energy demand. In an attempt to estimate the potential effect of deviations from established energy demand relationships, we have undertaken a literature and data review to identify factors that are most likely to affect the trend in future energy use and, where possible, have applied simplifying assumptions to derive an upper and lower bound for how we might expect these potential future changes to affect energy demand and emissions. It is important to note that, as the purpose of this analysis is to project 'baseline policy' emissions, we only consider trends that would still occur in the absence of energy and climate change policies enacted since 2009. Therefore, we do not include the effect of policies in place since the Low Carbon Transition Plan, that encourage take-up of more efficient appliances in households and more efficient use of energy in transport and industry sectors.

In the following sections, we describe our calculations to derive an exogenous adjustment to apply to our estimated emissions projections in order to account for future effects that are not taken account of in our empirically-estimated equations. It is noted that these estimates are based on a number simplifying assumptions and their purpose is purely to put an indicative lower and upper bound to adjustments that could be applied to our central emissions projections.

3.2 Trends in the residential sector

As our energy demand equations are defined at a top-down level, it is impossible to explicitly calculate the extent to which the equations pick up changes in a specific energy-using trend. However, if the trend is closely correlated to one of the explanatory variables in the equation, then it is reasonable to assume that its effects would be picked up, to some extent, in the estimated equation parameters and in the emissions projections. This could be, for example, changes to the rate of future population growth, the effects of which would be reflected in our real income input projections and, therefore, taken account of in our econometric modelling of future energy demand and emissions.

Adjustments to our econometrically-estimated energy demand and emissions projections could be justified for two main reasons:

- an expected decoupling of the relationship between our explanatory variables and household behaviour, which would indicate a structural break that is not being picked up in our estimated equations (this could, for example, include a saturation effect in demand for electrical appliances, which have historically grown steadily over time in line with real incomes)

- the effect of an exogenous factor that is not correlated with other explanatory variables and so is completely unaccounted for in the equation, which could lead to omitted variable bias if it is shown that it has a significant positive or negative correlation with energy demand

Potential future trends in the residential sector that would not be accounted for in our top-down econometric equations include:

- future changes to the profile of the housing stock
- changes to the relationship between income and purchase/use of appliances (including lighting, wet appliances, consumer electronics and home computing)
- changes to the socio-economic structure of the UK population (which may not necessarily be picked up in the income term)
- changes to the relationship between real incomes and internal room temperatures

To estimate the effect of these future trends, we must firstly identify whether (a) they are completely unaccounted for in our econometric model or (b) they are correlated with one of the explanatory variables in the model and we have reason to believe that the established relationship between the two variables will change in the future.

The effect of these potential future trends are summarised in Table 3.1 and are discussed in more detail in the following sections.

Table 3.1: Impact of recent trends in the residential sector on central emissions projections

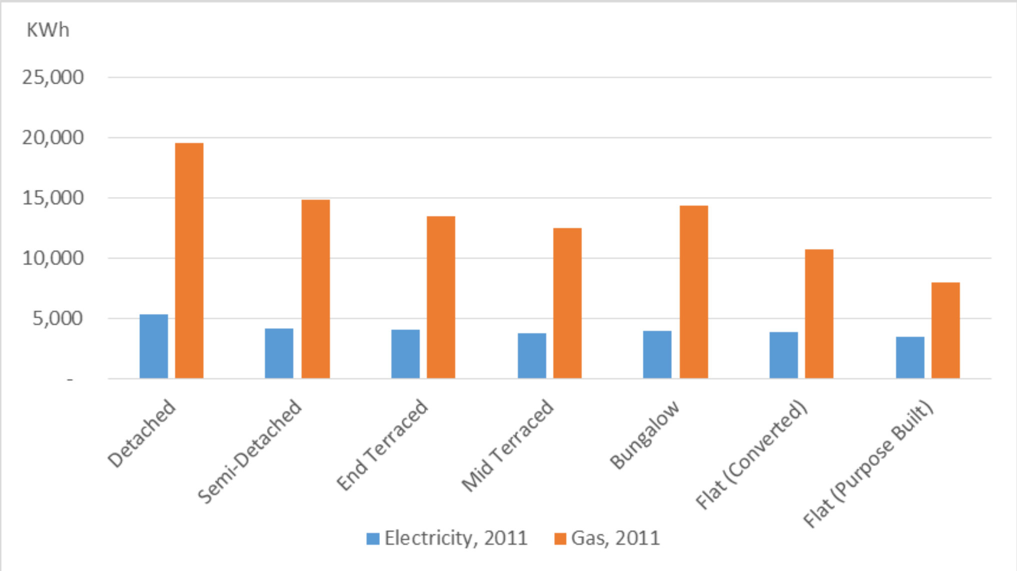
	Potential effect on emissions projections for 2035
Housing stock	
Change in the housing stock and, in particular, an increase in the proportion of people living in apartments	2.2 $MtCO_2$ reduction in domestic emissions (due to reduction in gas demand) 0.4 MtCO2 reduction in power sector emissions (due to reduction in electricity demand)
Use and purchase of appliances	
Change in use of Lighting	1.2 $MtCO_2$ reduction in power sector emissions (due to a reduction in electricity demand)
Change in use of washing machines and wet goods	1.5 $MtCO_2$ reduction in power sector emissions (due to a reduction in electricity demand)
Changes in use of electrical appliances	2.0 $MtCO_2$ reduction in power sector emissions (due to a reduction in electricity demand)

Other factors	
An increase in the proportion of people above pensionable age	0.4 $MtCO_2$ increase in power sector emissions (due to an increase in electricity demand) and 0.9 $MtCO_2$ due to an increase in gas demand
Stabilisation of room temperatures	8.2 $MtCO_2$ reduction in residential emission projections (due to a reduction in gas demand) 1.5 $MtCO_2$ reduction in power sector emissions (due to a reduction in electricity demand)
Total potential impact	-6.6 MtCO2 to +0.4 MtCO2 adjustment to power sector emissions -10.4 MtCO2 to +0.9 MtCO2 adjustment to residential emissions **Effect on total emissions uncertainty: -3.9% to +0.2%**

3.2.1 Changes to the housing stock

In recent years, there has been an increase in the proportion of apartments being built relative to other types of housing. Over 2008 to 2012, the stock of flats and apartments grew by 11%, compared to 2% growth for the total housing stock[5]. As shown in Figure 3.1: Mean demand for gas and electricity in different types of dwelling (KWh, 2011)Figure 3.1, apartments are, on average, more energy-efficient than other types of dwelling and, although the number of new homes built each year is small relative to total number of houses in the stock, an increase in the proportion of the relatively smaller and more energy-efficient apartments, could mean that our central emissions estimates would be biased upwards.

Figure 3.1: Mean demand for gas and electricity in different types of dwelling (KWh, 2011)



Source: DECC (2014), Energy Consumption in the UK (ECUK)

Under an assumption of an additional 220,000 homes built each year (to accommodate an expected increase in population), by 2035, the number of

[5] Data for 2008-2012 from the English Housing Survey

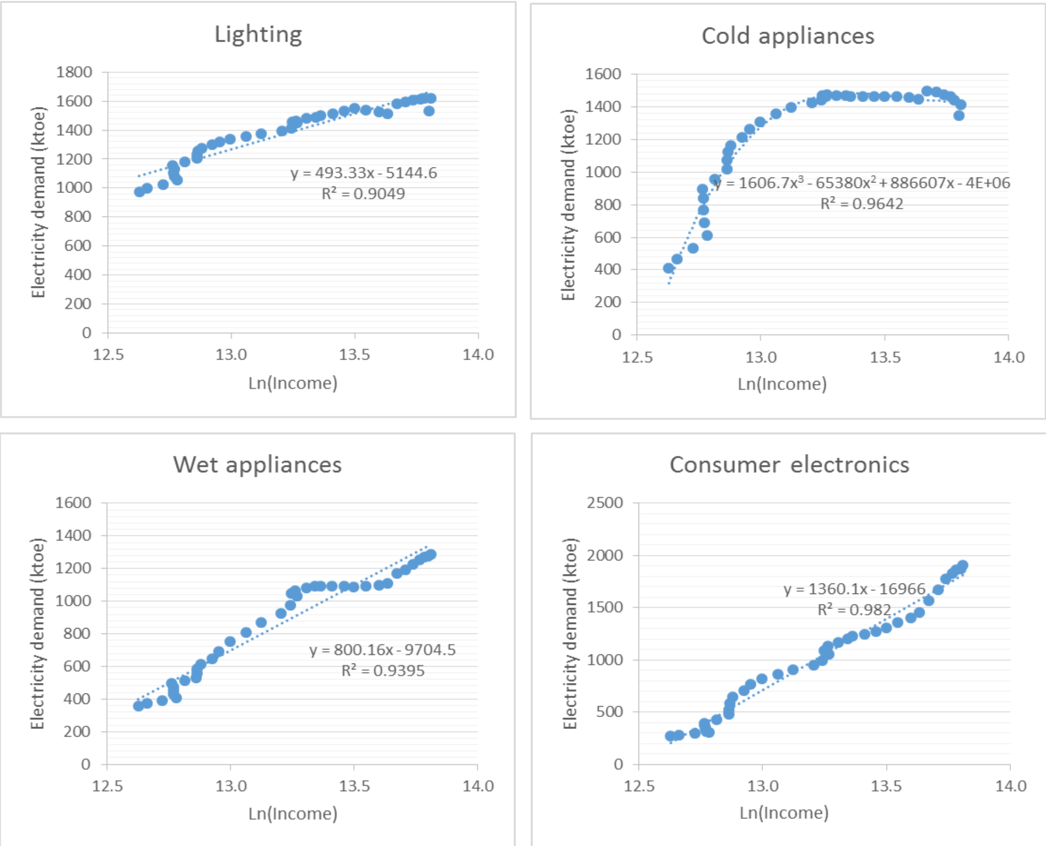
homes built over the period 2015-2035 will reach approximately 12% of the total stock. We tested the impact if 100% of new homes were relatively more energy efficient and, under the assumption that our equation does not pick up this trend at all, we find that the transition towards an increasing share of smaller (and relatively more efficient) flats and apartments could lead to a 2.6MtCO_2 revision downwards to our estimated baseline emissions projections.

3.2.2 Appliances

The use of household appliances in 2014 accounted for 6.9 Ktoe of electricity consumption, which is equivalent to around 14% of the UK's total CO_2 emissions (based on the average CO_2 intensity of electricity generation in that year). Of the total household electricity consumption for appliances, 15% is demand for lighting, 16% is use of cold appliances, 19% use of wet appliances, 27% consumer electronics, 8% home computing and 17% for cooking.

It is particularly difficult to quantify the extent to which our equations pick up recent trends in the purchase and use of electric appliances: we only estimate total electricity demand for the residential sector, so trends in the use of specific electrical appliances might be masked in the historical energy demand data by different or opposite changes in the use of other types of electric appliances or changes in residential use of electricity for other purposes. As shown in Figure 3.2, historically, there has been a strong correlation between use of appliances and real household incomes.

Figure 3.2: Historical relationship between real income and use of appliances



Source: DECC ECUK (2014), data for period up to 2008

In our top-down econometric equation, we do not model electricity demand for different household applications; the effect of an increase in the use of appliances is only picked up in our energy demand projections through the income term (because the use of electrical appliances is also positively correlated with real incomes). Therefore, for the purposes of this analysis, we implicitly assume that the household electricity demand equations pick up (via the income input projections) the effects of a continuation of the historical relationship between real incomes and use of appliances. We then estimate household electricity demand under the assumption of a complete de-coupling of this relationship. We calculate the difference between the two estimates and apply this exogenous adjustment to our projections for household electricity demand and emissions to derive a lower-bound estimate.

