Annex A. Energy demand forecast

August 2019

pwc

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Executive Summary

Introduction to the study and PwC high level approach

We have been commissioned by Guernsey Electricity Ltd (GEL) and the States of Guernsey (SOG) to forecast energy demand on the Island of Guernsey out to 2050. This report summarises our baseline forecast, the methodology undertaken (both at a high level and in detail) as well as a detailed breakdown of the forecast results by energy market segment and over time.

As the following slides document, the overall methodology undertaken has been to forecast energy demand separately for each energy market segment on the Island of Guernsey using a "drivers based" approach. This means that the forecast for each energy market component is based on the relationship between the underlying drivers of energy demand in each segment, and energy demand itself.

As a result, where historical data is available, we have used econometric analysis to quantify the exact relationship between each energy demand component in Guernsey, and the underlying drivers. The methodology subsections of each energy demand component explain this in more detail. In terms of the 'drivers' themselves, we have used a combination of external data sources (notably the National Grid Future Energy Scenarios), econometric forecasting, prior analysis (PwC Hydrocarbon Study 2016) and expert input (from GEL and SOG) to forecast out the individual drivers. In each case, the exact approach used has been made explicit.

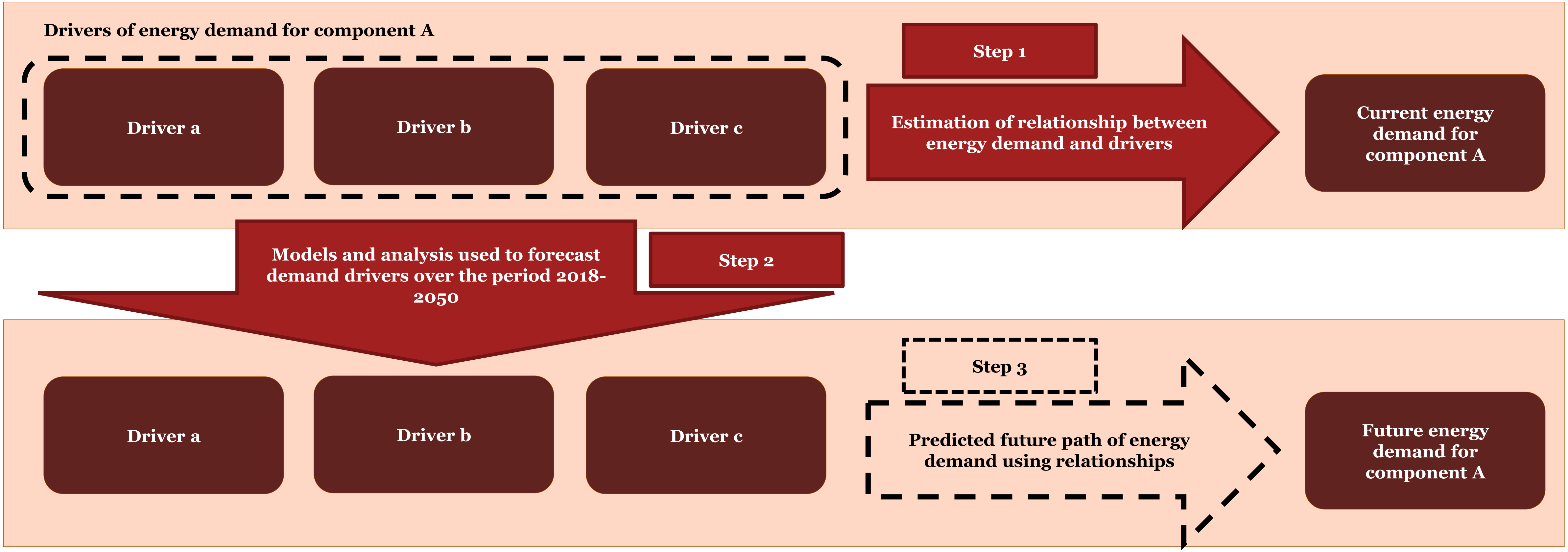
Note, this methodology is broadly comparable to the methodology undertaken in the previous Hydrocarbon Demand forecast produced for SOG in 2016. The forecasts are broadly consistent across the two studies, with any differences in quantified changes in energy demand being driven by two factors: 1) new data made available since the Hydrocarbon study was published, 2) Use of econometric methods with historical data to produce more refined relationships between energy demand and its drivers.

The project deliverables for this study comprise of this report (updated for scenario sensitivities) and an excel energy demand modelling tool to be handed over to GEL. The purpose of the excel model is to allow GEL to adjust some of the underlying forecast assumptions and explore the impact on electricity demand. This report focusses on forecast assumptions in the baseline and the impact these are expected to have on forecasted energy demand. The aim of this report is to provide a comprehensive methodological justification for the produced forecast and, as a result, provide the most sensible and likely picture for the future path of energy demand in Guernsey.

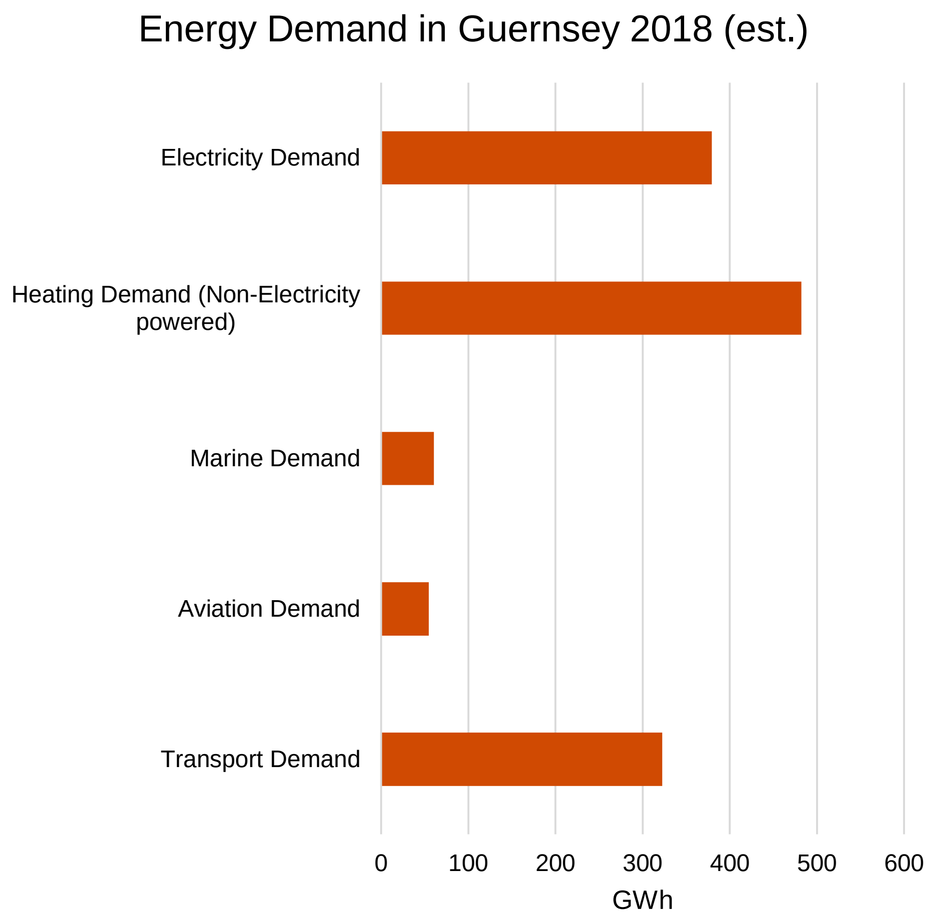
Our framework for modelling each energy market segment

Our approach to modelling energy demand for Guernsey over the period 2018-2050 follows 3 steps for each energy demand component:

- **Step 1** builds a model to estimate the relationship between energy demand and its drivers - either using historic data or prior analysis
- **Step 2** uses forecast assumptions and – where feasible – additional econometric models to project out the drivers to 2050
- **Step 3** combines the forecast for the drivers of energy demand with the estimated relationships from step 1 to forecast energy demand



Summary of Guernsey energy market segments and forecasting approach taken



Source: States of Guernsey Facts and Figures 2018 and PwC analysis

Energy component	GWh (2018 est.)	Approach used	Key drivers
Electricity demand (incl. HFO and heating)	379	Econometric analysis	Appliance ownership per person, appliance efficiency EV uptake and underlying commercial demand
Non-electricity heating demand	482	Multiplicative Model	Population, number of visitors and fuel efficiency
Marine demand	61	Multiplicative Model	Population, number of visitors and fuel efficiency
Aviation demand	55	Econometric analysis	Aircraft movement, passengers per aircraft and fuel efficiency
Road fuel demand	322	Econometric analysis	EV uptake, business activities and fuel efficiency

We have modelled the transition to electric vehicles and electric heating using a combination of data analysis, modelling and assumptions

The two most important drivers of future changes in energy demand are **electric vehicle (EV) uptake** and the **transition rate towards electricity sourced heating** in Guernsey. Our analysis has explicitly forecasted rates of changes in these factors using data analysis, modelling and informed assumptions.

EV uptake

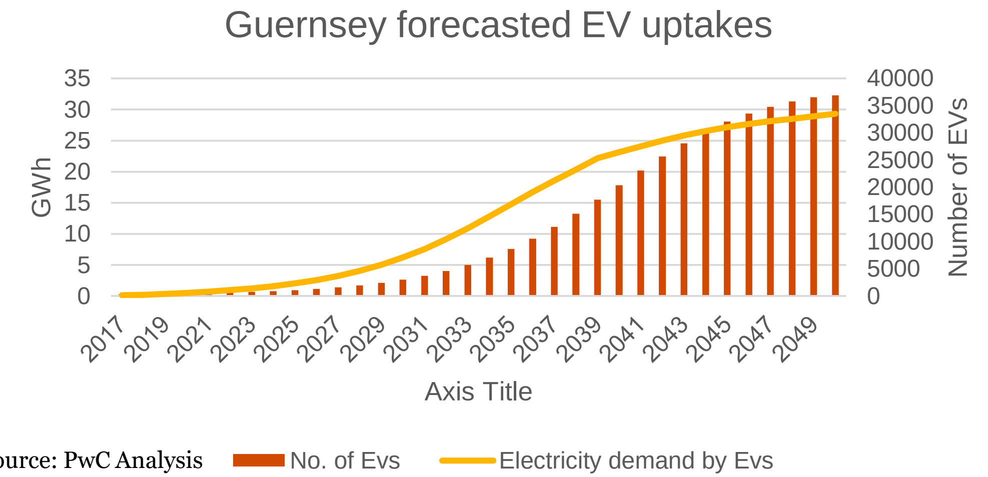
We used the average of conservative National Grid Future Energy Scenarios (2018) forecasts of EV uptake as a 'naïve' measure of Guernsey EV uptake. Our analysis adjusts this naïve measure using **population differences**, data on **average miles travelled per person** and assumptions around **relative market penetration** when comparing Guernsey to the UK. The EV uptake forecast plays a substantial role in boosting electricity demand and reducing road transport fuel demand.

Transition rates to electricity sourced heating

National Grid Future Energy Scenarios (2018) also produce forecasts for heating transition rates towards electricity sourced heating. We have modified these transition rates using a model-based approach relating the transition rate to the relative total cost of electricity heating versus competing technologies.

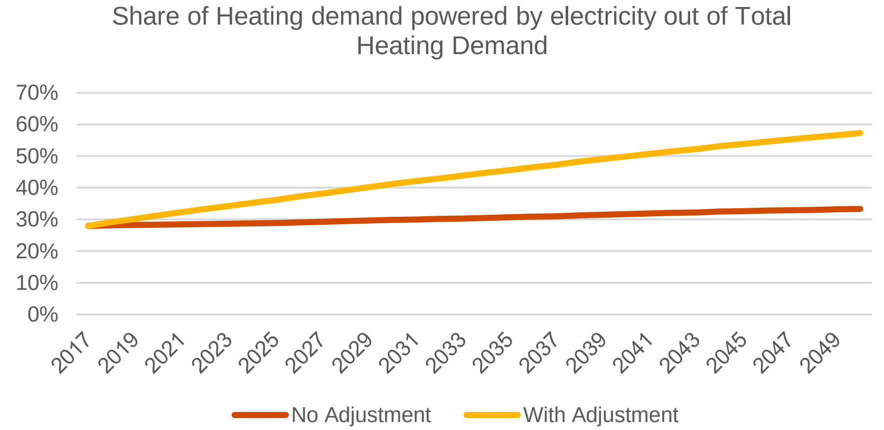
We have been able to adjust this forecast to reflect Guernsey's economy by using information on the relative fuel prices and market shares of different fuels. The resulting transition rate is considerably faster and plays an important role in curbing non-electricity heating demand, whilst increasing electricity demand in our baseline.

EV Uptake



Source: PwC Analysis

Transition to electricity sourced heating



Source: PwC Analysis

Headline forecast results by energy demand component

Headline forecast results in our baseline show a decline in total energy demand by over 450GWh. Although numerous factors drive the individual forecasts for each component, one consistent factor contributing to the overall demand decline is an increase in **technological efficiency.**

This is captured both in terms of **fuel efficiency** (for example in diesel efficiency, petrol efficiency, and thermal efficiency), as well as the uptake of **new technologies** (such as electric vehicles replacing internal combustion engine (ICE) vehicles).

The largest absolute and relative declines in demand are forecasted to come in the **road transport** and **non-electricity heating demand** segments.

Road transport demand is forecasted to decline substantially from roughly 322GWh to 34GWh in the baseline, taking up only a 4% share of demand by 2050. This is due to assumptions around electric vehicles, which are expected to almost entirely replace ICE vehicles by 2050.

Non-electricity heating demand is forecasted to decline from roughly 482GWh to 218GWh owing to a forecasted transition to electric heating. Total heating demand including electric heating is also forecasted to decline, owing to thermal efficiency improvements

Electricity demand is the only component forecasted to expand in both volume and demand share. This is predominantly caused by absorbing demand from road transport and non-electricity heating sectors through EV uptake and heating technology transitions.

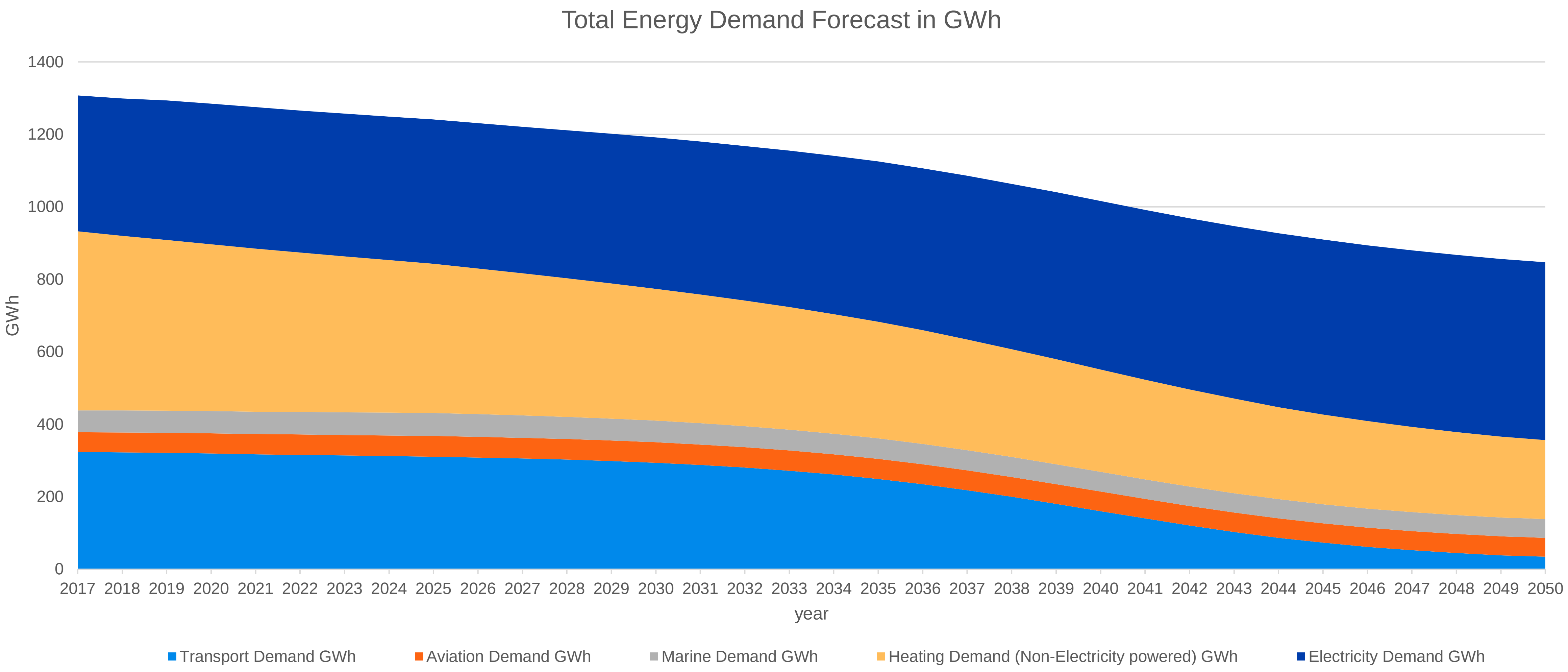
Although the level of carbon emissions is expected to fall to 215M kg by 2050, **this natural transition may not be sufficient to meet the Kyoto / Paris carbon goal.** If this is the case, Guernsey will need to take action to increase the rate of carbon reduction.

