The role of technical improvements in decarbonising passenger transport

Matteo Craglia

Supervisor: Dr. Jonathan Cullen

Department of Engineering
University of Cambridge

This thesis is submitted for the degree of
Doctor of Philosophy

Homerton College

June 2020

Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the Preface and specified in the text. It is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. I further state that no substantial part of my thesis has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. It does not exceed the prescribed word limit for the relevant Degree Committee

Matteo Craglia
June 2020

Abstract

Title: **The role of technical improvements in decarbonising passenger transport**

Passenger vehicles are a leading driver of anthropogenic greenhouse gas (GHG) emissions. The majority of efforts to reduce vehicle GHG emissions focus on technical improvements, due to difficulties in reducing travel demand and shifting to alternative modes of travel. However, the rate at which technical improvements can be deployed is highly uncertain. Furthermore, the benefits of technical efficiency improvements may be offset by consumer trends towards larger and more powerful vehicles, filled with a greater number of accessories. Similarly, efficiency improvements can lower running costs, which may stimulate drivers to travel more. These consumer trends create further uncertainty about the impact of technical improvements. The aim of this thesis is to estimate the extent to which future technical improvements might be offset by consumer trends, and the risks they pose to reducing CO_2 emissions.

Firstly, technical efficiency improvements in vehicles over the past two decades are quantified, using driver-reported data for the first time. This is important as vehicle fuel consumption reported by drivers on the road is found to be $\approx$35% higher than official tested values in 2017-18. The analysis shows that technical improvements had the potential to reduce fuel consumption by 1.8 L/100km between 2001 and 2018. However, two thirds of this potential was offset by the increasing size and power of vehicles. Finally, the introduction of new EU vehicle efficiency regulations in 2008/09 is found to have had little effect at stimulating the rate of real technical efficiency improvements in British vehicles.

If efficiency improvements stimulate drivers to travel more, due to lower running costs, potential emissions reductions from technical improvements may be further offset. Past estimates of the magnitude of this effect, known as the Rebound Effect, have varied widely, partly due to data constraints and a reliance upon highly aggregated government statistics. The analysis of this thesis instead uses a novel dataset of over 275 million vehicle road-worthiness tests. Results show that the Rebound Effect in Great Britain is small, with magnitude 4.6%, meaning efficiency improvements are unlikely to greatly stimulate increased mileage.

Having quantified the extent to which technical efficiency improvements in vehicles have been offset by consumer trends in the recent past, the analysis then explores their future role. A range of technology and policy actions can be put in place to reduce carbon emissions, this thesis aims to prioritise between them, based upon their likely impact and uncertainty. Formal sensitivity analysis techniques are used for the first time to determine the relative importance of factors affecting future emissions from passenger vehicles.

The findings show that over 80% of the uncertainty in future cumulative CO_2 emissions can be attributed to uncertainty in electric vehicle uptake and vehicle size and power. These variables are therefore of primary importance for transport policy makers. The analysis also highlights variables of comparatively low importance; these include the carbon intensity of the electricity grid, the share of hybrid electric vehicles, the magnitude of the Rebound Effect and the rate of incremental improvements within powertrain technologies.

The core contribution of this thesis is to compare efforts to improve the technical efficiency of vehicles, with the impacts of consumer trends and factors affecting future transport emissions. The majority of potential emissions savings from engineering improvements in the past two decades have been lost, strong policy action is required to avoid this trend continuing in future.

Matteo Craglia

Acknowledgements

This work was funded under EPSRC grant numbers: EP/M506485/1 and EP/M508007/1. I am also grateful to have been recipient of a Homerton College Graduate Charter Scholarship.

This thesis would not have been possible without the help and support of my family, friends and supervisor. It is thanks to them that I consider my time in Cambridge to have been the best period of my life so far. Iacopo, Leo, Harry, Karla, Simon, Sarah, Catherine, Ana, the Resource Efficiency Collective and the Use Less group, my PhD would not have been anywhere near as enjoyable without your chats. Thank you to Professor Julian Allwood for your guidance, I have learnt so much from you. Thank you to Veronica as well as Oliver Feng and the team at the statistics clinic for enduring my statistics questions.

A particularly special thank you to my supervisor and friend Jon, for reviewing my work, granting me the freedom to pursue particular ideas and being relentlessly positive and encouraging.

Finally, thank you Ingrid, you are my rock.

Publications
Material in this thesis has been published in journals and presented at conferences.
Journal Papers:

- Matteo Craglia, Jonathan M. Cullen, *'Do technical improvements lead to real efficiency gains? Disaggregating changes in transport energy intensity'*, Energy Policy (2019) 134
- Matteo Craglia, Jonathan M. Cullen, *'Do vehicle efficiency improvements lead to energy savings? The Rebound Effect in Great Britain'*, Energy Economics (2020) 88
- Matteo Craglia, Jonathan M. Cullen, *'Modelling transport emissions in an uncertain future: What actions make a difference?'*, Transportation Research Part D (Accepted)

Conference Proceedings and Presentations:

- Poster: *'Fuel for thought: What is the powertrain efficiency of British cars?'*, Cambridge University Fluids, Energy and Turbomachinery Expo (FETE) Conference, 8th July 2017, Duxford, UK
- Presentation: *'Historical trends in the delivery of energy services of passenger transport and space heating'*, 9th biennial conference of the International Society for Industrial Ecology (ISIE) 25-29 June 2017, Chicago, USA
- Presentation and Conference Proceedings: *'Fuel for thought: powertrain efficiencies of British vehicles'*, 9th International Conference on Applied Energy (ICAE), 21-24th August 2017, Cardiff, UK
- Presentation and Conference Proceedings: *'The quality rebound effect in transportation'*, European Centre for an Energy Efficient Economy (ECEEE) Summer Study 2019, June 2019, France

Other published work during the course of the doctoral programme, not directly included in this thesis:

- Pierpaolo Cazzola, Sacha Scheffer, Leonardo Paoli, Matteo Craglia, Uwe Tietge and Zifei Yang *'Fuel economy in major car markets- Technology and policy drivers 2015-2017'*, International Energy Agency and International Council on Clean Transportation (2019)

- Joe Ritchie, Kevin Lane, Jeremy Sung, Sacha Scheffer, Matteo Craglia, Brian Dean, Ian Hamilton, Jessica Glicker, Luis Lopez and Hugo Salamanca, *'Energy Efficiency Market Report 2018'*, International Energy Agency (2018)
- Coenraad Westbroek, Jennifer Bitting, Matteo Craglia, Jose Asevedo, Jonathan Cullen, *'Mapping the Global Flow of Glass: From Raw Materials to End-of-Life'*, Journal of Industrial Ecology (2020)
- Cyrille Dunant, Trishla Shah, Michal Drewniok, Matteo Craglia, Jonathan Cullen, *'A new method to estimate the life-time of long life product categories'*, Journal of Industrial Ecology (2020)

Also contributor to:

- *The Future of Rail: Opportunities for energy and the environment*, International Energy Agency (2019)
- *The Future of Cooling: Opportunities for energy efficient air conditioning*, International Energy Agency (2018)

Table of contents

Chapter 1

Introduction

1.1 Transportation and Climate Change

Motor cars were first introduced in the 1890's following the inventions of compact engines by *Otto* in 1876, and the first motorised vehicles built by *Benz* and *Daimler* in 1886. The motor car rapidly revolutionised western economies, shaping urban environments and stimulating economic growth. The number of registered motor vehicles in Great Britain rose from 32,000 in 1905 to 2,034,000 in 1939 (DfT, 2020d), the growth was even more spectacular in the USA, rising from 79,000 in 1905 to 29,443,000 in 1938 (Rostow, 1978). Writing in 1913, Kennedy (1913), an eminent engineer, summarised the excitement of technological progress at the time:

> *We are all motorists in these days, if not in actual fact as owners or drivers, at least as users and in our hopes.*

Vehicle ownership continued to rapidly expand after the Second World War, as vehicles became ubiquitous and increasingly intertwined with the functioning of modern economies. The number of registered vehicles in Great Britain doubled every ten years between 1946 and 1976. By 2006, they had doubled again with 26 million vehicles on the road (DfT, 2020d). Amid astonishing growth in vehicle ownership and deployments of new technologies, one thing has remained historically constant since the mass adoption of the motor car: their reliance on oil.

Globally, oil provides 94.7% of the energy used in the transportation sector (IEA, 2019c). The combustion of oil, necessary to release its energy and power vehicles, produces carbon dioxide which contributes to climate change (IPCC, 2014). The transport sector as a whole accounted for 24% of global CO_2 emissions from fuel combustion in 2018 (IEA, 2019b). What's more, global CO_2 emissions continue to grow (fig. 1.1, left) with emissions from the transport sector moving in lock-step. Emissions from the burning of fossil fuels in vehicles makes up the same share of the global total today, as it did almost 50 years ago (fig. 1.1, right). Half of global transport emissions are produced by light duty passenger vehicles (IEA, 2017). This thesis investigates measures to reduce their environmental burden.

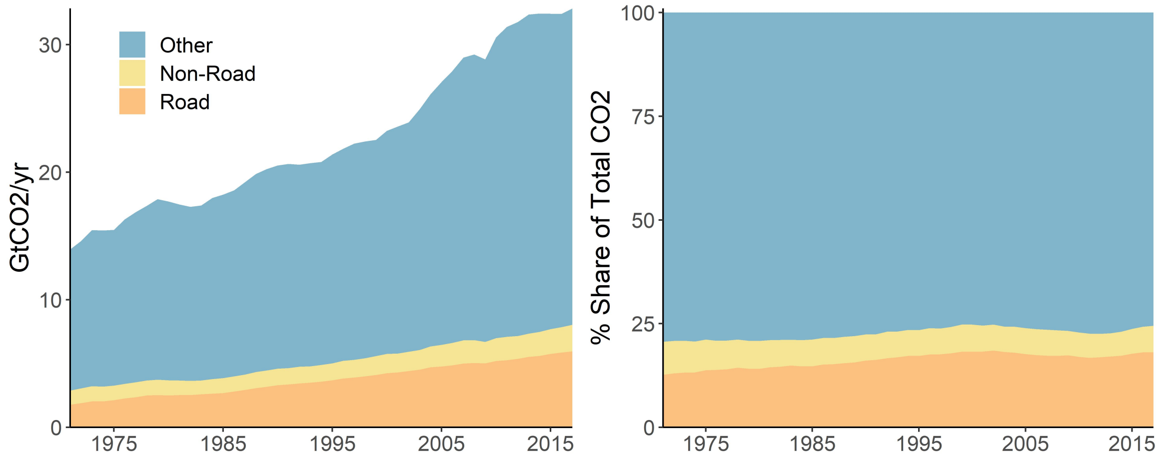

Fig. 1.1 Global annual CO_2 emissions from fuel combustion from road and non-road transportation and other sectors (IEA, 2020)

The need for energy efficiency

Greenhouse gas (GHG) emissions from transport can be considered using the following identity, that splits the drivers of GHGs into an emissions intensity term, a fuel efficiency term and the demand for vehicle miles travelled (VMT).

$$\text{GHG} = \underbrace{\frac{\text{GHG}}{\text{Energy}}}_{\text{Emissions Intensity}} \times \underbrace{\frac{\text{Energy}}{\text{VMT}}}_{\text{Fuel Efficiency}} \times \underbrace{\text{VMT}}_{\text{Service Demand}} \tag{1.1}$$

Reducing any one term in equation 1.1 will help to reduce GHG emissions. The emissions intensity term has historically been challenging to reduce. This is due to the difficulty in de-carbonising the energy sources required to provide mobility, which must be affordable, convenient and high energy density, making it challenging to displace oil based fuels. Equally challenging is reducing the demand for VMT, which is so connected to ideas of mobility and freedom in society. The difficulty in reducing the emissions intensity of fuels and reducing demand for VMT, has historically made improving fuel efficiency (Energy/VMT) the only available measure to reduce emissions.

1.2 Past and present vehicle efficiency policy

The rates of efficiency improvements in vehicles were high during the period of their early adoption. Vehicles in 1938 were approximately 40% more fuel efficient than those in 1924 (Fouquet, 2012), implying an improvement rate of $\approx$3.5% per annum (pa).

Some of the first energy efficiency policies for vehicles in the UK were introduced following the oil crisis of the early 1970s. In 1978, the UK Working Group on Fuel Consumption Targets (WGFCT) called for a 10% improvement in new vehicle fuel efficiency between 1978 and 1985 (Sorrell, 1992). This target was achieved two years ahead of schedule, with average annual improvement rates of $\approx$2.5% pa meaning emissions intensities decreased from 236 gCO_2/km in 1978 to 204 gCO_2/km in 1983 (Rice and Parkin, 1984).

The low, stable oil prices of the 1980's then meant that political interest in fuel efficiency subsided, and no new policies were implemented. In 1983, the WGFCT forecast that the average fuel efficiency of new cars would improve without further policy intervention by 2% pa up to 1985, and then a 1% pa improvement rate until the year 2000 (Sorrell, 1992), amounting to a predicted fleet average emissions intensity of $\approx$168gCO_2/km in 2000. This prediction of future improvements turned out to be optimistic, as average emissions in 2000 were 181 gCO2/km (SMMT, 2018) meaning annual improvement rates were just 0.5% pa, half those predicted by the WGFCT.

The growing importance of climate change in the 1990's, revived discussions about energy efficiency policies. In 1994, the European Commission began to explore introducing new measures to pressure vehicle manufacturers to improve the energy efficiency of their vehicles:

> *Improving the fuel efficiency of cars through the application of available technologies, therefore, is a cornerstone in a strategy to limit CO_2 emissions from transport. (...) The Environment Council in December 1994 more specifically requested the Commission to look into the possibility of substantially lowering the fuel consumption of newly registered cars by 2005. In this context, an average fuel consumption of 5 L/100km for petrol cars and 4.5 L/100km for Diesel cars (equivalent to 120 gCO_2/km) has been mentioned by twelve Member States and the European Parliament as a target.*
>
> *European Commission (1995)*

This proposed target of 120 gCO_2/km was subsequently watered down to a voluntary agreement with the main vehicle manufacturer associations for a target of 140 gCO_2/km by 2008 (Bonilla and Foxon, 2009). This voluntary target was then not met, with European average CO_2 in 2008 reaching 154 gCO_2/km (ICCT, 2019). This failure highlighted the futility of voluntary targets without sufficient incentives or penalties to pressure vehicle manufacturers to improve the energy efficiency of their vehicle fleets. Prompted by the short comings of the past voluntary targets, new binding measures were introduced in 2008/09, requiring that manufacturers meet a target of 130 gCO_2/km by 2015 and 95 gCO_2/km by 2021 or face significant financial penalties. It was expected that manufacturers would rely principally on incremental efficiency improvements to meet these new targets, as summarised in the following statement from the *UK Department for Transport*:

> *Our strategy is designed to ensure that by 2022, the vehicles on our roads will be vastly more energy-efficient. This will primarily be delivered through advances in the efficiency of the internal combustion engine. Alongside this, new ultra-low emission vehicles will be available on the mass-market. Together, this will mean that, for example, new cars will emit on average 40 per cent less CO_2 than they do today.*
>
> DfT (2009)

Whilst the interim 2015 target was met, the diesel-gate scandal (US EPA, 2015) and increasing sales of large vehicles mean meeting the 2021 target looks increasingly challenging. The European Commission set further targets in 2018, requiring a 15% improvement by 2025 and a 37.5% improvement by 2030 from 2021 levels (ICCT, 2019). It is expected that achieving these future targets will require both significant incremental improvements in the efficiencies of vehicles, as well as the uptake of new vehicle technologies and powertrains such as electric vehicles (Mock, 2018). Indeed, current EU and UK government policy continues to rely heavily on assumptions about technical improvements and sales of alternative fuelled vehicles. The future uptake of these technologies is both highly uncertain and historically unprecedented. Past failures of policy-makers to predict future efficiency improvements, highlights the challenges of estimating the impacts of vehicle technologies on future emissions.

1.3 The challenges of predicting future emissions

The future of the transportation sector is vigorously debated by industry and academics alike, with outlooks varying considerably between stakeholders. *Saudi Aramco* suggest 90% of transportation will be still be fuelled by oil in 2040 (Waldmeir, 2018), others maintain all vehicles in Western nations will be purely electric (Seba, 2017).

Nonetheless, it is likely there will be large changes in the transportation sector in coming years. Both British and French governments have recently announced an end to traditional diesel and petrol engine vehicles by 2040 (Asthana and Taylor, 2017), with consultations taking place to bring this forwards to 2035 (Campbell, 2020). Similar developments include announcements by *Volvo* (Vaughan, 2017) and *Maserati* (Sheehan, 2017) that all new models will be hybrid or full electric by 2019. *Mercedes* have stated that they aim to only sell 'carbon-neutral' vehicles by 2039 (Brodie, 2019) and *Fiat Chrysler Automotive* (FCA) aim for more than half their range to include some form of electric propulsion by 2022 (Sheehan, 2017).

It is perhaps worth noting that vehicles propelled by electricity are not new and were first invented in the late 1800's alongside the invention of the internal combustion engine vehicle. The following excerpt from 'The Book of the Motor Car' (Kennedy, 1913) shows the thinking behind electric vehicles over 100 years ago; they were considered to be more than technologically adequate at the time and likely to enjoy significant uptake:

> *(...) the electrical vehicle properly managed should prove of great advantage and the cost per ton mile much less than with petrol engines. It has a well-defined sphere of usefulness. (...) In America the electrical vehicle has asserted itself and has proved its value in large towns. In Boston, for example, there were only 10 electrical vehicles in 1905, increasing to 120 in 1910, and to 300 in 1912, and the rate of increase is going up still. At present there are 30,000 electric vehicles in service all over America; in 1912, 10,000 were built, 6000 pleasure cars and 4,000 commercial cars, and it is estimated 1913 output will be 15,000. At present rates of increase in numbers there should be 100,000 electric cars on the roads in 1915. These figures speak for themselves as to the practical success of present-day electric vehicles. When their significance is realised in this country there will be a mild revolution in automobilism.*

This prediction turned out to be incorrect, as it took more than a century for there to be 100,000 battery electric vehicles on American roads (IEA and ICCT, 2019). The relatively low range and low speed of electric vehicles compared with internal combustion engine vehicles, as well as under-developed battery recharging stations in rural areas, meant internal combustion engine vehicles became the dominant technology (Kirsch, 1998). However, this example serves to further highlight the challenges of making predictions about the uptake of new technologies based on past trends.

1.4 The importance of consumer trends

Current government efforts to reduce CO_2 emissions from transport are reliant on technical improvements to passenger cars. The focus of this thesis is therefore to determine the plausible impact that technical improvements might have on carbon emissions. For the purposes of this thesis, **technical improvements** refer to engineering changes that serve to reduce the carbon emissions intensity (gCO_2/km) of vehicles. These include both **incremental technical efficiency improvements** in existing technologies (such as internal combustion engine vehicles) and **technology shifting** between distinct vehicle powertrain technologies (such as petrol, diesel, battery electric vehicles and hydrogen vehicles).

A technical improvement represents the possibility to reduce carbon emissions from the status quo, either by reducing the amount of energy required to move a vehicle, or by using an energy source with a lower emissions intensity (CO_2/unit energy). A technical improvement therefore has an associated potential emissions saving, and possibly a potential energy saving. However, potential emissions savings might not be fully attained if they are offset by changes in **vehicle attributes** such as increased size and power. The hierarchy of the terms used in this thesis is presented in figure 1.2.

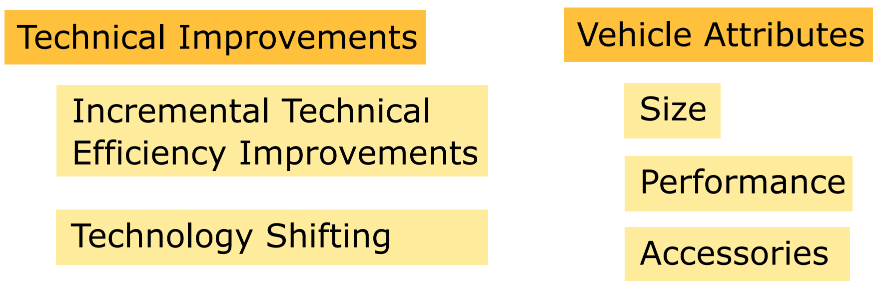

Fig. 1.2 Hierarchy of terms used in this thesis.