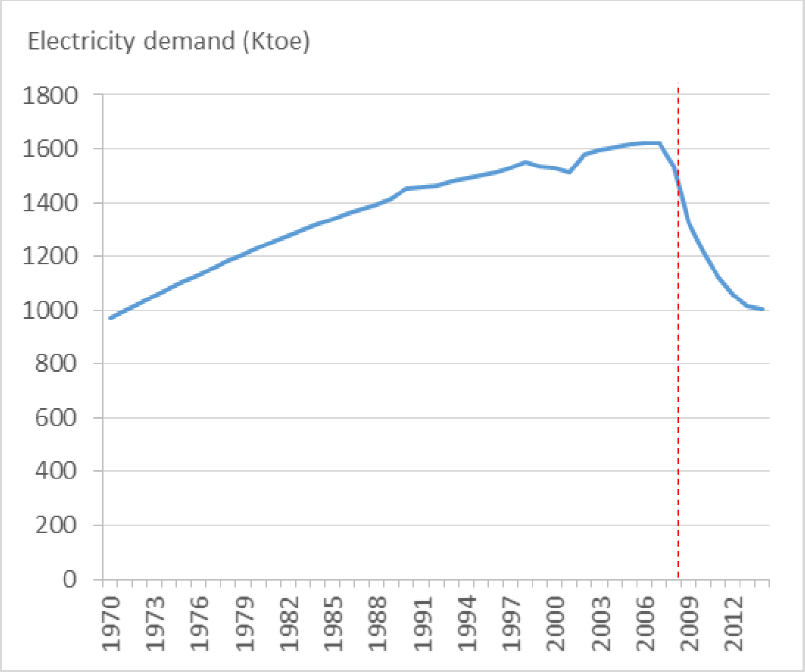
Based on this method for quantifying the effects of recent trends in the use of appliances, the following sections describe the effects of a decoupling of the relationship between real incomes demand for lighting, wet (washing) appliances and consumer electronics.

Lighting

Total electricity consumption for household lighting in 2014 was 1,006 Ktoe and has declined somewhat since the 2007 peak, where total electricity demand for lighting reached 1,623 Ktoe.

Recent data suggests that electricity consumption for lighting is falling, as households approach a comfortable level of internal light and energy-efficient lightbulbs start to replace halogen bulbs in the existing stock. Although it is highly likely that a large part of this reduction in electricity demand is driven by recent policy (such as product efficiency standards), as shown in Figure 3.6, there is evidence of a small decline in the use of lighting prior to the introduction of the 2009 Low Carbon Transition Plan.

Figure 3.3: Electricity demand for lighting before and after the Low Carbon Transition Plan



Source: DECC (2014), ECUK

Counteracting this effect, there is also some evidence to suggest that demand for lighting might continue to increase, as real incomes rise and people choose to install more spotlights in kitchens and bathrooms, particularly given that internal levels of light are still much lower than external.

Despite an apparent negative correlation between income and use of electricity for lighting in recent years, because this decline in electricity use for lighting is mostly due to policy impacts, we use, as our lower bound estimate, zero relationship (rather than a negative causal relationship) between real income and demand for lighting. We believe that this is a conservative lower bound estimate as, although there is evidence of a weakening of the relationship between income and use of electricity for lighting over time, we expect that the relationship will still be positive. A recent study by Fouquet and Pearson (2012)[6] suggests that over the period 1970-2000, the income elasticity of demand for lighting fell from 0.7 to 0.3. This means that, in 2000, a 1% increase in income would correspond to a 0.3% increase in electricity demand for lighting. This compares to an income elasticity of 0.4 in our central residential electricity demand projections.

Table 3.2 Historical changes to the estimated income elasticity of demand for lighting

	1970	1980	1990	2000
Income elasticity of demand for lighting	0.7	0.3	0.2	0.3

Source: Fouquet, R. and Peter J.G. Pearson (2012) 'The long-run demand for lighting: elasticities and rebound effects in different phases of economic development.' *Economics of Energy and Environmental Policy* 1(1) 83-100.

We find that, if there was no longer a significant causal relationship between real incomes and lighting demand, our central projections could be over-predicting 2035 emissions by up to 1.2 $MtCO_2$ (based on the CO_2 intensity of electricity generation implied by DECC's Baseline Policies scenario).

Wet (washing) appliances

The direction of future trends in the use of washing machines and other wet appliances are somewhat ambiguous. Whilst some recent studies have suggested a decline in the temperature of washing machine loads[7], there is also evidence to suggest an increase in the frequency of use and a rise in the use of tumble dryers[8]. As shown in Figure 3.7, there is some evidence of a recent saturation in demand for wet appliances, such as washing machines and dishwashers in the energy demand data, which would suggest that the relationship between real income and use of wet appliances is weakening. Applying the method described above to calculate the impact on household emissions if there was no future causal relationship between real incomes and use of wet appliances (as a lower bound estimate), we find that our equations could be over predicting 2035 demand for wet appliances by up to 1.5 $MtCO_2$.

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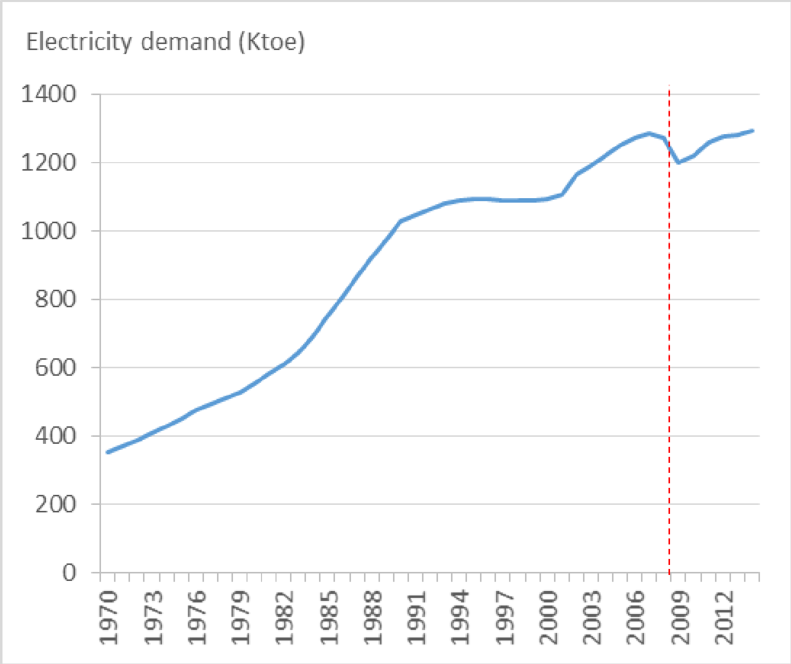
[6] Fouquet, R. and Peter J.G. Pearson (2012) 'The long-run demand for lighting: elasticities and rebound effects in different phases of economic development.' Economics of Energy and Environmental Policy 1(1) 83-100.

[7] EST,DECC,DEFRA (2012), 'Powering the Nation: Household electricity-using habits revealed'

[8] Dale Southerton (2015), 'Behaviour Change Review'; EST,DECC,DEFRA (2012), 'Powering the Nation: Household electricity-using habits revealed'

Figure 3.4: Electricity demand for wet, washing appliances before and after the Low Carbon Transition Plan

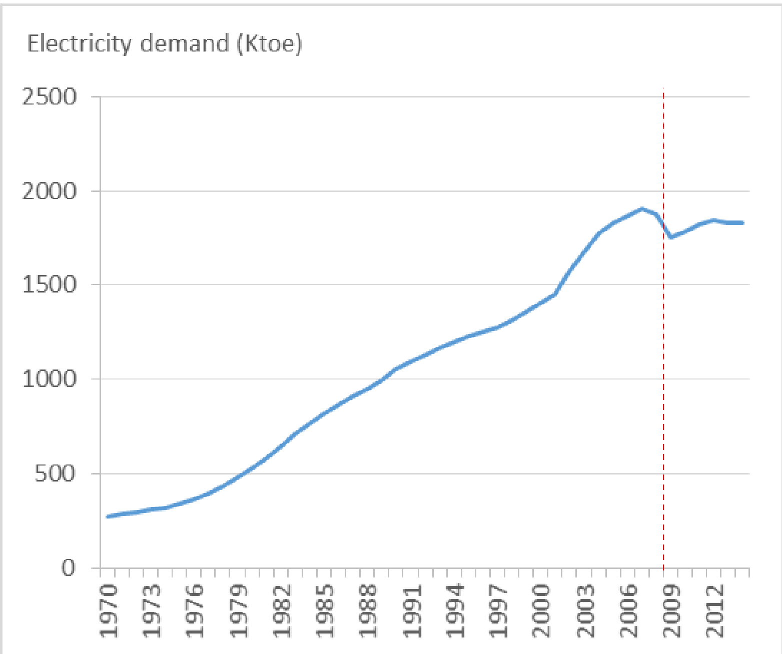


Source: DECC ECUK (2014)

Consumer electronics

As shown in Figure 3.5, there is only mild evidence of energy demand from consumer electronics tapering off and the historical evidence of the relationship between income and electricity demand from consumer electronics is strong and positive. However, if there is saturation of this market in the future, then the projections could be over-estimating residential electricity demand and, therefore, over-estimating emissions by around 2.0 $MtCO_2$ by 2035.

Figure 3.5: Electricity demand for consumer electronics before and after the Low Carbon Transition Plan



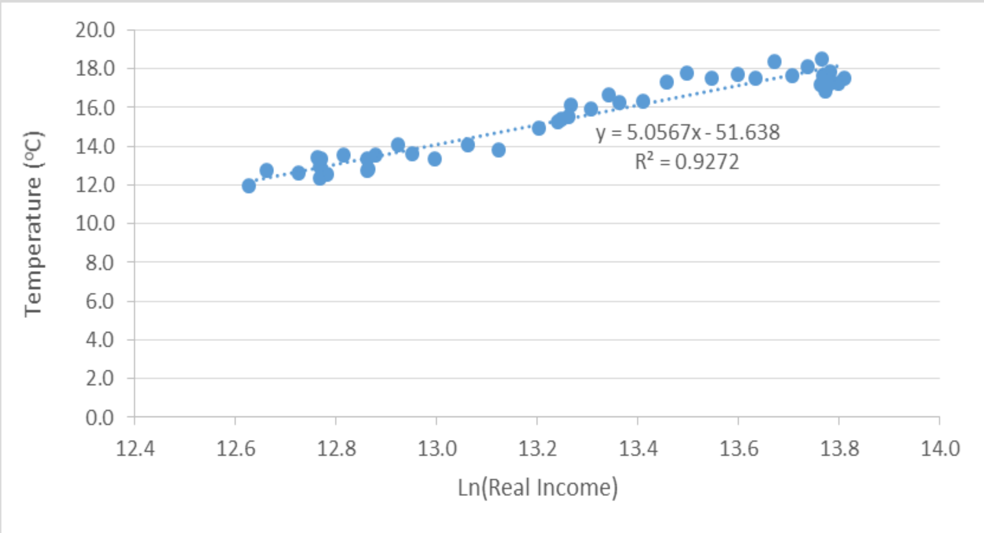
Source: DECC ECUK (2014)