Guernsey energy demand and carbon emissions forecast by component in 2018 and 2050

Fuel segment	2018			2050		
	Energy Demand		Carbon Emissions kg CO2e	Energy Demand		Carbon Emissions kg CO2e
Transport demand (Petrol and Diesel)	**322**	24.8%	76,930,902	**34**	4.0%	8,187,938
Aviation demand	**55**	4.2%	13,606,665	**52**	6.2%	12,887,782
Marine demand	**61**	4.7%	16,753,479	**52**	6.1%	14,402,886
Heating demand (Non-electricity powered)	**482**	37.1%	118,962,924	**218**	25.7%	53,741,472
Electricity demand	**379**	29.2%	41,552,350	**491**	58.0%	42,110,628
Non-energy emissions*			129,975,849			83,831,876
Total	**1299**		397,782,169	**847**		215,162,582

**This includes agricultural, land use, land use change, forestry, waste, fluorinated gases and other emissions*

Baseline total energy demand forecast in GWh



Source: PwC Analysis

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Electricity Demand Forecast

Electricity demand model in depth

Our modelling of the relationship between electricity demand and its drivers (step 1 of the overall framework) has two layers. The first layer of the model decomposes electricity demand into electricity demand per capita and population in Guernsey. The second layer of the model decomposes electricity demand per capita into its four drivers:

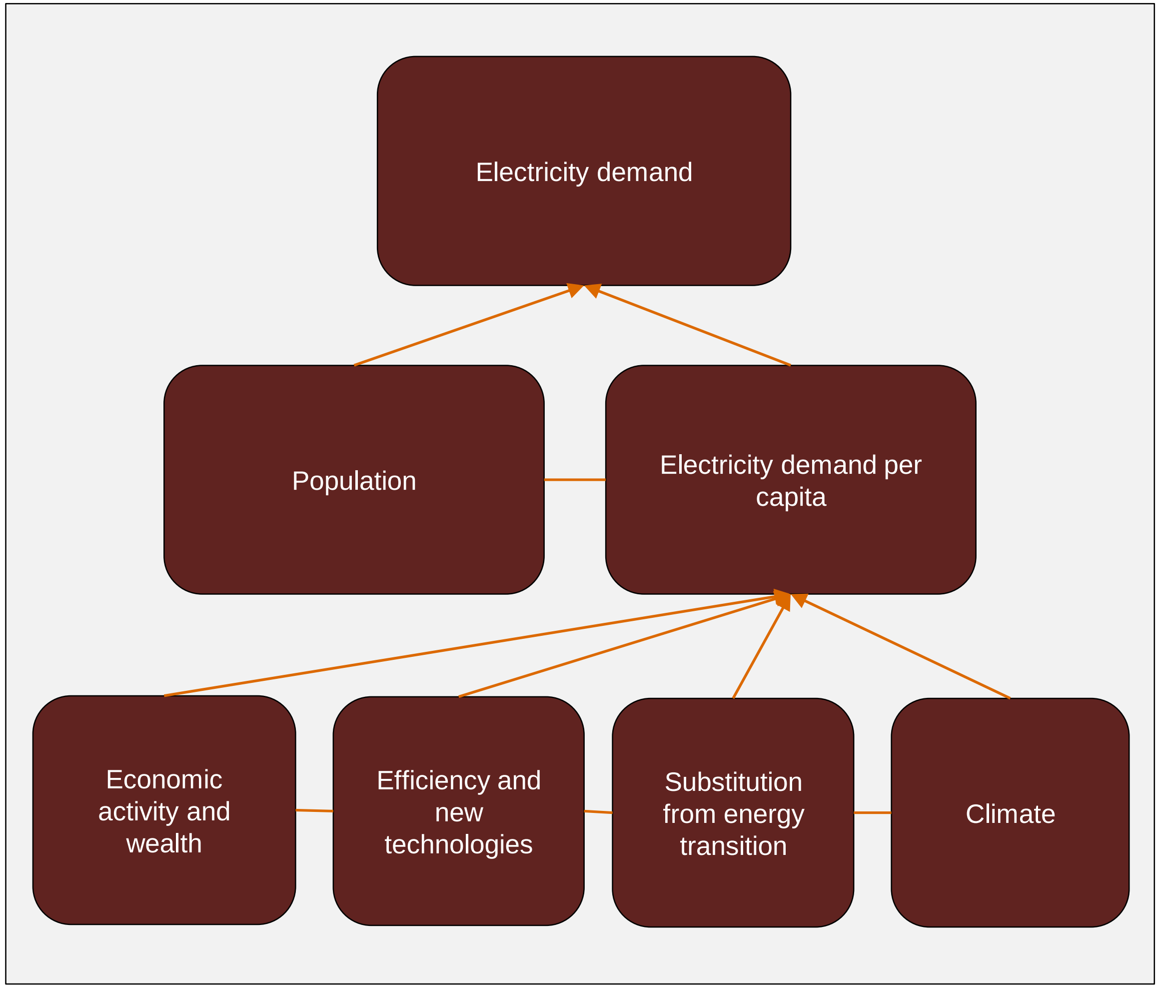
- Economic activity and wealth (per capita)
- Efficiency and new technologies
- Substitution from energy transition
- Climate effects

The relationship between these drivers and electricity demand per capita has been quantified using Bayesian Stochastic Search Variable Selection (see appendix for details)

Our model structure and regression approach has some key advantages over other related approaches:

1) It captures interaction effects between the different drivers
2) It allows us to impose theory and knowledge about drivers of electricity demand in the mode to limit spurious relationships
3) It is superior in variable selection to traditional regression

Electricity demand model layers



Electricity demand model results

Below we list the variables that feed into the electricity demand model. The grey rows correspond to variables that are explicitly modelled using our econometric approach, while the other variables are either used to scale demand per capita to total demand (e.g. population), or are used to make off-model adjustments (e.g. smart meters and electric vehicles uptake).

We document the estimated elasticities that have come out of the econometric model in the far right column. These ‘elasticities’ represent the impact of each variable on electricity demand. An elasticity of 0.1 for a given variable means that a 100% increase in the variable corresponds to a 10% increase in energy demand. These elasticities essentially determine the importance of different variables in the model.

It should be noted that although this model has tried to quantify the impact of all historical drivers of electrical **heating** demand (efficiency indicators and temperature variables), we recognise that there is likely to be a future energy transition towards electricity sourced heating, which this model cannot capture. This has been separately captured using the heating demand model (see section 5) and the model has been adjusted to prevent double counting.

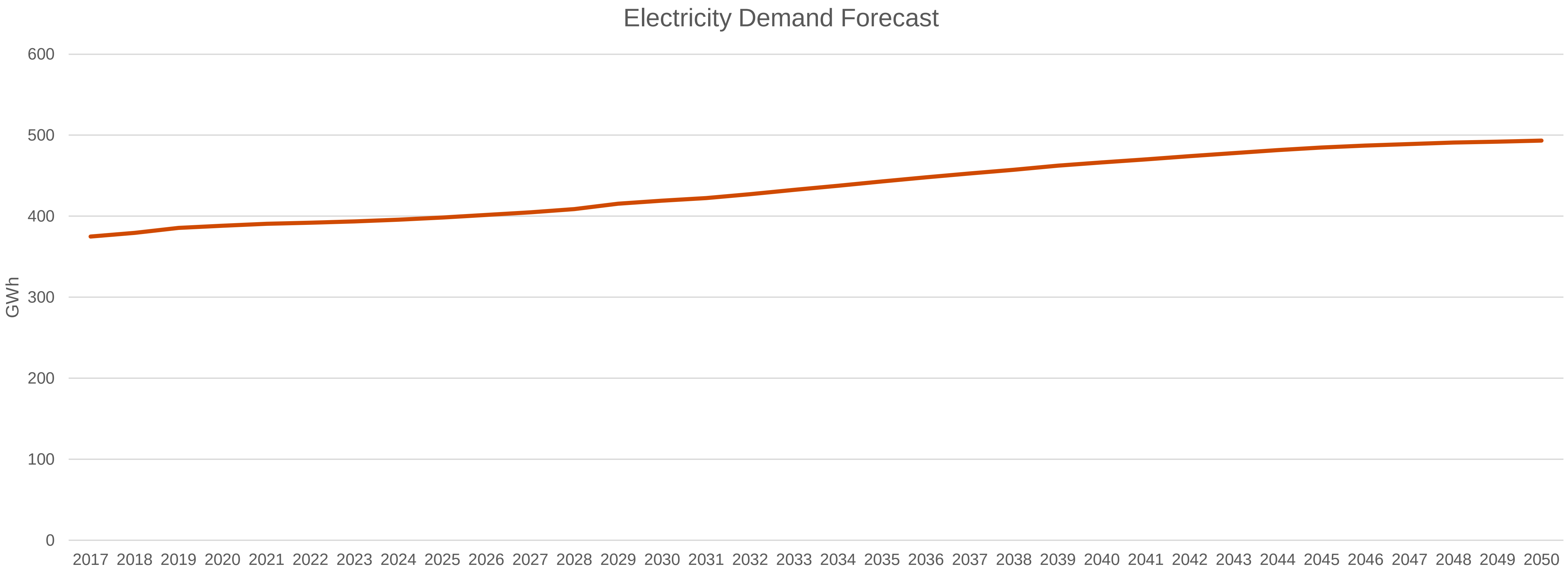
Variable	Effect captured	Hypothesised impact on electricity demand	Model estimated elasticity of electricity demand per capita
Population	Scale consumption effects	Positive	N/A – Used as multiplier for per capita electricity demand
Commercial demand per person	Economic activity and wealth	Positive	***0.176***
Winter Average Air temperature	Energy substitution, Climate	Negative	***-0.246***
Summer Average Air temperature	Climate	Positive	***0***
Electrical appliance efficiency	Efficiency and new technologies	Negative	***-0.238***
Electrical appliance demand per capita	Economic activity and wealth	Positive	***0.810***
GEL Historical Tariff (lagged)	Economic activity and wealth	Negative	***-0.137***
Smart meter installations	Efficiency and new technologies	Negative	N/A – additive effect to be derived from average proportional Guernsey energy consumption vs. UK
EV uptake	Energy substitution, Efficiency and new technologies	Positive	N/A – additive effect to be derived from average proportional Guernsey energy consumption vs. UK

Electricity demand baseline forecast assumptions

Variable	Baseline forecast assumption
Population	States of Guernsey 2018 population baseline forecast
Commercial demand	National Grid average of all FES18 scenarios
Winter Average Air temperature	Constant (in line with historic data)
Summer Average Air temperature	Constant (in line with historic data)
Electrical appliance efficiency	National Grid average of all FES18 scenarios
Electrical appliance demand per capita	National Grid average of all FES18 scenarios
GEL Historical Tariff (lagged)	1% per annum increase
Smart meter installations	National Grid Average of all FES18 scenarios
EV uptake	National Grid average of lower FES18 scenarios, adjusted by relative travel distance by car per person between Guernsey and the UK

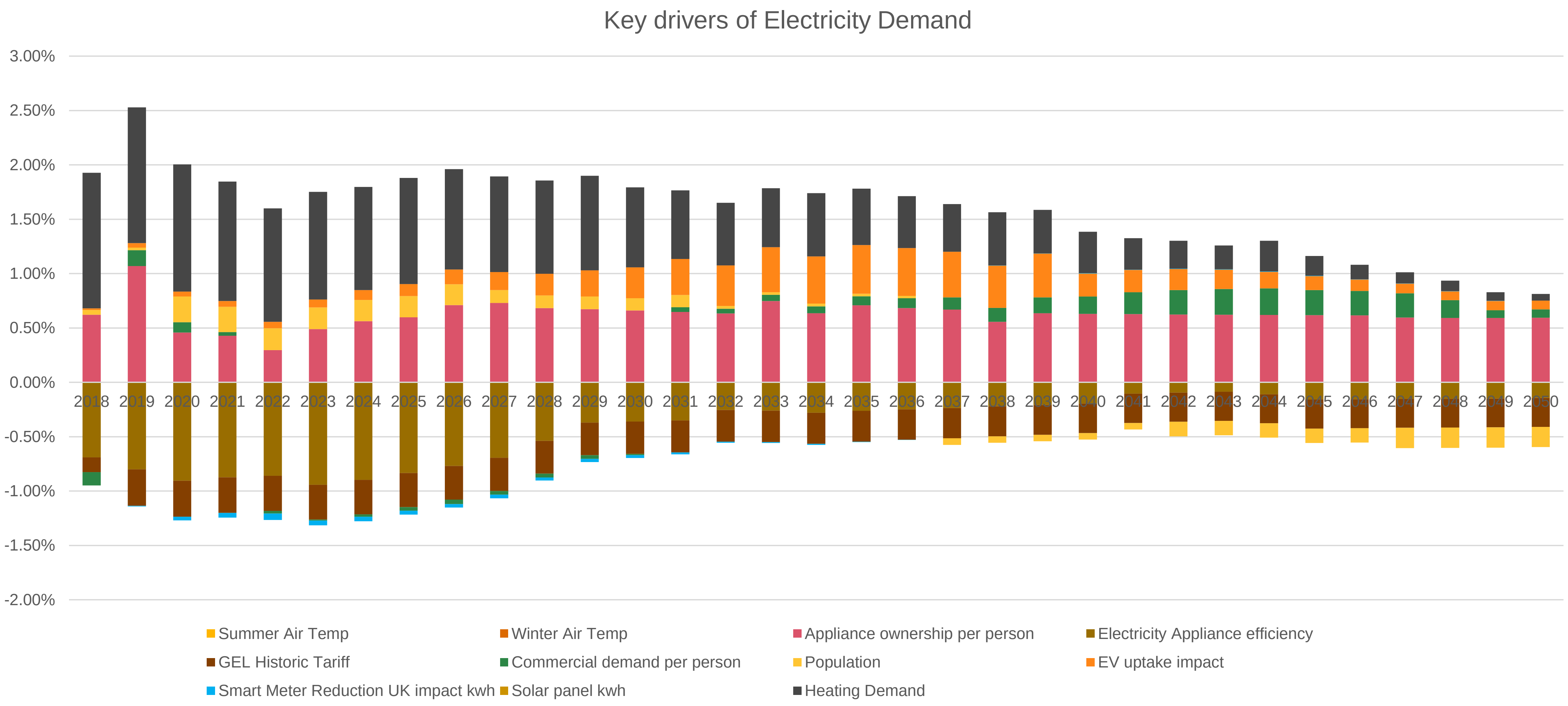
Baseline forecast for electricity demand

Our baseline electricity demand forecast for Guernsey shows a steady demand flow over the next ten years, followed by a second period of gentle incline fuelled by slowing efficiency gains, rising EV uptake and increasing commercial demand per person on the island.
Note this forecast includes the electricity component forecasted from the heating demand model. See Section 5 for details on how this was forecast and combined to avoid double counting.



Source: PwC Analysis

Drivers of changing electricity demand

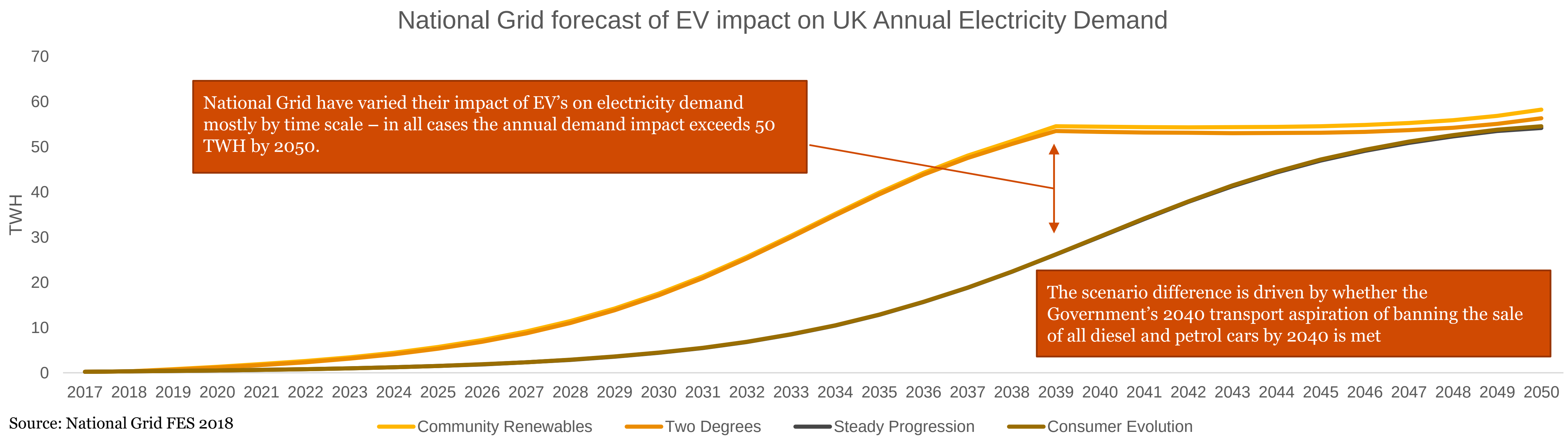


Source: PwC Analysis

We have adjusted the impact of EVs for Guernsey's market and consumer habits

Our approach to forecasting EV uptake in Guernsey was to modify the existing forecast produced by National Grid in their future energy scenarios for the UK to ensure the trajectory and scale of impact per capita reflect the market for EVs and consumer behaviour in Guernsey. Specifically, in our baseline forecast, we have scaled the impact using **population adjustments** and **differences in miles travelled per person per year in Guernsey vs the UK** (63% (75%) of UK in 2007 according to PwC Hydrocarbon study (National Travel Survey). We have also modified the impact in different scenarios by assuming differences in market penetration rates.

National Grid forecast that there will be up to 30 million EVs in the UK by 2040. Their impact on electricity demand is based on assumptions made around GDP growth, market penetration, smart charging and average miles travelled per person.

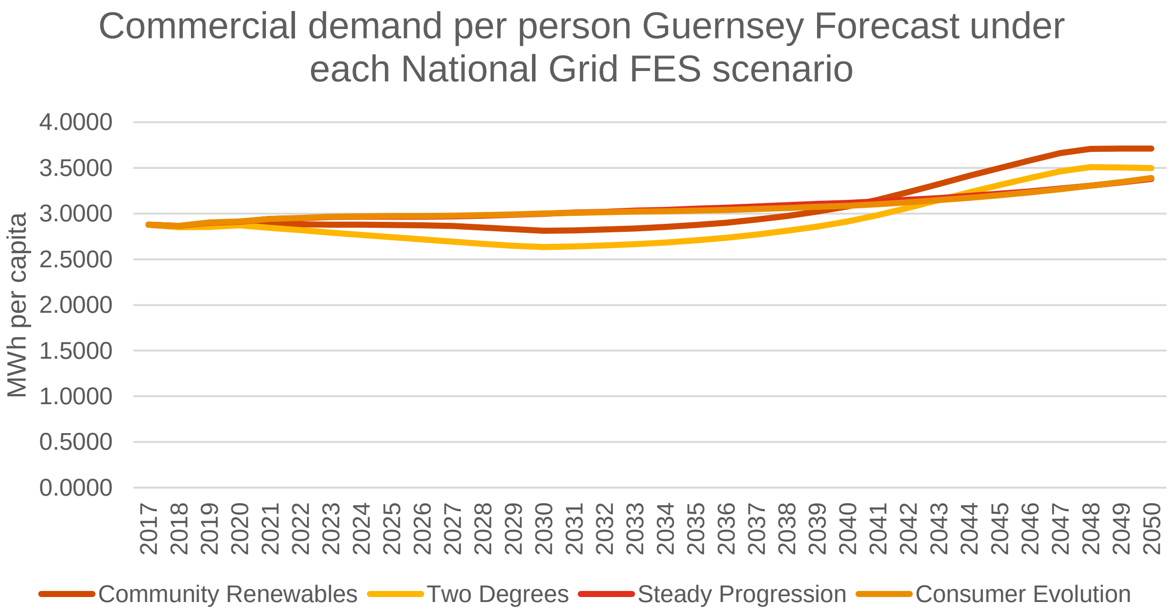


Source: National Grid FES 2018

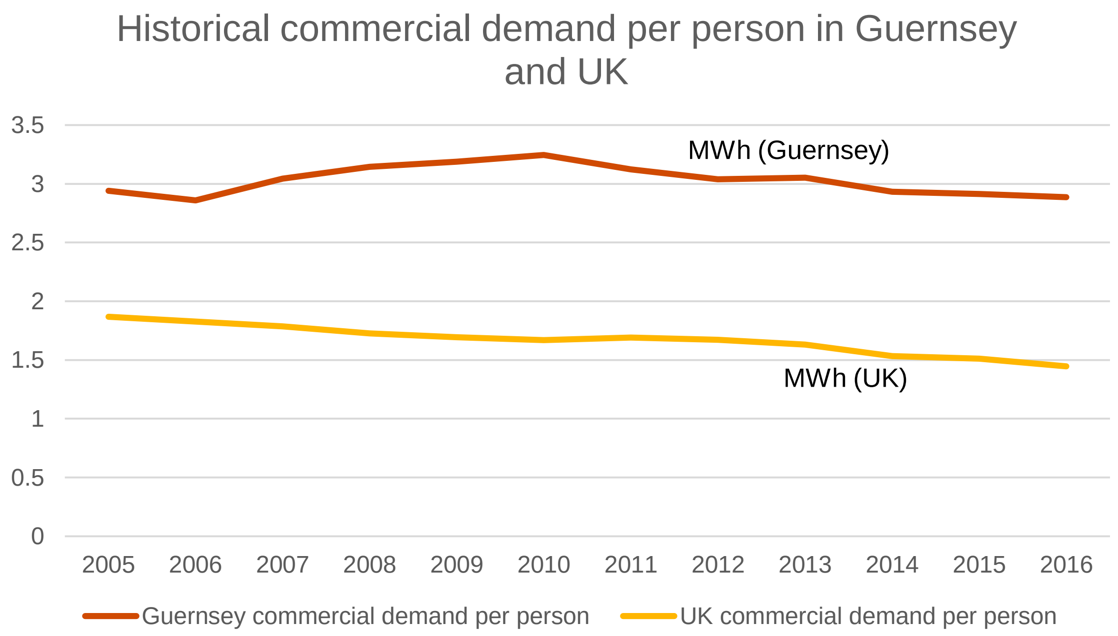
Commercial demand per person will stay relatively flat in the baseline but varies by scenario

We have assumed that Guernsey's commercial demand growth will follow a similar trend to that in the UK. This is supported by historically similar trends in GDP growth, appliance efficiency and appliance demand.