Estimates of future technical improvements in vehicles can be bounded by what is technically or physically possible. Despite over a century of technical improvements to internal combustion engine vehicles, there are still large theoretical efficiency gains to be unlocked (Cullen et al., 2011; Edwards et al., 2011; Paoli and Cullen, 2019). However, economic and practical limitations prevent these from being deployed, as vehicle manufacturers have to ensure vehicles are durable, safe, affordable and meet air pollutant restrictions (Paoli and Cullen, 2019).

Estimates of future technical improvements might be better bounded by what is economically feasible. However, according to the IEA (2018a), the transportation sector has the highest potential for cost-effective energy intensity improvements (where additional upfront costs of efficiency technologies are paid back in the lifetime of the asset) of all sectors in the energy system. Options to improve the efficiency of vehicles are evidently both technically and economically viable. Yet, global emissions in the sector continue to increase due to both growing demand and the slow rate of energy intensity improvements (IEA, 2018b).

The value of the motor car in society embodies more than simply its value as a means of transportation. Motor cars encompass a wide range of additional values including individual freedom, self-expression and social status (Cairns et al., 2014; Jensen, 1999). These additional values mean that costs and time are not the only metrics that consumers consider regarding transport, which presents challenges to moving from the current car-dominated paradigm. A substantive body of literature has shown that few members of the public make economically rational decisions regarding improving fuel economy (Allcott and Greenstone, 2012; Allcott and Wozny, 2014; Turrentine and Kurani, 2007).

This thesis will therefore contend that estimating future emissions from transport, requires considering more than estimating efficiency improvements from a purely technical or economic perspective. Technical improvements may be offset by consumer trends towards larger and more powerful vehicles, filled with a greater number of gadgets. Similarly, efficiency improvements can lower running costs, which may stimulate drivers to travel more.

The aim of this thesis is to estimate the extent to which future technical improvements might be offset by these consumer trends, and the resulting impacts upon CO_2 emissions. This thesis aims to account for the future uncertainty of both technical improvements and consumer tendencies, to provide useful insights that might help inform current and future decision-making.

1.5 Research goals and thesis structure

Reducing transport emissions is essential to tackle climate change (IPCC, 2014). This will require technical improvements both in the form of incremental efficiency improvements in existing technologies and a shift to lower emissions intensity powertrains. The unprecedented changes required to achieve the necessary reductions are highly uncertain, this thesis aims to shed light on this uncertainty by answering the following primary research question:

Can technical improvements in passenger cars lead to energy and CO_2 savings?

This main over-arching research question is assessed primarily using quantitative methods including engineering statistical analysis and numerical modelling. However, given the broad nature of the topic at hand, methods are also borrowed from the field of energy econometrics. This thesis focusses on Light Duty Passenger Vehicles (Cars) and therefore does not consider Light Commercial Vehicles (Vans) or Heavy Duty Vehicles (Trucks). The geographical scope of the analysis is broadly confined to Great Britain, though much of the analysis and methods can be readily applied to other countries. The data underlying the analysis of this thesis is drawn from various different sources, including national statistical agencies, public databases and websites.

This thesis is split into 6 chapters. Chapter 2 surveys the literature exploring the primary research question. Past work is assessed for research gaps, which are then condensed into the specific research questions that will be addressed in this thesis. Chapters 3, 4 and 5 contain details of the empirical analysis used to answer each research question. This includes the particulars of the methods adopted, the obtained results and a discussion of the key findings. In Chapter 6, the findings are assembled to answer the main research questions and to highlight areas of future work.

Chapter 2

Literature Review

This thesis investigates the impact that technical improvements in passenger cars may have on reducing energy use and CO_2 emissions. This chapter reviews the large body of past work on this topic and is divided into 3 sections to structure the analysis of the state of the art.

Technical improvements may be offset by changes in vehicle attributes such as increases in size and power. This would mean that reductions in the energy intensity of vehicles may be less than the potential from technical improvements. Past work investigating this topic is explored in section 2.1. Next, consumers may respond to more efficient vehicles in ways that might further reduce the potential energy savings of technical improvements. Past work investigating these unintended effects are examined in section 2.2. Finally, studies examining future emissions from passenger cars and the effects of different technologies are explored in section 2.3. Each section identifies gaps in existing knowledge, these are summarised in section 2.4 and form the basis for the following chapters.

2.1 Trends in energy efficiency and technical improvements

This section presents an overview of the literature investigating trends in the energy efficiency of vehicles and quantifying technical improvements. Section 2.1.1 introduces the current ways that trends in the energy efficiency of vehicles are measured. In section 2.1.2, the literature quantifying the tradeoffs between technical improvements and vehicle attributes is presented.

2.1.1 Quantifying technical improvements

Vehicle efficiency regulations exist in the majority of large vehicle markets around the world (IEA and ICCT, 2019) and broadly have two main aims: 1. to improve the energy efficiency of new passenger vehicles sold, and 2. to help consumers make informed decisions about the relative performance of different vehicles and their likely fuel expenditure from driving.

Existing vehicle efficiency regulations are known as CO_2 emissions standards in the EU (EC, 2009) and fuel economy standards in China (Wagner et al., 2009), the USA (NHTSA, 2020) and Japan (Yang and Rutherford, 2019). Vehicle efficiency regulations require the legal measurement of vehicles' fuel efficiency. They also require that the average fuel efficiency (or CO_2 emissions/km) of new vehicles, sold in a given year, meet a defined target value. There is wide evidence that the fuel efficiency of vehicles in regulated markets improves notably faster than those in non-regulated markets (IEA and ICCT, 2019).

To ensure fairness and transparency between manufacturers, all vehicles are tested under the same laboratory conditions, known as the type-approval process, meaning the performance of vehicles can be directly compared. To help consumers make informed decisions about likely fuel expenditure, vehicles are tested in a variety of operating conditions (acceleration, high speed and low speed) in order to represent the driving conditions of the average driver.

In the EU (and the United Kingdom post-Brexit (DfT, 2017)), the fuel consumption and emissions of vehicles are tested on a rolling road (according to Directive 93/116/EC). Each vehicle is driven at a standardised set of speeds, known as a 'drive-cycle', and the fuel consumption is measured. Since the vehicle is stationary on the rolling road, a separate test is performed to determine the 'road-load' the vehicle would experience due to aerodynamic and friction forces. This test is known as a 'coast-down' test. Each vehicle is driven on a test track, initially at 120 km/h, the vehicle is then put into neutral and allowed to decelerate to rest. The time taken for the vehicle to decelerate can be used to determine a road-load force vs. velocity curve. This data is then programmed into the rolling road used in the laboratory test in each vehicle.

Problems with energy intensity as a measure of technical improvement

Most vehicle efficiency policies around the world are developed on a variation of mpg (in the USA), L/100km (in China), km/l (in Japan) or gCO_2/km (in the EU). These are measures of energy intensity and emissions intensity of vehicles and are useful for consumers to help estimate their fuel expenditure. However, as measures of *technical improvements*, they do not account for changes in other vehicle attributes such as vehicle size and power.

The energy intensity of a vehicle (energy/distance) can be reduced with efficiency improvements, such as light-weighting, improving aerodynamics and combustion, or changing powertrain types. Conversely, the energy intensity can increase with changes in other vehicle attributes, which are detrimental to energy intensity, such as increasing vehicle size and power.

Increasing the size of a vehicle generally increases the aerodynamic energy losses. Similarly, larger vehicles tend to be heavier, which leads to additional inertia and friction losses. These additional losses lead to higher energy requirements and therefore higher fuel consumption. The same is true of vehicle power and performance. Increasing the power of an internal combustion engine means the operating points during normal operation are further from their optimal efficiency point, resulting in lower powertrain efficiency and higher fuel consumption. Whilst this can be somewhat limited with technology improvements such as gear ratios, cylinder deactivation and hybridisation, Sovran and Blaser (2003) note 'there is a fundamental trade-off between fuel consumption and vehicle performance'. Increases in the size and power of vehicles are therefore generally detrimental to energy intensity.

Technical improvements that improve vehicle efficiency can therefore be offset by increases in vehicle attributes. Alone, measures of energy intensity, such as L/100km, cannot distinguish between the impacts of technical improvements and vehicle attributes. For example, the energy intensity of vehicles may remain constant over time if there are no new energy efficiency improvements in vehicles. However, it may also remain constant over time if energy efficiency improvements are offset by an increase in vehicle size and power.

This trade-off between performance, size and energy intensity can be seen in figure 2.1, which shows historical trends in average fuel economy (mpg), power and weight of new vehicles in the USA since 1975. In the decades of the 1970's and 80's, particular emphasis was made to improve the fuel economy of vehicles at the expense of increases in power and weight. However, these priorities were then reversed in subsequent decades, where power and weight increased and fuel consumption decreased. Tracking developments in the average energy intensity of vehicles therefore does not give an accurate representation of the potential energy savings over a time period from technical improvements. This leads to the question: How should technical improvements be quantified?

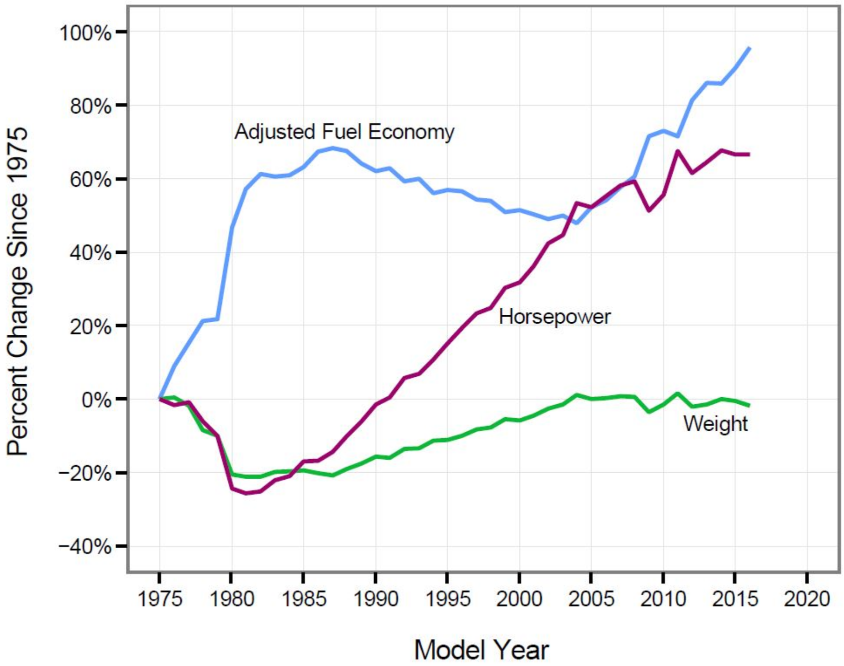

Fig. 2.1 Trends in US vehicle attributes, Source: EPA (2016)

Engineering measures of technical improvements

Quantifying the thermal efficiency of powertrains is fundamental to the engineering study of vehicles. This is defined as the ratio of kinetic work produced by an engine, to the chemical energy used as fuel. However, the efficiency of a vehicle is not solely dependent upon the powertrain efficiency, as vehicle light-weighting and aerodynamics may also have an impact.

One method proposed by Cullen and Allwood (2010a) to differentiate between improvements in powertrain efficiency and improvements in the body of the vehicle, is to distinguish between the ‘conversion devices’ and the ‘passive systems’. The efficiency of conversion devices is associated with the conversion of energy from one form to another (e.g. chemical to kinetic in a combustion engine). Passive system efficiencies quantify how efficiently useful energy (e.g. kinetic energy) provides an energy service (e.g. passenger km). This distinction gives greater insight into whether efficiency improvements have occurred in the powertrain or via light-weighting, aerodynamics and lower rolling resistance. Additionally, the efficiencies of conversion devices, like vehicle powertrains, can be compared to upper theoretical or practical limits (Cullen and Allwood, 2010b; Paoli and Cullen, 2019) which allows the quantification of the improvement potential for current technologies.

Several authors have used publicly available data from coast-down tests to estimate the powertrain thermal efficiency of vehicles on the road (Lutsey, 2012; Lutsey and Sperling, 2005; Pannone et al., 2017; Thomas, 2014). Coast-down tests quantify road loads experienced by vehicles and can therefore be used to determine the kinetic energy requirements of vehicles per distance travelled, which is equivalent to the passive system efficiency. This method was used in the initial stage of this PhD (Craglia et al., 2017)[1] to estimate the sales-weighted powertrain efficiency of vehicles for the first time. The powertrain efficiencies of new British vehicles in year 2010 varied between a minimum of 7.8% and maximum of 31.5% with a sales-weighted mean of 20.2%. Vehicles with larger, more powerful engines were found to have lower thermal efficiencies than smaller vehicles. This is likely because high powered vehicles operate inefficiently when driven at the road legal speeds of laboratory drive-cycles and shows the trade-off between vehicle performance and fuel consumption. The average efficiency of vehicle powertrains can be compared to work by Paoli and Cullen (2019) who estimated the maximum theoretical efficiency limit of internal combustion engine vehicles as 56-62%.

This difference between the current average thermal efficiency of engines, and the theoretical maximum, shows that large efficiency improvements are still theoretically possible, but may instead be limited by practical or economic limits. This suggests assessing potential efficiency improvements and energy savings from a purely technical perspective may have limitations.

Estimating trends in powertrain and passive system efficiencies can be useful to investigate the energy efficiency of vehicles in greater depth than solely considering energy intensities. However, the main challenge associated with this method is that it does not control for increases in vehicle attributes such as size and power. The following section investigates methods that can account for changes in vehicle attributes and how they affect vehicle fuel consumption.

2.1.2 Quantifying technical improvements with vehicle attributes

Several authors have used regression models to decompose changes in fuel consumption between incremental technical efficiency improvements and the impact of changes in vehicle attributes. Incremental Technical Efficiency Improvements (ITEI) will refer to incremental enhancements to the efficiency of vehicles within major powertrain technologies. These can occur from a variety of sources, from improving combustion efficiencies in engines to vehicle

[1] This analysis was carried out in the first year of this PhD and was presented at the *International Conference on Applied Energy* in Cardiff. Coast-down test data was used to determine powertrain and passive system efficiencies of British vehicles. This preliminary work helped to shape the topic of this thesis but was not pursued further, as it does not account for changes in other vehicle attributes such as size and power. Section 6.3 discusses possible future work on this topic.

light-weighting, improving aerodynamics or reducing friction forces with better lubrication or rolling resistance of tyres.

Past work quantifying Incremental Technical Efficiency Improvements (ITEI)

ITEI can be quantified in terms of the hypothetical fuel consumption that could have been attained, had vehicle attributes remained constant from a past year. The difference between this hypothetical fuel consumption and the real observed trend can be thought of as the effect that changes in vehicle attributes had on fuel consumption. This approach uses regression models, similar to equation 2.1, to explain the variance in fuel consumption (L/100km) of vehicles each year using a selection of vehicle attributes. Year fixed effects are used to quantify annual improvements in fuel consumption, independent of vehicle attributes such as size and power.

$$\ln(FC)_{it} = T_t + \beta \ln(X_{it}) + \varepsilon_{it} \tag{2.1}$$

Where FC is the observed fuel consumption of vehicle i in year t, T are the coefficients for year fixed effects/dummy variables which take the value of 1 in year t and 0 otherwise, X is a vector of vehicle attributes such as power, size or weight, β is a vector of their respective regression coefficients and ε is an error term.

Some of the first authors to use this technique were Sorrell (1992) and Kwon (2006) who aimed to quantify incremental technical efficiency improvements in the UK market between 1983-90 and 1978-2000 respectively. However, data limitations at the time meant that only the effect of engine capacity could be assessed. Knittel (2011) and MacKenzie and Heywood (2015) later investigated ITEI in passenger cars in the USA using a larger number of vehicle attributes. Together they showed that during times of high oil price, the rates of ITEI increased and size and power increases slowed.

Fuel economy standards may also stimulate increasing rates of incremental technical efficiency improvements. Hu and Chen (2016) and Klier and Linn (2016) studied the EU market between 1975-2015 and 2005-2010 respectively and reported higher rates of ITEI after the introduction of binding EU emissions standards in 2008/09.

Some past studies (Hu and Chen, 2016; Knittel, 2011; MacKenzie and Heywood, 2015) focused on comparing the hypothetical fuel consumption had all vehicle attributes remained constant, to the average fuel consumption of *available models*. Purely focussing on model availability neglects the effect of shifts in vehicle sales between models. If the type of vehicles on the market remains similar, but vehicle sales shift to larger cars (as has been the case in almost all countries (IEA and ICCT, 2019)), increases in vehicle attributes will have been considerably more than the average of vehicles available for sale might indicate.

Matas et al. (2017) applied similar methods to the Spanish vehicle market between 1988-2013 and sales-weighted results. Other notable improvements include adequately treating petrol and diesel vehicles separately. If two different technologies have different regression coefficients, then grouping them together in one regression can lead to a misleading model. Regression coefficients for hybrid and electric vehicles are likely to be even more different to conventional engines due to regenerative braking. This lowers the impact of vehicle weight and size on fuel consumption (as inertia losses from braking can be recouped by charging the battery) and means powertrains must be treated in separate regressions.

However, treating powertrain types separately in regressions can present constraints, as it means the rate of ITEI can only be quantified for each powertrain, rather than for the total population of vehicles sold. This is explained with the following example.

The missing effect of sales shifts

ITEI can be quantified as an index, using regression coefficients T_t from equation 2.1, and represents the theoretical energy intensity reductions that vehicles could attain in a given year, if vehicle attributes were held constant at the levels of time t0. An example is shown in figure 2.2 left, for two vehicle technologies X1 and X2 (which could represent diesel and electric vehicles). Between t0 and t1, the energy intensity of vehicle technology X1 could drop by 80% (since ITEI=0.2) due to incremental technical efficiency improvements. Similarly, the energy intensity of vehicle technology X2 could drop by 20% (since ITEI=0.8). Both technologies X1 and X2 show steady incremental improvements over the time period, but at differing rates.

Now consider that there may be different shares S of each technology type f sold each year, and that S_f may change over time. An example is shown in figure 2.2 right, which shows technology X1 initially dominates the market until time t^*, when X2 takes market share. The presence of different shares of technologies raises the question ‘what is the average rate of ITEI for all vehicles in the market?’.

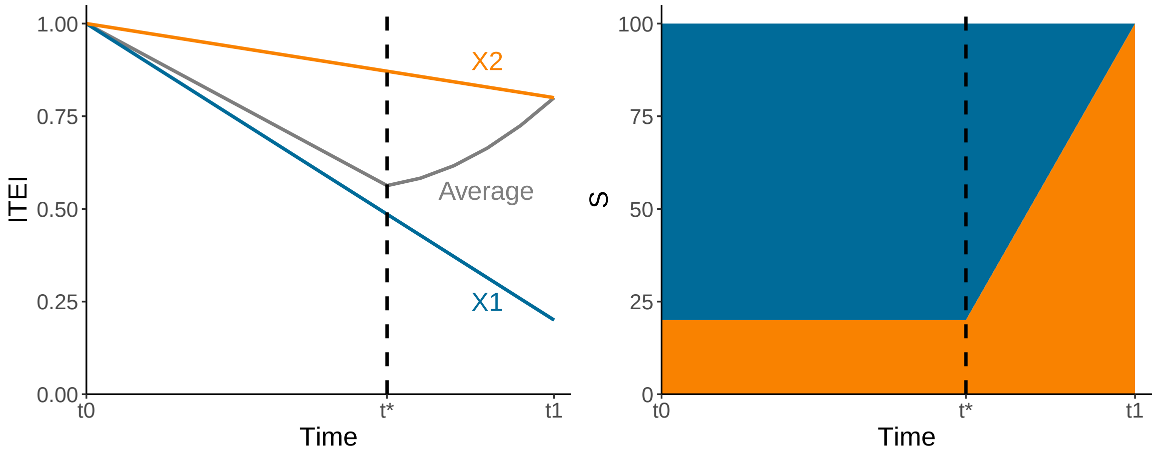

Fig. 2.2 Left= Incremental Technical Efficiency Improvements (ITEI) for technologies X1 and X2 and a sales-weighted average. Right= the percentage share of technology X1 (blue) and X2 (orange). At t^*, the share of X2 increases.