3.2.3 Other Factors

Internal room temperatures

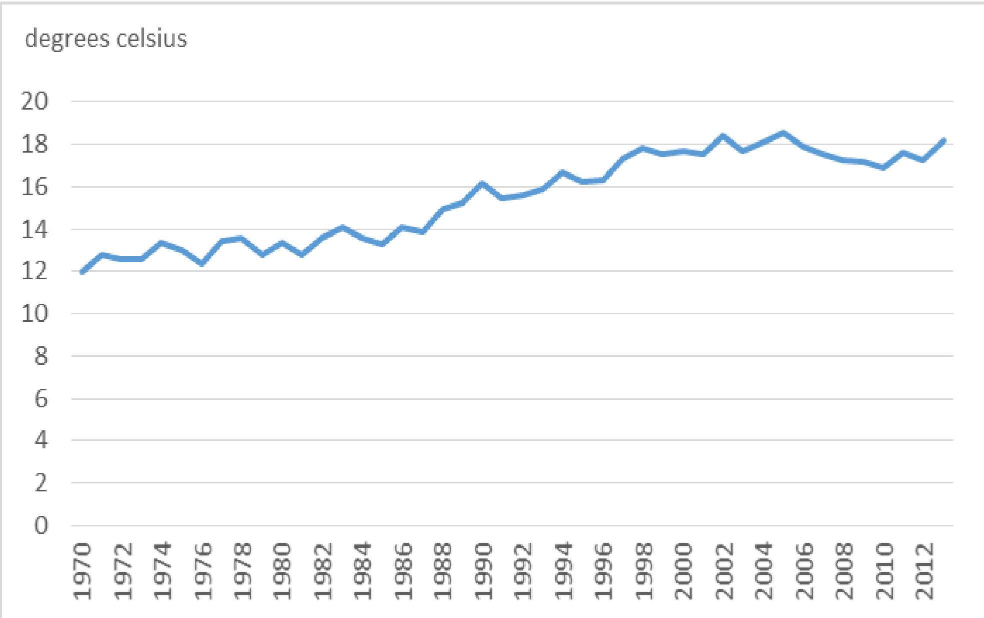
Data for the period 1970-2015, suggests a strong relationship between real income growth and increases in internal air temperatures (see Figure 3.6). However, it is noted that, despite a strong correlation evident in the past, average room temperatures have plateaued in recent years (as shown in Figure 3.7), even as real incomes have continued to grow.

Figure 3.6: Relationship between real incomes and internal room temperatures



Source: DECC ECUK (2014)

Figure 3.7: Historical trends in internal room temperatures



Source: DECC ECUK (2014)

If this recent stabilisation in room temperatures is a future trend that is not being picked up in our energy demand equations, we estimate that residential emissions arising from fossil fuel consumption could be over-estimated by 8.2 $MtCO_2$ by 2035. Emissions from the power sector that can be attributed to electricity required for residential heating could be over-estimated by up to 1.5 $MtCO_2$ by 2035.

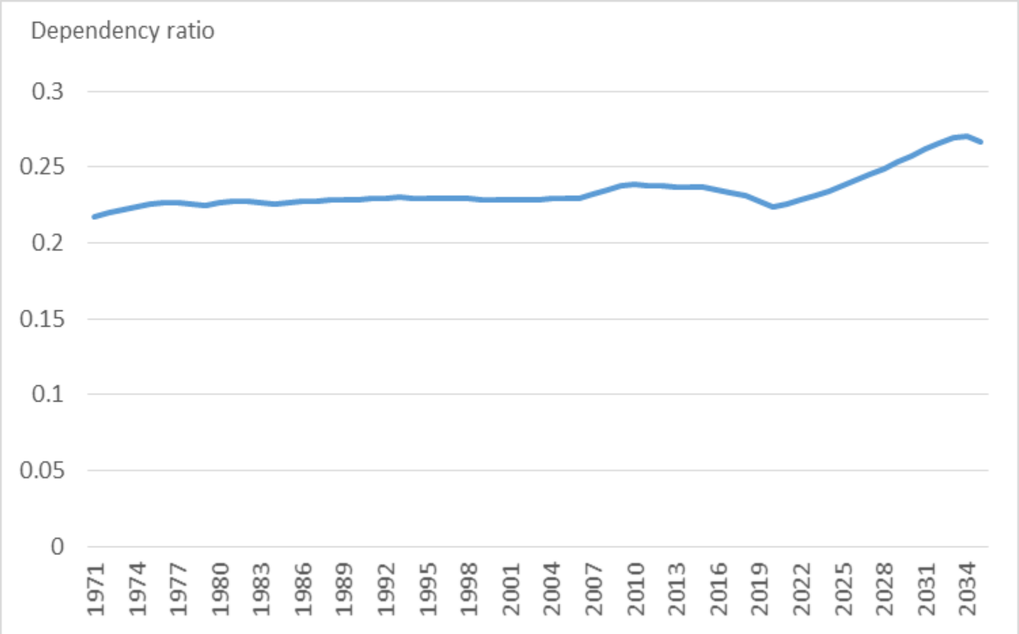
Heating and cooling

There is some data that has shown that households are heating their homes for shorter periods of time. This is particularly evident with an increasing proportion of women in work[9] and more time spent on out-of-home leisure activities. However, we would expect that this has been a gradual trend over the past 30-40 years and, therefore, we would expect this to be captured in our equations.

Demographic factors

The dependency ratio of the number of people of state pension age to the total population is expected to increase markedly from 2020 onwards (see Figure 3.8 below). According to the ONS, a retired person spends around 50% more on energy, on average, than a non-retired person[10].

Figure 3.8: Old age dependency ratio (ratio of population aged over 65 to working age population)



Source: ONS ‘Populations and Migration Projections’

The projections presented in Chapter 2 do not directly account for changes in demographic composition as presented above. Accounting for these trends could add 0.4 $MtCO_2$ to emissions from the power sector (due to increase in electricity consumption) and 0.9 $MtCO_2$ to emissions from the residential sector from increasing gas consumption.

[9] Dale Southerton (2015), ‘Behaviour Change Review’

[10] ONS (2014), ‘Household Energy Spending in the UK, 2002-2012’. Household energy spending figures have been adjusted to be on a comparable, per capita basis.

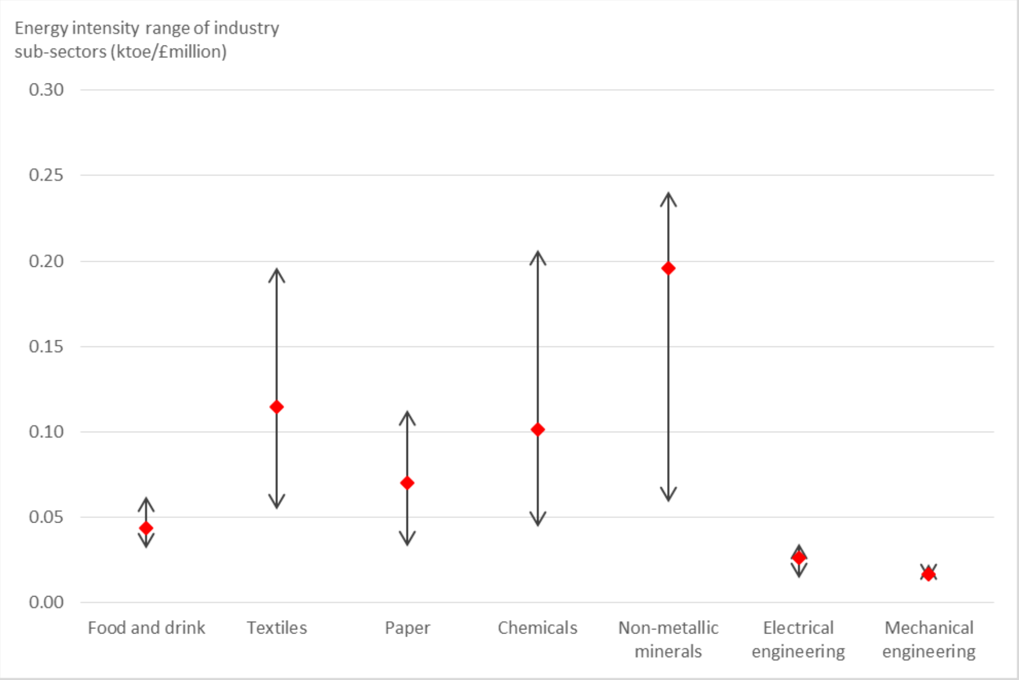
3.3 Trends in industry and service sectors

In industry and service sectors there are five key drivers of future energy demand:

- growth in real output (which is an explanatory variable in our estimated equations; uncertainty in the estimated relationship and the parameter are tested in Chapter 4)
- energy prices (which are also an explanatory variable in our estimated equations; uncertainty in the estimated relationship between energy demand and energy prices are also tested in Chapter 4)
- energy efficiency improvements due to policy-specific effects (which, by design, are not included in our baseline policy emissions projections)
- real accumulated investment and replacement of the energy-using capital stock (accounted for in our estimated equations)
- changes to the structure of industry (which are not necessarily accounted for in our framework)

In order to capture the effect of structural changes within an industry sector (e.g. strong growth in more energy-intensive food-processing activities, relative to the less energy-intensive sub sectors within the same industry), we looked at how energy intensity within an industry sector varies across sub-sectors (measured at the 4 digit level of detail). This is shown in Figure 3.9.

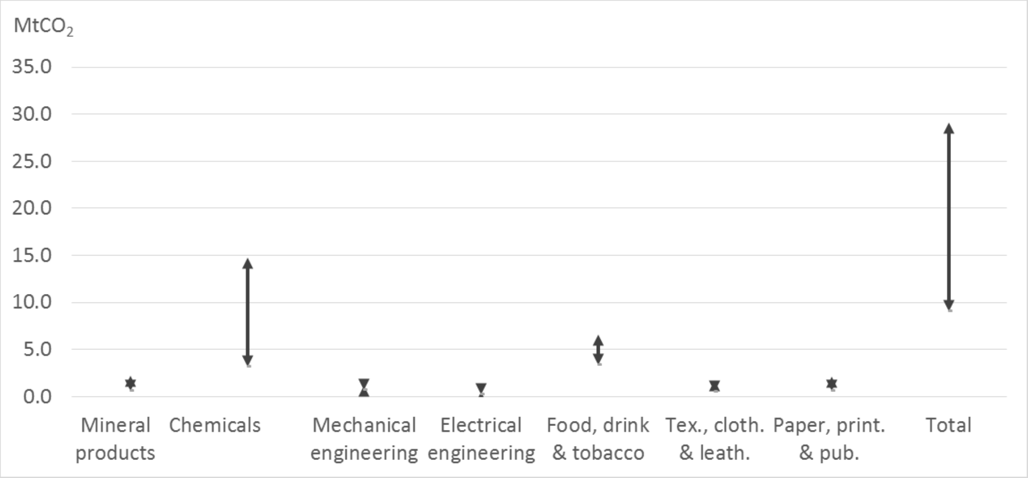
Figure 3.9: Energy intensity range of sub-sectors



Source: DECC (2014), 'Energy Consumption in the UK'; Eurostat 'Structural Business Statistics'

Whilst the structure of some industries at the 4-digit level consists of sub-sectors with similar energy intensity (eg engineering sectors), for other sectors (such as food and drink), there is a wide variation in the energy intensity of production. We estimated the impact on emissions if industry became more/less energy intensive, purely as a result of a change in the structure at the 4 digit level. To do this, we assess the impact on emissions of the average emissions intensity of the aggregate sector becoming that of the 75th percentile along the range of efficiency for each industry. This reflects plausible shifts in sector composition over a twenty year time horizon. Figure 3.10 shows the range of emissions projections depending on the structural composition of output for each sector in 2035.