National Grid have assumed that commercial demand will gradually rise in all scenarios over the whole period, however the profiles vary across the scenarios according to different assumptions. In some scenarios the rise is constant (e.g. Consumer Evolution) reflecting moderate efficiency gains and lower GDP growth. In other scenarios (e.g. Two Degrees), commercial demand declines in the short term due to appliance efficiency gains, then rises later as GDP growth gains outweigh efficiency increases.



Source: PwC Analysis and National Grid FES 2018

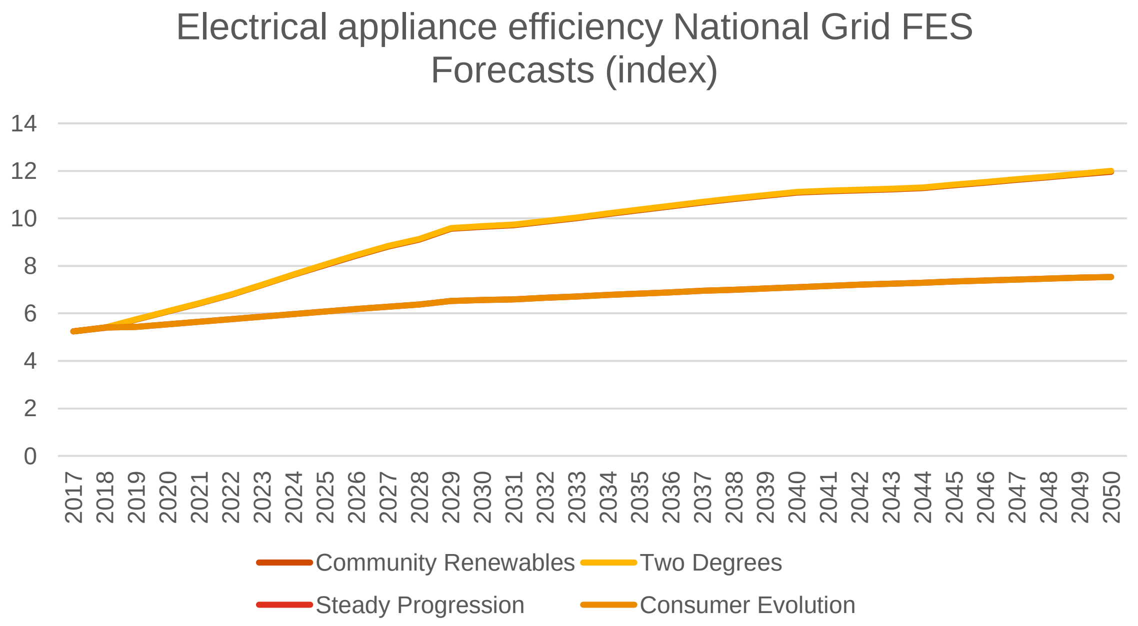


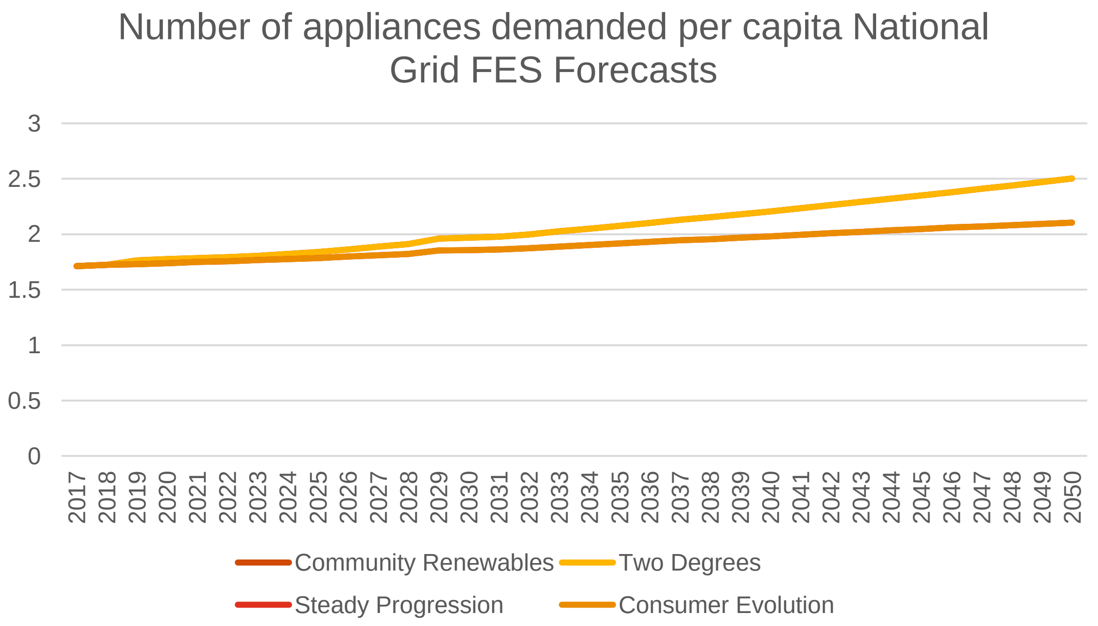
Source: PwC Analysis and States of Guernsey

Appliance demand per person and efficiency are both set to increase in all scenarios

The National Grid scenarios expect electrical appliance efficiency and appliance ownership per capita to increase in all scenarios. Our baseline forecast has taken an average across these four scenarios, which is one of the causes of the two stages of our baseline forecast (early stagnation followed by gradual incline).

In particular, electrical appliance efficiency is forecast to increase quickly in the period 2017-2030, before decelerating over the remaining period once most appliance efficiency improvements have been phased in by consumers and businesses. Meanwhile, appliance ownership per capita is forecast to grow gradually, despite trends in consumer awareness. As a result, appliance efficiency gains outweigh ownership increases in the short term – pulling electricity demand down – while ownership increases outweigh appliance efficiency increases in the longer term – pulling electricity demand up.





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Road Transport Demand

Road transport demand model approach in depth

Our model of transport fuel demand (step 1 of the overall framework) has two layers. The first layer of the model decomposes transport fuel demand into transport fuel demand per capita and population in Guernsey. The second layer of the model decomposes transport fuel demand per capita into its four drivers:

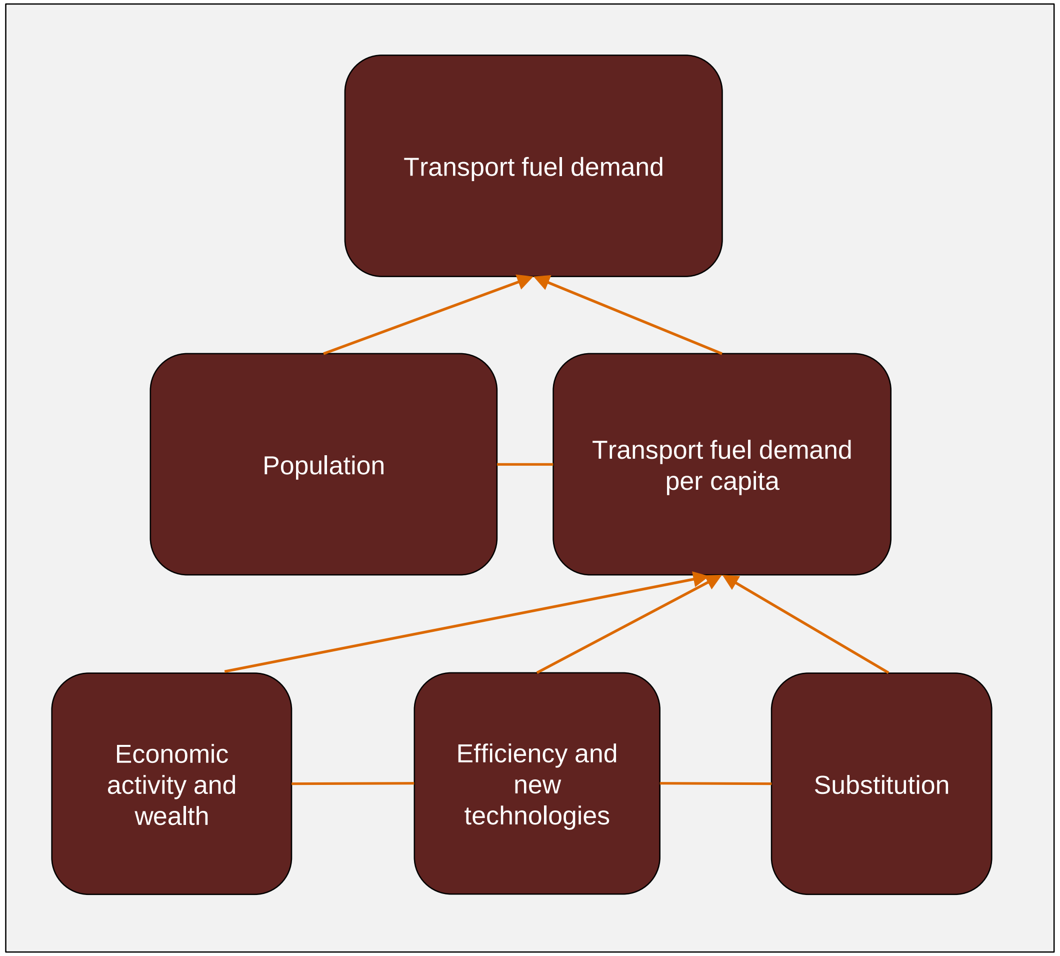
- Economic activity and wealth (per capita)
- Efficiency and new technologies
- Substitution from energy transition

The relationship between these drivers and electricity demand per capita has been quantified using Bayesian Stochastic Search Variable Selection (see slide 4 and in appendix for details) as with electricity demand.

Our model structure and regression approach has the same key advantages over other related approaches:

1) It captures interaction effects between the different drivers
2) It allows us to impose theory and knowledge about drivers of electricity demand in the mode to limit spurious relationships
3) It is superior in variable selection to traditional regression

Current Transport demand model layers



Road transport demand model results

Below we list the variables that currently feed into the transport fuel demand model. The grey rows correspond to variables that are explicitly modelled using our econometric approach, while the other variables are either used to scale demand per capita to total demand (e.g. population), or are used to make off-model adjustments (e.g. electric vehicle uptake).

We document the estimated elasticities that have come out of the econometric model in the far right column. These ‘elasticities’ represent the impact of each variable on transport fuel demand. An elasticity of 0.1 for a given variable means that a 100% increase in the variable corresponds to a 10% increase in energy demand. These elasticities essentially determine the importance of different variables in the model.

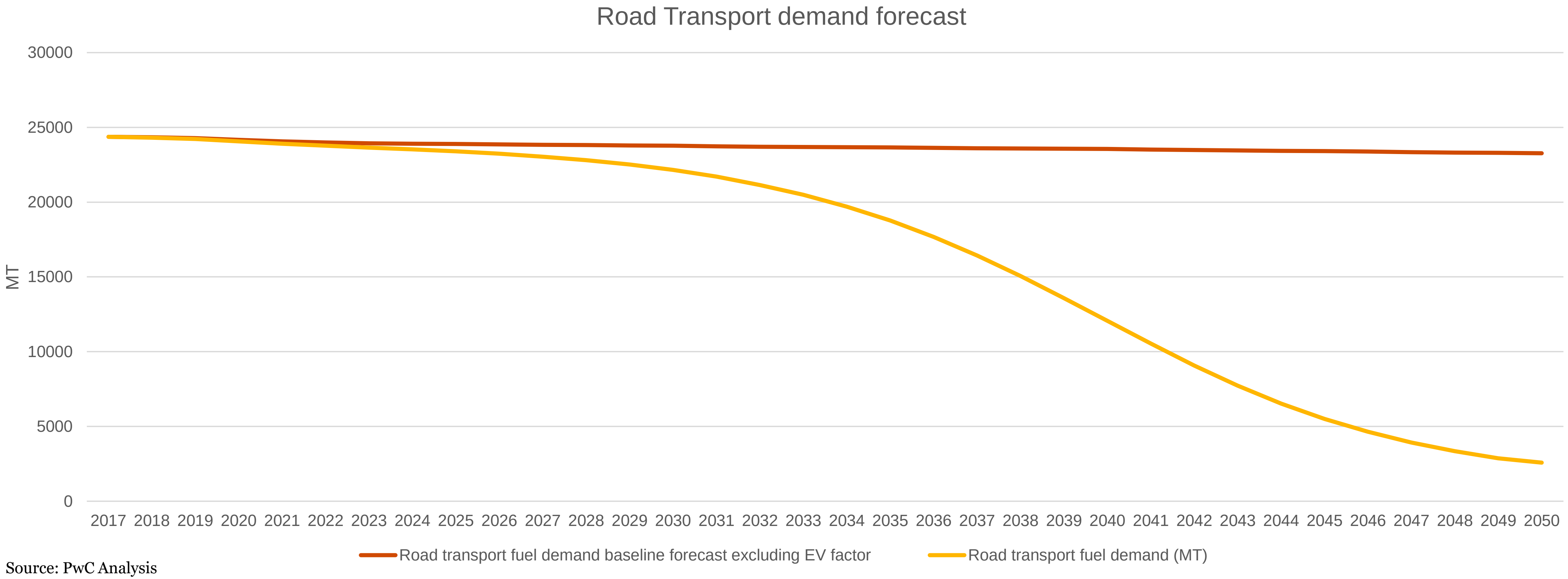
Variable	Effect captured	Hypothesised impact on transport fuel demand	Model estimated elasticity of transport fuel demand per capita
Population	Scale consumption effects	Positive	N/A – Used as multiplier for per capita transport fuel demand
Aggregate demand per capita	Economic activity and wealth	Positive	***0.091***
No. of visitors	Economic activity and wealth	Positive	***0.101***
Weighted average fuel prices (lagged)	Economic activity and wealth	Negative	***-0.062***
Diesel vehicles efficiency	Efficiency and new technologies	Negative	***-0.113***
Petrol vehicles efficiency	Economic activity and wealth	Negative	***-0.111***
No. of Bus journeys per person	Substitution	Negative	***-0.094***
EV uptake	Energy substitution, Efficiency and new technologies	Negative	N/A – subtractive effect to be derived from average Guernsey/UK EV usage proportionate to Normal Vehicles.

Road transport demand baseline forecast assumptions

Variable	Baseline forecast assumption
Population	States of Guernsey 2018 population baseline forecast
Real GDP per capita	Long term trend and UK real GDP forecast
No. of visitors	Augmented baseline target forecast from SOG (assumed 50% achieved due to scale of prediction)
Weighted average Fuel prices (lagged)	National Grid FES18 base case scenario
Diesel vehicles efficiency	Long term trend based on current data
Petrol vehicles efficiency	ARIMA (1,1,0) econometric model based on historical data
No. of Bus journeys	Weighted average growth in line with population and visitors forecast
EV uptake	National Grid Average of conservative FES18 scenarios

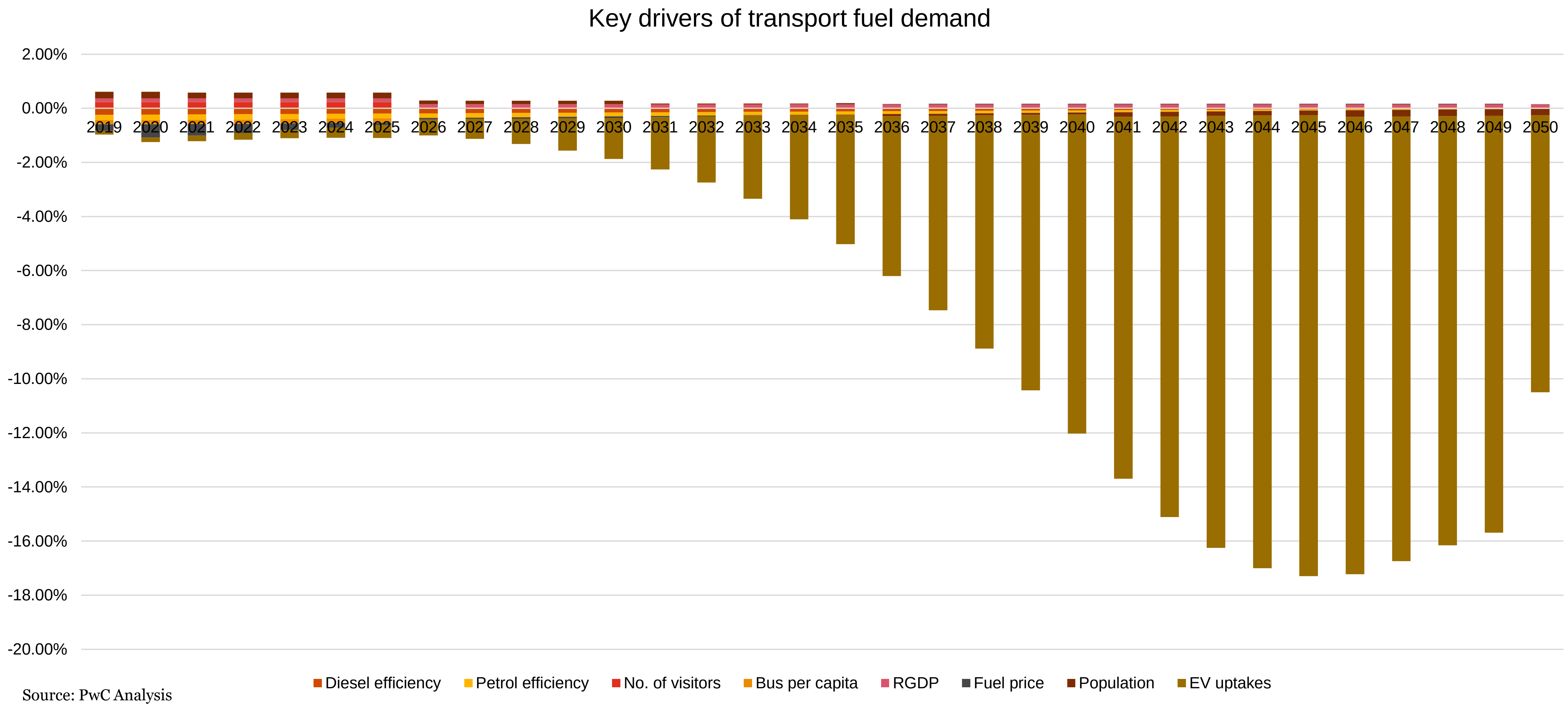
Baseline forecast for road transport demand

Our baseline road transport demand forecast shows a non-linear rate of decline overtime. In the first ten years of our forecast, the rate of decline is predicted to be moderate. In the following twenty years, the decrease in road transport demand is expected to accelerate, mostly caused by the uptake of EVs. The effect of EV uptake comes through an off-model adjustment: we first predict what would have happened to fuel demand if there was no EV uptake, and shrink the demand for fuel according to the ratio of ICE cars to EVs using conservative uptake assumptions from FES18.