One might imagine that the rate of ITEI for the total market will lie between technologies X1 and X2. The obvious (and incorrect) way to estimate ITEI for the total market would be to simply sales-weight the ITEI for each technology according to equation 2.2, where f represents each technology (X1 and X2).

$$\mathrm{ITEI}_{\mathrm{Average}} = \sum_f \mathrm{ITEI}_f \times S_f \tag{2.2}$$

Calculating the ITEI for the total market according to equation 2.2 results in the grey line shown in figure 2.2 left. This is correct in that $\mathrm{ITEI}_{\mathrm{Average}}$ lies between $\mathrm{ITEI}_{\mathrm{X1}}$ and $\mathrm{ITEI}_{\mathrm{X2}}$. However, it implies that incremental technical efficiency improvements worsened after t^*, which is incorrect, given both X1 and X2 improved over the time period. This problem arises when the effect of changes in the shares S of technologies are not separated. Past work has not been able to address this methodological obstacle. Sprei and Karlsson (2010) is one of few studies to estimate the effects of sales shifts between petrol and diesel vehicles. The authors seem to use univariate regressions (rather than multivariate) in a series of steps to assess the relationship between variables, though the authors also state that their methods are sensitive to the base year and order of calculation of steps.

Past literature has not been able to isolate the effect of shifting sales between powertrain technologies (e.g. petrol to EV). Without it, it is not possible to distinguish between incremental technical improvements (within powertrains technologies) and shifts in sales to more efficient powertrain technologies. In Europe, diesel powertrain sales are dropping precipitously (IEA and ICCT, 2019); failing to treat powertrains separately would result in incremental technical efficiency improvements within powertrains being masked by the shift back to petrol engines.

To summarise, using multivariate regression models to estimate technical improvements is ideal to determine how trends in fuel intensity have been affected by incremental technical efficiency improvements and changes in vehicle attributes. However, there is currently no way to incorporate how market shifts between different powertrain technologies may impact average fuel intensity. This is a significant limitation as it may bias estimates of ITEI. Furthermore, it will become an increasingly important limitation in future analysis of this type, as new powertrain technologies such as hybrid and electric vehicles are sold in greater numbers in coming years.

A second research gap is that past literature in this sphere is yet to address real-world fuel consumption reported by drivers, which has been found to be considerably higher than manufacturer-quoted values based on laboratory testing (known as type-approval tests). This second research gap is discussed in the following section.

2.1.3 Real-world fuel consumption

The drive-cycles used during type-approval tests are intended to represent how the 'average' driver uses a vehicle. This means the speeds, accelerations and operating conditions of the vehicle during testing ought to be representative of 'average' driving, to give consumers an adequate indication of their expected fuel costs.

In the real-world, drivers all use their vehicles differently, due to behavioural differences between drivers (high speed aggressive drivers vs. calm low speed drivers) and geographical differences (which impact the types of vehicles driven and the share of urban to rural driving). There will always be differences between real-world driving by individuals and the standardised drive-cycles used for type-approval testing (Greene et al., 2017). However, type-approval drive cycles ought to reflect *average* real-world driving conditions as closely as possible. There is increasing evidence that this is no longer the case in many vehicle markets (IEA and ICCT, 2019).

Several studies have attempted to compare estimates of the 'real-world' fuel consumption of several vehicles (also known as 'on-road' fuel consumption), to their type-approval values. In 1994, Schipper and Tax (1994) reviewed evidence across several countries and estimated that type-approval values underestimated real-world fuel consumption by 15-25%. At the time (before 1997), type-approval fuel consumption in Europe was measured using an urban drive-cycle followed by two constant-speed driving periods at 90 kph and 120kph respectively. To better reflect real-world driving, the constant-speed sections of the drive-cycle were replaced from the year 1997 with the introduction of the New European Drive

Cycle (NEDC) (Bonilla and Foxon, 2009). However, recent studies have shown that the NEDC cycle still largely underestimates driving in the real-world (Fontaras et al., 2017).

There are several different drive-cycles used globally for vehicle type-approval testing. The NEDC (figure 2.3, left) has been used in the European Union since 1997. During this time it was also adopted in other large vehicle markets outside of Europe, notably India, China, Australia, and Brazil. The USA uses a different drive-cycle for its CAFE standards, which was also adopted by Canada and South Korea. Japan uses a cycle known as the JC08 cycle (IEA and ICCT, 2019).

Each drive-cycle has different ranges of operation, speeds and accelerations. They also differ in their abilities to reflect real-world reported fuel consumption (IEA and ICCT, 2019). The CAFE cycles currently in use in the USA for example, have been found to be more representative of real-world driving than the NEDC and the JC08. Type-approval drive-cycles have been updated over time to better reflect real-world driving. In 2008, the American CAFE cycles were changed to a 5-cycle test including periods with air conditioning use, aggressive driving and cold temperature driving. In 2018, the NEDC was replaced in Europe by the Worldwide Harmonised Light-Duty Test Procedure (WLTP) and its associated drive-cycle, the WLTC (figure 2.3, right).

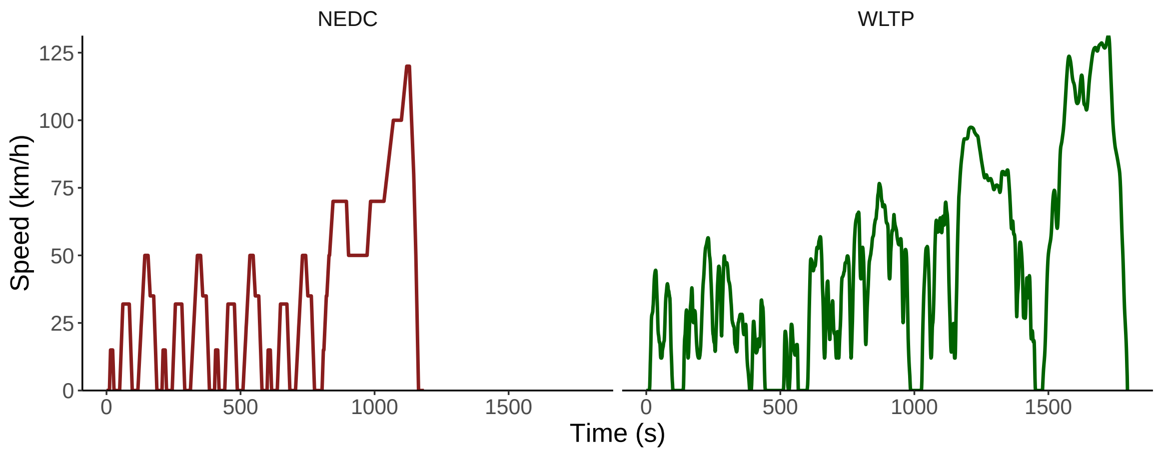

Fig. 2.3 Speed traces of the New European Drive Cycle (NEDC) and the Worldwide Harmonised Light-Duty Test Cycle (WLTC)

Data on vehicles' real-world fuel consumption has often been challenging to acquire. Early studies relied on survey estimates and reports by motor enthusiasts (Hughes, 1992; Schipper and Tax, 1994; Watson, 1989). This has continued in more recent literature, though an increasing availability of crowd-sourced data has allowed for more detailed estimates of the gap between type-approval and real-world values (Kühlwein, 2016; Ligterink and Smokers, 2016; Ligterink et al., 2016; Martin et al., 2015; Mellios et al., 2011; Mock et al., 2013; Ntziachristos et al., 2014; Pavlovic et al., 2016; Pelkmans and Debal, 2006; Tietge et al., 2019, 2017a; Wali et al., 2018a).

Perhaps the most comprehensive study to date for the European vehicle market is that of Tietge et al. (2019) in which the authors source driver-reported estimates of vehicle fuel consumption from 1.3 million different vehicles, 15 different publicly available sources and 8 different countries in the EU. The authors found that the average real-world fuel consumption of vehicles available in 2001 was 8% higher than manufacturer reported, type-approval values and by 2017 this gap had risen to 39%. The analysis by Tietge et al. (2019) is based on a large number of individual driver-reported entries of average mpg and fuel use. Depending on the composition of the vehicles reported in the sample, this may differ from the sales-weighted average fuel intensity of new vehicles in a country. There is yet to be an attempt to weight driver-reported entries by vehicle sales figures.

Fontaras et al. (2017) summarise the multitude of factors that affect the differences between type-approval and real-world fuel consumption estimates. These include:

- the degree to which the speeds and accelerations of vehicles on the tested drive-cycle resemble average driving (i.e. how representative type-approval drive-cycles are of real-world driving).

- simplifications to testing procedures intended to reduce the testing burden and avoid testing every permutation of vehicle and optional extra. These ‘flexibilities’ include testing ‘reference’ vehicles in inertia classes, on a single set of tyres. There is evidence to suggest that this has led to manufacturers (completely legally) testing vehicles with lower weight and rolling resistance than the equivalent vehicles sold on the road (Kadijk et al., 2012). Stewart et al. (2015) suggest the majority of the growing divergence between type-approval and real-world fuel consumption is due to an increasing degree of exploitation of test ‘flexibilities’ by manufacturers.

- the real-world energy use of vehicle auxiliaries (air conditioning, infotainment systems, electric seats), which are not included in type-approval testing. The increasing penetration of auxiliaries in vehicles is one reason explaining the growing divergence between type-approval and real-world fuel consumption (Stewart et al., 2015).

- technologies which have a greater impact on fuel consumption in testing than in real-world conditions such a stop-start ignition (Fontaras et al., 2017).

Discrepancies between type-approval and real-world fuel efficiency undermines the two aims of vehicle efficiency regulation: to track and reduce emissions, and to accurately inform consumers. Past authors (Hu and Chen, 2016; Matas et al., 2017) who used type-approval data to quantify incremental technical efficiency improvements (ITEI) noted that their findings may be biased due to the increasing divergence with real-world data, but there is yet to be a concerted effort to quantify ITEI using real-world fuel consumption data.

2.1.4 Research Gap

Quantifying the underlying technical improvements of vehicles over time is important to measure the energy saving potential from the deployment of new technologies. It can also determine the lost potential energy savings from consumer preference for larger, more powerful vehicles. Technical improvements in vehicles can be disaggregated to incremental technical efficiency improvements within powertrain technologies and sales shifts between powertrain technologies. This is important to understand past rates of change in vehicle energy intensity. Regression models developed in past work are well suited to estimating incremental technical efficiency improvements. However, there remain two notable research gaps.

Firstly, current methods are unable to quantify the effects of market shifts between technologies. This risks either limiting the analysis to individual powertrain technologies or biasing the results, as shown in figure 2.2.

Secondly, real-world data has not yet been used to quantify technical improvements. Given the divergence between type-approval and real-world fuel efficiency, this risks over-estimating the role of technical improvements over time. Since past work using type-approval data has suggested that the rate of ITEI increased following the introduction of EU emissions standards in 2008/09, it is important to ascertain whether this remains true using real-world data. These gaps in past literature can be addressed by answering the following research questions:

- What is the average ‘real-world’ fuel intensity of new vehicles? How has it changed over time?
- What is the magnitude of incremental technical efficiency improvements over time? How do estimates of this differ between type-approval and real-world values of fuel consumption?
- What effect did technology shifts have on fuel consumption?
- How do the effects of technical improvements compare to changes in vehicle attributes?
- What effect did the introduction of EU emissions standards have upon technical improvements?

2.2 Energy intensity and energy savings

The previous section presented an overview of past work quantifying technical improvements in vehicles, and revealed that the energy intensity of vehicles (L/100km) does not necessarily advance at the same rate as that of technical improvements, due to changes in vehicle size, performance and other auxiliary equipment. This section investigates the ensuing question: do changes in the energy intensity of vehicles always result in savings in energy?

2.2.1 Rebound effects

Countries and regions ranging from the European Union (EU) to the USA have implemented fuel economy and CO_2 emissions standards to stimulate manufacturers to produce more efficient cars. Equally, several national governments have adopted fuel taxes to shift consumers to more efficient travel alternatives. The energy saving potential of these policies depends on how drivers react to vehicle efficiency improvements and fuel price changes.

There is a possibility that improvements in the energy efficiency of vehicles, and the resulting fuel cost savings, may stimulate drivers to travel more. This phenomenon is known as the rebound effect, and if large, might offset potential energy savings from efficiency improvements. Quantifying the magnitude of the rebound effect is important to estimate realistic emissions savings and societal benefits from energy efficiency policies such as fuel economy standards.

The history of the rebound effect

Jevons (1865) is widely attributed as the first author to have investigated how energy efficiency improvements may stimulate energy use. In 1865, he wrote a book entitled '*The Coal Question*' in which he cautioned that Britain's coal-use was becoming unsustainable given the limited known reserves of coal and exponentially growing demand. Exploring different solutions to reduce coal demand, Jevons suggested that improving the efficiency of coal-use would be counter productive, in an argument has since been dubbed '*Jevons's paradox*':

> *It is wholly a confusion of ideas to suppose that the economical use of fuel is equivalent to a diminished consumption. The very contrary is the truth. (...) Whatever, therefore, conduces to increase the efficiency of coal, and to diminish the cost of its use, directly tends to augment the value of the steam-engine, and to enlarge the field of its operations.*

Khazzoom (1980) was one of the first to directly estimate the magnitude of the rebound effect by investigating how improvements in the energy efficiency of household appliances may stimulate an increase in their use, due to the reduced energy costs. There has since been a large body of research debating the definitions of this economic effect and quantifying its magnitude (Greening et al., 2000). Several early economists estimating the rebound effect postulated that energy efficiency improvements were likely to lead to increased energy use (Brookes, 1990; Saunders, 1992), an effect known as 'backfire', and that energy efficiency policies were therefore counter-productive. There has since been a more nuanced view that whilst the full potential energy savings of efficiency improvements are unlikely to be fully attained, as a certain amount of induced demand is possible, induced demand is unlikely to completely offset energy savings (Sorrell, 2009). There have been a wide range of competing definitions and interpretations of rebound effects in the literature. The consensus, established by Greening et al. (2000) and built upon by Sorrell and Dimitropoulos (2007), is that the effects of efficiency improvements can be split into three separate effects:

1. Direct rebound effects: improving energy efficiency can reduce the energy required to deliver an energy service (such as passenger transport, space heating or cooling). This in turn will reduce the energy costs of delivering the energy service and will lead to higher demand for the service. For example, a more efficient vehicle will have lower running costs and may stimulate higher vehicle mileage.

2. Indirect rebound effects: the cost savings from efficiency improvements in one service may lead to substitution effects and an increased consumption of other services and goods, which have can have energy impact. For example, lower running costs from a more efficient vehicle can lead to financial savings, these might be spent on a flight. Indirect rebound effects are estimated as partial equilibrium effects, holding prices and quantities fixed in other markets.

3. General equilibrium effects: changes in the costs of energy services and the associated shifts in demand can entail adjustments in supply chains and dependent sectors, thereby changing energy use across an economy. Unlike indirect rebound effects, general equilibrium effects to allow for changes in prices and quantities in other markets.

The sum of direct, indirect and general equilibrium effects can be considered to be the economy-wide effects of efficiency improvements. To estimate economy-wide effects, complex general equilibrium models are required, and there is currently limited consensus on the magnitude of these effects (Sorrell et al., 2018). Estimates of indirect rebound effects are similarly limited by complexity and the limitations in the required data. Druckman et al. (2011) and Chitnis et al. (2014) use household expenditure data to estimate how financial savings from efficiency improvements in one service might be spent on alternative goods.

Whilst several assumptions have to be made about expenditure elasticities (what consumers do with money saved), both authors suggest indirect rebound effects may be significant. Those from transport may be in the order of 25-65% because efficiency improvements in transport yield relatively large cost savings, which are then spent on goods with a comparable GHG intensity. The challenges associated with estimating economy-wide and indirect rebound effects, has meant they have received relatively little attention in the literature, with the majority of past work focussing upon direct rebound effects.

The aim of this thesis is to investigate the potential energy and emissions savings from technical improvements in passenger cars. This requires some understanding of direct rebound effects, and how they might undermine potential savings. However, assessing indirect and economy-wide rebound effects only makes sense for cross-sector or whole country analysis of carbon emissions. The focus of the literature review is therefore restricted to direct rebound effects.

The following section introduces the econometric theory of the direct rebound effect and some of the empirical constraints faced in estimating it reliably.

2.2.2 Theory: the rebound effect and the effects of fuel price

Energy efficiency improvements can have the effect of reducing the costs of an energy service S. For an energy service like passenger transport, efficiency improvements in vehicles can reduce the price of travel (P_S) and thereby stimulate travel demand. The cost of driving is dependent upon the price of fuel, P_E (with units price/energy) and the efficiency of the vehicle ε (with units distance travelled/energy) according to:

$$P_S = P_E/\varepsilon \tag{2.3}$$

The rebound effect in passenger transport is the effect that a change in energy efficiency (ε) has on travel demand (typically expressed as vehicle miles travelled, VMT). This is generally expressed as the elasticity $\eta_\varepsilon(S)$ of travel demand with respect to efficiency:

$$\frac{\partial S}{S} = \eta_\varepsilon(S)\frac{\partial \varepsilon}{\varepsilon} \tag{2.4}$$

This elasticity shows how much a percentage change in energy efficiency ε changes travel demand S. With an elasticity of $\eta_\varepsilon(S)$=0.5, a 10% increase in energy efficiency would lead to a 0.5×0.1=5% increase in mileage. This would therefore offset 50% of the potential energy savings.

Many studies distinguish between short-run and long-run elasticities. The former is a change in the order of one year and doesn't account for changes in the vehicle stock. Long-run effects are calculated over larger time periods, typically using dynamic models, and therefore account for longer-term social and behavioural responses to changes in travel costs. Estimates of the long-run rebound effect are generally larger than short-run effects (Dimitropoulos et al., 2016).

Using $\eta_{\varepsilon}(S)$ as a measure of the rebound effect is often problematic due to the possibility that energy efficiency is not an exogenous variable; independent of energy prices, travel demand S and other confounding variables (Sorrell et al., 2009). If consumers buy vehicles with better energy efficiency in times of high oil price, or because they expect to drive a greater annual distance (perhaps due to a change of employment or living circumstances), then estimates of efficiency elasticities could be biased. Empirical constraints mean it is often not possible to control for these factors sufficiently to calculate the impact of an exogenous efficiency improvement. For these reasons, fuel price elasticities $\eta_{P_E}(S)$ are often used as a measure of the rebound effect:

$$\frac{\partial S}{S} = \eta_{P_E}(S)\frac{\partial P_E}{P_E} \tag{2.5}$$

Empirically, calculating $\eta_{P_E}(S)$ has the advantage that the price of fuel can be considered exogenous in a way that efficiency ε rarely can. Another advantage is fuel prices typically have greater temporal variation as explanatory variables than efficiencies. The elasticity $\eta_{P_E}(S)$ can be assumed to be equal in magnitude and opposite in sign to $\eta_{\varepsilon}(S)$ under certain assumptions:

1. drivers react to changes in travel costs (P_S) from fuel price changes (P_E) and from efficiency improvements (ε) in the same way,
2. drivers are limited in shifting travel to other types of transport (Chan and Gillingham, 2015),
3. fuel prices P_E and efficiency ε are exogenous and independent of travel demand or other variables.

These assumptions can be used to gauge an estimate of the rebound effect $\eta_{\varepsilon}(S)$, by estimating -$\eta_{P_E}(S)$. If efficiency improvements are affected by fuel prices, $\varepsilon = f(P_E)$, as shown for example by (Li et al., 2009; Ryan et al., 2009), then the following equation can be derived (see appendix B.1):

$$\eta_{P_S}(S) = \eta_{P_E}(S) \times \frac{1}{1-\eta_{P_E}(\varepsilon)} \tag{2.6}$$

where $\eta_{P_E}(\varepsilon)$ is the elasticity of fuel prices on efficiency and is expected to be greater than zero if higher fuel prices stimulate higher efficiency. This means estimates of $\eta_{P_E}(S)$ are likely to underestimate the rebound effect (Sorrell and Dimitropoulos, 2007) since:

$$|\eta_{P_E}(S)| \leq |\eta_{P_S}(S)| \tag{2.7}$$

Literature estimates of $\eta_{P_E}(\varepsilon)$ lie between 0.005-0.04 in the short-run, rising to 0.1-0.2 in the long-run (Bento et al., 2009; Li et al., 2009; Ryan et al., 2009; Small and Dender, 2007). This means estimates of $\eta_{P_E}(S)$ are likely to underestimate the rebound effect by just 0.5-4% in the short-run and 11-25% in the long run.