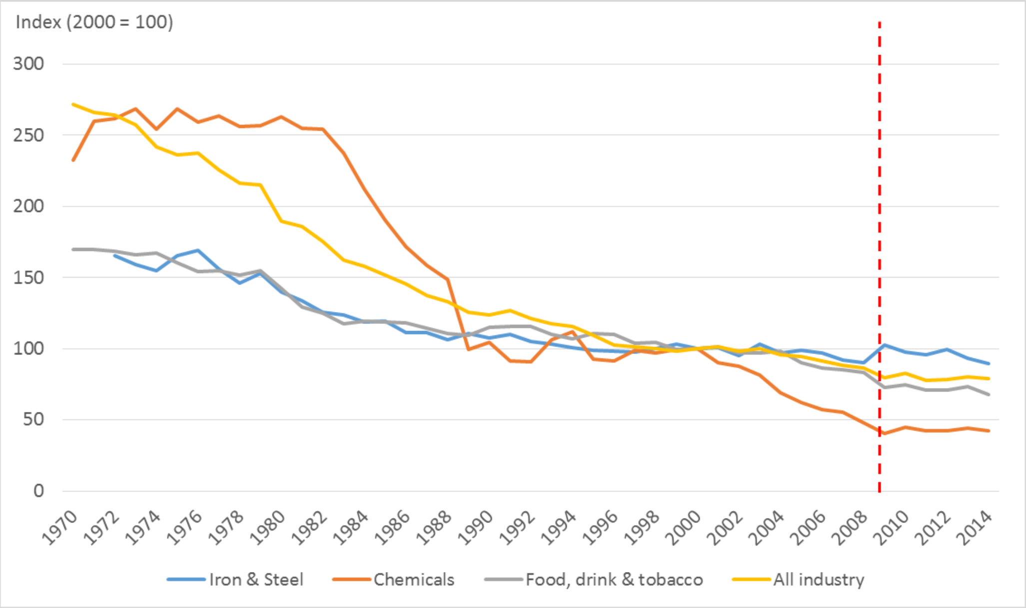
Figure 3.10: Industry emissions range uncertainty as a result of structural composition



Source: DECC (2014), 'Energy Consumption in the UK'

This idea could also be explored at a more detailed plant level. Following the 2009 recession, poor market prospects may have caused less efficient energy-intensive manufacturing plants to close down. It could therefore be argued that the energy-intensity of an average plant has fallen. In our equations, this would translate to a reduction in the coefficient on gross output. However, we looked at industry energy-intensity and despite a gradual efficiency improvement over the period 1970, we found no evidence of a structural break since the 2009 recession (see Figure 3.11).

Figure 3.11: Energy intensity trends in selected industries.



Source: DECC (2014), 'Energy Consumption in the UK'

To take account of the declining trend in energy intensity (as is evident from the chart above), we include real cumulative investment and R&D expenditure as a proxy for energy saving technical progress. This reflects replacement of old and inefficient capital stock.

We also considered trends in use of air conditioning due to global warming effects. To account for this, we included air temperature deviations as an explanatory variable in the model and tested the uncertainty around these temperature projections in Chapter 4.

Table 3.3 shows the trends that we considered and our estimate of the impact they could have on emissions arising from industry.

Table 3.3: Impact of recent trends in industry on central emissions projections

	Potential effect on emissions projections for 2035
Structure of industry sectors	
Change in the structure at the 4-digit level	+/- 6.9 $MtCO_2$ in industry emissions (due to changes in fossil fuel consumption) +/- 7.6 $MtCO_2$ in power sector emissions (due to changes in electricity consumption)
Total exogenous lower and upper bound adjustment to emissions in 2035	+/-14.5 $MtCO_2$ adjustment total emissions **Effect on total emissions uncertainty: +/- 3.3%**

3.4 Trends in transport sectors

The road transport sector accounts for over 90% of transport-related CO_2 emissions. For that reason, we focus on recent trends and expected future trends in road transport in this section of the report.

Specifically, we consider the effects of:

- changes in ownership and use of passenger cars
- potential efficiency improvements in the HGV sector

Comparing predicted and outturn data for the period 2008-2014 suggests that our top-down econometric approach is not a good predictor of energy demand from road transport: overall our equations over-estimate CO_2 emissions from road transport when compared to the DECC 'Baseline Policy' estimates over period 2009-2014. This is likely to be partly because our estimated equations do not take account of recent changes to trends in the use of passenger cars but also because they do not predict the gradual increase in sales of diesel cars relative to petrol cars.

Trends in car usage and car ownership

Our top-down road transport energy demand projections could be improved by using the most recent data and projections about car ownership and car usage. Using a vehicle stock model, we can account for changes to car ownership and trip demand due to factors such as:

- more home working
- car sharing schemes
- modal shift towards rail/bicycle
- telecommunication improvements (eg internet shopping, teleconferencing) replacing the need for people to travel
- increase in proportion of households living in urban areas

To put an upper and lower bound on passenger car emissions, we tested sensitivities in our vehicle stock model, based on scenarios published by the Department for Transport[11].

The Department for Transport published five road transport scenarios in which assumptions about trip rates, income elasticity of demand for car use and macroeconomic factors are varied. In all five scenarios, the number of cars in the vehicle stock increases, due to an expected increase in the population. However, projections for the number of passenger cars in the stock and the average distance travelled by passenger cars varies substantially between scenarios. We tested two sensitivities, based on the extreme range for vehicle sales growth and distance travelled from Department for Transport scenarios. Our high sensitivity assumes high sales growth and a high estimate for trip rates. We also tested a low sensitivity, where sales growth and trip demand were at the lower extremes of the Department for Transport scenarios. Information about the assumptions in the high and low sensitivity are shown in Table 3.4.

Table 3.4 Characteristics of the vehicle stock in the 'high demand' and 'low demand' sensitivities

	High Sensitivity	Low Sensitivity
Growth in average distance travelled (2015-2035)	10%	-10%
Growth in vehicle sales (2015-2035)	41%	21%
Growth in vehicle stock (2015-2035)	21%	14%

Source: Cambridge Econometrics, based on ranges from the Department for Transport Road Traffic Forecasts 2015

For the vehicle stock modelling, we also assumed that the share of petrol relative to diesel cars in the sales mix remained at 2015 levels. When compared to our central road transport demand projections, these sensitivities indicate a range of uncertainty on that estimate of between -24.8 $MtCO_2$ to +4.1 $MtCO_2$ by 2035.

Vehicle efficiency

Over recent decades there has been a gradual improvement in the efficiency of vehicles. In 1998, the EU introduced voluntary emissions standards for passenger cars and data shows that there have been some improvements to test-cycle efficiency since this date[12]. However, recent studies have suggested that much of this efficiency improvement is not a real-world effect but an improvement to test cycle emissions, as manufacturers improve the

[11] Department for Transport, 'Road Traffic Forecasts 2015'

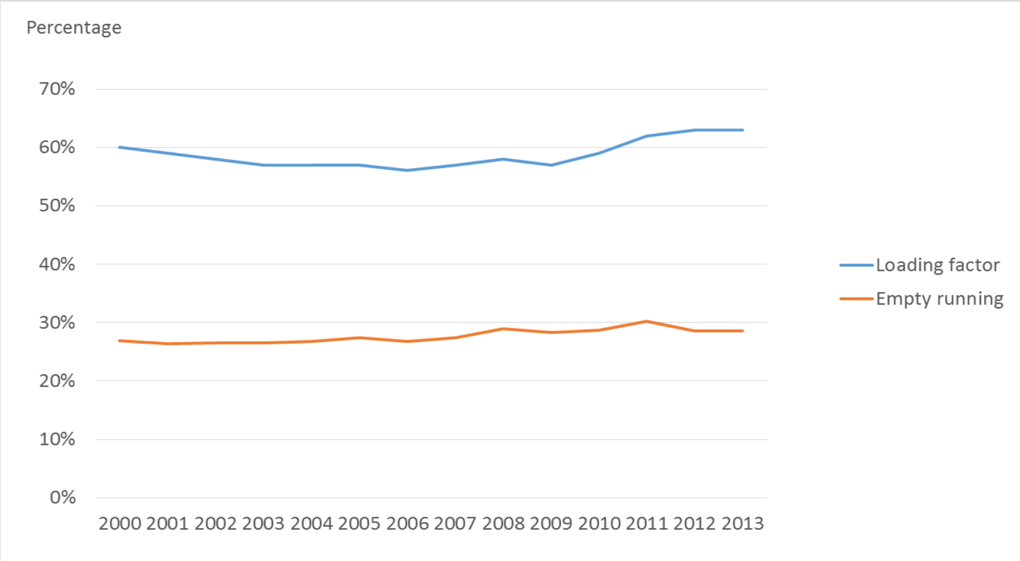
[12] ICCT Pocketbook

emissions-performance of vehicles on the test-track[13]. In 2009, a mandatory 2015 target of 130 gCO_2/km was introduced for the European car fleet. This was extended in 2013 when the 95 gCO_2/km emissions standards for 2020 were agreed and passed by the European Parliament. These emissions standards are likely to have a more significant effect on energy demand and emissions from cars, but these should not be taken account of in our baseline projections (which only account for policies that existed before 2009). Due to insufficient evidence of a change in the rate of vehicle fuel-efficiency improvements in the period prior to the 2009 Low Carbon Transition Plan, we did not make an exogenous adjustment to account for this trend.

HGV efficiency improvements

Data from the department for transport suggests a mild improvement in the loading factor for rigid and articulated vehicles in recent years. This is particularly evident in the period since the 2009 recession, as firms began to make cost savings and efficiency improvements. It is not obvious whether this efficiency improvement will continue but, as a lower-bound estimate on our transport emissions projections, we quantified the effect if HDVs were 5% more efficient (due to improved logistics) compared to that implied by our central energy demand estimates. We found that this scale of efficiency improvements could lead to a 2.8 $MtCO_2$ reduction in our emissions estimates for 2035.

Figure 3.12: Recent changes to the average loading factor and empty running of HDVs



Source: Department for Transport (2015), 'Road Freight Statistics'

Table 3.5 summarises the results for the recent and future trends analysis for the transport sector. We find the potential future trends identified in the road transport sector put an uncertainty bound on our central transport emissions projections of -27.6 $MtCO_2$ to +4.1 $MtCO_2$.

[13] ICCT, Element Energy, 'Quantifying the impact of real-world driving on total CO2 emissions from UK cars and vans'

Table 3.5: Impact of recent trends in transport on the central emissions projection

	Potential effect on emissions projections for 2035
Saturation of road transport and potential reduction in trip demand	-24.8 $MtCO_2$ to +4.1 $MtCO_2$ due to different activity assumptions in the car stock
Improved logistics in the HDV sector	-2.8 $MtCO_2$ due to a reduction in HDV fuel consumption
Total exogenous lower and upper bound adjustment to emissions in 2035	-27.6 $MtCO_2$ to +4.1 $MtCO_2$ adjustment to road transport emissions **Effect on total emissions uncertainty:** **-6.3% to + 0.9%**

3.5 Summary of recent trends

On balance, we find that the recent and expected future trends identified above define an uncertainty range around our central emissions projections of between -13.5% and +4.5% (see Table 3.6).