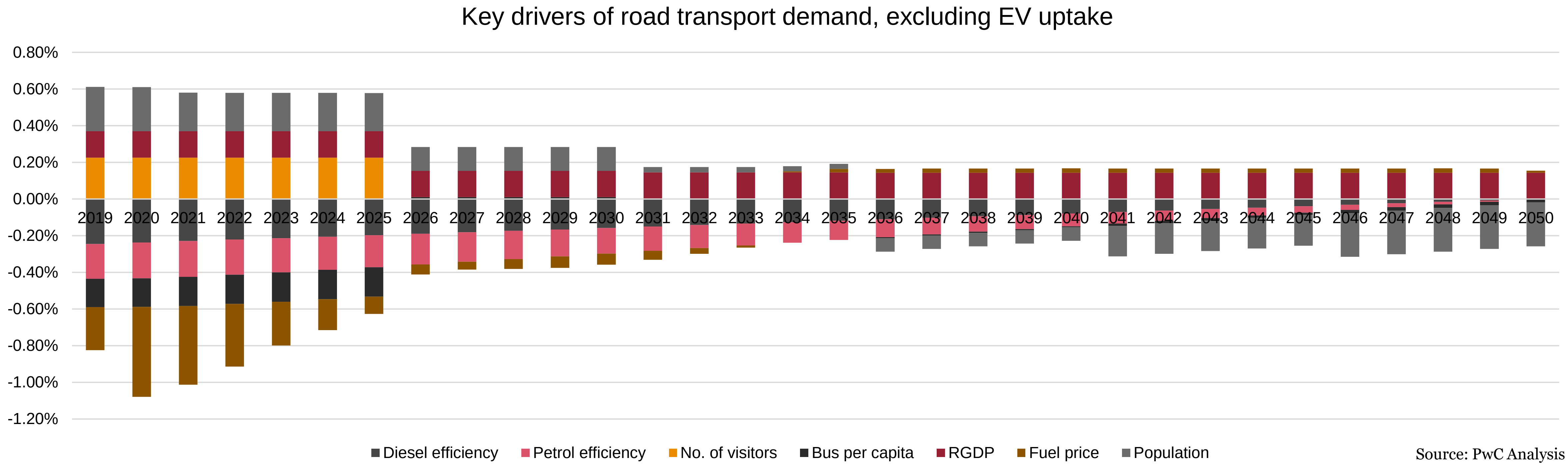
Source: PwC Analysis

Drivers of changing road transport fuel demand (1/2)



Source: PwC Analysis

Drivers of changing road transport fuel demand (2/2)



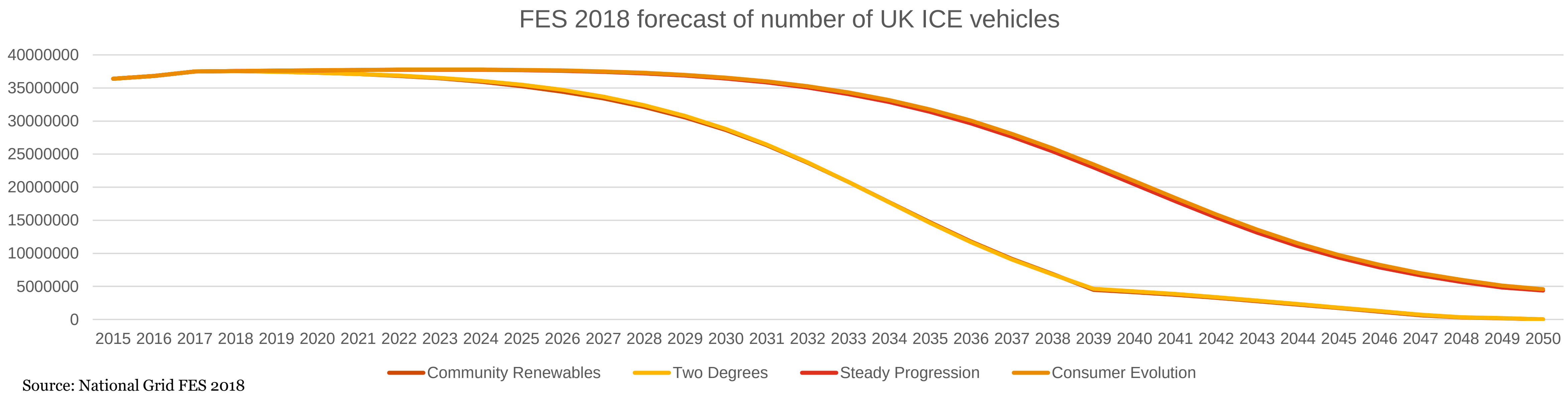
Source: PwC Analysis

- **Petrol and Diesel efficiency –** Over time, we have forecasted an increase in the efficiency of ICE vehicles due to technological advancements. However, we also expect the rate of efficiency improvements to shrink as R&D shifts from ICE vehicles to EVs and as diminishing returns gradually increase over time as efficiency improvements are squeezed out of the existing technology. This has been captured using our forecasting approach.
- **EV uptake –** This is the largest driver of future petrol and diesel demand. According to National Grid, the uptake of EVs is expected to reduce the usage of traditional transport fuels. In the National Grid FES the two scenarios which assume a faster rate of decarbonisation assume will be no ICE vehicles in 2050. More detail is provided on the following slide.
- **Population –** Initially, population growth will have a positive impact on fuel demand. From 2036 onwards, the population is expected to start decreasing and therefore transport fuel demand will fall.

Measuring the effect of EV uptake on road transport fuel demand

Our proposed approach to forecasting the impact of EVs on road fuel demand is to average the more conservative pair of National Grid FES forecasts for the share of road transport vehicles that will use internal combustion engines (ICE) between 2018 and 2050. This assumes that the market penetration of electric vehicles is smaller in Guernsey vs. the UK – reflecting the fact that there does not yet exist a clear SOG policy around electric and ICE vehicles.

- In National Grid FES scenarios with higher levels of decarbonisation, e.g. Two Degrees and Community Renewables, the number of petrol/diesel vehicles is expected to decline at a faster rate.
- In scenarios with lower levels of de-carbonisation, e.g. Consumer Evolution and Steady Progression, the number of petrol/diesel vehicles is predicted to decline at a slower rate.
- By assuming that the number of vehicles is proportional to energy demand, we multiply the predicted share of ICE vehicles under the relevant scenario to our ‘raw’ prediction for road transport demand using the econometric model (according to all drivers modelled explicitly), in order to quantify the effect of EV uptake on road transport demand.



Source: National Grid FES 2018

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Aviation Demand Forecast

Aviation demand model approach in depth

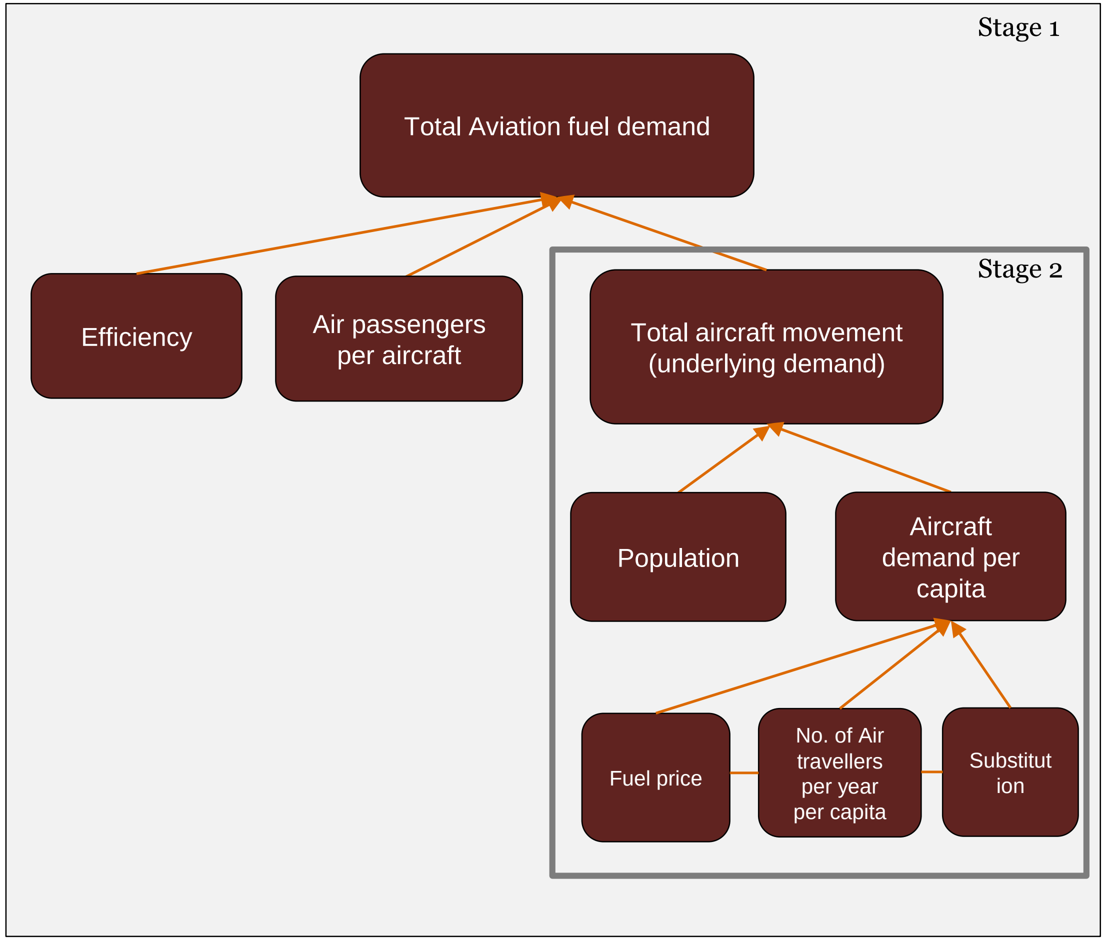
For aviation demand, we built a two-level econometric model to model to quantify the impact of key drivers of aviation demand, including aircraft movements, number of air passengers per aircraft and efficiency gains over time.

Stage 1 allows us to separate out the impact of airline schedule changes from increases in traffic flows as the model quantifies the effect of reductions in aircraft movements, holding the air passengers per aircraft constant. This is particularly useful when forecasting future aviation demand as it allows us to make reasonable assumptions to project out each driver as we can be confident that each driver is capturing a different channel.

In Stage 2, we model total aircraft movements separately by identifying potential drivers of underlying movements including fuel price (as this affects schedule decisions), the number of air travellers per year per capita and also the ease of substituting air travel. This stage allows us to model the underlying demand explicitly without having to make bold assumptions on what drives the aircraft schedule. This is important since this variable accounts for a large amount of the variation in aviation fuel demand.

SVSS regression was used, as per other econometric models of energy component relationships with drivers.

Aviation demand model layers



Aviation demand model results

Below we list the variables that currently feed into the aviation fuel demand model. The grey rows correspond to variables that are explicitly modelled using our econometric approach, while the other variables are either used to scale demand per capita to total demand (e.g. population).

We document the estimated elasticities that have come out of the econometric model in the far right column. These 'elasticities' represent the impact of each variable on aviation fuel demand. An elasticity of 0.1 for a given variable means that a 100% increase in the variable corresponds to a 10% increase in energy demand. These elasticities essentially determine the importance of different variables in the model.

Stage 1 : Estimating aviation fuel demand

Variable	Effect captured	Hypothesised impact on Aviation fuel demand	Model estimated elasticity of Aviation fuel demand per capita
Fuel Efficiency	Efficiency and new technologies	Negative	***-0.593***
Air-passengers per aircraft movements	Economic activity and wealth	Positive	***0.379***
Total Aircraft movement	Economic activity and wealth	Positive	***0.249***

Stage 2 : Estimating total aircraft movements

Variable	Effect captured	Hypothesised impact on Aviation fuel demand	Model estimated elasticity of Aviation fuel demand per capita
Population	Scale consumption effects	Positive	N/A – Used as multiplier for per capita Aviation fuel demand
Aviation Fuel price lagged	Economic activity and wealth	Negative	***-0.115***
No. of air travel per year per capita	Economic activity and wealth	Positive	***0.013***
No. of sea travel per year per capita	Substitution effects	Negative	***-0.033***

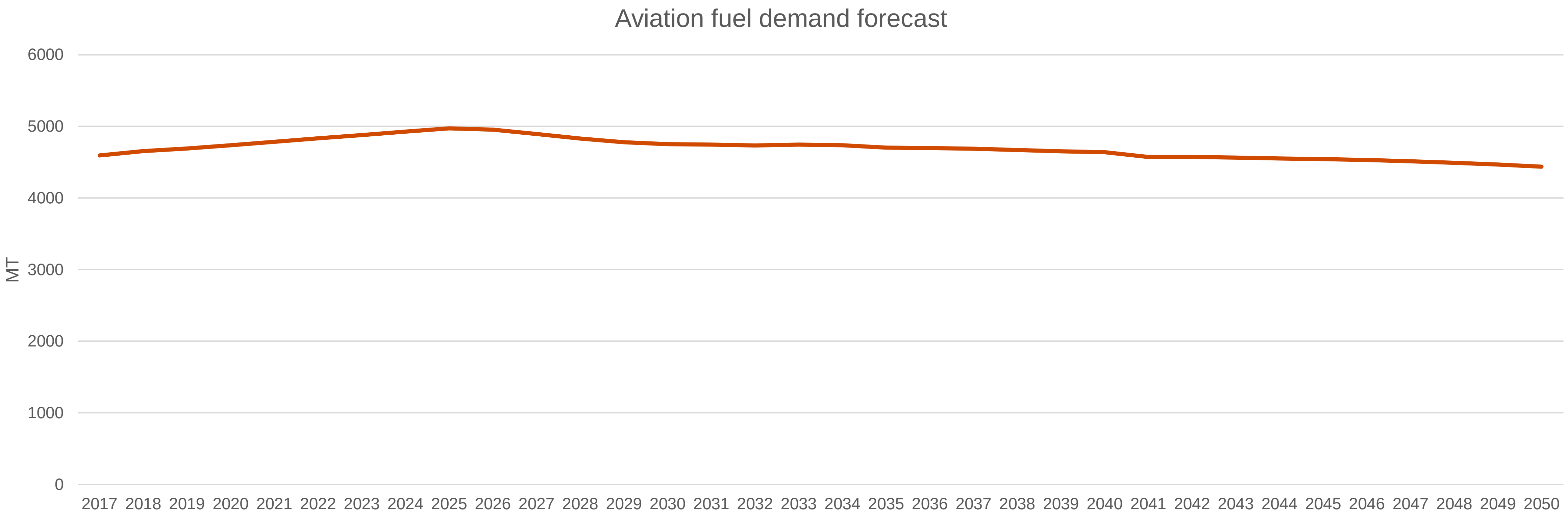
Aviation demand baseline forecast assumptions

Variable	Baseline forecast assumption
Population	States of Guernsey 2018 population baseline forecast
No. of air-passengers	Proportional increase to baseline forecast for number of visitors
No. of sea-passengers	Proportional increase to baseline forecast for number of visitors
Aviation Fuel prices (lagged)	National Grid FES18 base case scenario
Aviation Fuel efficiency	UK aviation forecast 2017 base case scenario

Baseline forecast for aviation demand

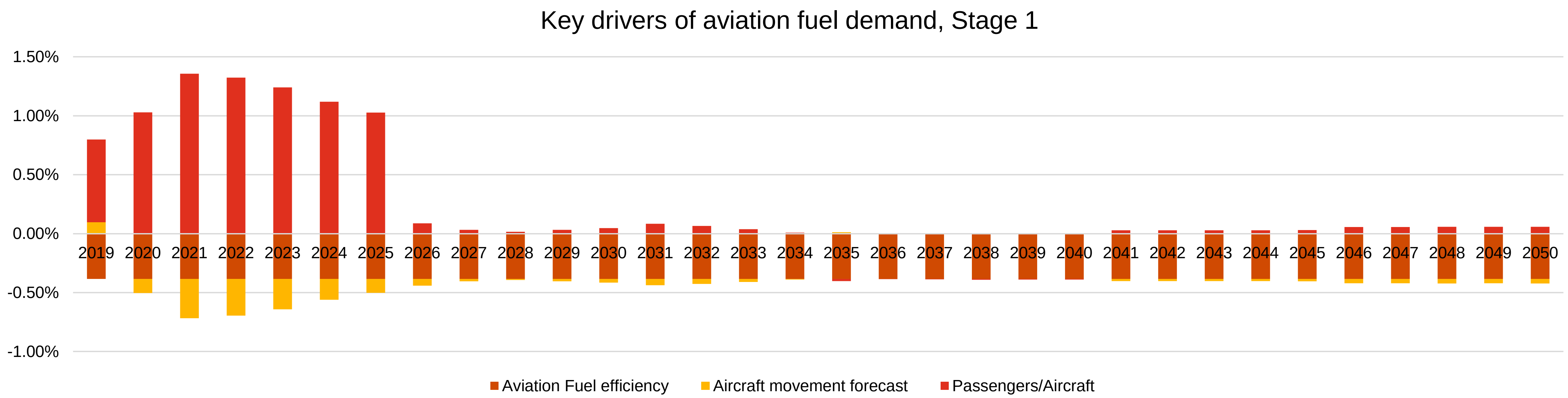
The baseline forecast for aviation fuel demand is shown in the graph below. The predicted growth in aviation fuel demand in the next few years is mainly caused by the increase in the projected number of visitors, as per the SOG Committee's suggestion. After 2026, the decline in aviation demand is mainly caused by improvements fuel efficiency over time.

Key drivers include aircraft movements, passengers per aircraft and fuel efficiency. We separately model aircraft movements which we believe relates to the underlying demand of aviation and flight schedule. Key drivers for are fuel prices, air-passengers and sea passengers (as a measurement of substitution).



Source: PwC Analysis

Drivers of changing aviation fuel demand



Source: PwC Analysis

The increase in passengers per aircraft from 2017 to 2025 positively impacts aviation fuel demand. These changes gradually decline as air passengers cease to grow, this is driven by the assumption that once visitor numbers will stay constant over time once Guernsey hits its visitors target.

The predicted long term increase in aviation fuel prices will lead to a reduction in aircraft demand per capita, causing a decline in total aircraft movements.

Improvements in fuel efficiency are also expected to reduce aviation fuel demand. We assume that the efficiency gain will be in line with the efficiency gain in the UK aviation market. The upward trend in efficiency matches with the announcement by Aurigny regarding the plan of acquiring 3 new ATR 72 aircrafts.