2.2.3 The need for micro-data

Past estimates of travel demand elasticities $\eta(S)$, based on efficiency ε (miles/energy), fuel price P_E (cost/energy) and the fuel costs of travel P_S (cost/mile) are documented in table 2.1. Subject to the assumptions discussed in section 2.2.2, these can all be considered estimates of the rebound effect, although their magnitude varies widely in the academic literature due to differences both in the type of data, geographic region, time period and estimation technique. Data can broadly be classified into aggregate and micro-level, based on the cross-sectional detail of the data. In turn, micro-level panel data can be further split into survey data and vehicle testing data with odometer readings. The former often benefits from data on socio-economic characteristics about drivers. The latter often lacks this data but benefits from much larger sample sizes.

Short-run estimates in transport are generally around 0.1, and long-run estimates rise to approximately 0.2. To date, the majority of rebound studies have made use of aggregate national statistics due to the availability of data (Sorrell et al., 2009). However, using aggregate data to estimate the effects of efficiency improvements or fuel prices on mileage presents three main limitations.

Firstly, using aggregate data often requires long time series in order to have a sufficient number of sample points to yield statistically significant results. Several authors (Fouquet, 2012; Greene, 1992; Hughes et al., 2008; Hymel and Small, 2015; Hymel et al., 2010; Small and Dender, 2007) have shown that the rebound effect may decrease as average incomes rise over time and drivers reach ‘saturation’ in demand for travel. Hughes et al. (2008) for example find that $\eta_{P_E}(S)$ in the USA decreased from between -0.21 and -0.34 in 1975-1980 to between -0.034 and -0.077 in the 2001-2006 period. The use of long time series data may therefore cover time periods in the past which are no longer appropriate for policy-making on future travel demand where saturation might occur.

Author	**Years**	**Country**	**Data**	**Type**	**η(S)**	**Run**
Haughton and Sarker (1996)	1972-1991	USA	Aggregate	P_S	-0.22	Long
Blair et al. (1984)	1967-1976	USA	Aggregate	P_S	-0.25,-0.4	Long
Mayo and Mathis (1988)	1958-1984	USA	Aggregate	P_S	-0.22	Short
Mayo and Mathis (1988)	1958-1984	USA	Aggregate	P_S	-0.26	Long
Gately (1990)	1966-1988	USA	Aggregate	P_S	-0.09	Short
Gately (1990)	1966-1988	USA	Aggregate	P_S	-0.09	Long
Greene (1992)	1957-1989	USA	Aggregate	P_S	-0.13	Long
Greene (1992)	1957-1989	USA	Aggregate	P_S	-0.13	Short
Greene (1992)	1957-1989	USA	Aggregate	P_S	-0.05,-0.19	Long
Greene (1992)	1957-1989	USA	Aggregate	P_S	-0.05,-0.19	Short
Jones (1993)	1957-1989	USA	Aggregate	P_S	-0.31	Long
Jones (1993)	1957-1989	USA	Aggregate	P_S	-0.13	Long
Puller and Greening (1996)	1984-1990	USA	HH	P_S	-0.49	Short
Goldberg (1996)	1984-1990	USA	HH	P_S	-0.22	Short
Greene et al. (1999)	1979-1994	USA	HH	P_S	-0.23	Long
Hensher and Smith (1986)	1981-1982	AUS	HH	P_S	-0.099	Short
Hensher and Smith (1986)	1981-1982	AUS	HH	P_S	-0.26	Long
Train (1986)	1978	USA	HH	P_S	-0.27	Long
Stapleton et al. (2017)	1970-2012	GB	Aggregate	P_S	-0.26	Long
Johansson and Schipper (1997)	1973-1992	OECD	Aggregate	ε	0.3	Long
Schimek (1996)	1950-1994	USA	Aggregate	ε	0.05,0.07	Short
Schimek (1996)	1950-1994	USA	Aggregate	ε	0.21,0.29	Long
Wheaton (1982)	1970-1972	OECD	Aggregate	ε	0.06	Long
Frondel et al. (2008)	1997-2005	DE	HH	ε	0.58	Short
De Borger et al. (2016)	2001-2011	DK	HH	ε	0.124	Short
De Borger et al. (2016)	2001-2011	DK	HH	ε	0.076	Short
Small and Dender (2007)	1961-2001	USA	Aggregate	P_E	-0.22	Long
Small and Dender (2007)	1961-2001	USA	Aggregate	P_E	-0.045	Short
Wheaton (1982)	1970-1972	OECD	Aggregate	P_E	-0.5	Long
Hughes et al. (2008)	1975-1980	USA	Aggregate	P_E	-0.21,-0.34	Short
Hughes et al. (2008)	2001-2006	USA	Aggregate	P_E	-0.034,-0.077	Short
Stapleton et al. (2016)	1970-2011	GB	Aggregate	P_E	-0.152	Long
Frondel et al. (2008)	1997-2005	DE	HH	P_E	-0.58	Short
Frondel et al. (2012)	1997-2009	DE	HH	P_E	-0.574	Short
Knittel and Sandler (2013)	1996-2010	USA	Odometer	P_E	-0.117,-0.265	Short
Knittel and Sandler (2013)	1996-2010	USA	Odometer	P_E	-0.147	Short
Gillingham et al. (2015)	2000-2010	USA	Odometer	P_E	-0.099	Short
Langer et al. (2017)	2009-2013	USA	Odometer	P_E	-0.15	Short
Gillingham (2014)	2001-2009	USA	Odometer	P_E	-0.22	Short
Gillingham & Munk-Nielsen (2019)	1998-2011	Denmark	Odo & HH	P_E	-0.3	Short

Table 2.1 Selected recent studies quantifying fuel price elasticities in different countries split by data type: aggregate national time series data, household (HH) survey panel data, vehicle testing odometer panel data.

Secondly, it is difficult to account for the many other underlying geographical and social trends affecting travel while using aggregate data. These can be controlled to a greater extent using micro-level panel data such as household surveys and vehicle odometer readings.

Finally, certain drivers may be more susceptible to fuel price or fuel efficiency changes, than others, based on their ability to pay or their ability to choose alternative modes of transport. Micro-data can help to reveal these differences that are otherwise masked by aggregate data. Understanding social and geographical heterogeneity is useful for comparing the results of studies in different countries. For example, Gillingham and Munk-Nielsen (2019) used odometer data and found fuel price elasticities were lower in the USA than in Denmark. The authors suggest this difference can be explained by the extremities of the mileage distribution (drivers with particularly high or low mileage) being more sensitive to fuel price in Europe than in the USA, perhaps due to greater public transport provision.

Understanding the spectrum of responses to fuel prices and efficiency improvements is important to factor into policy design. For example both Knittel and Sandler (2013) and Langer et al. (2017) use odometer level data to show owners of higher fuel consumption vehicles are more sensitive to fuel price changes in California and Arizona in the USA respectively. This suggests fuel taxes could affect the mileage of larger vehicles more than small vehicles, though there is yet to be a similar study in a European context, where fuel taxes are already high.

The past literature estimates of table 2.1 are presented graphically in figure 2.4, coloured by type of data and split by short-run estimates (left) and long-run estimates (right). Each study uses data from a range of years to produce a single estimate of $\eta(S)$ for the time period, these are shown as straight lines.

In figure 2.5, past literature is presented and coloured by country, split by short-run estimates (left) and long-run estimates (right). To date there have been limited studies estimating the rebound effect and fuel price elasticities in Great Britain. Stapleton et al. (2016) use national aggregate data covering 1970-2011 and estimate a long-run rebound effect of η_{P_E}=0.152 using fuel prices, later work produced an estimate of η_{P_S}=0.26 using fuel costs (Stapleton et al., 2017). There has neither been an estimate of the rebound effect, nor of the effects of fuel prices on mileage, in Great Britain using micro-data. Additionally, there is yet to be a study of how these may differ across different British drivers or geographically.

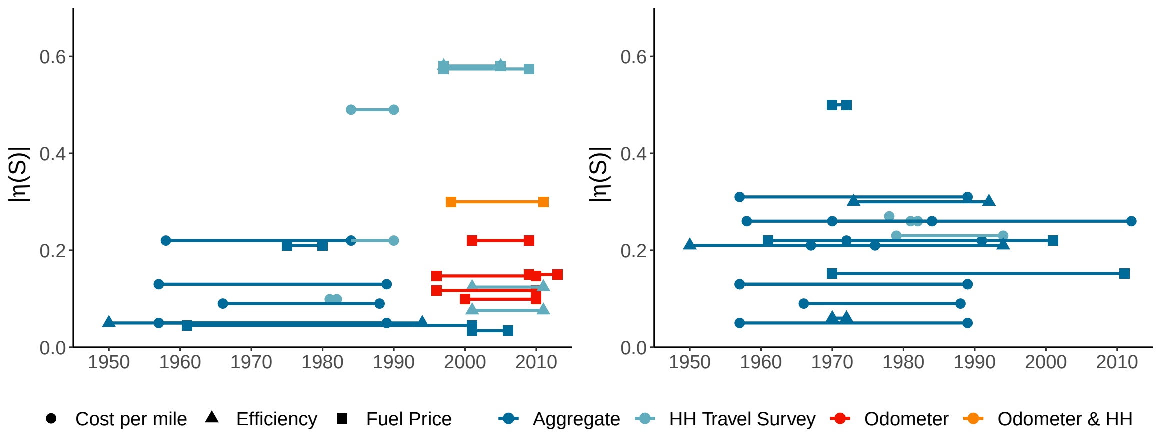

Fig. 2.4 Magnitude of past estimates of travel demand elasticities $|\eta(S)|$ quantified using energy efficiency, fuel prices and fuel costs per mile. Left=Short-run estimates, Right= Long-run estimates. Estimates are coloured according to the type of data used: Aggregate, Household travel survey and odometer readings from test results.

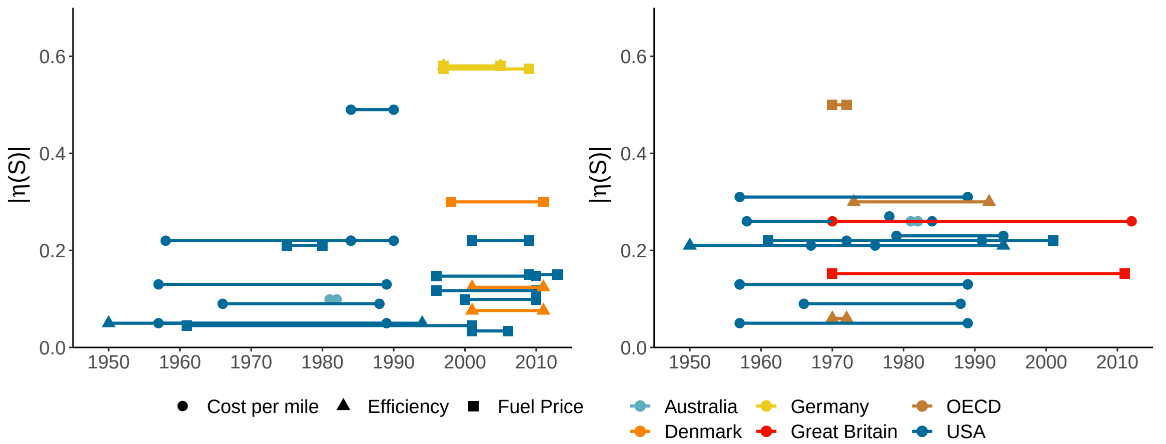

Fig. 2.5 Magnitude of past estimates of travel demand elasticities $|\eta(S)|$ quantified using energy efficiency, fuel prices and fuel costs per mile. Left=Short-run estimates, Right= Long-run estimates. Estimates are coloured according to the country of analysis.

2.2.4 The rebound effect in policy-making

In the late 1990's, debate about the rebound effect moved from being largely confined to academic journals, to a more public discussion about the merits of energy efficiency policy (Herring, 2006). Several policy making bodies now include estimates of rebound effects in their calculations of future energy demand. A report (Maxwell et al., 2011) written to inform the position of the European Commission on rebound effects, quotes an estimate of the rebound effect in private transportation of 0.1-0.3 from a review paper written by Sorrell et al. (2009).

The UK Department for Transport uses numerical modelling techniques to inform decision making; their National Transport Model includes travel cost elasticities, which are partly dependent on the efficiency of vehicles. A recent report outlining the steps taken to recalibrate the National Transport Model uses a travel cost elasticity of -0.3 (Jahanshahi, 2018). A 2018 report (Rohr et al., 2018) commissioned by the UK Department for Transport to review factors affecting travel demand, includes an elasticity of travel costs on mileage of -0.26 based on the work of Stapleton et al. (2017), though it is unclear whether these latest estimates have yet been integrated into the National Transport Model. Since rebound effects are used within future projections of travel demand and energy use, there is a need to ensure estimates are reliable and as detailed as possible.

2.2.5 Research Gap

Quantifying the magnitude of the rebound effect is important to accurately estimate the energy saving potential of efficiency improvements. If efficiency improvements stimulate travel demand, then the effects of energy efficiency policies may be lower than expected from engineering calculations. It is common in past literature to quantify the rebound effect by estimating the response to changes in fuel price. This has the side benefit of estimating how drivers might react to changes in fuel taxation.

Estimates of the rebound effect have varied widely, which may partly be explained by the majority of past work being dependent upon aggregate data, which relies on older data points and may omit important explanatory factors. To overcome these limitations, a small number of studies use detailed 'micro-data'. However, this type of analysis is yet to be extended to Great Britain.

An important aspect in policy appraisal is understanding how measures can impact different socio-economic groups differently. Micro-data can be used to investigate how the response to changes in travel costs may differ between members of the population based on the vehicles they drive, their geographical location and socio-economic situation. This has not yet been studied in Great Britain, would aid comparison between literature estimates and help better evaluate the effects of efficiency improvements and fuel taxation policies.

These gaps in past literature can be addressed by answering the following research questions:

- What is the magnitude of the rebound effect in passenger cars?
- How do estimates calculated using micro-data in Great Britain compare to those using aggregate data?
- How does the responsiveness to travel costs differ between vehicles?

2.3 The future potential of technical improvements

Section 2.1 explored past work investigating the degree to which technical improvements lead to more efficient vehicles. Section 2.2 then explored the degree to which more efficient vehicles might be expected to save energy. Together, answering the research questions from these two sections will establish the energy savings that are likely to have been attained by the deployment of technical improvements in the past. In this section, the literature concerning potential future emissions savings from vehicles is reviewed. In particular, this section investigates methods to estimate the effects of incremental technical efficiency improvements, changes in vehicle attributes, technology switching and rebound effects on future energy use and CO_2 emissions.

2.3.1 Scenario analysis

Scenario analysis has become a popular tool to investigate future transport emissions and to help inform policy measures. Scenarios of future transport emissions are typically guided by a numerical model, which draws in a series of input variables (such as the share of electric vehicles in the future, the prevalence of biofuels, the efficiency of future vehicles) and computes an estimate of future energy use or CO_2 emissions. Scenarios are defined by choosing a set of values for each input variable. This is generally structured in the form of ‘what if’ research questions, which allow the researcher to compare different possible futures to each other. Scenario analysis can be useful for policy appraisal to understand the possible effects that different actions or policy targets may have on future emissions.

Scenario analyses of future transport CO_2 emissions now exist for most major vehicle markets. Studies can generally be grouped by the various points of academic interest that they share. Some have focused mostly upon a projection of ‘business-as-usual’ emissions (Daly and O Gallachoir, 2011). Numerous studies investigate different scenarios of technology uptake of vehicle powertrains and low carbon fuels and compare these to a business-as-usual scenario (Baptista et al., 2012; Bodek and Heywood, 2008; Melaina and Webster, 2011; Nocera and Cavallaro, 2016; Reichmuth et al., 2013; Singh and Strømman, 2013).

Fewer papers compare technology uptake policies to other measures involving demand reduction and modal shift, though the latter are increasingly seen as an essential measure of many decarbonised futures (Brand, 2016; Brand et al., 2019, 2013; McCollum and Yang, 2009). The importance of modal shift and demand reduction policies is further accentuated when life-cycle impacts from embodied emissions in materials are considered (Garcia and Freire, 2017). Several papers have focused on the life-cycle aspects of future transport emissions models (Cheah et al., 2009; Kagawa et al., 2013; Knobloch et al., 2020; Pauliuk et al., 2012), with some placing particular emphasis on the potential for vehicle light-weighting (Bandivadekar et al., 2008; Garcia et al., 2015; González Palencia et al., 2012) and material substitution (Modaresi et al., 2014; Serrenho et al., 2017).

Whilst informative, scenario analyses are often hampered by the uncertainty of the future. Many authors stress that scenarios are not to be considered *forecasts* of the future but rather *possible* futures (Brand et al., 2019; IEA, 2018b). To create each scenario, several permutations of assumptions for input variables are required. The choices regarding input variables, from the carbon intensity of energy sources, to the uptake of different vehicle technologies, life-cycle factors, future travel demand and the size of vehicles demanded, can have large impacts upon the scenario. Even the best assumptions of input variables are subjective, and often fail to pass the test of time. A scenario remains useful if it covers a possible and actionable future. When this is no longer the case, due to outdated assumptions, the scenario becomes less relevant.

Bodek and Heywood (2008) for example develop fleet models for European countries and produce scenarios for the 2005-2035 period, yet no electric vehicles are considered, as the authors 'do not expect them to account for a significant fraction of new vehicle sales (e.g. equal to or greater than 5 percent) in Europe by 2035'. Baptista et al. (2012) compare 5 different technology scenarios for Portugal but with a high EV uptake scenario which conservatively assumes 20% new car sales in 2050. These assumptions may have been considered reasonable at the time of their publication, and seem conservative only with the benefit of hindsight. The latest Electric Vehicle Outlook published by the IEA (2019a) estimates that EVs will account for 26% of new car sales in Europe by 2030 in their conservative New Policies Scenario, and almost 50% in their high ambition scenario. History may, in turn, prove these latter estimates to be overly ambitious, or excessively conservative. However, these examples serve to highlight the dependence of scenarios on the values of input variables selected by modellers.

In addition to difficulties dealing with future uncertainty, a further challenge with scenario analyses is assessing the relative importance of individual input variables, when several choices have had to be made in each scenario. Common methods to assess a variables' importance involve choosing a selection of values (e.g. different sales shares of EVs), whilst holding all other variables constant. However, this becomes increasingly challenging as the number of variables inputted into the model increases, and as variables interact/are not independent. This can make it difficult to know which variables to prioritise and investigate in greater depth.

This raises the question 'which are the most important variables to consider'? To paraphrase *Prof. Art B. Owen*: 'Unimportance is important, as it lets you focus on the key inputs. Often most variables are unimportant, and they cannot all be relatively important.'

2.3.2 Stochastic methods to account for uncertainty

Rather than focusing on a limited set of deterministic scenarios, stochastic methods can be used to consider a range of scenarios given uncertainty ranges in each of the input variables. Stochastic analyses use Monte Carlo techniques to obtain likely ranges of future emissions (Bastani et al., 2012; Martin et al., 2015; Onat et al., 2016) and are useful for defining a future solution space, from which the probability of any given outcome can be gauged. All future looking analyses are inevitably dependent upon the input variables used. Conservative estimates of the uptake of a particular low-carbon technology will produce conservative estimates of its potential to reduce future carbon emissions. The benefit of using stochastic methods over deterministic scenario analysis is that they define a *range* for each input parameter rather than a single arbitrary value. This requires specifying upper and lower bounds for each input variable, forcing the modeller to question the future potential of each variable and account for its uncertainty.