Table 3.6: Impact of recent trends on central CO_2 emissions in 2035

	Potential effect on emissions projections for 2035
Trends in the residential sector	-6.6 $MtCO_2$ to +0.4 $MtCO_2$ adjustment to power sector emissions -10.4 $MtCO_2$ to +0.9 $MtCO_2$ adjustment to residential emissions **Effect on total emissions uncertainty:** **-3.9% to +0.2%**
Trends in the industry sector	+/-14.5 $MtCO_2$ adjustment total emissions **Effect on total emissions uncertainty:** **+/- 3.3%**
Trends in the transport sector	-27.6 $MtCO_2$ to + 4.1 $MtCO_2$ adjustment to road transport emissions **Effect on total emissions uncertainty:** **-6.3% to + 0.9%**
Total uncertainty range to CO_2 emissions in 2035	-59.1 $MtCO_2$ to + 19.9 $MtCO_2$ adjustment to total CO_2 emissions **Effect on total emissions uncertainty:** **-13.5% to + 4.5%**

4 Uncertainty Analysis

In addition to our central energy demand and emissions projections, we undertook several sensitivity analyses in order to quantify the underlying uncertainty around those projections. We focussed on four different sources of uncertainty:

- uncertainty due to historical data inaccuracies (Section 4.1), which could affect the starting point for our emissions projections
- uncertainty of a point forecast attributable to the unexplained random noise (error term) in each equation (Section 4.2)
- uncertainty around the exogenous input projections (Section 4.3) for key drivers of fuel demand (including economic activity, energy prices and temperature, which are the key explanatory variables in our fuel demand equations)
- econometric uncertainty reflected in the estimated confidence intervals around our equation parameters (Section 4.4)

We combined the latter two sources of uncertainty to derive an estimate of total uncertainty from those two sources (Section 4.5).

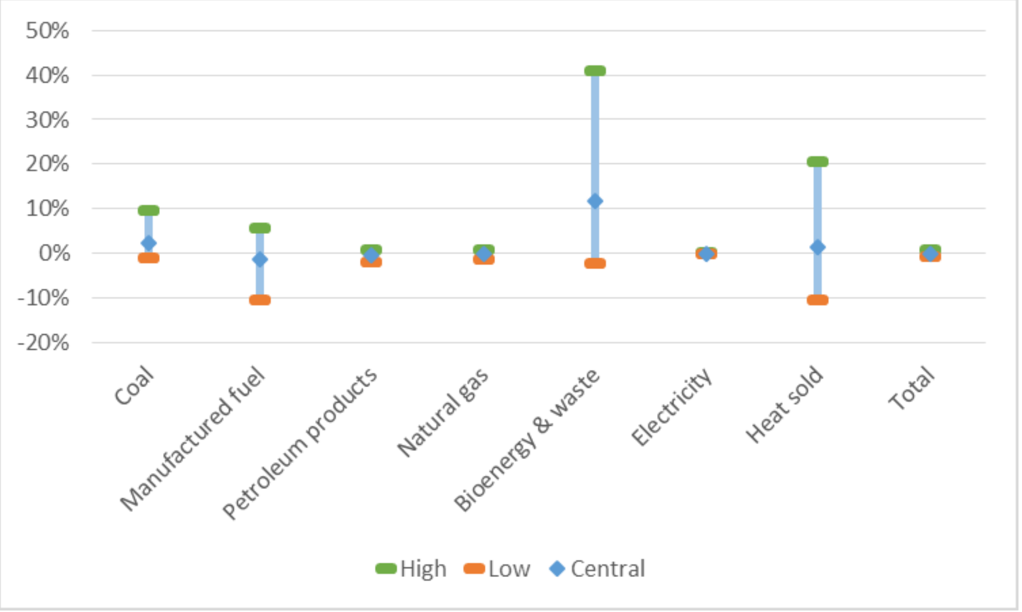
In order to quantify the various sources of uncertainty, we carry out a Monte Carlo simulation. To do so, we run the model thousands of times, each iteration varying our inputs and parameters within plausible ranges. Running the model thousands of times allows us to capture uncertainty stemming from these alternate runs as it translates to multiple sets of model outputs. This way we get a large number possible projections that can be used to form prediction intervals around the baseline view.

By calculating empirical prediction intervals of these model outcomes, we can quantify the range of this impact. We present the results in fan charts, where the solid line represent our baseline run and shaded areas around it represent the 30%, 60% and 95% confidence intervals.

4.1 Uncertainty derived from recent data revisions

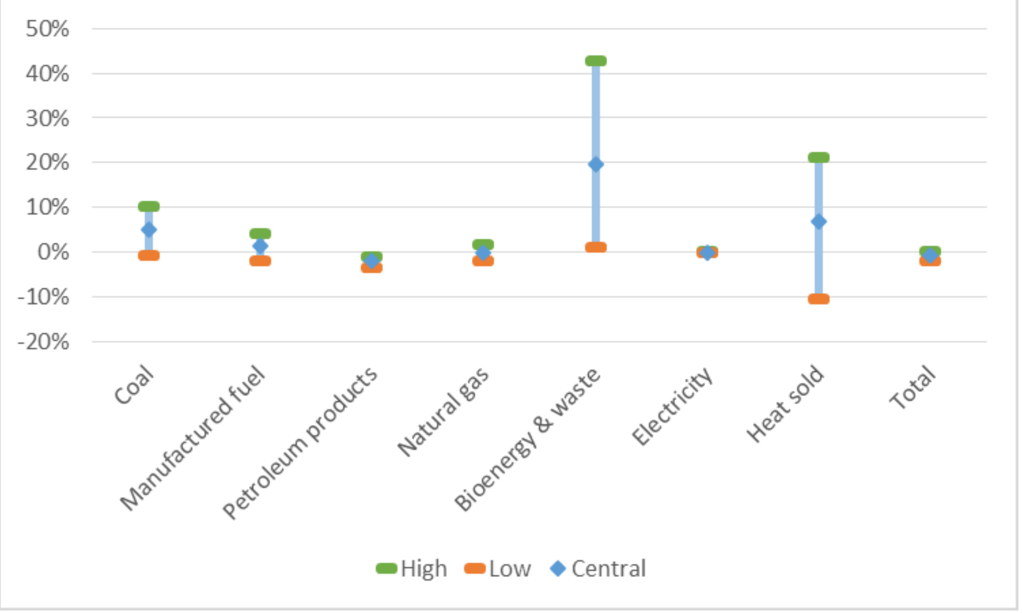
In order to measure the impact of revisions to historical energy demand data, we collated the most recent eight publications of the Digest of UK Energy Statistics (DUKES) and compared energy demand data corresponding to the same year across successive DUKES editions. This allowed us to measure the degree to which data have been revised over a period of up to eight years after being first published.

Figure 4.1: Range of revisions to DUKES historical data after one year, by fuel



Source: DECC, 'Digest of UK Energy Statistics'

Figure 4.2: Range of revisions to DUKES historical data after four years, by fuel



Source: DECC, 'Digest of UK Energy Statistics'

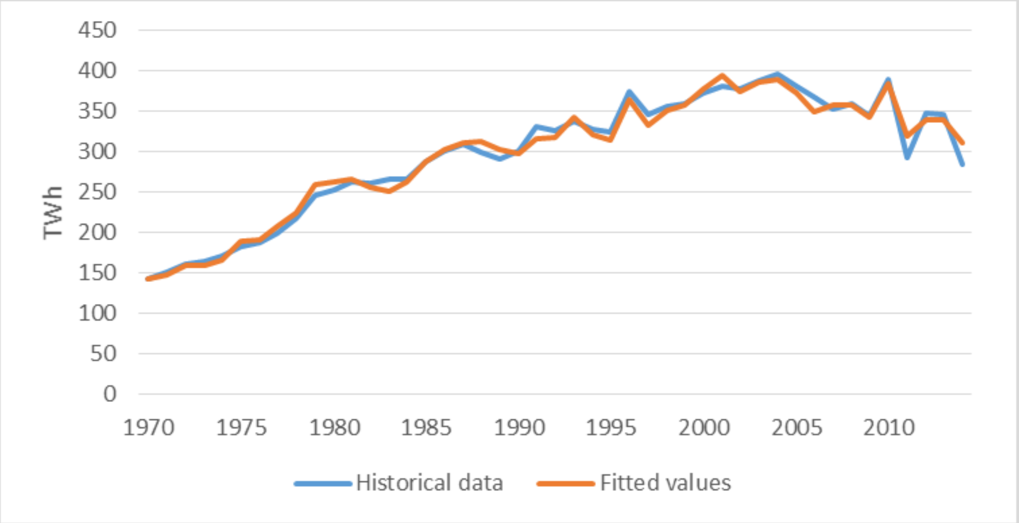
We found that the largest revisions to the energy demand data tended to occur in the year immediately after first publication. Revisions to data in the three subsequent years combined were smaller, on average. Revisions to the historical data in the year following first publication and four years after fist publication are shown in Figure 4.1 and Figure 4.2, respectively. There is little difference between the two charts, reflecting that most of the revisions occur in the first year after initial publication.

We observe that data for fuels where final consumption is metered (eg gas and electricity) is not substantially revised in successive publications of DUKES. Conversely, solid fuels revisions tend to be sizeable in both upwards and downwards direction.

4.2 Forecast error

For each equation explaining energy demand for a given sector and fuel there is an error term in each year. The error represents the part of the data not explained by the equation: the random noise. Figure 4.3 below shows the fitted (modelled) estimate for residential gas demand compared to the actual data. The error is the difference between the two series in any given year and over the historical period should have a mean of zero and be normally distributed.

Figure 4.3: Comparing historical data and fitted values for residential gas demand

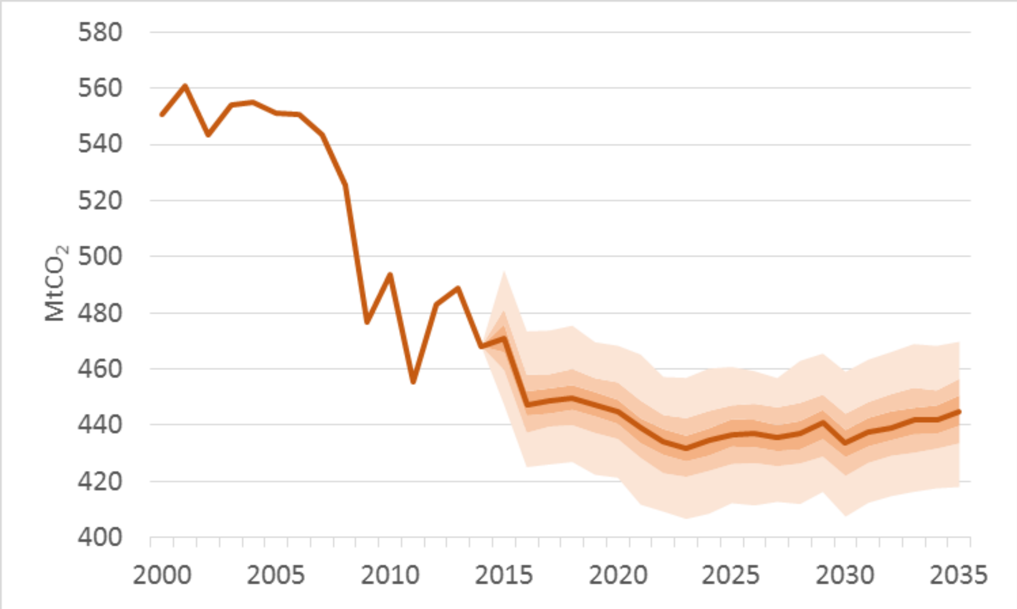


Source: DECC, 'Digest of UK Energy Statistics', Cambridge Econometrics

In a trend analysis, the uncertainty caused by random noise over the projection period would also be expected to average out to zero. However, in any given year there could clearly be an error. By calculating the distribution of the error term it is possible to generate an uncertainty range for each sector and each year. In total we estimate that for any individual year, the range of accurate prediction is +-6% for a 95% confidence interval. The uncertainty range over a carbon budget period is slightly lower (-4.6% to +4.0%) and is asymmetric due to the log-normal distribution of the error term. This is the uncertainty bound even assuming that the model is correctly specified and the input drivers are known.