5

Marine Demand Forecast

Marine demand model approach and baseline forecast assumptions

Gas oil is the main source of fuel that used by Marines, however we do not observe a historical time-series of the split of Gas oil between heating and marine demand. Therefore, we are not able to perform econometric analysis. Instead, we have built a simple multiplicative model consistent with the PwC Hydrocarbon Study (2016) that estimates how marine demand evolves on the basis of underlying demand and efficiency:

$$Marine\ gas\ oil_t = A * Population_t \frac{Visitors_t}{Efficiency_t}$$

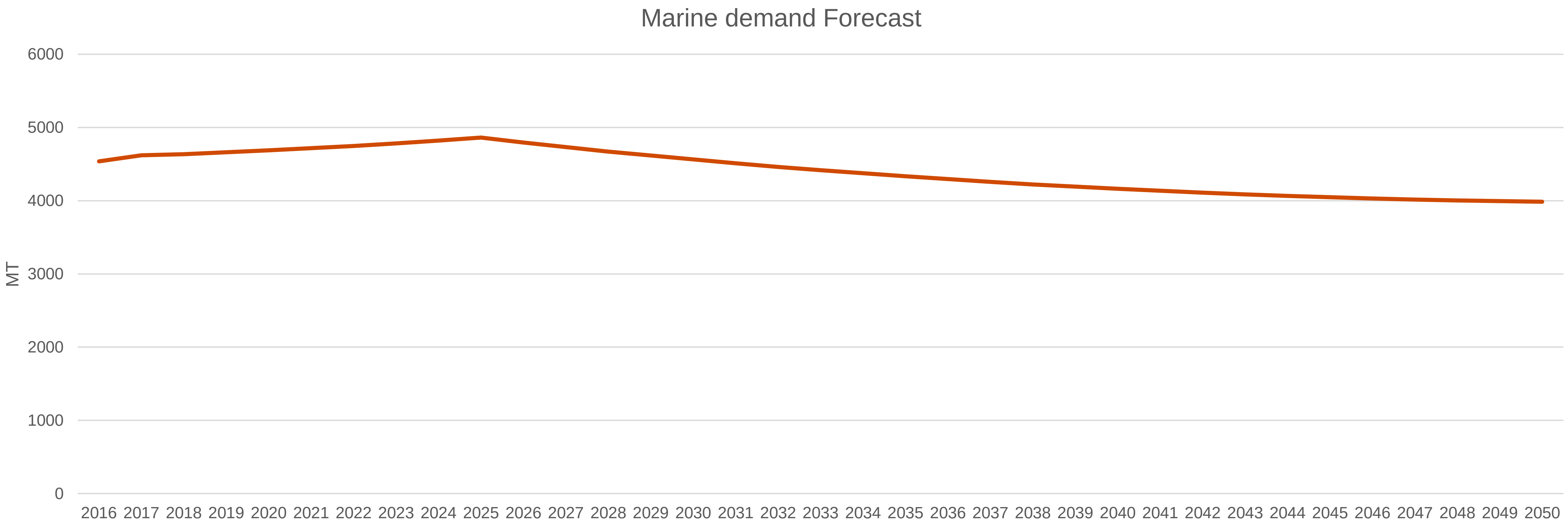
$$1 + G_t = 1 + g_{pop,t} \frac{1 + g_{v,t}}{1 + g_{eff,t}}$$

A is a constant term that will not change overtime and is estimate from known current data on marine demand. In other words, we calibrate the model to current known levels of marine demand (as of 2016) and then forecast out the growth rate of Marine fuel demand by looking at the growth rates in different drivers. According to our model, the gross growth in marine demand is then proxied by visitors growth and efficiency growth. Essentially this proxy assumption assumes that if efficiency increases by 5%, demand decreases by 5%. The table below outline the forecast assumptions for each of the three key drivers.

Variable	Baseline forecast assumption
Population	States of Guernsey 2018 population baseline forecast
No. of visitors	Augmented baseline target forecast from SOG (assumed 50% achieved due to scale of prediction)
Marine Fuel efficiency	Average of petrol and diesel efficiency forecast

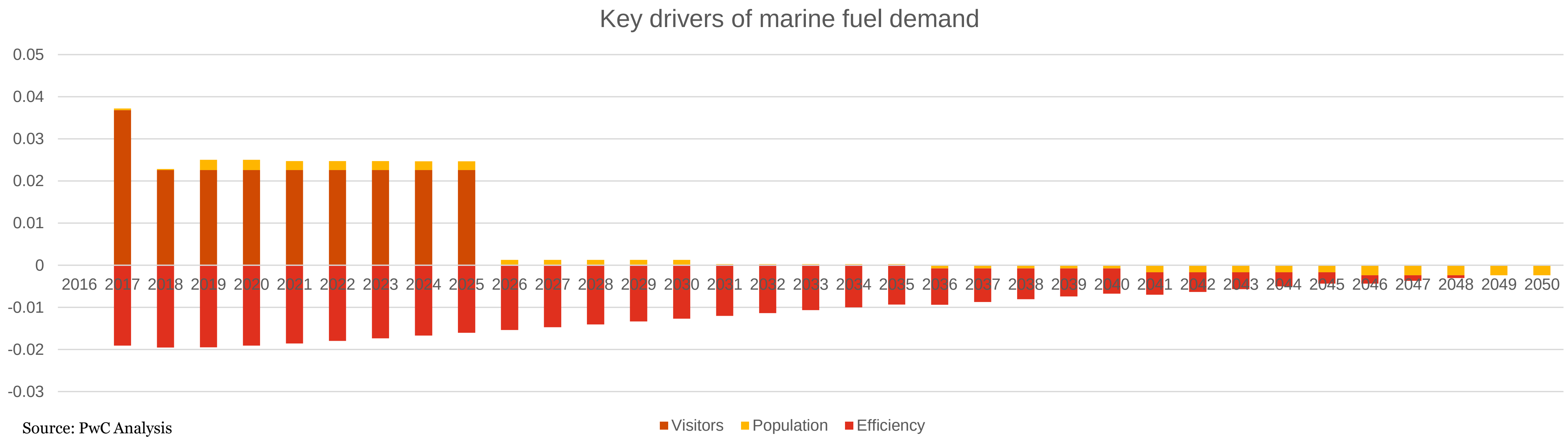
Baseline forecast for marine demand

The baseline forecast of Marine Fuel demand is shown in the graph below. The predicted rise in aviation fuel demand in the next couple of years is mainly caused by the increase in number of visitors which was suggested by the SOG committee (as seen in the aviation demand forecast). After 2026, the decline in marine demand is mainly caused by the improvement of fuel efficiency overtime. The kinked point at 2025 is caused by the assumption that there is no further increase of no. of visitors once it reaches the target in 2025 (as previously noted)



Source: PwC Analysis

Drivers of changing marine fuel demand



Source: PwC Analysis

- The predicted upward trend in marine fuel demand in the coming few years is mainly driven by the increase in number of visitors, and also the increase in population. However, we have assumed that the SOG would like to remain the no. of visitors at the targeted level after 2025 to be consistent with the PwC Hydrocarbon Study assumptions.

- The particularly large increase in 2017 is mainly caused by the actual change in number of visitors from 2016 to 2017.

- However, these increases are partially offset by the increase in vessels efficiency, which gradually dampens out overtime. Note that although vessel efficiency is expected to increase in step changes as and when new vessels are invested in, in the long-run, these step changes can be proxied by a smooth transition and this will not affect the efficiency forecast substantially. Additionally, it is impossible to predict the step-changes currently without making heavy assumptions about when and how much is invested in new vessels.

6

Heating Demand Forecast

Heating demand model in depth

Gas oil, heating oil, LPG and electricity are the four main energy sources that are used for heating in Guernsey. Historical time-series data is only available for heating oil and LPG demand in Guernsey, therefore we cannot perform econometric analysis to forecast total heating demand. Instead, we assume that total heating demand follows the multiplicative model below:

$$Total\ Heating\ demand_t = A * \frac{Population_t^{\alpha} * Visitors_t^{1-\alpha}}{Efficiency_t}$$

$$1 + H_t = \left(1 + g_{pop,t}\right)^{\alpha}$$

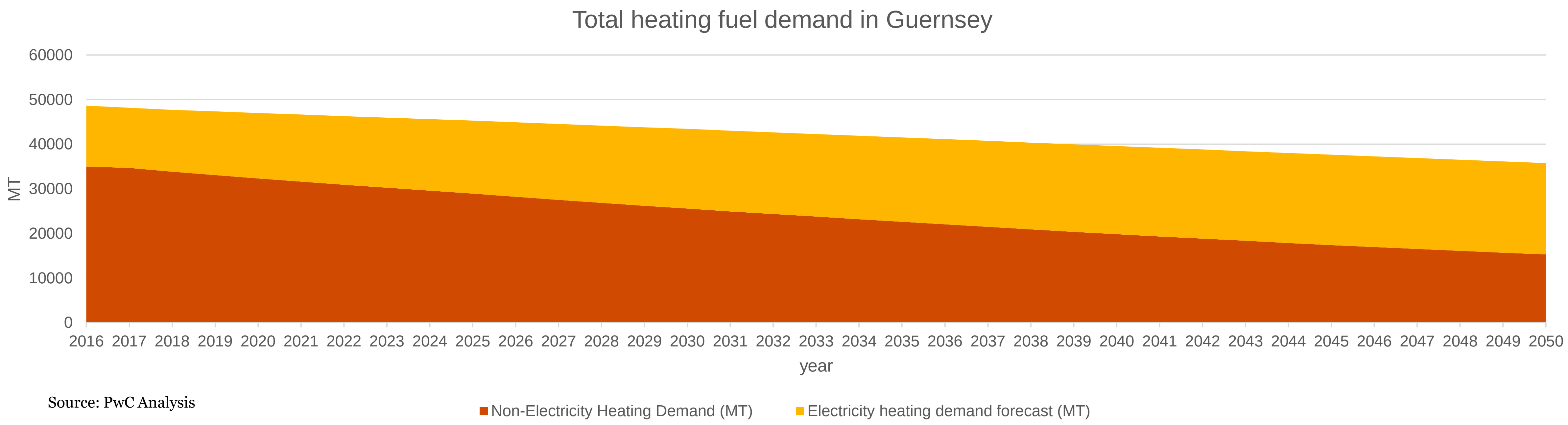
Percentage changes in population, visitor numbers and efficiency feed through to percentage changes in heating demand. Using this model, we have forecasted the growth rate of heating demand by analysing the growth rates in different drivers. As per the marine fuel demand model, we use 2016 data on total heating demand to calibrate the model using the constant (A). Note that in contrast to the marine fuel demand model, we use weight α as the indicator of the importance of the population growth rate relative to the visitor growth rate, due to the fact that visitors usually stay in the Island for a short period of time. The way that we calibrate this is to multiply population by 365 (population days) and multiply the number of overnight visitors by 3 (estimated number of nights stayed by visitors on average), and calculate the fraction of population days out of the sum of the two.

Variable	Baseline forecast assumption
Population	States of Guernsey 2018 population baseline forecast
No. of visitors	Augmented baseline target forecast from SOG (assumed 50% achieved due to scale of prediction)
Heating Fuel efficiency	National Grid FES18 forecast on Energy Performance of UK homes

Baseline forecast for heating demand

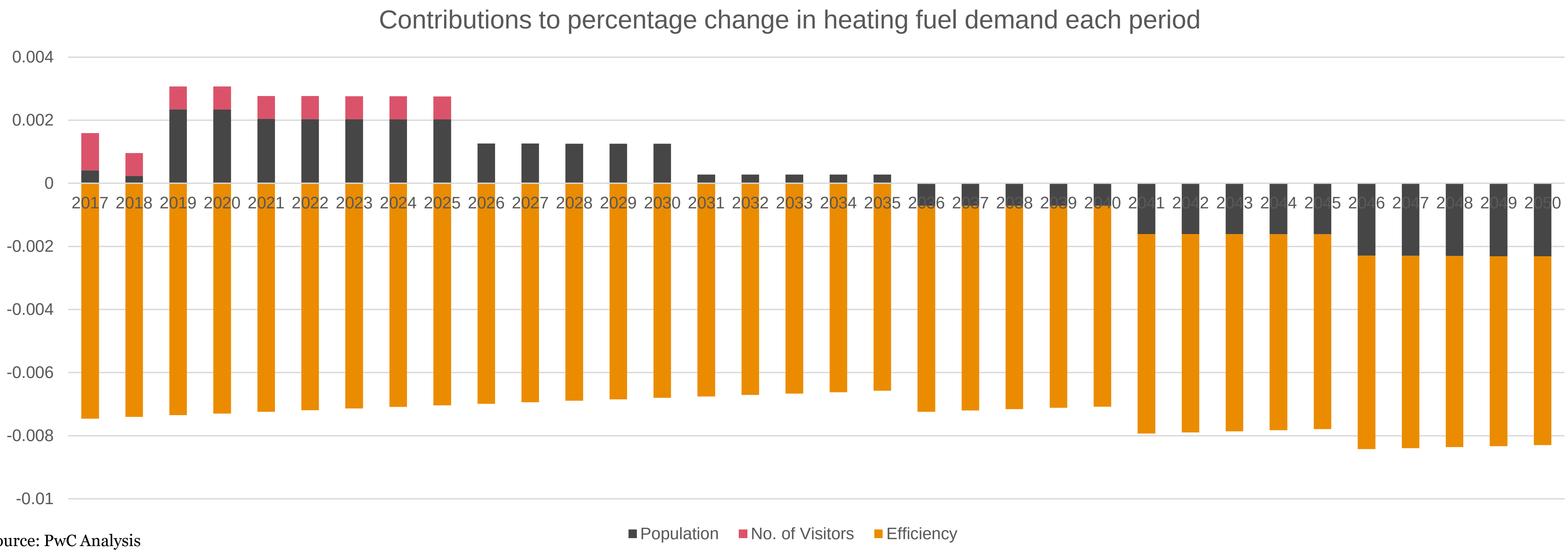
The baseline forecast of heating demand is shown in the graph below. Heating demand is forecast to remain constant in the near future owing to two counteractive forces: 1) the predicted increase in the population and number of visitors; and 2) the decrease in fuel demand owing to efficiency improvements. From 2026 onwards, efficiency improves sharply over the following five years, creating a steeper downward slope for heating fuel demand. After 2030, the decline in heating demand becomes more moderate, due to slowing efficiency gains and also a decrease in Guernsey's population.

The core electricity demand model uses a set of variables which accurately predict the electricity demand market in 2017, however it does not account for future changes in heating demand source shares and thermal efficiency gains. Therefore, when adding the components together to forecast future electricity demand, we only add the additional unit change in electricity heating demand forecasted by the heating demand model (along with the forecasted demand for other heating sources), to our core electricity demand model.



Source: PwC Analysis

Drivers of changing heating fuel demand



Source: PwC Analysis

The impact of population changes and visitor numbers are in line with our forecasts for other energy demand components, i.e. initially increasing then falling in later years).

The efficiency gain in heating demand over time is the largest driver of heating demand reduction over the period. This is largely caused by the installation of new insulation technologies, underfloor heating, solar panels etc. In particular, the sharp increase in efficiency between 2026 and 2030 is caused by a forecasted more rapid decline in EPC D houses (see following slide for details).

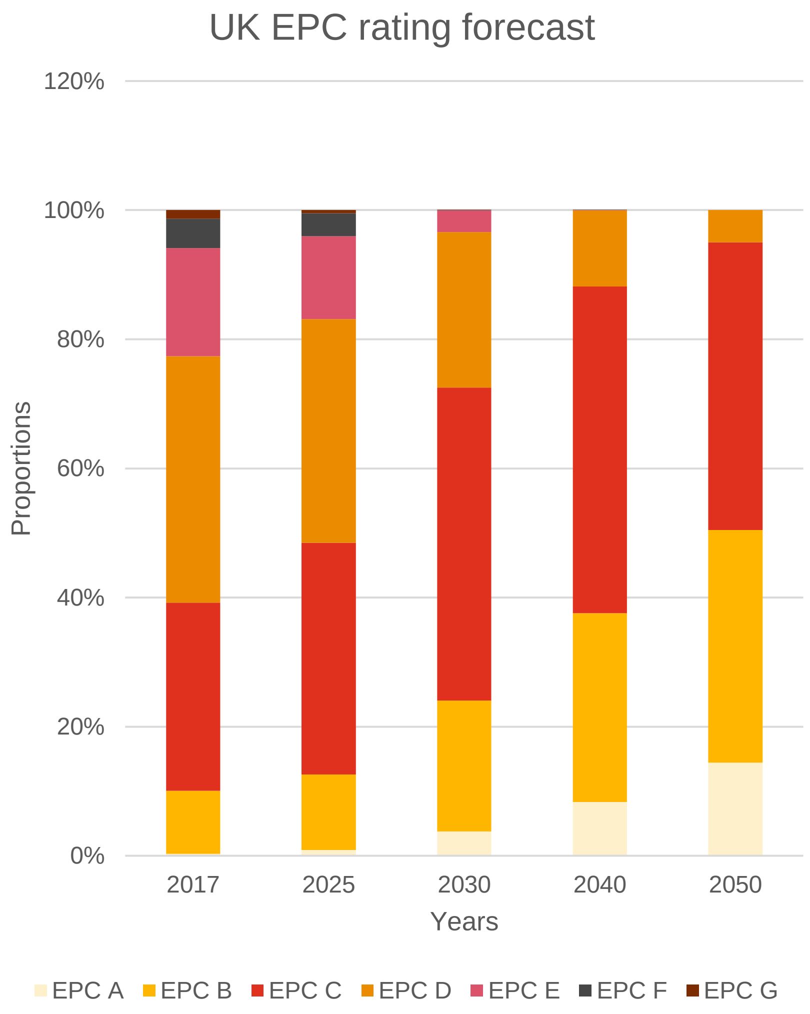
Measuring efficiency gains in the heating market

Energy Performance Certificate ratings

The FES18 forecasts the EPC rating based on expected thermal efficiency performance improvements in the UK. Houses are classified as the most efficient in band A and least in band G. There are many factors considered in the classification of houses, such as:

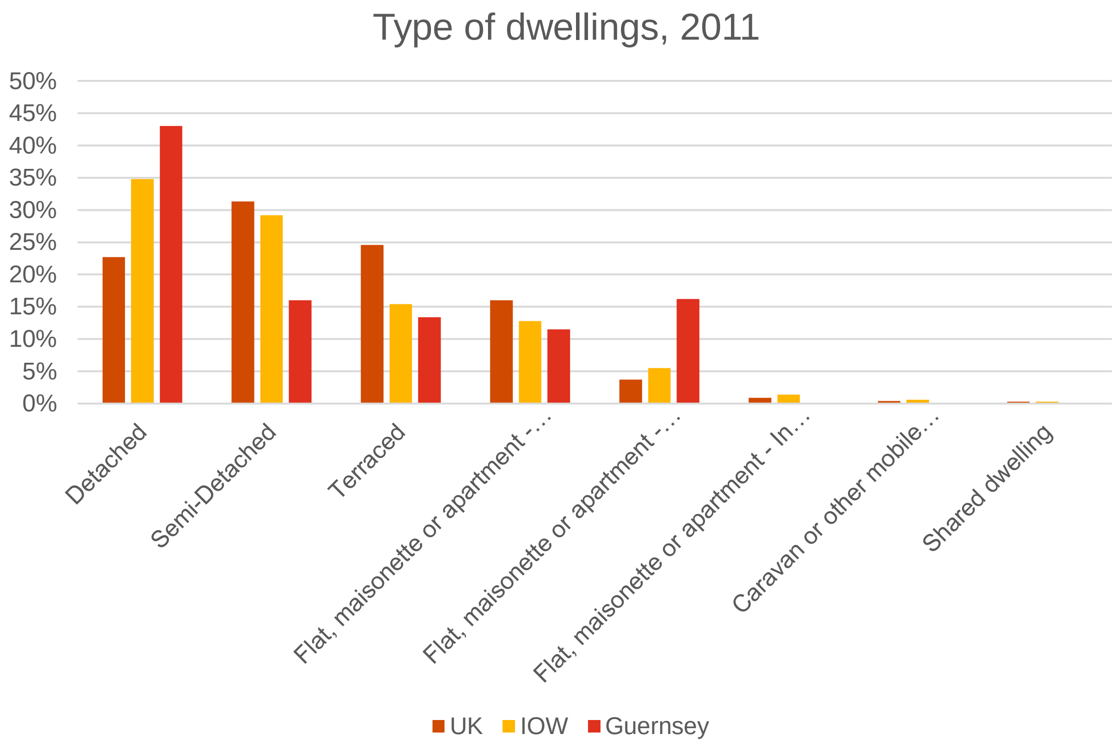
- Materials used for construction of the dwelling
- Thermal insulation of the building fabric
- Air leakage from the building
- Efficiency and control of the heating system(s)
- South facing windows
- The fuel used to provide space and water heating
- Ventilation and lighting
- Energy for space cooling
- Renewable energy technologies

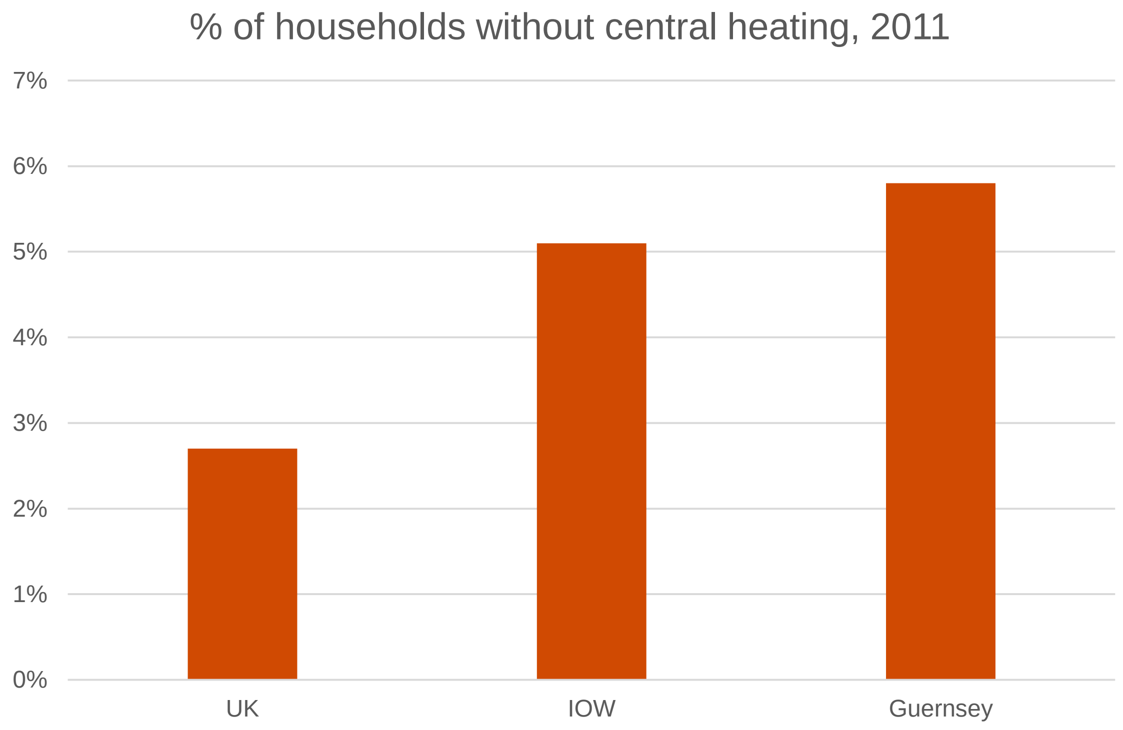
By assigning numbers to each band (e.g. 7 to band A, 1 to band G) we are able to quantify the average level of efficiency in the UK.