Using Monte Carlo methods to define the uncertainty in future emissions pathways is important for assessing the feasibility of policy proposals. It can also be useful to examine the likelihood of attaining a desired result; this is known as 'Uncertainty Analysis' and serves to answer the question 'how uncertain is this inference?' (Saltelli and Annoni, 2010). Uncertainty analysis can be coupled with 'Sensitivity Analysis' which asks the complementary questions: 'what input variables define the given uncertainty?' and 'what is their relative importance?' Sensitivity analysis is used for a variety of purposes from understanding a model's behaviour and calibration, to supporting decision making by prioritising actions based on uncertainty (Pianosi et al., 2016). To quote the *US office for Management and Budget*: 'Sensitivity analysis is particularly useful in pinpointing which assumptions are appropriate candidates for additional data collection to narrow the degree of uncertainty in the results. Sensitivity analysis is generally considered a minimum, necessary component of a quality risk assessment report.' (Saltelli and Annoni, 2010)

2.3.3 Sensitivity Analysis

In many modelling studies, the influence of input variables are investigated by changing their values one-at-a-time (OAT analysis) and observing the change in the output. However, this method is compromised if there are interactions and dependencies between variables (Saltelli and Annoni, 2010). For example, the emissions impact of a 10% increase in electric vehicles is dependent on other variables such as the assumed carbon intensity of grid electricity and the size of vehicles.

Regression techniques can be used as an alternative sensitivity analysis method to OAT analysis. A vehicle stock model may be expressed as a function f that maps k inputs X_i (such as uptake of electric vehicles, rate of future efficiency improvements...), to produce an output Y (e.g. annual life-cycle emissions) as shown in equation 2.8.

$$Y = f(X_1, X_2, ...X_k) \tag{2.8}$$

Function f can be approximated as a linear statistical model given by equation 2.9 or a variation thereof (for example including quadratic terms or some interactions between variables).

$$\hat{Y} = \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k \tag{2.9}$$

The coefficients β_i can be estimated using regression techniques and give a measure of the effect that a change in a model input X_i may have on the output Y, holding all else equal. This is the approach taken by Bastani et al. (2012), who use Monte Carlo methods with a stock model of vehicles in order to produce a range of estimates of future CO_2 emissions from transport. To investigate the importance of model input variables, the authors estimate a statistical model of the form of equation 2.9 to approximate the stock model. The coefficients β_i are then used to measure the sensitivity of the output variables to a unit change in a given input variable.

Using the correlation coefficients β_i as measures of importance is useful in its simplicity and ease of interpretation. However, it suffers two main limitations. The first is that it doesn't account for variance that may be present in the input variables. Two inputs may have the same magnitude correlation coefficient (meaning a unit change in either would have the same impact upon the model output), but the first input may have much higher variance/uncertainty than the second, making its effect more important upon the uncertainty in the model results. This limitation can be addressed using standardized regression coefficients (SRCs) (Monod et al., 2006) shown in equation 2.10. These scale the correlation coefficient of an input variable X_i, by its variance s_i divided by the variance of the output $s_{\hat{Y}}$. Using SRCs therefore normalizes the regression coefficients by the variances of the model variables giving a better measure of the 'importance' of different variables.

$$\hat{\beta}_{i,\mathrm{SRC}} = \hat{\beta}_i (s_i / s_{\hat{Y}}) \tag{2.10}$$

However, SRCs still suffer from a second limitation as they are dependent upon the statistical validity of the regression model (eqn. 2.9) used to approximate the model output values (Pianosi et al., 2016). In practice, it is difficult to account for non-linear relationships and interactions between variables, meaning higher order effects might be omitted.

To address both of these limitations, an alternative method, first proposed by Sobol (2001), can be used to quantify the importance of different input variables. This method decomposes the variance in the output of a model, to calculate a 'sensitivity index' for each input. Furthermore, it acts upon the variance of the output directly, without requiring an intermediate regression model (such as eqn. 2.9) to approximate the output results (Monod et al., 2006). This has the advantage that the model can be treated as a 'black box' and can account for interactions between variables, thereby addressing the main limitations of regression and OAT methods.

Sobol indices have been used in a wide range of fields, from estimating the relative importance of different sources of radiative forcing on climate change (Smith et al., 2019), to building energy analysis (Wei, 2013), railway design (Quaglietta and Punzo, 2013) and crop yield predictions (Monod et al., 2006). However, Sobol indices have yet to be applied in the study of future emissions from the transport sector.

2.3.4 Research Gap

Studying future transport emissions is important to explore possible actions to reduce emissions and their impact on reaching greenhouse gas reduction targets. It is essential to determine the relative impacts of different variables to prioritise measures that reduce emissions. Past work using scenario analysis is ill-suited to this task, as exploring the impact of variables one-at-a-time does not explore the whole solution space. This means the importance of variables becomes particularly dependent on subjective assumptions of parameter values.

This limitation might be overcome using formal sensitivity analysis techniques (known as Sobol indices) that have yet to be applied to study future emissions from the transport sector. Sensitivity analysis ranks variables by their relative importance thereby helping to prioritise efforts, support policy-making and aid researchers to identify the most sensitive and important variables to consider in future work.

Using sensitivity analysis will help to answer the following research questions:

- How much can incremental technical efficiency improvements contribute to decarbonising vehicles?
- What role could shifts to new powertrain technologies, such as electric vehicles, play?

- What impacts would a continuation of current trends of increasing size and power have on future emissions?
- How important are rebound effects and modal shifts for reducing CO_2 emissions?
- How do the above factors compare in their importance on future emissions?
- Which are the most important measures that require the most policy attention?

2.4 Definition of Research Questions

This thesis investigates the role of technical improvements in reducing CO_2 emissions from passenger cars. A first step towards examining their impact is to quantify historical trends in technical improvements and the degree to which they have been offset by consumer trends towards larger and more powerful vehicles. To increase the detail of the analysis requires distinguishing between incremental technical efficiency improvements (ITEI) and market shifts between powertrain technologies. The literature reviewed in section 2.1 shows that ITEI can be quantified using existing multivariate regression techniques, but there is no existing method to quantify the effects of market shifts between powertrain technologies. A second important research gap in existing literature is that past analyses have not made use of real-world fuel consumption data. Given the increasing divergence between type-approval (tested) and real-world data, this risks over-stating past improvements in the energy efficiency of vehicles. These research gaps and the questions of section 2.1.4 are explored in chapter 3 by answering the research question: *'Have technical improvements led to more efficient vehicles?'*

Next, efficiency improvements typically lower running costs, which may stimulate drivers to travel more. If consumers' respond to more efficient vehicles via rebound effects then potential energy savings of technical improvements will be further reduced. Quantifying the rebound effect is therefore an important second step to understand how technical improvements in vehicles can lead to energy and emissions reductions. The literature reviewed in section 2.2 shows that estimates of the rebound effect have varied widely and have been dependent on aggregate data, with its associated empirical limitations. Using micro-data can provide a more detailed method to quantify rebound effects, but has not yet been pursued for Great Britain. This research gap and the questions of section 2.2.5 are explored in chapter 4 by answering the research question: *'Have more efficient vehicles led to energy savings?'*

The literature reviewed on technical improvements (section 2.1) and on rebound effects (section 2.2) has been largely self-contained. By addressing the research questions of chapters 3 and 4, this thesis aims to unite these two strands of academic work, for the first time, to estimate the degree to which technical improvements have led to energy savings.

Armed with insights on the historical role of technical improvements, the analysis of chapter 5 then aims to shed light on the future role of technical improvements. The literature reviewed in section 2.3 shows that the majority of past work uses scenario analysis to estimate the impact of future technology deployments. Most past studies creating future scenarios use deterministic values of input variables, which struggle to account for uncertainty in the future and are particularly dependent on subjective assumptions. This thesis aims to account for future uncertainty and reduce the subjectivity of analysis to the greatest degree possible, by applying formal sensitivity analysis techniques (known as Sobol indices). Sensitivity analysis can help to prioritise measures that reduce future energy and CO_2 emissions from passenger cars, and therefore determine the relative role of technical improvements. Sobol indices have not yet been used to study future emissions from the transport sector, this research gap and the questions of section 2.3.4 are explored in chapter 5 by answering the question: *'What is the likely impact of technical improvements in the future?'*.

The main research questions of this thesis are presented in figure 2.6 and each is investigated in chapters 3-5.

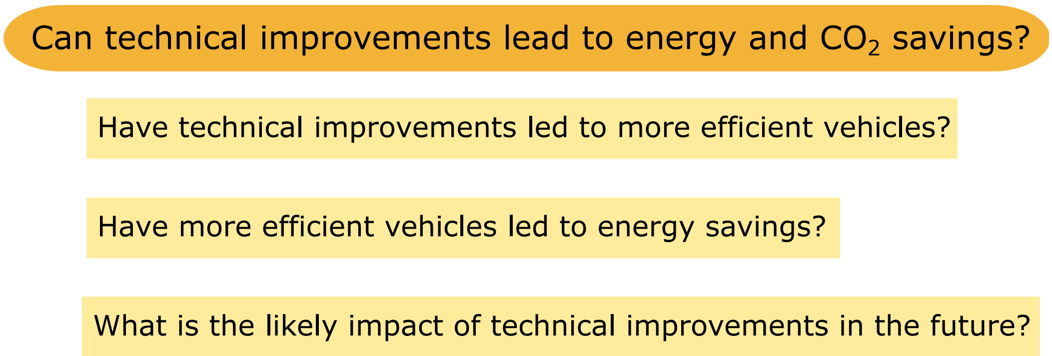

Fig. 2.6 Framework for chapters 3-5.

Chapter 3

Have technical improvements led to more efficient vehicles?

3.1 Introduction

> *Without a slowing or even reversing of the seemingly endless upward spiral of vehicle weight and power, 'technology' per se will not be deployed solely to reduce fuel intensity, but also and possibly preferentially to provide more vehicle performance (. . .). In short, it is not clear how much (or how rapidly) technology can reduce fuel [consumption] as long as much or all of the technology goes to boost power or weight.*

Schipper (2008)

This chapter aims to quantify past technical improvements for passenger cars in the UK. This is important to measure the potential energy savings of vehicle technologies and determine the degree to which they were offset by consumer preference for larger, more powerful vehicles. Quantifying the historical rate of incremental technical efficiency improvements is important to give a broad estimate of the likely rate of future incremental improvements, accounting for vehicle manufacturers' economic and physical constraints (explored in chapter 5). It can also be used to gauge the effectiveness of past regulations, such as CO_2 emissions standards, at stimulating the deployment of efficiency technologies.

Chapter 2 highlighted two important research gaps in past literature estimating technical improvements. Firstly, there are difficulties in distinguishing between incremental technical efficiency improvements, and market shifts between powertrain technologies. Secondly, real-world fuel consumption data has not yet been used to quantify incremental technical efficiency improvements (ITEI). Both of these limitations can potentially bias estimates of ITEI and lead to incorrect forecasts of future emissions savings. This chapter aims to address these research gaps by quantifying technical improvements for British vehicles between 2001 and 2018 using driver-reported data.

3.2 A new framework for estimating Technical Improvements

Past literature investigating the trade-off between technical improvements and vehicle attributes is not able to sufficiently address the effect of shifting sales between powertrains, as discussed in the example of figure 2.2. This means the rate of ITEI can only be quantified for each powertrain rather than for the whole population of vehicles sold. To address this limitation in past literature, this thesis proposes a modified framework in which changes in average fuel consumption (L/100km) of all new vehicles are split between three distinct factors:

- **Incremental Technical Efficiency Improvements (ITEI)** within a given powertrain technology (fig. 3.1A); these are quantified as the incremental reduction in average fuel consumption of vehicles, holding vehicle attributes (such as power and size) constant. ITEI are driven by engineering innovation such as light-weighting, improved combustion, lubrication and aerodynamics and once learnt are unlikely to be lost. ITEI are therefore almost always unidirectional (Goerlich and Wirl, 2012); the energy intensity of a vehicle with the same vehicle attributes such as power, size and accessories will tend to improve over time as greater R&D pushes engineering developments to an economic or physical limit (Cullen et al., 2011).
- **Technology Switching (TS)** between different powertrain technologies (fig. 3.1B); Diesel vehicles offer a more efficient alternative to petrol-engined vehicles of similar size and performance, as do hybrid and electric vehicles (IEA and ICCT, 2019). Policies to incentivise sales of one technology over another, tend to rely on subsidies (e.g. diesel fuel is taxed less than petrol in many European countries), efficiency labelling schemes and taxes (e.g. registration taxes for electric cars may be lower). Unlike ITEI, technology switching is not necessarily unidirectional; in the EU, consumers shifted towards more efficient diesel powertrains between 2000-2014 but have since reverted back to petrol vehicles in light of the 2015 diesel scandals (IEA and ICCT, 2019).

- **Vehicle Attribute changes (VA)** within a powertrain technology (fig. 3.1C); quantified as the change in energy intensity from changing vehicle attributes such as power, size and number of accessories in vehicles (such as air conditioning, heated seats and infotainment systems).

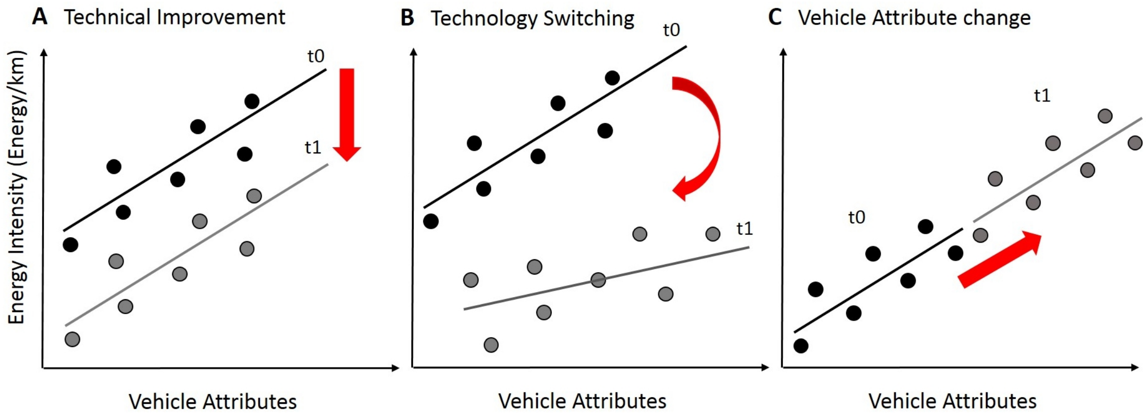

Fig. 3.1 Energy intensity of vehicles (shown as points with trend lines) can change over time (from t0 to t1) in 3 different ways: Technical Efficiency Improvements within a given technology, ITEI (**A**), Technology Switching, TS (**B**) and Vehicle Attribute changes, VA (**C**). Examples of ITEI in vehicles include improving vehicle aerodynamics and engine combustion. TS involves changing from e.g. petrol to diesel or hybrid vehicles, VA covers increasing vehicle power/performance and size.

Breaking down efficiency improvements into these three drivers gives a new lens with which to examine the potential of different technologies. Vehicles having a similar relationship between vehicle attributes (such as power and size) and fuel consumption are assigned to a single ‘technology’. This chapter limits itself to separating technology groups by powertrain type (petrol, diesel and hybrid). In this context, the relationship between vehicle attributes and energy intensity within a technology are assumed to remain constant over time. Any changes in this relationship at the aggregate level can only occur via ‘Technology Switching’ (TS) between different technologies.

The three effects of figure 3.1 drive changes in the average energy intensity of vehicles. Their magnitudes will be quantified using a novel decomposition technique to combine the powertrain specific results, presented in the following section.

3.3 Methods and Data

This study investigates newly registered vehicles in Great Britain from 2001 to 2018. A dataset is built from several publicly available sources and matched together, details are provided in section 3.3.1. Next, multivariate regressions are used to isolate annual incremental technical efficiency improvements for each powertrain type, as explained in section 3.3.2. Finally, annual changes in sales-weighted average fuel consumption are decomposed using log mean divisia index (LMDI) methods into ITEI, technology switching and vehicle attribute changes, explained in section 3.3.3.

3.3.1 Compiling a vehicle database for Great Britain

The dataset used in this study is created by matching vehicle sales data to other information on vehicle technical characteristics. Vehicle sales data is sourced from DfT (2018b). This provides annual new registration data at manufacturer and detailed model level (including some trim level characteristics) for vehicles sold in Great Britain between years 2001 and 2018. Using regular expressions, the fuel type, transmission type (Manual/Automatic) and some entries of engine power, turbo-charging and driven-wheels could be extracted for each model. Other technical details for vehicles are limited in this dataset, with no information given for engine capacity, vehicle mass, fuel consumption or dimensions. For years 2010-17, these additional variables are added from the European Environment Agency dataset EEA (2018), which has the same unique model names as the DfT data allowing for an exact match of each model.

Data from the UK Vehicle Certification Agency (VCA, 2019) is used to find the remaining fuel consumption values and engine size of vehicles. This data contains official type-approval (tested) fuel consumption of new vehicles sold in the UK, for each year between 2001 and 2018. Vehicle model names differ in this dataset to the DfT data, therefore 'fuzzy' matching algorithms are used to find the best match for each vehicle. Vehicles are screened by manufacturer, sales year fuel type and any other known technical details such as engine capacity, power, hybridisation, turbocharging, drivenwheels and transmission, before being given a score based on the similarity of model names. If the score is above a user-defined threshold the best match is selected, and then manually screened for errors, see appendix A.2 for further details. Further missing information on variables such as weight and engine power is supplemented with publicly available online technical datasets (McGregor, 2017), also using the fuzzy matching algorithms and based on the range of years each model variant was sold in. High-level trends are compared to external sources for validation (IEA and ICCT, 2019; SMMT, 2018).

To present trends in the British vehicle market and ensure the dataset adequately covers all types of vehicles, cars are grouped into one of seven size segments: City Car, Medium Car, Small Sedan, Large Sedan, SUV/MPV (Sports Utility Vehicle/Multiple Passenger Vehicle), Sports and Small SUV. This is achieved with clustering and classification algorithms, based on vehicle dimensions and body types (see appendix A.1). The fuel consumption of each vehicle is expressed as litres/100km tested over the NEDC combined cycle and converted to gasoline equivalent for all vehicles (one litre of diesel is equal to 36.1/33.5 litres of gasoline based on the respective energy contents of the fuels). Vans and caravans are removed due to limited publicly available fuel consumption data. Registrations of non-new vehicles are also removed.

The 'New European Drive Cycle' (NEDC) used for type-approval testing is known to be unrepresentative of real-world driving (Ntziachristos et al., 2014; Tietge et al., 2019). However, there are still no official government sources of real-world fuel consumption available to use in its place. Real-world fuel consumption data for this study is instead sourced from three online publicly available websites: Honest John (Harrison and Powell, 2018), Fiches-Auto (Naudot, 2018) and Spritmonitor (Fischl, 2018), which have also been used in past work investigating the growing divergence between type-approval and real-world fuel consumption (Tietge et al., 2019, 2017a). All three websites host user-submitted data and are based in the UK, France and Germany respectively, summary statistics of the real-world fuel consumption data used in this study are shown in table 3.1.

Tietge et al. (2019) showed the gap between type-approval fuel consumption and real-world driving conditions was consistent across datasets, despite possible differences in driving habits and weather conditions between countries. The authors also showed the gap to be comparable between data sources from automotive magazines, which tested new vehicles in a more standardised format (controlling for weather conditions etc.) and with national surveys designed to be representative of the population as a whole, assuaging fears of self-selection bias.

	Honest John	**Fiches-Auto**	**Spritmonitor** (Sample)
No. Vehicles	5753	3279	1915
No. User Entries	159544	61804	-

Table 3.1 Summary statistics of real world data sources. Vehicles are present in multiple sales years. Spritmonitor user entries were not collected as each user submits numerous mileage and fuel readings. Fuel consumption data for vehicles not present on the Honest John and Fiches-Auto webistes was sourced from a sample of the full Spritmonitor database.

Fiches-Auto and Honest John data are matched to the vehicle sales data using fuzzy matching scripts by sales year, manufacturer, model, engine capacity and any other available technical information such as power and drivenwheels. For example, a 2015 VW Golf TSI 1.8L in the DfT registration data would be matched with the appropriate car from the Honest John dataset sold between e.g. 2014 and 2017. Any remaining vehicles without real-world fuel consumption estimates were manually entered from Spritmonitor, in particular for early years where Honest John and Fiches-Auto lacked coverage. Overall, 92% of vehicle registrations in each year were given a real-world fuel consumption estimate, this covers over 80% of registrations in each vehicle segment (apart from the sports segment) to ensure a representative sample. Figure 3.2 shows the real-world fuel consumption source attributed to each vehicle as a share of registrations each year in the data. For most of the data, vehicles were attributed a match in both the Honest John and the Fiches-Auto data. In these cases the average of the two is taken. In section 3.4.4, the sensitivity of the results to the choice of real world fuel consumption data is investigated.