Correct interpretation of this source of uncertainty is imperative: unlike the input and parameter uncertainty presented in the next sections, the range presented in Figure 4.4 is the range of uncertainty for each year (individually) of random noise. The uncertainty outcomes from year to year are not correlated.

Figure 4.4: Uncertainty range of model error for each year in the projection



Source: Cambridge Econometrics

4.3 Uncertainty analysis on input variables

To understand the uncertainty in emissions projections that arises from not knowing how drivers of emissions will develop in the future, we undertook a combined Monte Carlo simulation around the three main input drivers in our model of energy demand:

- economic activity
- energy prices
- external air temperature

The analysis does not consider the full range of uncertainty associated with short term volatility but instead focusses on developing uncertainty around long term trends. For each variable we define a central, high and low projection and fit a distribution around the central series with the high/low outcomes in the tails. We then draw from these distributions for a Monte Carlo simulation

Economic activity

The range of economic output is defined by looking at the rolling long-term twenty year average growth rates over the historical period. The range between the minimum and maximum twenty year average is then centred on the long-term central economic projection based on a projection from the Office for Budget Responsibility (OBR) with a normal distribution. The 95% confidence interval captures the range between the minimum and maximum growth rates. The range of annual growth rates that are applied to the central projection for each sector are shown in Table 4.1.

For GDP, the scenarios capture an increase over the period 2015-2035 of between 40% and 80%. In the Monte Carlo each sector is modelled collectively (so the lower bound is applied for all sectors) rather than modelling different combinations for each sector.

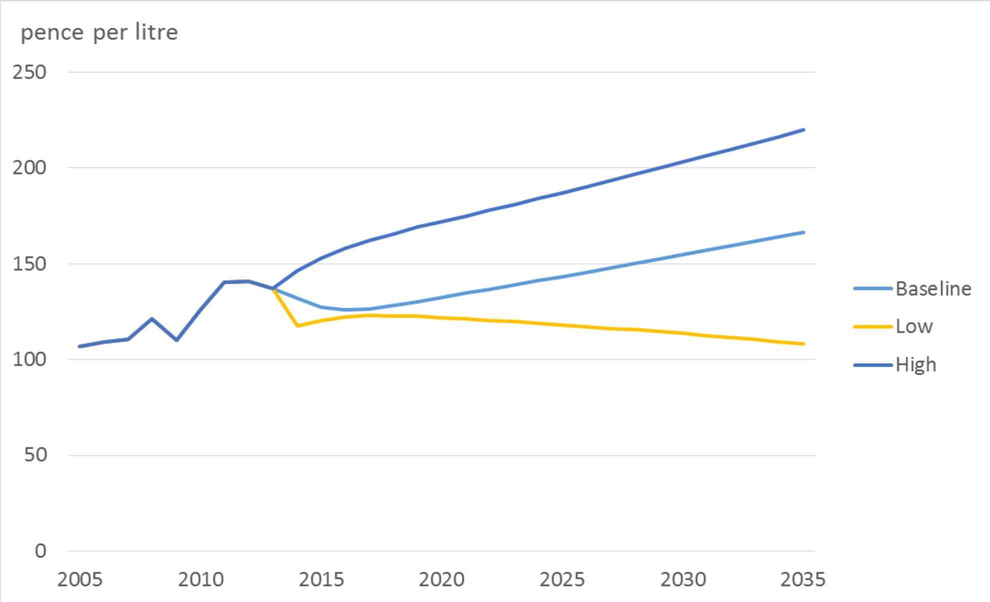
Table 4.1: Economic output projections (long term annual average growth rates)

	Central	High	Low
Industry			
Iron & steel	-1.0%	-0.1%	-1.5%
Non-ferrous metals	-1.0%	-0.1%	-1.5%
Mineral products	0.3%	1.1%	-0.3%
Chemicals	0.0%	0.8%	-0.6%
Mechanical engineering	1.1%	1.9%	0.5%
Electrical engineering	0.7%	1.5%	0.2%
Vehicles	1.8%	2.6%	1.2%
Food, drink & tobacco	0.9%	1.7%	0.4%
Tex., cloth. & leath.	-2.3%	-1.4%	-2.9%
Paper, print. & pub.	-0.3%	0.6%	-0.8%
Other industries	1.0%	1.8%	0.5%
Construction	2.4%	3.2%	1.9%
Transport			
Air	1.0%	1.8%	0.5%
Rail	1.9%	2.6%	1.3%
Road (GDP plus imports)	2.4%	3.2%	1.9%
Water	2.8%	3.5%	2.2%
Other final users			
Domestic (Disposable Income)	2.2%	3.0%	1.7%
Public administration	0.0%	0.8%	-0.6%
Commercial	3.2%	4.0%	2.7%
Agriculture	2.4%	3.1%	1.8%
Miscellaneous	2.6%	3.4%	2.1%
GDP	2.3%	3.1%	1.7%

Energy prices

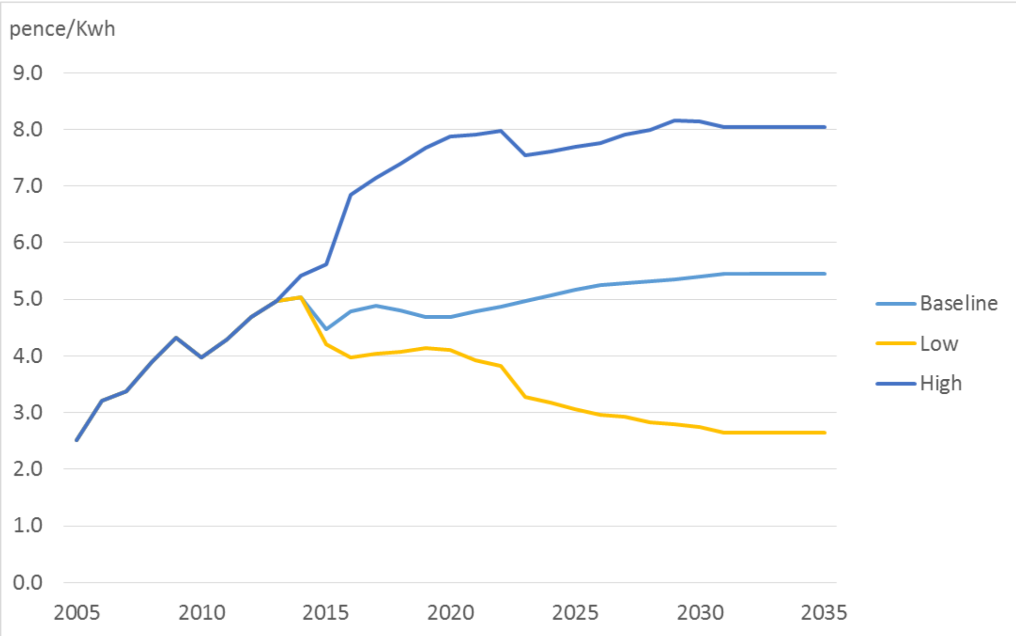
Energy prices are taken from the 2014 release of 'Updated Energy and Emissions Projections' (UEP) by DECC. To develop an input distribution, we assume that the high and low projections each represent one standard deviation around the mean (central) projections. The distribution applied in the modelling is then drawn from the 95% confidence interval (two standard deviations either side of the mean). Figure 4.5 to Figure 4.7 show the range of inputs analysed for selected fuels.

Figure 4.5 Petrol prices (pence per litre)



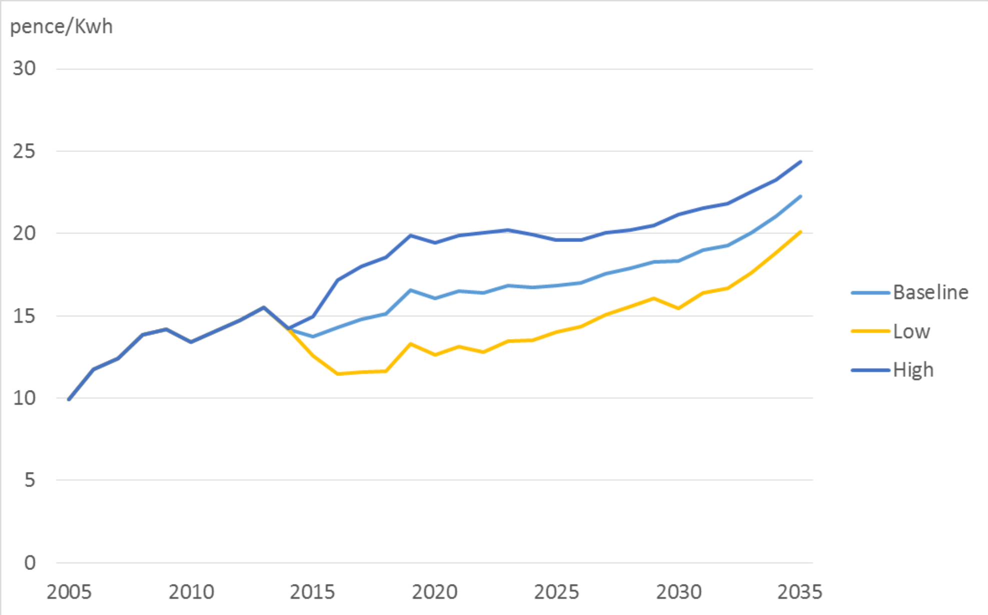
Source: DECC (2014), 'Updated Energy and Emissions Projections'

Figure 4.6: Residential gas price range (p/kWh)



Source: DECC (2014), 'Updated Energy and Emissions Projections'

Figure 4.7: Residential electricity price range (p/kWh)



Source: DECC (2014), 'Updated Energy and Emissions Projections'

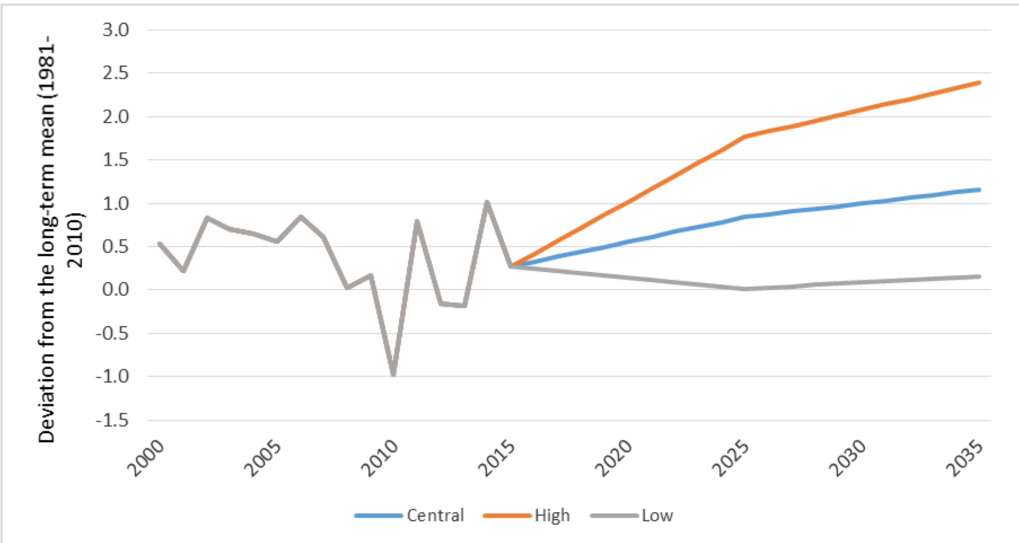
Note that although the range is wide in the long term, the short term uncertainty range of DECC's prices even extended by an additional standard deviation from the central view do not capture the current price of petrol.