Source: National Grid 2018 FES

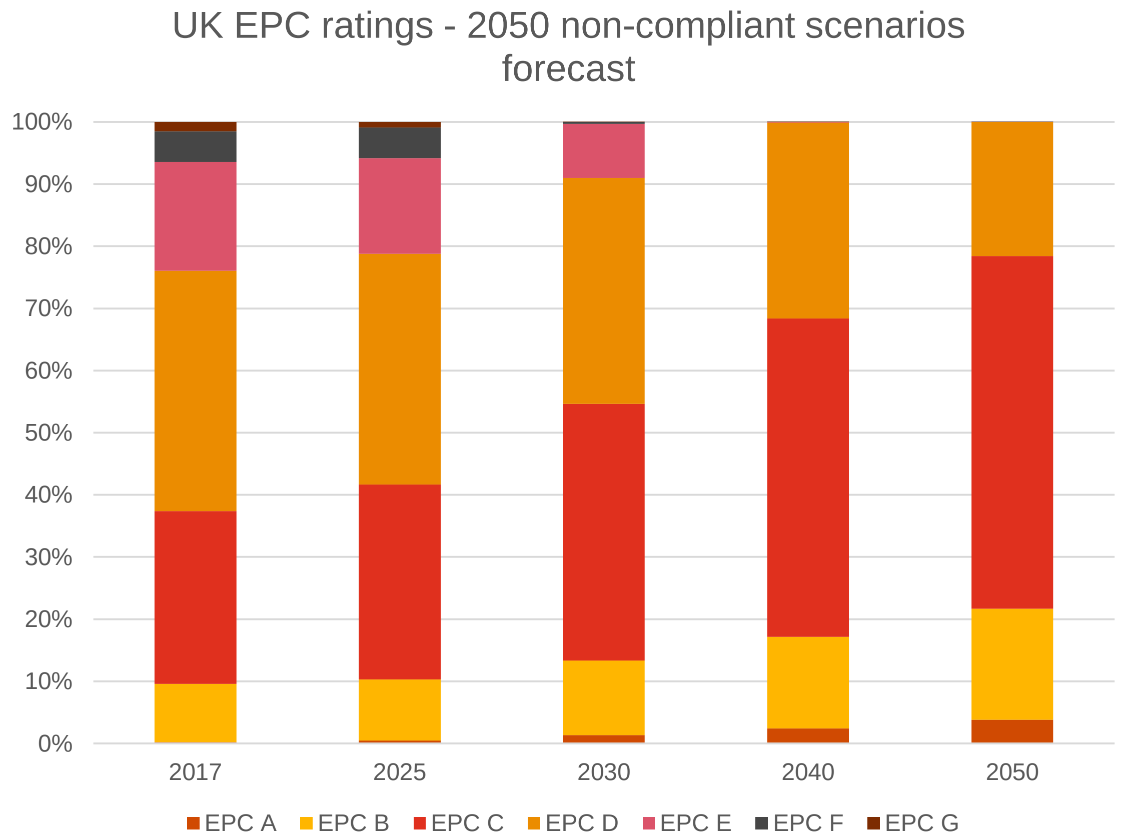
Understanding the Guernsey housing stock

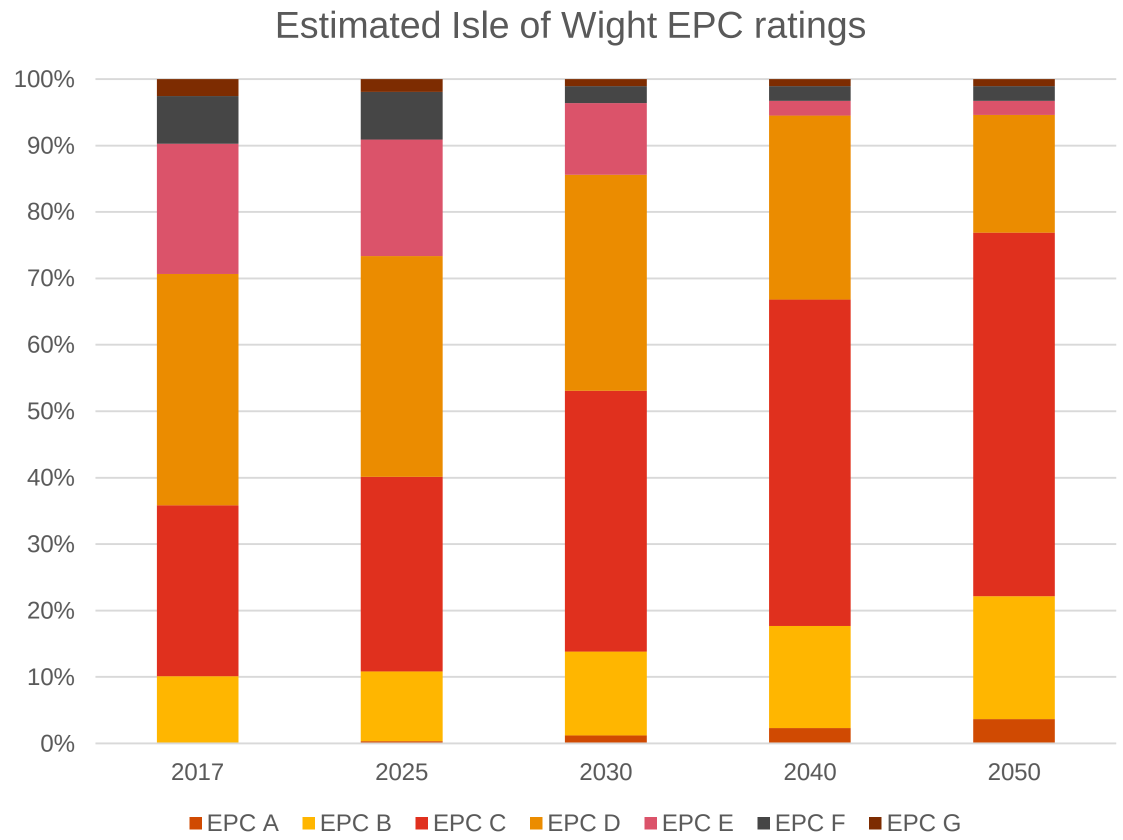




The Guernsey housing stock is notably older than the UK housing stock, therefore is likely to have poorer heating efficiency. Therefore, a better comparator would be a UK county with more similar housing properties. In terms of type of dwellings and percentage of household without central heating, Isle of Wight has similar characteristics to Guernsey. Moreover, it is a relatively small county within the UK with 60,000 households (Guernsey has 23,000).

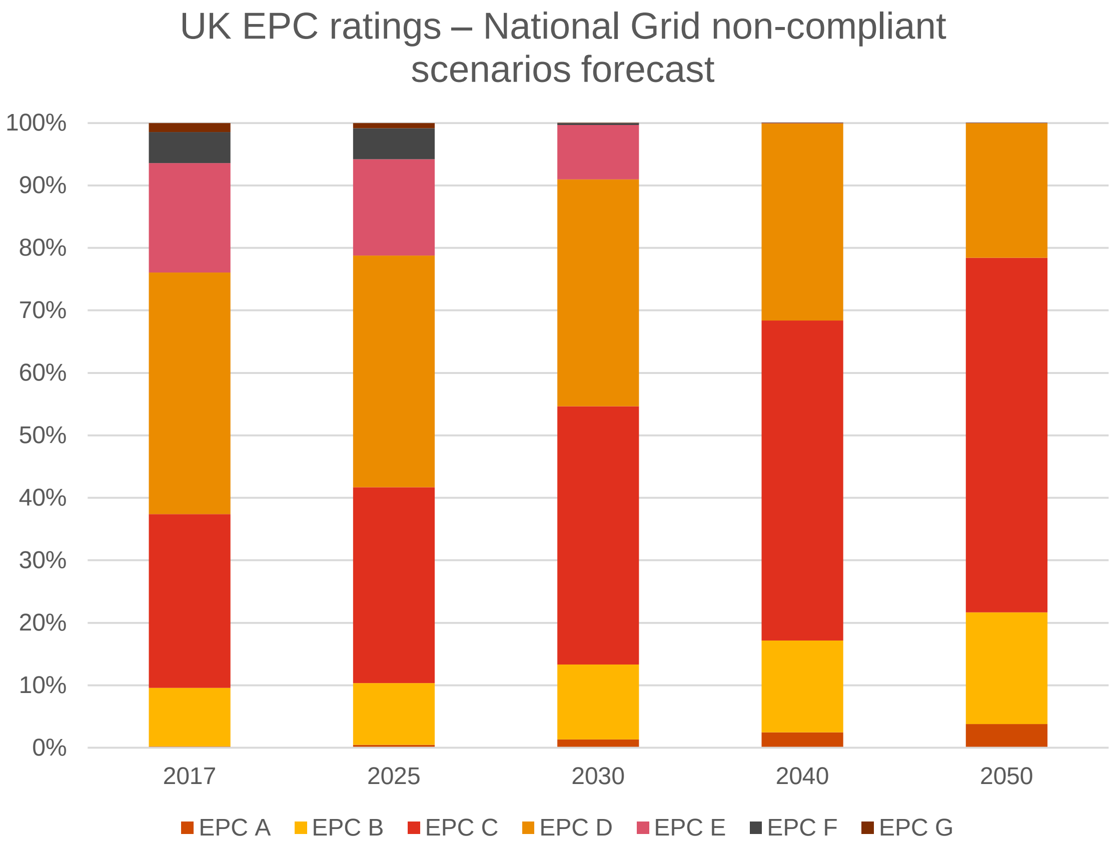
EPC ratings – UK vs Isle of Wight

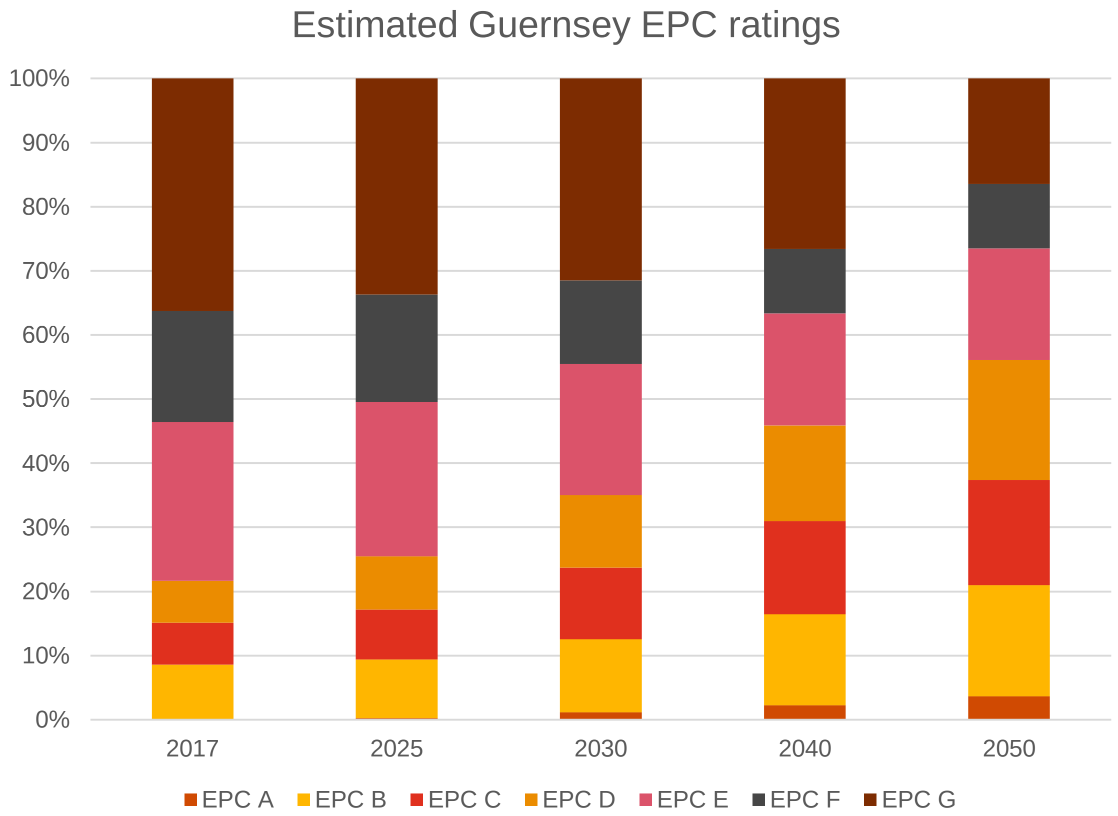




The National Grid Future Energy Scenarios predict that the UK housing stock will be more efficient than the forecast for the Isle of Wight in all periods. This poorer heating efficiency performance indicates that Isle of Wight is a better initial proxy for Guernsey's EPC rating composition as it would capture the fact that the Guernsey housing stock is older than that in the UK, and so less efficient. However, the percentage of households without central heating suggests that the housing stock in Isle of Wight is marginally more efficient than that in Guernsey. Therefore, Isle of Wight's distribution should be considered the upper bound.

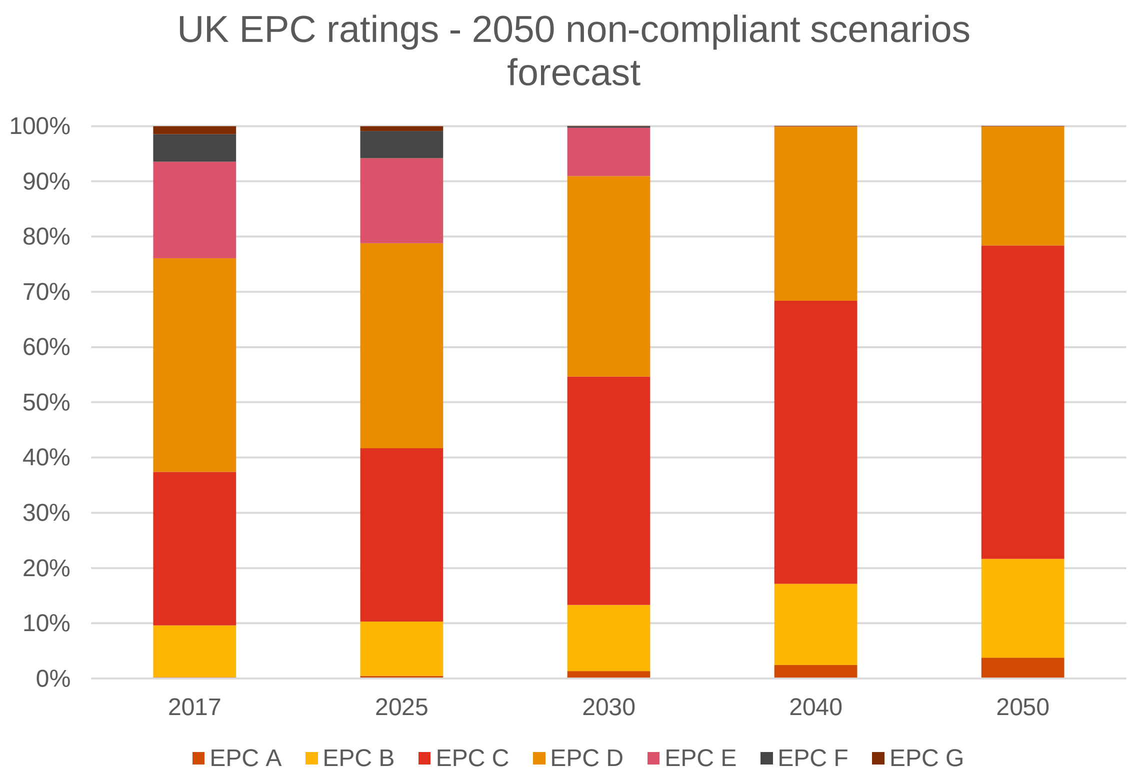
EPC ratings – UK vs Guernsey estimate

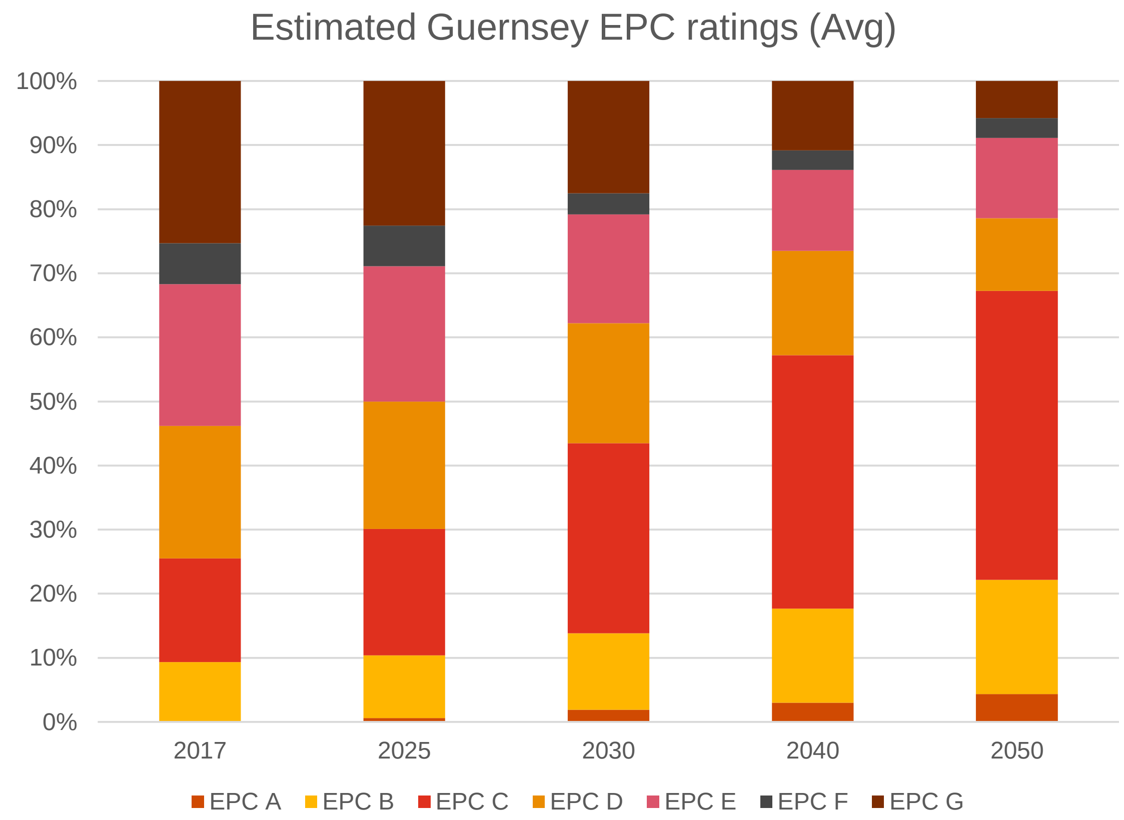




We have approximated Guernsey's housing stock EPC ratings using the age of properties in Guernsey. We have assumed that the older the houses are, the less efficient they are. This reveals a significant difference between the UK and Guernsey housing stock as 30% of houses in Guernsey were built before 1910. However this method ignores the fact that the houses may have been renovated since, and therefore the heating efficiency would have changed. As this proxy underestimates the efficiency of the Guernsey housing stock, this should be considered the lower bound.