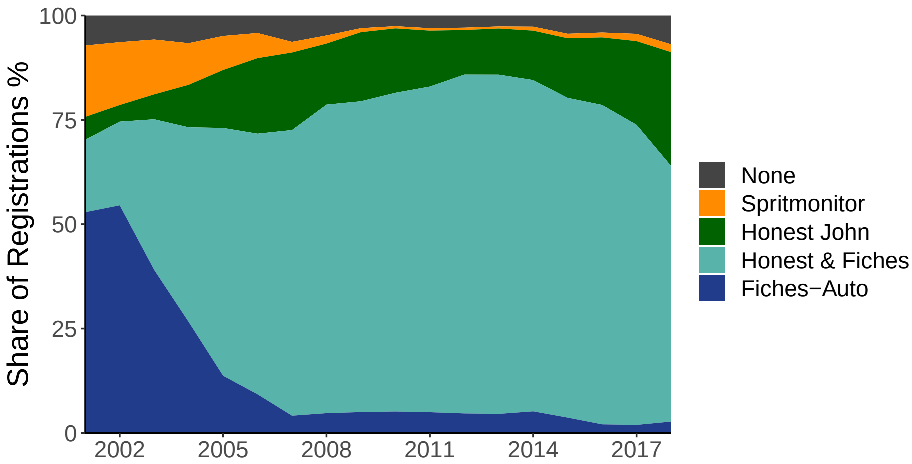

Fig. 3.2 Source of real-world fuel consumption data as a share of new registrations. Data from Honest John and Fiches-Auto are matched to vehicle sales data. For a large share of vehicles, both Honest John and Fiches-Auto data are available (Honest & Fiches). Spritmonitor data is manually entered to bring real-world fuel consumption coverage to over 92% in each year. The remaining vehicles could not be attributed a real-world fuel consumption estimate (None).

3.3.2 Using multivariate regressions to isolate technical improvements

In this study, a regression model similar to previous work (Knittel, 2011; MacKenzie and Heywood, 2015; Matas et al., 2017) is used to disaggregate changes in fuel consumption between changes in vehicle attributes (such as size and power) and ITEI over time for each powertrain type (equation 2.1). The effect of each vehicle attribute in the model is determined from the regression coefficients. ITEI is determined from the year fixed effects (T_t, eqn. 2.1) and is expressed as the change in fuel consumption had vehicle attributes remained constant at 2001 levels. The model is run for petrol, diesel and petrol hybrid vehicles separately as regression coefficients are not the same between each type. Battery electric, plug-in hybrid and other fuel type vehicles are not present in large enough quantities to yield statistically significant results.

The fuel consumption of a vehicle is broadly dictated by powertrain losses (a function of engine size, power, torque and technology such as turbocharging and fuel type) (Sovran and Blaser, 2003), transmission inefficiencies (a function of number gears, transmission type and drivetrain) and passive system losses (Cullen and Allwood, 2010a) from aerodynamic drag (drag coefficient C_D and frontal area), tyre friction (mass and tyre friction coefficient), inertia losses (mass), as well as driving style, which impacts many of the above.

Data on tyre friction and drag coefficients for each vehicle are not publicly available, nor are they reliable given that manufacturers can take advantage of flexibilities in testing procedures, allowing for drag and rolling resistance coefficients to be improved (Kühlwein, 2016).

The torque and number of gears for each vehicle was not available in the data used in this study and vehicle weight data could not be associated with a sufficient number of vehicles at detailed model level to attain a representative sample (only 76% of vehicles could be given a weight value). However, this is not an issue. In order to predict real-world fuel consumption, vehicle weight is likely to be associated with a high degree of error. Vehicles are allowed to be type-approved with levels of weight equivalent to the 'reference' model. This avoids the weight of accessories such as air conditioning, infotainment systems and electric seats (Kadijk et al., 2012). This means the weight of vehicles on the road can be considerably different to type-approval values (without accounting for the fact certain vehicles may allow for more average passengers and luggage). Vehicle dimensions on the other hand are far less subject to variation between testing and the real world. Since frontal area and length are highly correlated with weight (correlation coefficients 0.72 and 0.81 respectively), the dimensions can also be used as a proxy for weight.

Using engine capacity in the regression captures improvements from a given engine capacity using less fuel. However, technical improvements from engine downsizing, which allow for a reduced engine capacity because more power can be extracted, cannot. For this reason engine rated power is used instead.

The independent variables in each regression model are chosen to capture ITEI to the greatest extent, given data constraints and with an effort to ensure variables are consistent between type approval and real-world conditions. The variables used are: rated power, frontal area (the product of width and height), vehicle length as well as whether the vehicle has a manual/automatic transmission, four wheel drive or a turbocharger. Tests for multicollinearity show variance inflation factors are below 2.1 (Kleinbaum, 1998). Breusch-Pagan tests showed heteroskedasticity in the model residuals (meaning the model is less accurate for larger, more powerful vehicles) and therefore standard errors are corrected to ensure heteroskedastic consistency (Long and Ervin, 2000).

These regressions quantify the fuel consumption that petrol, diesel and petrol hybrid vehicles could have had if their size, power and other vehicle attributes had remained constant at 2001 levels. This allows for an insight into the ITEI in each powertrain type. However, to understand the magnitude of ITEI for all vehicles (i.e. not split by powertrain type), decomposition techniques are required; these are explained in the following section.

3.3.3 Decomposition of changing fuel consumption

To better interpret the results of the regressions, a decomposition technique is used to split changes in sales-weighted average fuel consumption of all new vehicles in the UK into three separate components (all expressed in units of fuel consumption, L/100km). These are: incremental technical efficiency improvements within powertrain technologies (ΔITEI), a structural technology shift in sales between powertrains (ΔTS) and a change in fuel consumption due to vehicle attribute changes (ΔVA). By using decomposition techniques, any change in fuel consumption (ΔFC), can be split into the sum of these three drivers as shown in equation 3.1.

$$\Delta\mathrm{FC} = \Delta\mathrm{ITEI} + \Delta\mathrm{TS} + \Delta\mathrm{VA} \tag{3.1}$$

Decomposition techniques have been well studied and applied to a variety of fields (Liu and Ang, 2003) with various proposed methods to allocate changes between different terms. Methods are favoured if they avoid a residual term (i.e. the left hand side of equation 3.1 perfectly equals the right) and are symmetrical (i.e. splitting a change in energy intensity from I_1 to I_2 gives the same result as from I_2 to I_1). The Log Mean Divisia Index (LMDI) decomposition technique is used in this study as it satisfies these criteria.

Past work (Ang and Choi, 1997) used this technique to decompose a change in energy intensity into two terms: changes in energy intensity within subcategories and changes in the volume/importance of subcategories. In this study, the LMDI technique is expanded to include the three drivers in equation 3.1.

The average fuel consumption in year t is equal to the product of a technical index, Tech (equal to e^{T_t} where T_t are the year fixed effects from equation 2.1), the share of sales S of each powertrain p and the fuel consumption that vehicles would have had in the absence of ITEI (the final term in eqn. 3.2).

$$\mathrm{FC}_t = \sum_p \mathrm{Tech}_{t,p} \times \mathrm{S}_{t,p} \times \frac{\mathrm{FC}_{t,p}}{\mathrm{Tech}_{t,p}} \tag{3.2}$$

By taking the derivative with respect to time t we have:

$$\frac{d\mathrm{FC}}{dt} = \sum_p S_p \frac{\mathrm{FC}_p}{\mathrm{Tech}_p}\frac{d\mathrm{Tech}_p}{dt} + \mathrm{Tech}_p \frac{\mathrm{FC}_p}{\mathrm{Tech}_p}\frac{dS_p}{dt} + \mathrm{Tech}_p S_p \frac{d\mathrm{FC}_p/\mathrm{Tech}_p}{dt} \tag{3.3}$$

Dividing both sides by FC and rearranging:

$$\frac{dln(\mathrm{FC})}{dt} = \sum_p w_p \Big[\frac{dln(\mathrm{Tech}_p)}{dt} + \frac{dln(\mathrm{S}_p)}{dt} + \frac{dln(\mathrm{FC}_p/\mathrm{Tech}_p)}{dt}\Big] \tag{3.4}$$

where $w_p = (Tech_p \times S_p \times \frac{FC_p}{Tech_p})/FC = (S_p \times FC_p)/FC$. Equation 3.4 then needs to be integrated between time t to $t+1$ and discretised to use non-continuous data. Past work has used a parametric approximation to this integral (Ang and Choi, 1997; Ang, 2015), this yields:

$$ln\Big(\frac{\mathrm{FC}_{t+1}}{\mathrm{FC}_t}\Big) \approx \sum_p w_p^* \Big[ln\Big(\frac{\mathrm{Tech}_{p,t+1}}{\mathrm{Tech}_{p,t}}\Big) + ln\Big(\frac{\mathrm{S}_{p,t+1}}{\mathrm{S}_{p,t}}\Big) + ln\Big(\frac{\mathrm{FC}_{t+1,p}/\mathrm{Tech}_{t+1,p}}{\mathrm{FC}_{t,p}/\mathrm{Tech}_{t,p}}\Big)\Big] \tag{3.5}$$

where w_p^* is a weighting function (equation 3.6) using logarithmic percentage changes which are desirable in order to attain a decomposition that is symmetrical and leaves no residual term. This weighting function was originally proposed by Vartia (1976) and Sato (1976) and is widely used in other LMDI studies (Ang and Choi, 1997; Ang, 2015).

$$w_p^* = \frac{L(w_{p,t+1}, w_{p,t})}{\sum_p L(w_{p,t+1}, w_{p,t})} \tag{3.6}$$

and $L(x,y) = \frac{y-x}{ln(y/x)}$

Reorganising equation 3.5 yields equations 3.7-3.9, the three desired drivers of fuel consumption change, expressed in units of fuel consumption (L/100km) between time t and $t+1$.

$$\Delta\mathrm{ITEI} = \mathrm{FC}_t \times exp\Big[\sum_p w_p^* \times ln\Big(\frac{\mathrm{Tech}_{p,t+1}}{\mathrm{Tech}_{p,t}}\Big)\Big] - \mathrm{FC}_t \tag{3.7}$$

$$\Delta\mathrm{TS} = \mathrm{FC}_t \times exp\Big[\sum_p w_p^* \times ln\Big(\frac{\mathrm{S}_{p,t+1}}{\mathrm{S}_{p,t}}\Big)\Big] - \mathrm{FC}_t \tag{3.8}$$

$$\Delta\mathrm{VA} = \mathrm{FC}_t \times exp\Big[\sum_p w_p^* \times ln\Big(\frac{\mathrm{FC}_{p,t+1}/\mathrm{Tech}_{p,t+1}}{\mathrm{FC}_{p,t}/\mathrm{Tech}_{p,t}}\Big)\Big] - \mathrm{FC}_t \tag{3.9}$$

This decomposition offers a new solution for the problem of figure 2.2 and is able to separate the effects of technology shifts and thereby correctly determine the average rate of incremental technical efficiency improvements. This decomposition is performed for both type-approval fuel consumption and real-world fuel consumption to compare the magnitude of the drivers.

3.4 Results and Discussion

Disaggregating vehicle fuel consumption into the underlying drivers of change highlights trends in the British vehicle market and aids in retrospective policy assessment. This section is organised as follows: section 3.4.1 shows trends in the British vehicle market between 2001 and 2018, section 3.4.2 presents the results of the multivariate regression models and section 3.4.3 discusses the results of the decomposition analysis allowing for new insights into the real rates of technical improvements in vehicles.

3.4.1 Trends in the British Vehicle Market 2001-2018

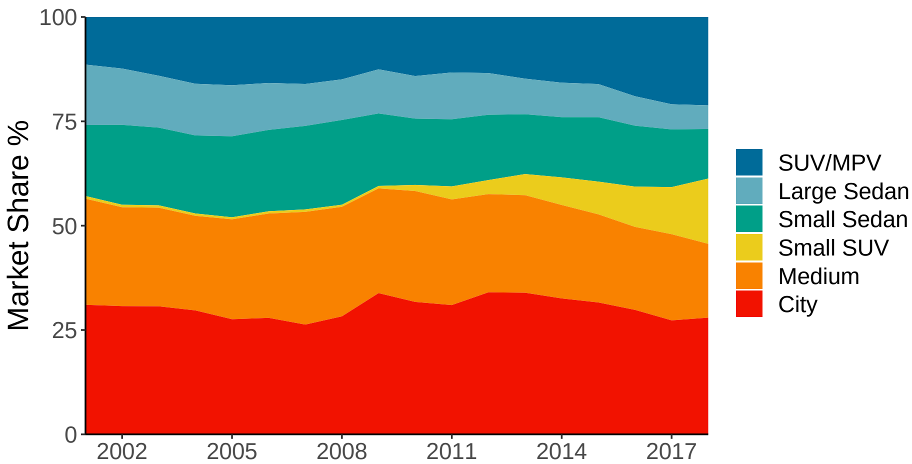

Fig. 3.3 Trends in British vehicle size segment market share 2001-2018.

The market shares of different vehicle size segments in the British market have varied with time as shown in figure 3.3. In the years before the financial crisis of 2008/9, city and medium cars accounted for over half of the British market, though their market share was dropping steadily in favour of the SUV/MPV segment and small sedans. The shock of the financial crisis caused the total number of registrations to drop sharply between 2008 and 2011. Sales suffered in particular in the larger vehicle segments meaning smaller segments increased as a share of the total. However, since the financial crisis the share of smaller vehicles has again begun to drop, partly due to increased popularity of the small SUV segment. Figure 3.3 suggests that since 2001, SUV/MPV type vehicles took market share from large sedans, while small SUVs acquired market share from the city and medium car segments.

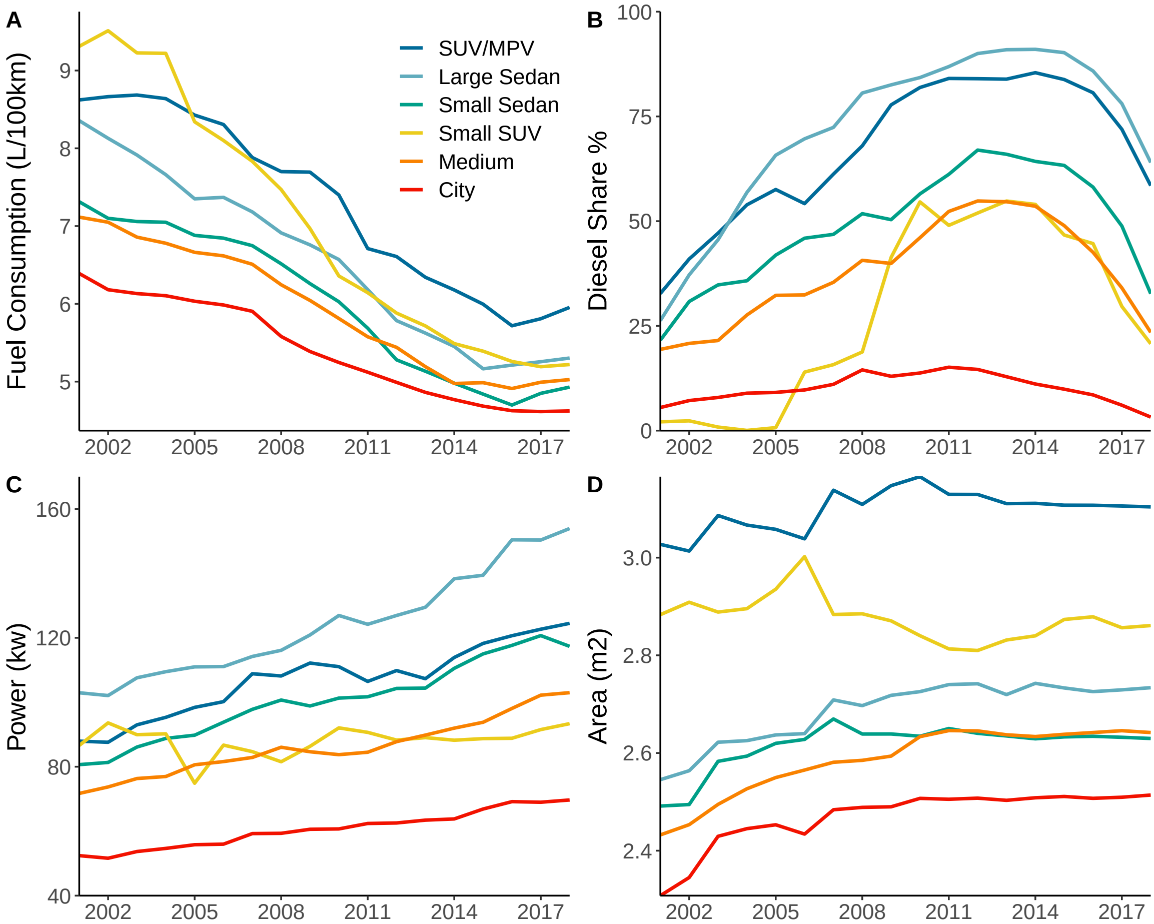

Fig. 3.4 Trends in sales-weighted, type-approval fuel consumption (NEDC) (**A**), diesel shares (**B**), average engine power (**C**) and average frontal area (**D**) of British vehicles 2001-2018 by size segment.

Figure 3.4A shows the sales-weighted, type-approval fuel consumption of each segment over the period. Whilst the fuel consumption of all segments has been improving over time, the shifts in sales to the larger segments, which have higher fuel consumption, has reduced the potential for energy efficiency improvements. Figure 3.4B shows the share of diesel powertrains in each size segment. Diesel powertrains saw a rapid uptake between 2001 and 2012, particularly in the larger size segments. However, after the diesel-gate scandal in 2015 (US EPA, 2015), the share of diesel powertrains across all segments has dropped. The average engine power of vehicles increased from an average of 74 kW in 2001 to 102 kW in 2018, an increase of 38%, the average frontal area of vehicles also increased by 12%. This increase in size and power of vehicles is due to both a shift in sales to larger size segments as well as increases in size and power of vehicles within size segments (figures 3.4C-D).

3.4.2 Regression Results

The regression models presented in table 3.2 isolate the effects of vehicle attributes on fuel consumption and thereby leave ITEI in the year fixed effects (appendix table A.2). Using these fixed effects, the hypothetical fuel consumption had vehicle attributes in each powertrain remained constant at 2001 levels can be quantified.

It can be seen that regression coefficients vary between different powertrain technologies highlighting that split regression models are indeed needed. Coefficients in the regression using type-approval fuel consumption data are of similar size to past estimates; although true comparisons can only be made between models using the same explanatory variables. The variance explained by the dependent variables (R^2 coefficients) is lower than in past studies (Knittel, 2011; MacKenzie and Heywood, 2015; Matas et al., 2017). This is likely due to two factors. The first is that the present study uses a larger number of vehicles than many previous studies, thereby including the full spectrum of vehicle designs; vehicles with high residual fuel consumption not explained by the model are found to have atypical designs (e.g. the Land Rover Defender, which has unusually low power for its size). The second is that the year fixed effects are based on vehicle sales year (like that of Matas et al. (2017)) rather than vehicle model year (like that of Knittel (2011) and MacKenzie and Heywood (2015)). The year fixed effects for petrol hybrids are only statistically significant after 2008 and after 2013 for type-approval and real-world fuel consumption respectively.

The regressions for real-world fuel consumption of petrol and diesel vehicles have a lower R^2 coefficient than those using type-approval data, due to the inherent noise in real-world estimates from a variety of factors that affect fuel consumption outside of laboratory testing conditions, such as driving style and weather (see Fontaras et al. (2017) for a comprehensive breakdown). The models are nonetheless able to give an insight into the magnitude of ITEI over the period studied.