Air temperature

Long term temperature changes are calculated from the UKCP09 climate projections. These contain a large number of scenarios with confidence bands on each, further disaggregated on a regional basis.

We take the low, medium and high emissions scenarios from the UKCP09 to inform the range of temperature projections. The regional series are weighted by population to arrive at national averages and then calibrated to the historical time series (see Figure 4.8).

Figure 4.8: Air temperature input uncertainty range

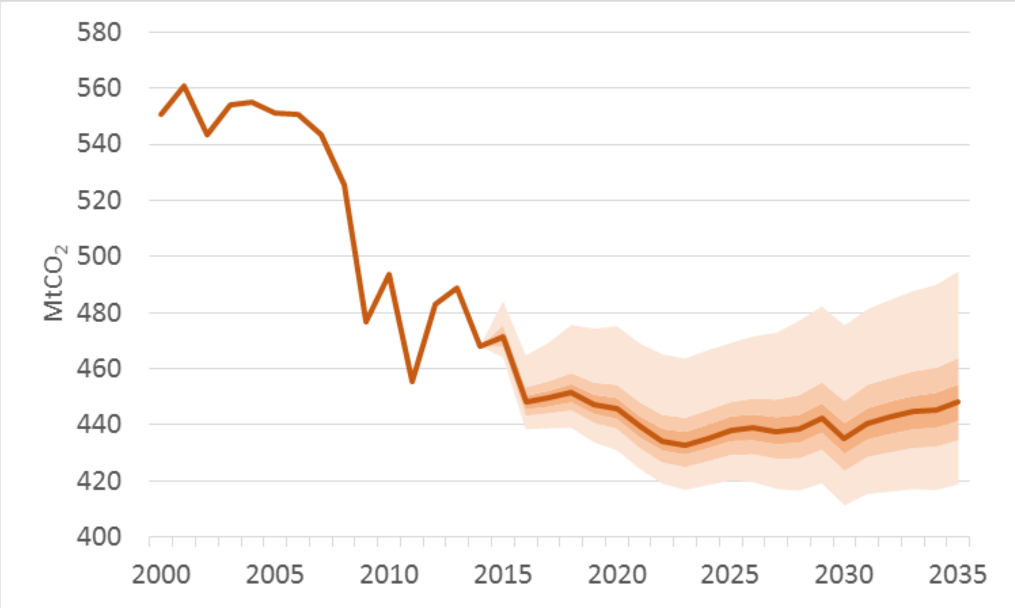


Source: Met Office UKCP09 climate projections; own calculations

The historical temperature data is taken as the deviation from the long-term mean, defined as 1981-2010 (see DECC ‘Energy Trends’ publication).

The range of uncertainty around the long-run input assumptions is narrow. We find that the uncertainty range for the 95% confidence interval around total CO_2 emissions is between -6.7% and +10.4% by 2035 (see Figure 4.9).

Figure 4.9: Uncertainty range from variation in exogenous input assumptions



Source: Cambridge Econometrics

DECC also undertakes an input uncertainty analysis of its emissions projections. The input uncertainty ranges between our analysis and DECC are however not directly comparable.

- DECC applies uncertainty ranges for policy as well as economic activity, prices and temperature
- DECC assumes a narrower range around the long term plausibility of economic activity, defining the long term annual average GDP growth to have an uncertainty range of +-0.3pp (compared to +-0.6pp which the history suggests is plausible even over a 20 year period).
- DECC assumes a narrower range around the long term uncertainty of energy prices, defining the 95% confidence interval between the high and low projections (rather than the 68% confidence interval)
- DECC models changes to the power sector and refining, whereas our projections assume a fixed (baseline) emissions coefficient for the power sector (so that total emissions from the power sector increase and decrease in proportion to changes demand for electricity) and fixed total emissions for refining and energy extraction.

However, the results are broadly comparable for the non-traded sector, after narrowing the distribution for energy prices to be consistent with DECC (see Table 4.2). Our uncertainty range (between +5% and -4%) remains narrower than DECC’s (+6% and -8%), which implies that the elasticities (responsiveness) of the CE model are smaller (in absolute terms) than the DECC elasticities on a weighted average basis.

Table 4.2: Comparison of DECC and CE input uncertainty (price range adjusted)

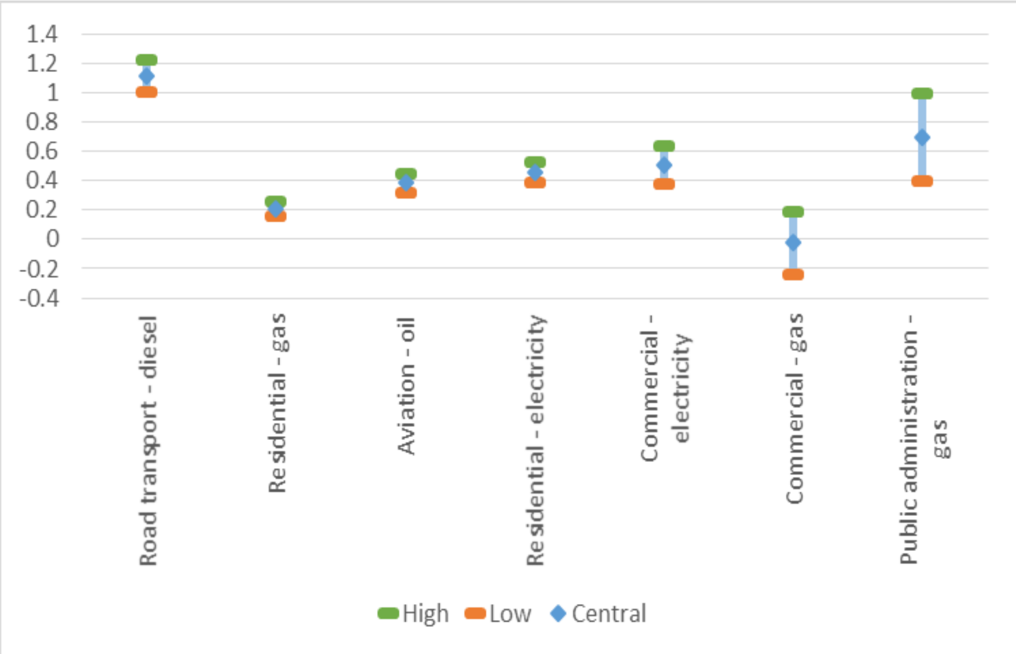
		DECC			CE		
		Carbon Budget Period			Carbon Budget Period		
		2	3	4	2	3	4
Traded	Low	93%	88%	87%	100%	98%	98%
	Central	100%	100%	100%	100%	100%	100%
	High	103%	109%	113%	101%	102%	103%
Non-traded	Low	98%	95%	92%	99%	97%	96%
	Central	100%	100%	100%	100%	100%	100%
	High	102%	104%	106%	101%	104%	105%

4.4 Uncertainty in estimated equation parameters

The econometric design of our model lends itself to undertaking an uncertainty analysis of the model parameters. The standard errors for the estimated long-run parameters define a confidence interval that can be applied in a Monte Carlo sensitivity analysis.

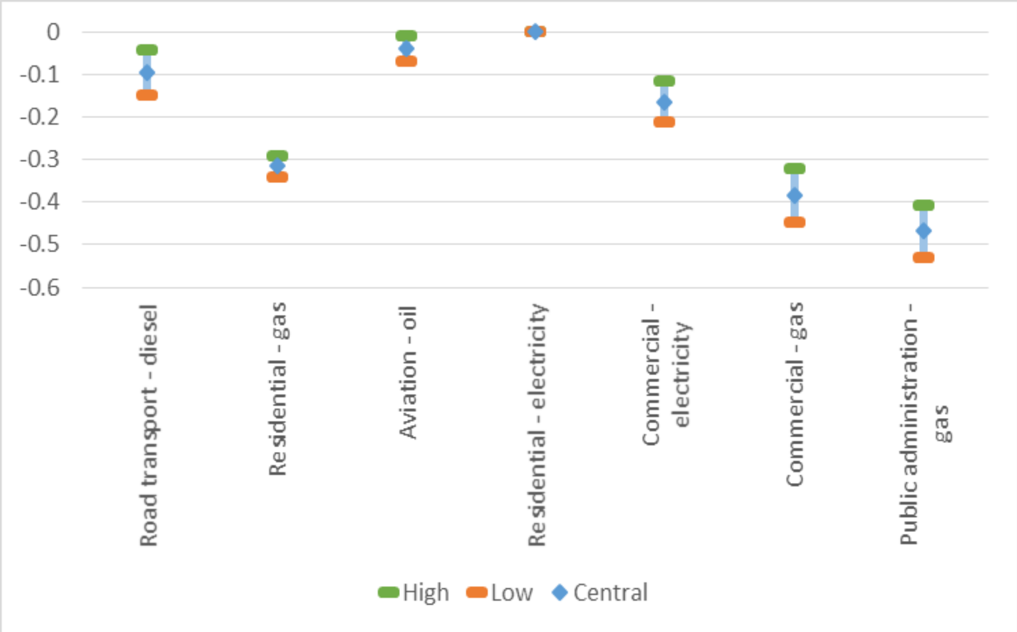
Figure 4.10 and Figure 4.11 show the uncertainty range around income/economic output and price elasticities for selected sectors and fuels, respectively. For the most part these are narrow, reflecting the statistical significance of the model parameters.