EPC ratings – Average of Isle of Wight and Guernsey estimate





By averaging the upper and lower bound estimates, we achieve a less skewed distribution of EPC ratings. EPC E/F/G households are less dominant but remain a significant proportion of the housing stock.

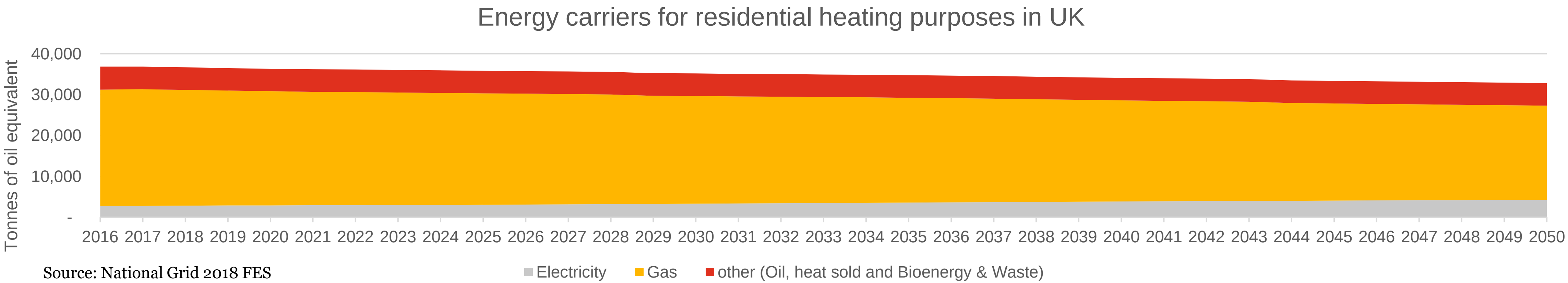
Our approach to forecasting the share of non-electricity heating demand

We combine data on Guernsey's heating source shares from 2016 with UK forecasts of the energy transition to electric heating from the National Grid FES

$$Non\ Electricity\ Heating\ Demand_t = Total\ Heating\ Demand_t\ *\ Share\ of\ Non\ Electricity\ Heating\ Demand_t$$

Assumptions about the transition to electric heating are a key determinant of our estimated demand for heating from electricity and non-electricity sources. We only have an estimate of the heating demand split by fuel source from 2016, as provided by the PwC Hydrocarbon study, therefore we cannot directly forecast the trend in any transitions towards electricity sourced heating. Additionally, there is limited data and information on the rate of energy transition towards electricity sourced heating in Guernsey.

Our approach to calculating the transition has been to use the forecast of residential heating market shares in the UK out to 2050 by combining data from National Grid FES and National Statistics on heating demand shares in the UK, as well as data on relative heating fuel prices in Guernsey and the UK. We first calculated the increase in the ratio of electricity to non-electricity sourced heating in the UK, and then applied this to the market share estimate for Guernsey's heating demand in 2016, to derive the percentage increase in the market share of electric heating demand. This estimate is then adjusted using an econometric model (see following slides) which is used to estimate the impact of relative fuel prices on energy transition. This estimate is subsequently used to adjust the forecasted UK energy transition to be more applicable to Guernsey by using data on relative energy pries in Guernsey.



Source: National Grid 2018 FES

The role of relative prices in adjusting our estimate

It is reasonable to assume that consumers consider the relative total cost of life time operation when deciding whether or not to switch from a gas boiler to an electric boiler. Below we show an example calculation of the lifetime cost of electricity and gas boilers in the UK using data from GEL, National Grid and ONS, assuming the life span of a boiler is 15 years.

Gas boiler	
Unit price per kWh	13.0 p
Amount of energy needed per year	(7500/0.8) kWh
Life time	15
Capex	£2,000
Total cost	£20,281

VS

Electricity boiler	
Unit price per kWh	8.7 p
Amount of energy needed per year	7,500 kWh
Life time	15
Capex	£4,000
Total cost	£13,788

If we assume that households are rational enough to make these types of decisions on average, we can econometrically model the historical heating demand ratio between gas and electricity as follows:

$$\Delta Electricity\ Share_{t+1} = \alpha + \beta k^{\frac{E_t(Total\ Cost\ for\ Electricity)}{E_t(Total\ Cost\ for\ Alternatives)}} + e_t$$

Where α captures the growth trend, β captures the linear relationship between relative prices and the electricity share, and e is the residual error. Note that k is a parameter that we calibrate in order to prevent unrealistic transitionary path by enabling non-linear relationship between the change in electricity share and total cost ratio, and the calibration also allows us to maximise the R-squared of the regression.

Calculating relative total costs

On the previous slide we provided a simple example of how households may reasonably evaluate different heating options, which we can rewrite in the following form. In particular, total cost calculations for different technologies are expected to change over time as households update their information.

$$E_t(Total\ Cost) = price_t * Energy\ needed_t * T + Capex_t$$

That is, expected total cost is equal to unit price times energy needed annually and the number of years in use plus the initial capital expenditure. What we are interested in here is the relative total cost of different technologies, so we then divide one equation by another:

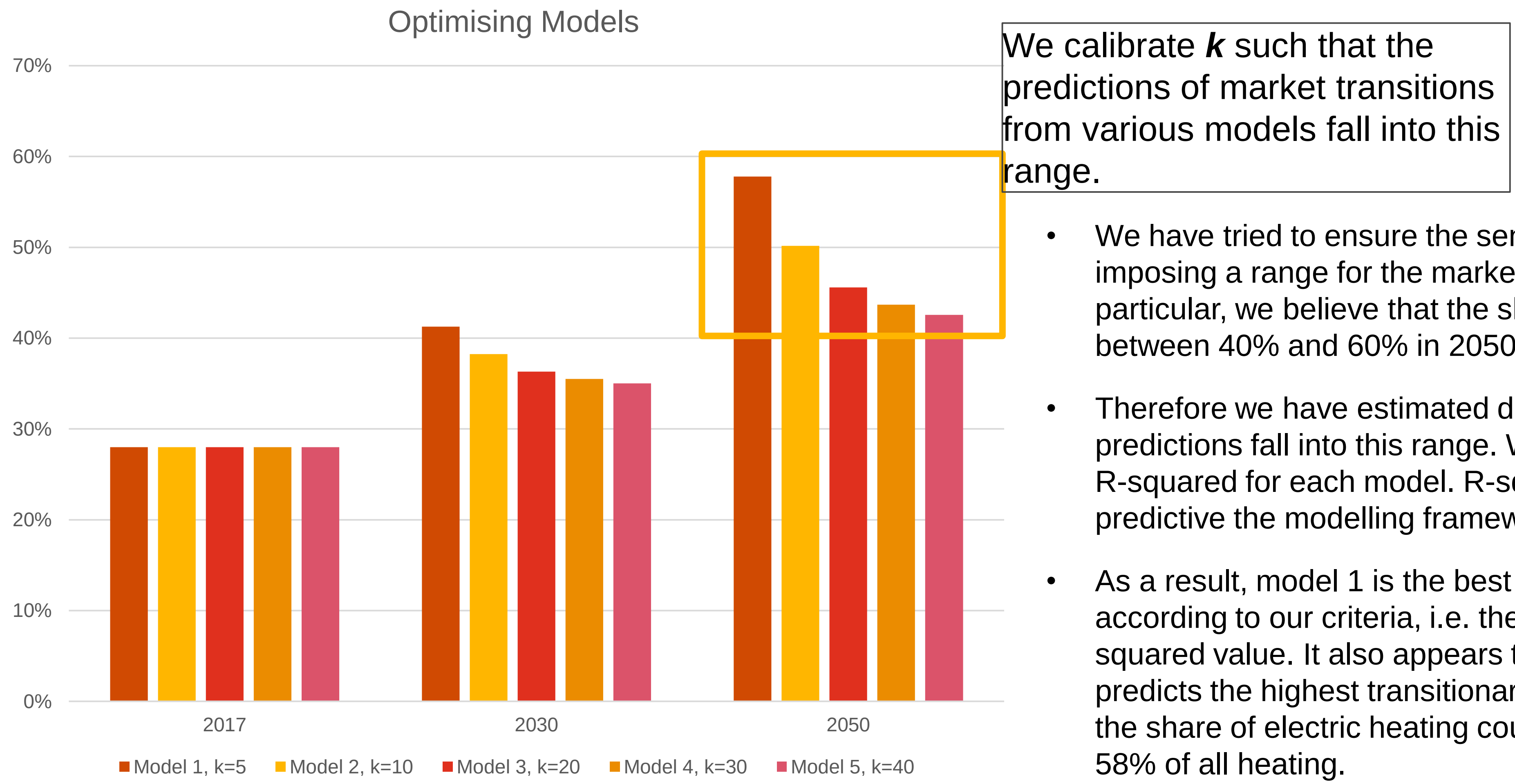
$$\left(\frac{\boldsymbol{E_t}(\boldsymbol{Total\ Cost\ of\ Electricity})}{\boldsymbol{E_t}(\boldsymbol{Total\ Cost\ of\ Alternatives})}\right) = \frac{\boldsymbol{E_t}(\boldsymbol{Total\ Cost\ of\ Electricity})}{\boldsymbol{w_{gas}E_t}(\boldsymbol{Total\ Cost\ of\ Gas}) + \boldsymbol{w_{oil}E_t}(\boldsymbol{Total\ Cost\ of\ Oil})}$$

We estimate the econometric model on the previous slide (using OLS as an exception due to the small number of variables) using historical UK data for this equation. We then input Guernsey forecasted total cost estimates to derive the implied growth path for electricity demand in Guernsey.

Therefore, this model suggests that we would need to forecast the future relative prices and efficiencies between different technologies if we were to model the transition to electricity. To do so, we use the following assumptions:

- **Gas/Oil prices in Guernsey**: increase 1% p/a and **Electricity prices in Guernsey**: increase 2.5% p/a in line with electricity demand model
- **Energy needed for gas, oil and electricity boiler**: we used data from Building Energy Performance Assessment on Gas boiler efficiency and use a trend forecast out to 2050, we assume Electricity boiler efficiency remains unchanged as they are already 99% efficiency (VHL)
- **CAPEX costs:** rise with inflation, we have assumed roughly £2,000 for Gas/Oil boilers and £4,000 for Electricity boilers

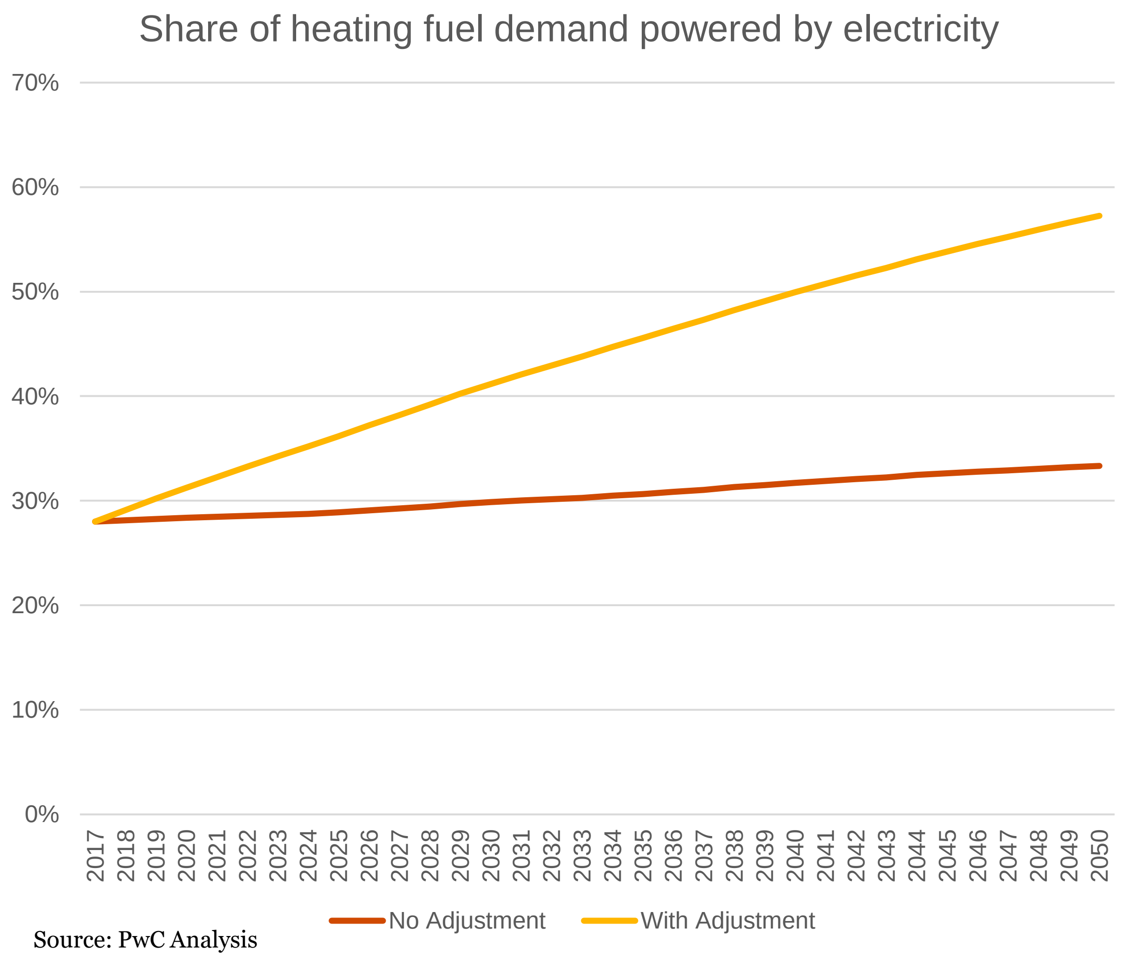
Impact of the relative total cost adjustment on the energy transition forecast (1/2)



Source: PwC Analysis

- We have tried to ensure the sensibility of the model by imposing a range for the market share in 2050. In particular, we believe that the share should be bounded between 40% and 60% in 2050 as a sensible result.
- Therefore we have estimated different models whose predictions fall into this range. We compare them using the R-squared for each model. R-squared indicates how predictive the modelling framework is.
- As a result, model 1 is the best performing model according to our criteria, i.e. the model with the highest R-squared value. It also appears to be the model which predicts the highest transitionary effects. Under this model, the share of electric heating could increase up to around 58% of all heating.

Impact of the relative total cost adjustment on the energy transition forecast (2/2)



Source: PwC Analysis

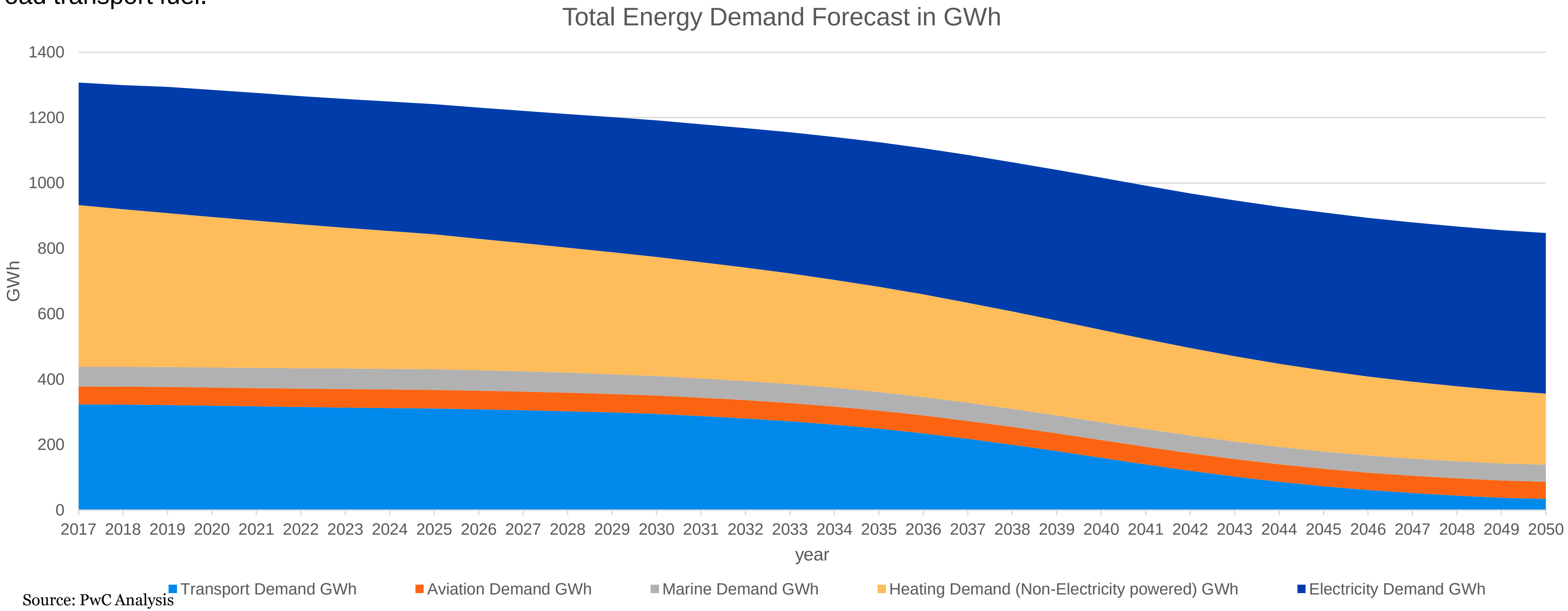
- The adjusted predicted market share of electricity sourced heating is considerably higher after relative price differences are taken into account between Guernsey and the UK.
- This reflects the fact that the total cost of electricity is cheaper in Guernsey vs. the UK and this is forecasted to remain true (in 2017, Guernsey's electricity to gas price ratio was 0.67, whilst in the UK it was 3.88).
- After taking into account future growth rates of different prices, the difference in relative total costs in the two locations becomes smaller, indicating a smaller adjustment needed over time. However the absolute difference remains significant due to the large cross-sectional differences in prices.
- Note we have now also included the transitionary effect from oil boilers to electricity boilers. We have also assumed that the sub-share of heating oil and gas oil remains the same throughout our forecasted period. In other words, there is equal rate of transition from each market segment.