Type Approval	**Petrol**	**Diesel**	**Hybrid**
(Intercept)	-6.915 (0.11)***	-14.912 (0.127)***	-3.982 (0.84)***
log(kw)	0.401 (0.002)***	0.289 (0.003)***	0.406 (0.009)***
log(Area)	0.425 (0.008)***	0.977 (0.008)***	0.271 (0.058)***
log(Length)	0.12 (0.008)***	0.142 (0.012)***	
Manual	-0.021 (0.001)***	-0.067 (0.001)***	
AWD	0.033 (0.002)***	0.066 (0.002)***	0.119 (0.031)***
Turbo	-0.077 (0.001)***		
R^2	0.841	0.771	0.858
R^2adj	0.841	0.771	0.854
Observations	49034	36313	717

Real World	**Petrol**	**Diesel**	**Hybrid**
(Intercept)	-8.808 (0.105)***	-13.893 (0.107)***	-9.51 (0.749)***
log(kw)	0.334 (0.002)***	0.34 (0.002)***	0.368 (0.008)***
log(Area)	0.589 (0.008)***	0.96 (0.007)***	0.66 (0.052)***
log(Length)	0.093 (0.008)***	0.019 (0.01)*	
Turbo	-0.031 (0.001)***		
R^2	0.753	0.759	0.885
R^2adj	0.753	0.759	0.882
Observations	47212	36219	733

Table 3.2 Regression results using equation 2.1 for Petrol, Diesel and petrol Hybrid vehicles separately. Dependent variable is the natural log of type-approval fuel consumption (litres of gasoline equivalent/100km), standard errors for each coefficient are included in parentheses. Independent variables are vehicle power (kw), frontal area (m^2), vehicle length (m), transmission type (Manual/Automatic), four wheel drive (AWD) and turbo-charging (Turbo). Each model also includes year fixed effects which are presented in the appendices. Statistical significance of t-tests: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The regressions isolate year-on-year ITEI, which can be used to quantify the hypothetical fuel consumption that vehicles could have attained had vehicle attributes remained constant at 2001 levels (table 3.3). This is shown in figure 3.5 for each type of powertrain and both type-approval and real-world data. Comparing this hypothetical case to the trends in sales-weighted fuel consumption shows the amount that ITEI were offset by increases in size and power.

	2001				2018			
	Diesel	HEV	Petrol	Total	Diesel	HEV	Petrol	Total
Power (kw)	75	53	74	74	116	84	97	102.8
Area (m^2)	2.6	2.5	2.5	2.5	2.9	2.7	2.7	2.8
Length (m)	4.4	4.3	4.1	4.2	4.6	4.4	4.2	4.4
TA FC (L/100km)	6.5	5.1	7.5	7.3	5.1	3.9	5.3	5.2
RW FC (L/100km)	6.8	5.4	7.8	7.6	6.9	5.2	7.0	7.0
Share (%)	17%	0%	83%	100%	28%	4%	69%	100%
Registrations ($\times 10^3$)	436	0.6	2066	2502	569	73.1	1418	2060

Table 3.3 Sales-weighted average statistics of vehicles split by powertrain type (Petrol, Diesel and Petrol Hybrid vehicles). Engine power (kw), frontal area (m^2), vehicle length (m), type-approval fuel consumption (TA FC), real world fuel consumption (RW TC) and percentage share and number of registrations. All fuel consumption in litres of gasoline equivalent per 100km.

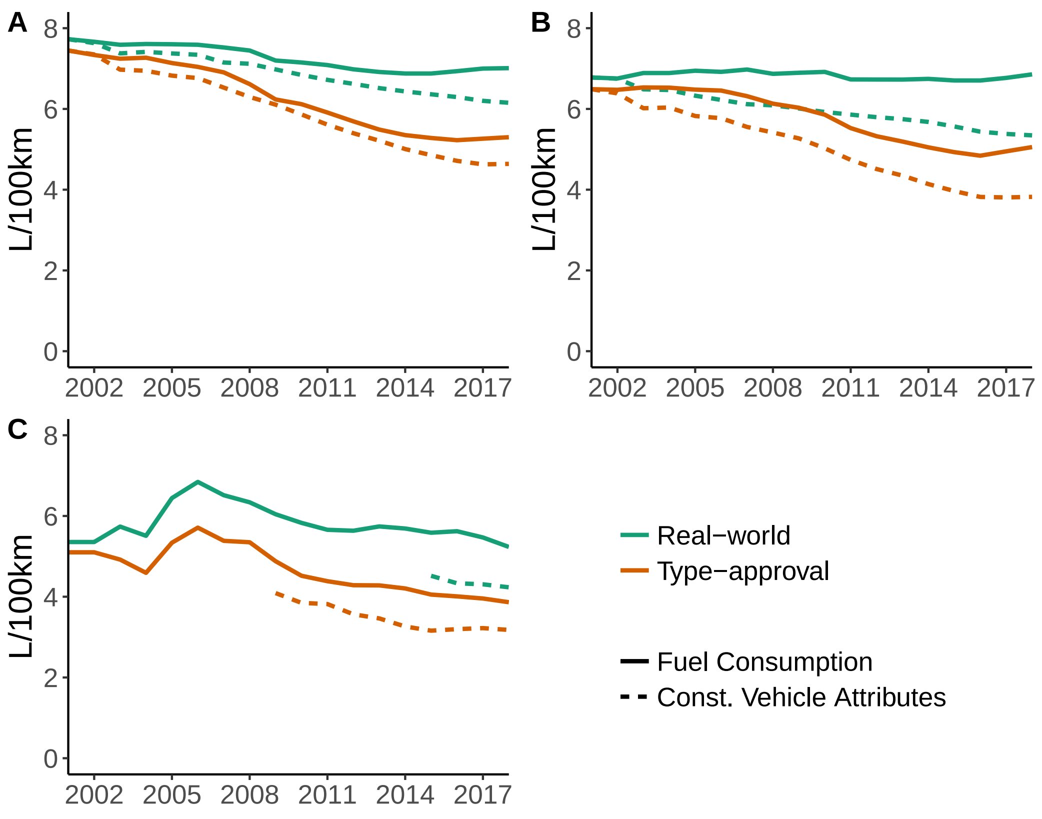

Fig. 3.5 Changes in sales-weighted type-approval and real-world fuel consumption (FC) between 2001 and 2018 (solid lines) for **A**= Petrol vehicles, **B**= Diesel vehicles, **C**= Petrol Hybrid vehicles. Also shown is the hypothetical fuel consumption vehicles could have attained had vehicle power and size and other vehicle attributes remained constant at 2001 levels (dashed). Hypothetical fuel consumption for Petrol Hybrid vehicles is only shown where year fixed effects are statistically significant at the $p<0.05$ level.

Over the period studied, the gap between type-approval and real-world fuel consumption grew for all three powertrains investigated. In 2001, sales-weighted real-world fuel consumption for petrol, diesel and petrol hybrid vehicles was 4%, 4% and 5% higher than type-approval fuel consumption respectively. By 2018 this gap grew to 34%, 36% and 35% higher. These results are similar to the non-sales-weighted results presented by Tietge et al. (2019) for the EU.

The real-world fuel consumption of petrol cars improved by just 0.8 L/100km over the time period; had ITEI been maximised, fuel consumption could have improved by 1.6 L/100km, instead size and power increases (table 3.3) offset 54% of this potential. The real-world fuel consumption of diesel vehicles increased from 2001 by 0.1 L/100km, ITEI could have reduced fuel consumption by 1.4 L/100km but this was more than offset by vehicle attribute increases.

The fuel consumption of hybrid vehicles increased sharply in 2005/06 as large hybrid powertrain SUVs entered the market which had previously only featured small sedan type vehicles such as the Toyota Prius. Had vehicles remained at the size and power of a 2001 Toyota Prius, the average real-world fuel consumption could have been 4.2 L/100km instead of the observed 5.2 L/100km average.

3.4.3 Decomposition Results

This section presents the results of the LMDI decomposition which splits changes in British average fuel consumption into the contributions from ITEI, TS and VA using the powertrain specific results shown in figure 3.5. Figure 3.6A shows type-approval fuel consumption in 2001 and 2018 and the magnitude of ITEI, TS and VA over the period. Between 2001 and 2018, incremental technical efficiency improvements contributed to reducing type-approval fuel consumption by 3.0 L/100km. Switching from petrol to diesel and hybrid vehicles improved fuel consumption by 0.2 L/100km. The relatively meagre gains from sales shifts in powertrains are due to two factors. The first is that the average fuel consumption of petrol and diesel vehicles was relatively similar, particularly in later years. The second is that hybrid vehicles had a low effect due to their low market share, which was just 4% of sales in 2018.

If vehicle attributes had remained constant at 2001 levels in each powertrain (table 3.3), registration weighted type-approval fuel consumption could theoretically have improved from 7.3 L/100km in 2001 to 4.1 L/100km in 2018. Instead, increasing vehicle size and power led to a 1.1 L/100km deterioration in type-approval fuel consumption.

Over the 18 year period, real-world average fuel consumption improved by just 0.65 L/100km (fig.3.6B). The effects of technology switching has been similar between the real-world and type-approval cases (-0.21 and -0.18 L/100km respectively), as have the effects of vehicle attributes changes (+1.2 and +1.1 L/100km respectively). Real-world ITEI on the other hand were just 1.6 L/100km. This means that total technical improvements (from technology switching and ITEI) had the potential to reduce vehicle fuel consumption by 1.8 L/100km. Instead, 65% of this potential was offset by increasing vehicle attributes.

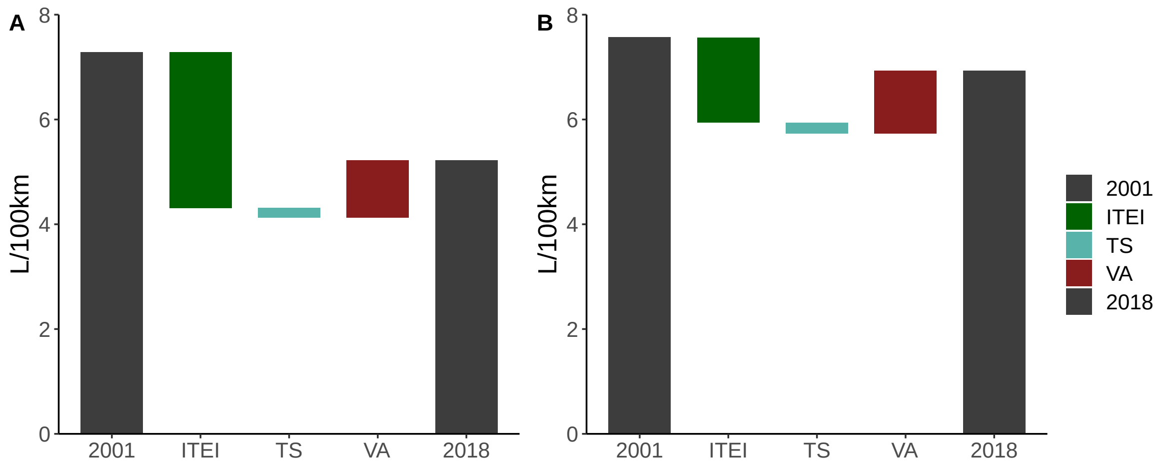

Fig. 3.6 Decomposition of changes in British vehicle fuel consumption between 2001 and 2018, **A** = Type-approval, **B**= Real-world. ITEI= Incremental Technical efficiency improvements within a powertrain technology (petrol, diesel and hybrid), TS= Technology switching between different powertrain technologies and VA=Vehicle Attribute changes in power and vehicle size. Hybrid vehicles are only included when year fixed effects are statistically significant at $p<0.05$.

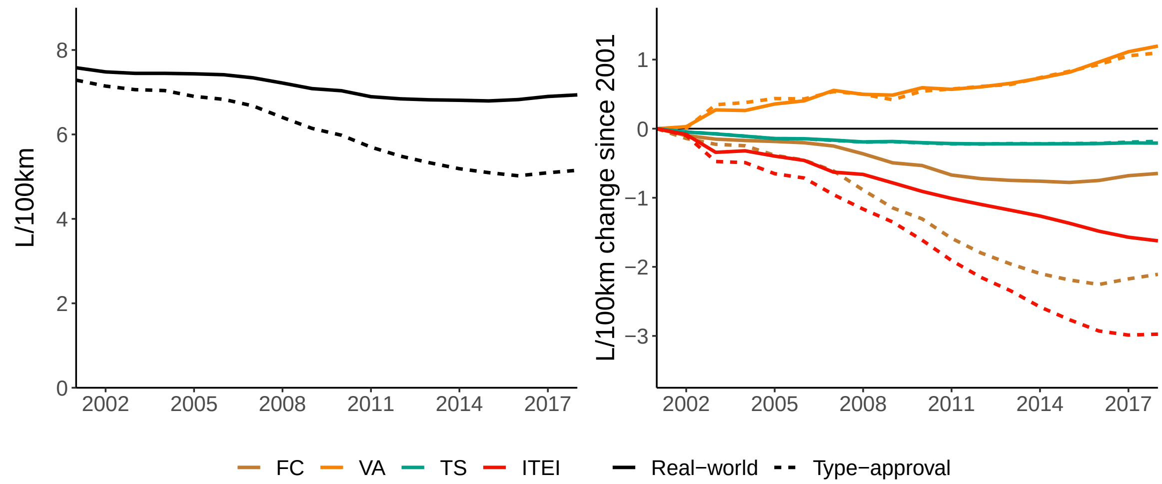

Fig. 3.7 Left= Trends in sales-weighted type-approval fuel consumption (NEDC) and reported real-world fuel consumption (litres of gasoline equivalent/100km). Right= Trends in incremental technical efficiency improvements (ITEI), Technology switching (TS), vehicle attribute changes (VA) and sales-weighted fuel consumption (FC) split by type-approval and real-world fuel consumption. Results are expressed as the cumulative change since year 2001.

Figure 3.7 (left) shows yearly trends in sales-weighted type-approval and real-world fuel consumption. The rate of improvement in type-approval fuel consumption increased after 2008-09 coinciding with mandatory EU emissions standards, suggesting they were effective at improving vehicle fuel consumption. However, real-world fuel consumption trends offer a contrasting picture, with a limited improvement between 2001 and 2018. Between 2016-18 the average fuel consumption of British vehicles deteriorated, both for type-approval and real-world. Disaggregating these changes in fuel consumption into the underlying drivers can help to explain these trends.

Figure 3.7 (right) shows the change in fuel consumption (FC) since 2001 and the cumulative change in ITEI, TS and VA for both real-world and type-approval data (also shown in table 3.4). The sum of the contributions of ITEI, TS and VA in any year in figure 3.7 (right) is equal to the change in FC (see eqn. 3.1). Vehicle attribute increases continue to offset ITEI, and at an increasing rate in later years.

	Type Approval				**Real World**			
Year	FC	VA	TS	ITEI	FC	VA	TS	ITEI
2001	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2002	-0.14	0.01	-0.05	-0.10	-0.10	0.03	-0.05	-0.08
2003	-0.23	0.35	-0.07	-0.48	-0.15	0.27	-0.08	-0.34
2004	-0.25	0.38	-0.11	-0.49	-0.17	0.26	-0.11	-0.32
2005	-0.38	0.44	-0.14	-0.65	-0.18	0.36	-0.14	-0.40
2006	-0.46	0.43	-0.15	-0.71	-0.20	0.40	-0.15	-0.46
2007	-0.61	0.54	-0.17	-0.96	-0.25	0.55	-0.17	-0.63
2008	-0.89	0.50	-0.19	-1.16	-0.36	0.50	-0.19	-0.66
2009	-1.15	0.42	-0.19	-1.35	-0.49	0.49	-0.19	-0.78
2010	-1.31	0.54	-0.21	-1.61	-0.53	0.59	-0.20	-0.91
2011	-1.59	0.57	-0.22	-1.91	-0.67	0.57	-0.22	-1.01
2012	-1.80	0.61	-0.22	-2.15	-0.72	0.60	-0.22	-1.10
2013	-1.96	0.64	-0.22	-2.35	-0.75	0.66	-0.22	-1.18
2014	-2.10	0.74	-0.22	-2.58	-0.76	0.73	-0.22	-1.26
2015	-2.19	0.83	-0.21	-2.77	-0.78	0.82	-0.22	-1.37
2016	-2.26	0.93	-0.21	-2.93	-0.75	0.96	-0.22	-1.48
2017	-2.17	1.05	-0.19	-2.99	-0.68	1.11	-0.21	-1.57
2018	-2.11	1.10	-0.18	-2.97	-0.65	1.20	-0.21	-1.62

Table 3.4 Decomposition results for type approval and real world incremental technical efficiency improvements (ITEI), technology switching (TS), vehicle attribute changes (VA) and sales-weighted fuel consumption (FC). Results are expressed as the cumulative change (in units L/100km) since year 2001.

Examining the rates of ITEI calculated using type-approval data reveals two findings. The first is that ITEI accelerates after the introduction of EU emissions standards in 2008/09, as reported by Klier and Linn (2016) for vehicles in the EU. However, this trend is less significant for real-world data. This suggests the introduction of the EU emissions standards increased the use of test flexibilities rather than stimulating real increases in the rate of ITEI. Secondly, the rates of ITEI using type-approval data slow in 2017/18, but this effect is again not evident with real-world data. This could be due to manufacturers reducing the exploitation of test flexibilities in order to comply with the incoming World Harmonised Light Vehicle Test (WLTP) cycle which will become mandatory from 2019 in the UK.

3.4.4 Sensitivity of data source

Over half of vehicles were attributed a real-world fuel consumption estimate from both the Honest John and Fiches-Auto datasets (see fig. 3.2). For these vehicles, there is a choice between preferring British data, French data or using the average of both (as performed in the preceding sections). This section investigates the sensitivity of this choice.

Figure 3.8A shows the sales-weighted percentage difference between real-world and type approval fuel consumption for all vehicles, split by preference towards Honest John or Fiches-Auto data for vehicles with multiple matches. Between 2001 and 2008, both datasets show similar levels of divergence. However, in later years the divergence grows more rapidly when using the French dataset. The data limits the analysis of this difference but reasons could include the increasing penetration of air conditioning and its likely higher use in France.

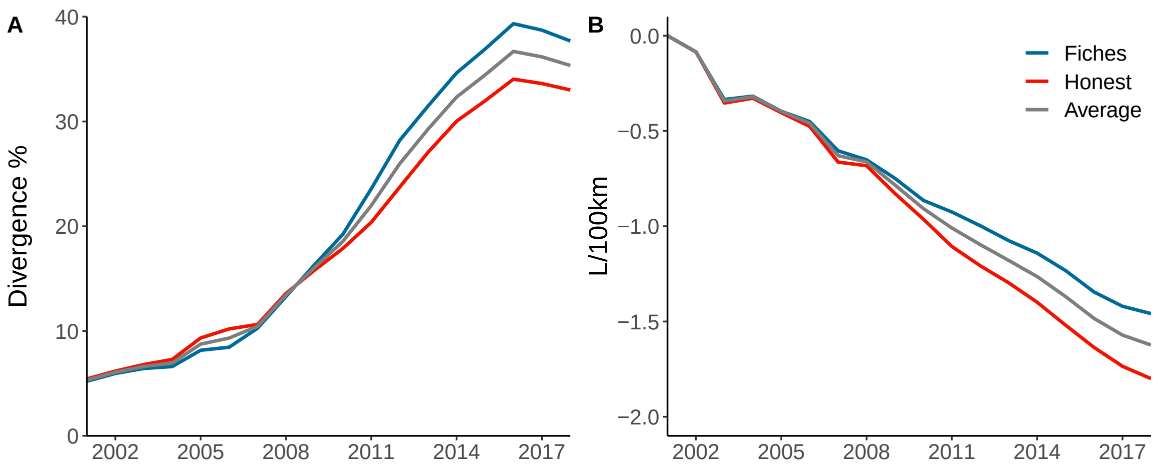

Fig. 3.8 **A**= Percentage Divergence between real-world fuel consumption and type approval data and **B**=ITEI using real-world data for all vehicles, split by preference towards Honest John data, Fiches-Auto data and the average of both for vehicles with multiple matches.