Figure 4.10: Uncertainty in output/Income elasticity of demand



Source: Cambridge Econometrics

Figure 4.11: Uncertainty in price elasticity of demand

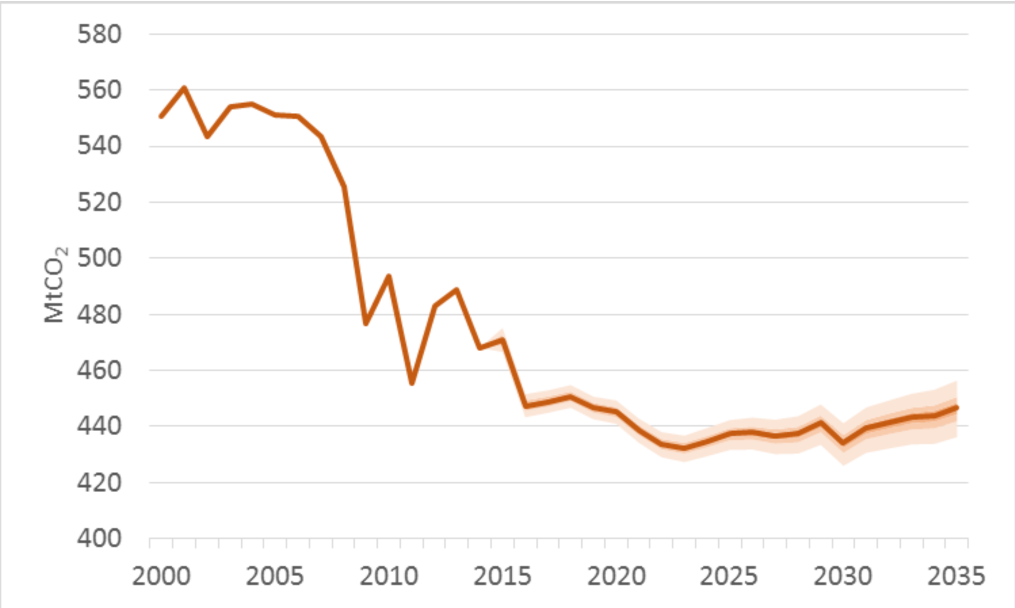


Source: Cambridge Econometrics

By accounting for the covariance between parameters, we then construct a joint distribution, from which we draw alternative parameters for our model runs. This is done to account for the interrelationships between the estimated parameters, to limit the scope of variation to plausible combinations.

As a result of the tightly bound long term elasticities and allowing for the covariance between parameters, the long-run parameter uncertainty for the model is very narrow (see Figure 4.12)

Figure 4.12: Uncertainty range from variation in exogenous input assumptions



Source: Cambridge Econometrics

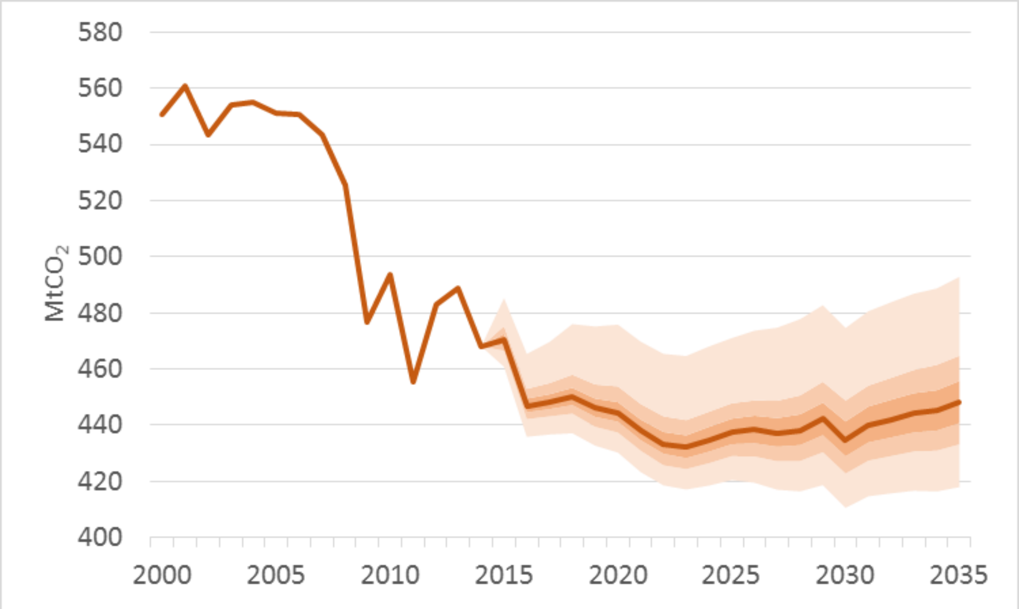
4.5 Combining quantified sources of uncertainty

Sensitivities on parameters and input data measure different sources of uncertainty. To calculate the total uncertainty from combining input *and* parameter uncertainty, it is important to take account of the joint distribution between the different sensitivities that are being tested. For this reason, it is not possible to directly obtain the overall measure of uncertainty from the two individual analyses. Instead it is necessary to undertake a combined Monte Carlo simulation where both the equation parameters and the exogenous inputs are varied to arrive at prediction intervals that account for both sources of uncertainty.

After taking account of the joint distribution of the parameter estimates and input projections, the resulting uncertainty range is slightly wider than the ranges found by varying parameters and inputs separately, but not as wide as the respective low-low and high-high combinations (because the probability of the combination of those events is 0.025*0.025).

By 2035, we find a combined range of parameter and input uncertainty of between +6.8% and -4.6% for traded sector CO_2 emissions and between +13.5% and -9.7%for non-traded sector CO_2 emissions. For total CO_2 emissions, the range is slightly narrower (between +10.0% and -6.7%, see Figure 4.13) because the probability of selecting the lowest traded sector emissions and the lowest non-traded sector emissions in combination falls outside the 95% confidence interval.

Figure 4.13: Combined parameter and input uncertainty



Source: Cambridge Econometrics

5 Concluding remarks

5.1 Summary of findings

In this analysis we have investigated different forms of uncertainty arising from:

- model design and specification
- recent and future trends that are not taken account of in our econometrically-estimated equations
- statistical characteristics of the model, including the error term, the model parameters, and the model inputs

DECC's central baseline projection of emissions vary from those presented in Chapter 2, with the fairly obvious implication that projections and, indeed, uncertainty analysis for a given model depend upon the model design and specification. Given the broad similarity between the DECC Energy Demand Model and the approach we applied (based on the MDM-E3 model) and the data used by both models, it is not surprising that the results are broadly similar. However, this provides only limited confidence for interpreting the robustness of the projections, as there are considerable deviations between some sectors (such as road transport). In aggregate these net out to only relative small differences in total CO_2 emissions. Ideally, a wider range of modelling approaches would be compared to allow for a more sophisticated interpretation of differences in the projected trends.

The analysis of recent trends highlights a broad range of uncertainty that could arise from a set of possible recent trends identified in the literature and potentially not captured by the modelling approach applied:

- Residential energy demand
  - changes to the composition of the future housing stock
  - changes to the use and purchase of appliances
  - stabilisation of desired room temperatures
  - demographic factors
- Industrial energy demand
  - changes in energy intensity as a result of changing structural composition of industries
- Road transport energy demand
  - changes in car ownership and trip demand
  - improved logistics in the heavy goods vehicles sector

Taken together, we estimate that by 2035 these factors could lead to total CO_2 emissions being between 13.5% lower and 4.5% higher.

The statistical uncertainty in the model demonstrated a relatively narrow range: in combination, the parameter and input uncertainty suggested a 95% confidence interval between +10% and -6.7% of the central emissions projection. However, the assessment of the equation error suggested that, for any single year, the estimate for total emissions could be out by +/-6%, even if the forward-looking input drivers to the equations were known with perfect certainty. The uncertainty range over a carbon budget period is slightly lower (-4.6% to +4.0%) and is asymmetric due to the log-normal distribution of the error term.

Total emissions uncertainty for the economy as a whole is lower than if you simply aggregated levels of uncertainty estimated across individual sectors. This is because, when sectors are combined, the likelihood of conditions leading to the lowest/highest emissions for multiple sectors actually occurring is less than for each sector individually.

There is a valid question about the degree to which the uncertainty of recent trends can be combined with the statistical uncertainty in the model. On the one hand, it could be argued that the uncertainty of recent trends not captured by the central projection would be captured, to some degree, in the uncertainty analysis on parameter estimates and input projections. For example, energy demand from lighting might be reaching saturation, and this is not captured in the central projection, but the effect on energy demand for lighting could be implicitly captured in a world with a lower income elasticity (parameter uncertainty) or a future with low incomes and high electricity prices (input uncertainty). On the other hand, it could be argued that the two types of uncertainties are independent: in the example, energy demand for lighting is saturated regardless of income and price projections and hence the uncertainty ranges can be combined.

Assuming that the two sources of uncertainty analysed are independent, the combined range of uncertainty in our projections to be between +15.0% and -19.3% by 2035 (a range of 34.3%, 153MtCO_2 pa).

5.2 Considering uncertainty

Overall, even if the uncertainty range of recent trends is considered wholly independent of the statistical uncertainty, the range of long-term emissions projections presented might be considered relatively narrow. This range is predominantly a function of the following factors:

- relatively few recent trends have been identified and fewer still are considered quantifiable
- the statistical characteristics of the model; in the CE model the long term elasticities (parameters) are often small and even more often have extremely small standard deviations (they are highly significant)
- input range assumptions: the uncertainty in the projections reflects assumptions about the projected uncertainty of the inputs. Although expert judgement has been applied to define these ranges and/or they have been defined by external projections from DECC or the Met Office, it is clearly possible that economic activity, energy prices or temperature could all fall outside the projected long term ranges

In addition to the input and parameter uncertainty and the extent to which the model captures recent trends, in any given year the analysis suggests that the factors unexplained in the model empirically could account for between +/- 6 % in any given year around the projections.

Beyond the quantifiable uncertainty considered in this report, there is clearly also an inexhaustible list of fairly unpredictable and unquantifiable uncertainty that would have an unknown impact. This could include:

- disruptive technological breakthrough
- behavioural change
- geo-political shocks with long-lived consequences
- persistent economic crises

A common mis-interpretation of quantified uncertainty analysis is that it is deemed to represent the entire range of uncertainty and therefore outturn emissions must fall within the range, rather than a conditional range of uncertainty defined by the modelling and analytical inputs.

5.3 Implications for setting carbon budgets

The research was motivated by a requirement to quantify uncertainty around emissions projections, to better inform the approach for setting carbon budgets and interpreting whether policies are in place to allow the UK to meet its carbon budgets or whether there is a policy gap.

Projections of energy consumption and greenhouse gas emissions are key pieces of information used to set carbon budgets. However, if projections vary greatly from one year to the next then the usefulness of such projections is diminished. If, for non-policy reasons, realised greenhouse gas emissions turn out to be much higher than projected greenhouse emissions then there is an implied larger policy burden to meet carbon budgets. In contrast, if realised greenhouse gas emissions are much lower than projected emissions, there is a risk that policies put in place have been overly burdensome and could have been relaxed.

The uncertainty analysis presented in this report focusses on the uncertainty around a baseline emissions projections which exclude the impacts of new policies. This is consistent with the approach to informing carbon budgets, which is to:

1) Develop a baseline that (broadly) excludes carbon abatement policies
2) Quantify the impacts of policies in place (and proposed)
3) Determine whether there is, and the scale of, a policy gap between projected emissions (allowing for proposed policy) and the proposed carbon budgets

However, in the future, as policy to reduce greenhouse gas emissions becomes the norm, it becomes ever more questionable as to whether this approach remains valid:

1) Do the statistical parameters associated with the baseline remain valid in the projection period? As projections move on from year to year, how can empirical/econometric models, which become inherent in decision making, exclude the impacts of policy?
2) To what extent do technology, behaviour and policy interact and how does this affect the uncertainty range?

As policy to reduce greenhouse gas emissions becomes embedded in the day-to-day decisions made across all aspects of society in relation to investments in technology and changes in behaviour, it seems inevitable that the approach will have to change to developing a central projection that either implicitly (using top down modelling approaches) or explicitly includes all policies.