7

Total Baseline Energy Demand Forecast

Baseline total energy demand forecast

We forecast a downward trend in total energy demand for Guernsey. This is largely due to the fact that technological efficiency improvements will reduce underlying energy requirements in all markets. Another driver of this downward trend in the baseline is the expected rapid reduction in ICE vehicles, which results in much lower demand for petrol/diesel in the future. However, the EV uptake built into our forecast, and general transition of the heating market towards electricity sourced heating, is expected to increase the demand of electricity and counteract the fall in road transport fuel.

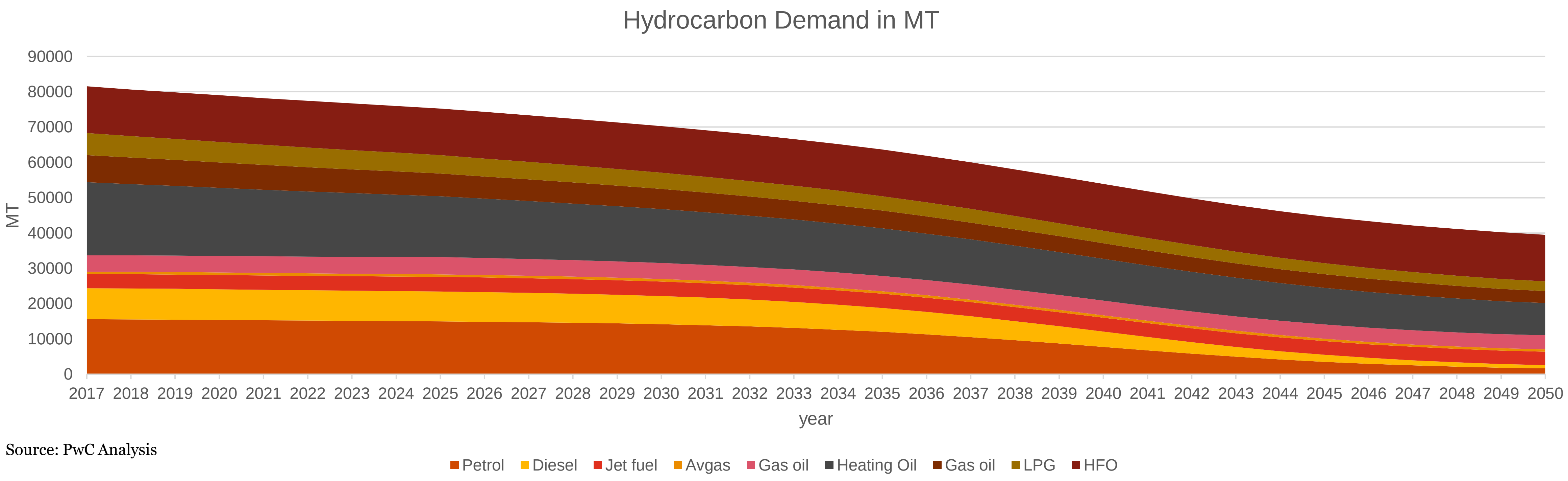


Source: PwC Analysis

Baseline total hydrocarbon demand forecast

This graph shows the amount of hydrocarbon energy that is forecasted to be consumed within Guernsey. The forecasted demand trend is downwards as in the PwC Hydrocarbon study, with the only main difference being a much steeper reduction in the road transport market. This is driven by assumptions around EV uptake which reflect an ambitious government agenda launched in 2017 to eliminate the sale of all ICE vehicles by 2030.

In Guernsey, electricity is either generated domestically using HFO or imported through interconnectors. We apply the same assumptions around the forecasted share of electricity generation as those used in the PwC Hydrocarbon study.

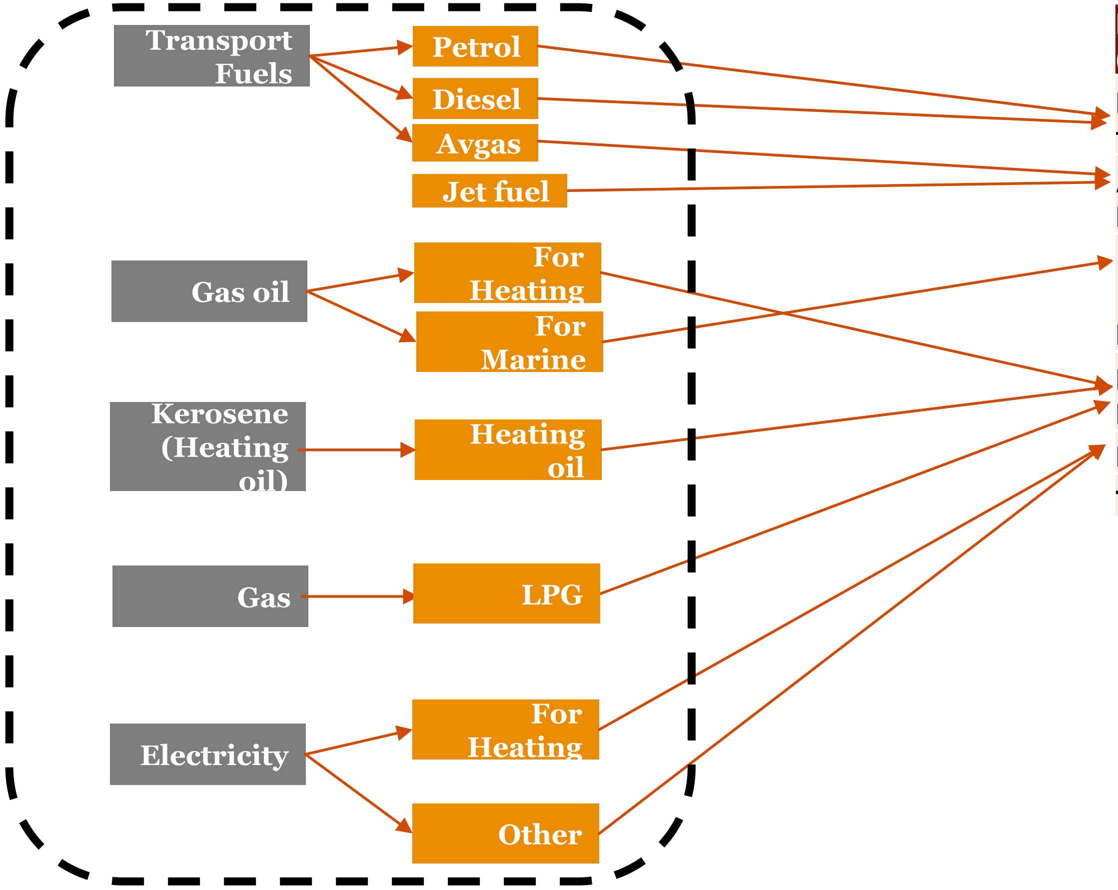


Source: PwC Analysis

Different market segments in 2018 and 2050

Electricity demand is expected to be the most significant market segment in 2050, taking up around 53% of total demand. In contrast, road transport fuel demand will only take up around 1.8% of demand, reflecting the significant effect of EV uptake in the baseline. Heating, aviation and marine fuel demand are all expected to have relatively moderate changes in terms of shares.

Guernsey energy market source mapping



Guernsey energy market shares in 2018 and 2050

Demand segment (GWh)	2018		2050	
Road transport fuel demand	322.3	24.8%	34.3	4.0%
Aviation demand Forecast	55.1	4.2%	52.2	6.2%
Marine demand	60.6	4.7%	52.1	6.1%
Non-Electricity Heating Demand	481.9	37.1%	217.7	25.7%
Electricity	379.4	29.2%	491.0	58.0%
Total	1299.2		847.3	

8 Appendix

Econometric modelling approaches used

Where econometric models are used, we have employed one of two approaches, documented below. All models use annual data and stationarity testing on residuals has been undertaken in cases where data are suspected to be non-stationary. Additionally, all variables are expressed in logs to automatically capture variable interactions in levels.

Approach 1: Bayesian Stochastic Search Variable Selection (SSVS) - used for modelling relationships between drivers and energy demand

As noted, for a number of energy demand components, we have available historic data on demand and demand drivers, enabling us to econometrically estimate the relationship between energy demand and its drivers. A typical approach used is linear regression estimated using ordinary least squares (OLS).

Whilst we still employ a linear regression approach, we use an alternative approach called Bayesian Stochastic Search Variable Selection (SSVS) to estimate the regression coefficients. SSVS prevents overfitting by incorporating a hierarchical mixture prior on regression coefficients and produces much more accurate coefficient estimates in settings where the ratio of variables to observations is too large to use valid asymptotic or nonparametric frequentist inference. This is true for our analysis – as we only have small sample sizes available (<20 observations).

More detail on the SSVS model approach can be found in the following slides

Approach 2: Autoregressive-Integrated-Moving Averages (ARIMA) – used for time-series forecasting of drivers

ARIMA modelling is popular for time-series analysis and is typically used to forecast variables using information about the historical time-series.

An ARIMA model has three components, the ‘AR’ component – which relates to the role of the historic values of the variable being forecasted, the ‘I’ component – which relates to whether the data has been differenced to eliminate any stochastic trends which can make forecasting unstable, and the ‘MA’ component – which relates to the role of past model errors in being adjusted for.

As our datasets are extremely limited in size, we typically employ a a simpler version of the ARIMA model which only incorporates Autoregressive (AR) and Integrated (I) components. This again motivated by our extremely limited datasets, as only simple relationships can be reliably estimated in such settings.

More detail about the ARIMA approach can also be found in the following slides

Regression approach details: Bayesian Stochastic Search Variable Selection (SSVS)

Bayesian stochastic search variable selection is a method of selecting variables and estimating regression coefficients in linear regression in settings with many regressors or few observations.

The approach uses a hierarchical discrete mixture prior on the coefficients. More specifically, it is assumed that coefficients may be described by one of two zero-mean Normal distributions. The difference between the two distributions is in the variance – one distribution assumes an almost zero variance, whilst the other assumes an extremely large variance. The parameter θ_i describes the probability that the coefficient is drawn from each density. This parameter itself follows it's own (hierarchical) Bernoulli prior distribution.

The intuition behind this approach is that it allows the data to tell the researcher whether each variable should be selected according to the estimated (posterior) probability θ_i. Note that if θ_i=0 and the prior with zero variance is selected, the coefficient 'i' is set to (almost) zero. Using well known Markov-Chain-Monte-Carlo methods to compute model draws iteratively, the distribution of parameter draws converges to the true conditional distribution of all parameters (θ,B,σ). Bayesian Model Averaging is used on each model draw using an MC-3 algorithm.

The advantages of this approach are two-fold:

- Like many Bayesian shrinkage priors, variable selection is much more accurate than frequentist measures of model selection (such as stepwise selection or t-testing) and does not suffer from the same statistical drawbacks. This is especially true in settings where the ratio of variables to observations is too large to appeal to asymptotic inference.
- However, unlike other Bayesian shrinkage priors (e.g. Bayesian LASSO or Elastic-Net), SSVS has been shown to possess optimal asymptotic properties, and this is partially due to the fact that there is separate control over variable selection and coefficient sizes.

SSVS Model equations

Regression equation

Outcome variable

$$y_t = B'x_t + e_t \qquad e_t \sim N(0, \sigma_e^2)$$

Vector of coefficients

Vector of input variables

Error term

Error variance

Hierarchical prior

$$B_i \sim \theta_i * N(0, \sigma_1^2) + (1 - \theta_i) * N(0, \sigma_0^2)$$

Model coefficient for regressor 'i'

Prior weights

Prior variances

$$\theta_i \sim Bernoulli(p_i)$$

Hierarchical prior on weights

Regression approach details: Autoregressive-Integrated-Moving Average (ARIMA)

ARIMA models are highly popular in time series forecasting due to their simplicity and effectiveness at forecasting using historical time-series.

As noted in Section 1. ARIMA models have three components, an autoregressive (AR) component – which captures information from past lags of the dependent variable. An integrated (I) component, which refers to whether the data has been differenced to account for stationarity concerns, and a moving average (MA) component, which captures the role of historical model errors in adjusting the forecast.

Typically information criteria such as AIC and BIC are used to select variables (i.e. the number of AR and MA components), however the datasets we use to estimate ARIMA models are very small, and so we restrict estimation to an ARIMA (1,1,0). This means that current growth in any time-series (e.g. diesel prices in the road fuel demand model), are forecasted purely based on their historical relationship with last periods growth.

ARIMA models are estimated using maximum likelihood estimation (MLE) However in our case we use ordinary least squares since we do not include any MA components, which are not physically observable and so require MLE to be used. This does not affect the estimation results.

ARIMA Model equations

Illustrative ARIMA(p,1,q)

$$\Delta y_t = \underbrace{\sum_{i}^{p} \rho_i \Delta y_{t-i}}_{\text{Autoregressive component}} + \underbrace{\sum_{i}^{q} \pi_j u_{t-j}}_{\text{Moving average component}}$$

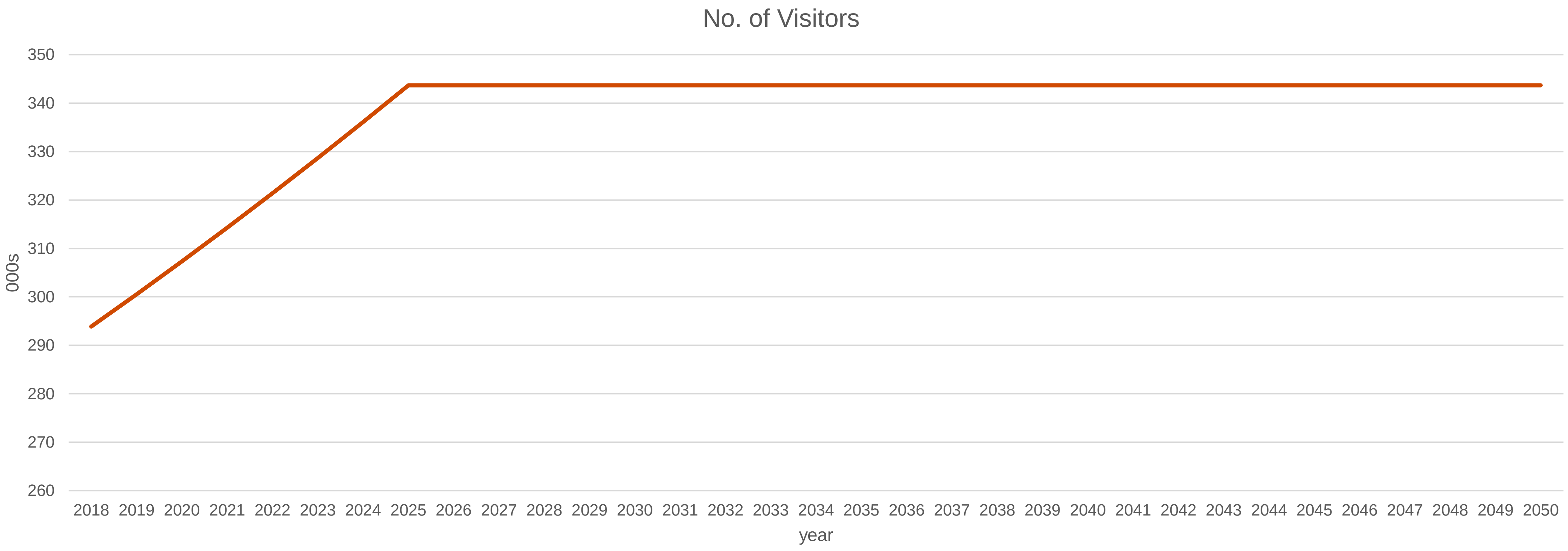
Removal of first order of integration

$$u_t \sim N(0, \sigma_u^2)$$

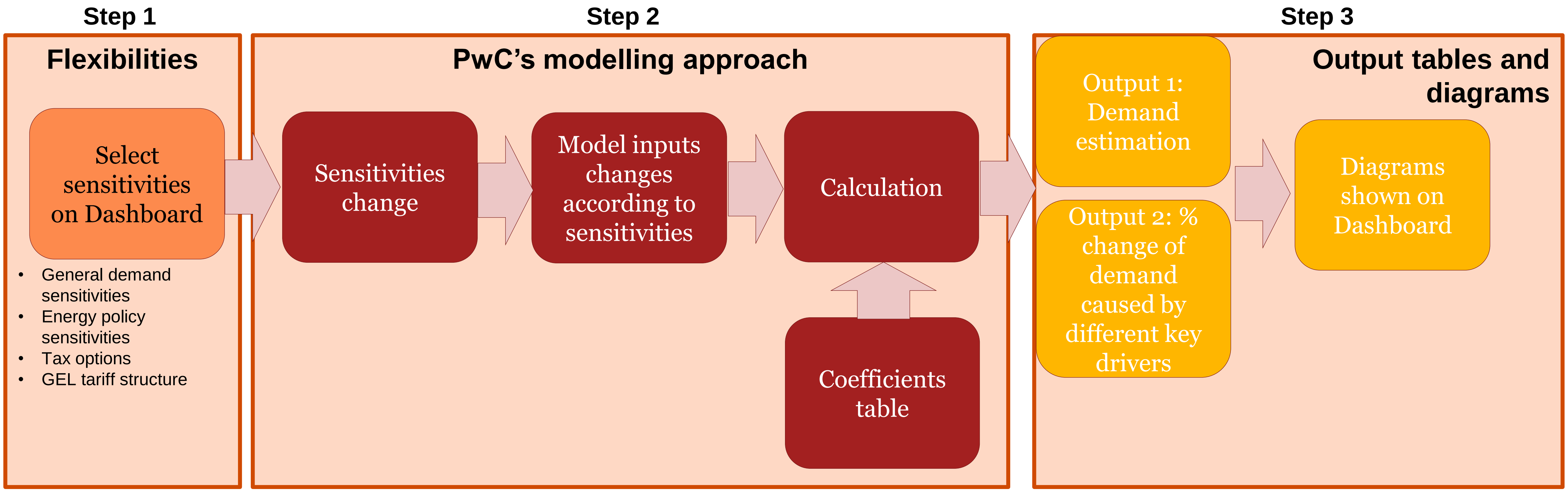
Error variance (normally distributed likelihood)

Number of visitors – baseline forecast

SoG has a visitor target of 400,000 in 2025. However, the current trend suggests that this target may not be achieved. Therefore, we have assumed that only half of the necessary growth will be achieved, i.e. 344,000 visitors in 2025. This is calculated by taking half of the gross growth rate (39.1%), which is 19.6%, and multiplying by the current level of visitors.



Graphical illustration of the Excel model for different forecast assumptions



Step 1: Select sensitivities on the Dashboard tab.

Step 2: Check Cell AP5 on the Dashboard tab. If it displays “Need to update", press the “Update" button above to update model output. If it displays “Up to date", proceed to next step.

Step 3: Diagrams and output tables are updated on the Dashboard tab, based on PwC’s modelling approach.

Step 4: Outputs are shown on the Output-Demand tab.

Thank you

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