Figure 3.8B shows how the choice of real-world fuel consumption data, for vehicles with multiple matches, influences ITEI. The rates of improvement (in L/100km per year) of fuel consumption and ITEI are also detailed in table 3.5 and averaged over one of three periods for ease of interpretation: 2001-2008 before the introduction of EU CO_2 emissions standards, 2008-2016 the period following the introduction of the standard and 2016-2018, the period following diesel-gate in which the average fuel consumption of British vehicles worsened. A preference of British data (Honest John) means the rates of improvement in both fuel consumption (FC) and incremental technical efficiency improvements (ITEI) increase slightly post 2008. However, the main conclusion remains that real-world rates of ITEI remain well below those calculated using type approval data and the introduction of EU CO_2 emission standards had a limited effect at increasing rates of real-world ITEI.

		FC			**ITEI**		
	Source	2001-08	2008-16	2016-18	2001-08	2008-16	2016-18
TA		-0.13	-0.17	0.07	-0.17	-0.22	-0.02
RW	Fiches-Auto	-0.05	-0.03	0.05	-0.09	-0.09	-0.05
	Honest John	-0.05	-0.07	0.06	-0.1	-0.12	-0.07
	Average	-0.05	-0.05	0.05	-0.09	-0.1	-0.06

Table 3.5 Comparison of average improvement rates (L/100km per year) in average fuel consumption (FC) and Technical Efficiency Improvements (ITEI) using both type approval (TA) and real world (RW) data. Real world data is split by a preference toward using Fiches-Auto data, Honest John data and the average of both sources.

Following the publication of Craglia and Cullen (2019a) (which forms the basis of the results of this chapter), a similar study estimating ITEI from passenger vehicles using real-world data was published by Weiss et al. (2019). The authors use data from Spritmonitor (Fischl, 2018) for three models of vehicle (Volkswagen Golf, Opel Astra, and Ford Focus) tracked over their various generations from 1980-2018. Using regression models (for petrol and diesel cars separately) the authors conclude that over 50% of ITEI were offset by increases in size and power of vehicles, similar to the findings of this chapter. Despite the comparable findings there are several differences between the two analyses:

1. Different data: Weiss et al. (2019) cover three models between 1980-2018 giving $\approx$700 observations. Craglia and Cullen (2019a) uses data covering the entire fleet between 2001-2018 giving 84,164 observations. The analysis of Weiss et al. (2019) also focusses solely on real-world fuel consumption rather than type-approval data.

2. Different model specification: the equation used in Craglia and Cullen (2019a) uses log-log regression and uses year dummy variables. The equation used by Weiss et al. (2019) includes the year as a continuous variable, this results in a single coefficient estimate and cannot control for changes in the rate of ITEI over time. Including the year as a continuous variable is also susceptible to bias from other variables that change over time (such as power and size), which may lead to multicollinearity and impaired results.

3. The analysis of Weiss et al. (2019) focusses on the quantification of ITEI and does not consider the effects of sales shifts between technologies (TS).

3.4.5 Limitations

The decomposition analysis isolates the hypothetical fuel consumption that vehicles could have attained if their vehicle attributes *in each powertrain* remained at 2001 levels (table 3.3). It also isolates the fuel consumption lost to increases in vehicle attributes in each powertrain. However, when two powertrains have different average vehicle attributes, then technology switching also entails a measure of VA. Switching from an average petrol car to an average diesel car involves an improvement in engine efficiency, but also a slight increase in average vehicle size and power. This means the magnitudes of TS and VA are likely to be conservative. This cannot be captured using the decomposition used in this study and merits further consideration.

Next, users of the real-world fuel consumption websites likely upload information on vehicles which have a range of ages. A model year 2017 vehicle on the websites is likely to have been relatively new when the user uploaded their fuel consumption estimates, this may not be the same for a 2001 year vehicle. This raises two sources of potential bias: 1. driver type bias; an older vehicle could be owned by a different type of driver who drives their vehicle in a different way (e.g. more urban vs. rural driving) 2. vehicle age bias; if the vehicle is older and has higher cumulative mileage, it could have different technical characteristics compared to when it was new (e.g. engine wear and tear).

The real-world fuel consumption data for this study reports the average fuel consumption reported by all users for each model of vehicle. The data did not include individual user entries with the age of the vehicle at the time it was reported, meaning vehicle age cannot be explicitly controlled for. When reporting data to all three websites, users select whether they were driving in mostly urban environments, mostly rural or mixed. The data sourced for this study only used mixed data. This will reduce potential driver type bias, though some may remain and is an inevitable product of this type of data, which benefits from large samples but lacks standardised test conditions. It is possible that drivers of older vehicles also have a different average driving style to those of newer vehicles (e.g. more aggressive or more eco-driving). Tietge et al. (2017b) investigate this and show users of the Spritmonitor database report relatively constant driving styles. There is no reason to believe this would be different for the other two data sources used in this analysis.

Regarding vehicle age bias, there is relatively little literature reporting the effect of cumulative vehicle mileage or age on vehicle fuel economy. The only paper found is a study by Greene et al. (2017) in which the authors investigate real-world fuel economy of vehicles as they age in the USA. The authors show that the fuel economy of gasoline vehicles improves by approximately 2% in a vehicle's first 20,000 miles (which is around 2 years of driving) before remaining within 1% of a saturation value. Interestingly, the fuel economy of hybrid vehicles is found to gradually worsen over time (by 1% after 20,000 miles and 3% after 150,000 miles), potentially due to battery degradation. If these findings were to hold for British vehicles, it could introduce vehicle age bias for hybrid vehicles in particular. However, given that hybrid vehicles make up a negligible share of vehicle sales in the UK (4% in 2018) and the fuel consumption of gasoline vehicles stabilises after approximately 2 years, vehicle age bias is unlikely to affect the rates of ITEI reported in this study or the main finding regarding the response to EU CO_2 standards in 2008/09. Quantifying the impact of cumulative mileage and age on vehicles in Europe, and diesel vehicles in particular, is nonetheless an interesting avenue for future work.

3.5 Policy Considerations

Ensuring that fuel economy standards are effective at driving real efficiency improvements is essential to reduce CO_2 emissions from vehicles. The new framework presented in this study allows for changes in vehicle fuel consumption to be split into three underlying drivers: incremental technical efficiency improvements, market shifts between powertrain types and the effect of increasing vehicle attributes such as power and size. By quantifying these effects using driver-reported, real-world fuel consumption data, the success of policies aiming to stimulate efficiency improvements can be evaluated.

Between 2001 and 2018 real technical improvements could have reduced fuel consumption by 1.8 L/100km, instead 65% of this potential was offset by increasing size and power of vehicles. The introduction of EU fuel economy standards in 2008/09 had little effect on the rate of real ITEI in British vehicles. These results suggest that instead of adopting technical improvements at a higher rate, or limiting the size and power of vehicles, manufacturers met emissions standards by increasing the divergence between laboratory tests and real-world fuel consumption.

The real-world fuel consumption of new British vehicles deteriorated in 2017 and 2018. Three main policy strategies are suggested to avoid this continuing. The first is to increase the rates of ITEI in powertrains. This can be stimulated by ensuring fuel economy standards are based on a drive-cycle that is representative of real-world driving, to avoid the exploitation of test flexibilities. The WLTP test is expected to be a step in the right direction compared with the outgoing NEDC. Furthermore, in 2019 the European Commission (2019) introduced regulation (EU) 2019/631, which from 2021, requires the introduction of on-board fuel consumption monitoring devices (OBFCM) to accurately measure real-world fuel consumption and prevent a divergence from the WLTP.

The second strategy is to reduce vehicle size and power by further increasing registration taxes on larger vehicles. This can also be aided by making tests more representative of real-world driving. Tietge et al. (2019) found that sedans have a higher gap between type-approval and real-world fuel consumption than smaller cars. Making tests more representative of real-world fuel consumption would therefore push larger vehicles into higher registration tax bands. The final strategy to improve fuel consumption is to increase technology switching by further stimulating the adoption of hybrid and electrified vehicles, for example, through differentiated taxation with subsidies for low emission vehicles.

Future work could extend this analysis to countries such as Japan and the USA, which do not use the NEDC cycle for type-approval testing procedures, to investigate whether the rate of real-world ITEI increased in response to fuel economy standards. This analysis could also include electric and plug-in hybrid vehicles as more data becomes available.

Chapter 4

Have more efficient vehicles led to energy savings?

4.1 Introduction

The findings of chapter 3 show that 65% of real technical improvements between 2001 and 2018 were offset by the increasing size and power of vehicles. This means the rate of energy intensity improvements was lower than that of the underlying technical improvements. This chapter investigates how much energy intensity improvements may have stimulated increased mileage, further offsetting the potential of technical improvements and limiting energy savings.

If energy intensity improvements stimulate travel demand via the rebound effect, then the effects of energy efficiency policies may be lower than expected from engineering calculations. Estimating the magnitude of the rebound is important to evaluate the effects of technical improvements. However, as summarised in Chapter 2, estimates of the rebound effect have varied widely, which may partly be explained by the majority of past work being dependent upon aggregate data. Using aggregate data to estimate the rebound effect may omit important explanatory factors and relies on data points from historical periods that may no longer be appropriate for current or future travel demand. To overcome these limitations, a small number of studies use detailed 'micro-data', this type of analysis is yet to be extended to Great Britain.

It is common in past literature to quantify the rebound effect by estimating the response to changes in fuel price, $\eta_{P_E}(S)$ and is the approach taken in this study. This has the side benefit of estimating how drivers might react to changes in fuel taxation. The use of micro-data can highlight how elasticities might vary between different socio-economic groups or drivers of different types of vehicles. This can give insights as to how policies such as fuel taxes or CO_2 emissions standards may impact different members of the public. The aim of this chapter is to quantify the rebound effect, in Great Britain, using micro-data and examine how it may vary across the population.

4.2 The MOT dataset

This study uses data from annual vehicle roadworthiness tests, known as MOT tests in the UK, between years 2006-2017 (DVSA, 2019) from over 50 million individual vehicles. This dataset has not yet been used for longitudinal analysis to estimate changes in vehicle mileage over time. Past work using this data focused on cross-section analysis between different areas in Great Britain for the year 2011. This showed, for example, that British vehicle ownership and mileage is lower in urban centres than in rural areas (Cairns et al., 2017; Chatterton et al., 2015). The use of geographic information in the MOT data also permitted studies into socio-economic differences in vehicle mileage. Chatterton et al. (2016) study the financial implications of vehicle ownership by quantifying annual vehicle tax and fuel expenditure by income groups and geographical areas. This work was complemented by Mattioli et al. (2017) who developed an index describing the financial vulnerability of drivers to further price increases. The present study adds to this work by quantifying how drivers react to fuel price changes over time and thus how quickly different drivers may be able to adjust to changes in travel costs.

4.3 Method

This section begins with a discussion of the model specification and independent variables chosen for this investigation. Section 4.4 then presents the details of the MOT data and other data sources used in this study.

This study makes use of vehicle roadworthiness testing data which includes odometer readings at the time of testing. The miles travelled (S) by vehicle i in each driving period t is calculated as the change in odometer readings between test dates divided by the time between tests. This is modeled as a function of the average price of fuel in Great Britain (Price_t), national gross domestic product (GDP_t) and vehicle age (A_{it}). To capture seasonal effects, controls are included for the average rainfall in each postcode (R_{it}) and heating degree months (HDM_{it}), a measure of how cold the weather is over the time period in each postcode. Dummy variables are used to control for the month of each test (M_{it}) as well as the time between tests (γ_{it}), and are included to account for remaining seasonal effects (for example a driving period covering two Christmas holidays may have lower average mileage), as well as other unobserved heterogeneity (e.g. vehicles tested much earlier than the average 52 weeks may have abnormal mileage if they have technical issues requiring premature testing). To capture structural differences and any remaining unobserved heterogeneity, vehicle fixed effects (θ_i) are included, which is equivalent to using a dummy variable for each vehicle and captures the average mileage of each individual vehicle. This results in the following logarithmic form:

$$\ln(S_{it}) = \beta X + \varepsilon_{it} \tag{4.1}$$

where X is a vector of variables:

$$X = [\ln(\text{Price}_t), \ln(\text{GDP}_t), \ln(\text{HDM}_{it}), \ln(R_{it}), A_{it}, M_{it}, \gamma_{it}, \theta_i] \tag{4.2}$$

β is a vector of the coefficients for each variable and ε_{it} is an idiosyncratic error term with zero mean. The elasticity of fuel price on mileage (β_{Price}) is our primary interest as it is equal to $\eta_{P_E}(S)$.

The vehicle fixed effects (θ_i) capture any time-invariant differences between vehicles meaning variables that do not change over time cannot be used as regressors. Any effects associated with the type of vehicle, rated fuel consumption and location of each vehicle are therefore absorbed into the fixed effects. The effects of these variables can be investigated separately by running regressions on subsets of the data or by using dummy variable interaction.

Since vehicle fixed effects are used, the coefficients shown in equation 4.1 are ‘within’ estimates (measured at the individual vehicle level) and represent the change in mileage from a temporal change in the explanatory variables rather than ‘between’ estimates which would measure cross-sectional differences in the data. These elasticities could differ from household elasticities due to substitution effects if multiple vehicle households use a more efficient car in times of high oil price. Possible substitution effects are investigated by considering heterogeneity by vehicle type.

The interest of this study is the effect that an exogenous change in fuel prices may have on the mileage of vehicles. However, there is a possibility that short-term increases in the mileage of British vehicles may have an effect on the price of fuel at the pump. If this were true, then the fuel price would not be exogenous and the effects of changes in travel demand on fuel prices would have to be accounted for. The price of fuel at the pump in the UK is comprised of the underlying price of oil on the international market, an additional government duty and a value added tax (VAT). The international price of fuel is unlikely to be affected by short term fluctuations in the mileage of a small country such as the UK. Similarly, fuel price duty and VAT have remained relatively constant over the period of investigation, though it is possible these may have changed in response to changes in travel demand. To ensure that this is not the case, the Europe Brent spot price is used in a model run as an instrumental variable. This removes the possible effects of government fuel duties and VAT changes. Finally, the model specification estimates an average response to fuel price changes and does not account for any differences in fuel price increases versus decreases.

Given the relatively short time series and data constraints, this study focusses on short-run, 'direct' rebound effects. Finally, the estimates of rebound effects produced in this chapter are based on vehicle miles travelled (VMT) rather than the energy service of passenger miles travelled (Cullen and Allwood, 2010a).

4.4 Data

In the United Kingdom, all vehicles over 3 years old undergo mandatory annual roadworthiness tests known as MOT tests. From 2005 onwards, the Department for Transport moved to storing the MOT results on a digital system. These results were released in the public domain and the latest 2019 release (DVSA, 2019) covers years 2005-2017, though the 2005 year was incomplete meaning the year 2006 is chosen as the start year of the data. In total, there are 275,866,597 test entries in the dataset for 50,155,603 unique cars who passed MOT tests.

Information on vehicle registration plates of each vehicle is removed by the Department for Transport to ensure the data remains anonymous. Instead, each vehicle is given a unique vehicle_id number. Other fields of interest include the vehicle manufacturer and model, engine capacity, fuel type, date of first registration and the odometer reading at each test date. This final entry can be used with the vehicle_id to track the mileage of each vehicle between tests. Each observation in the dataset therefore consists of a driving period between two MOT tests (e.g. 04/01/2007 - 05/02/2008) for each individual vehicle (e.g. vehicle_id=789, Volkswagen Golf 2004 turbo 1200cc Diesel) and the mileage driven (the difference between odometer readings). The data is cleaned to remove erroneous entries (such as removing entries where the mileage rate exceeds 100,000 miles/year or is negative) as performed by past studies (Wilson et al., 2013). A full list of cleaning procedures is included in appendix B.

The publicly available MOT data also includes the general postcode area of the garage performing the test. It is reasonable to assume that drivers test their vehicles close to home, and for the majority of tests, the garage and location of residence fall within the same relatively large postcode area. This approach was also taken by past studies using the MOT

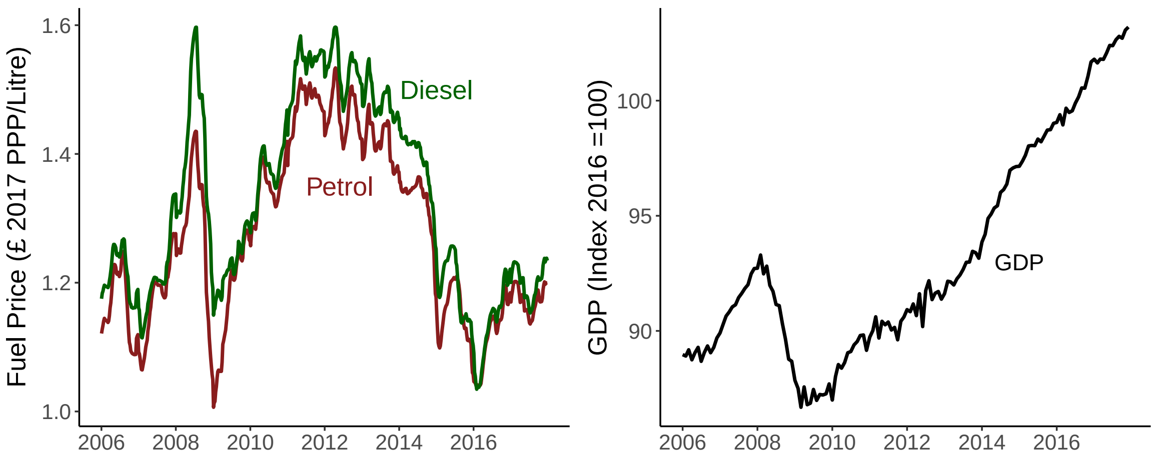

Fig. 4.1 Left=Price of petrol (gasoline) and diesel fuel at pump (including government fuel taxes) and converted to 2017 £ PPP. Right=UK National Gross Domestic Product (indexed to 2016 levels).

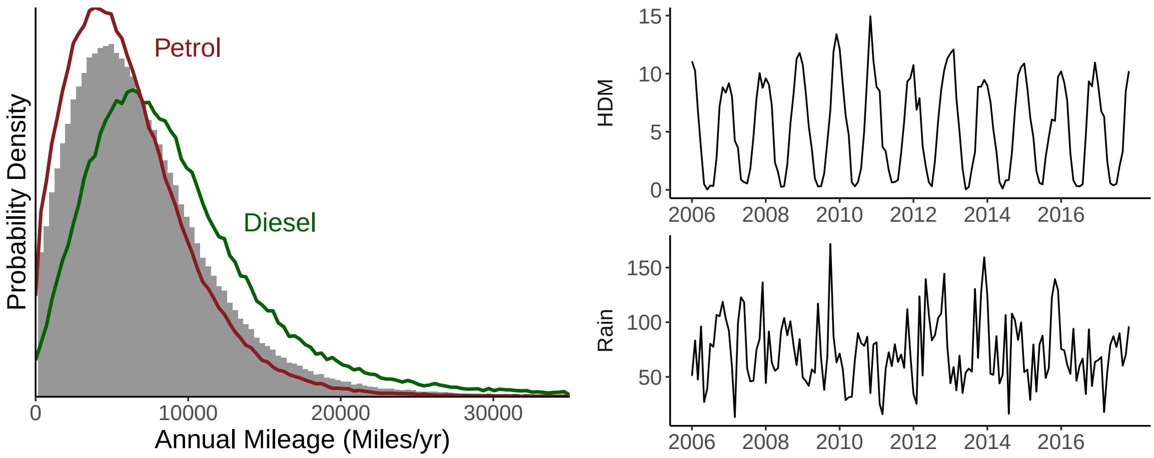

Fig. 4.2 Left=Histogram of vehicle mileage in MOT data (grey) and frequency plots of petrol (red) and diesel vehicles (green). Right=Heating degree months and monthly average precipitation across Great Britain (mm).

data (Chatterton et al., 2015). In the absence of data on the socio-economic characteristics of the drivers in the data, the average characteristics of the postcode can be used as a rough proxy for the general social and geographical context of the vehicle.

Weekly fuel price data is sourced from BEIS (2019b) (fig. 4.1, left) and Europe Brent spot price data is sourced from the EIA (2019). Both are corrected to pounds Sterling and 2017 purchasing price parity using OECD consumer price indices (OECD, 2018). Due to data availability, the average UK fuel price is used, rather than any more detailed geospatial differences. Monthly, seasonally adjusted GDP data for the UK is sourced from the ONS (2019a) and shown in figure 4.1 (right).

Figure 4.2 (left) shows a histogram of the annual mileage of the vehicles in the dataset. This resembles a shifted gamma distribution (Wilson et al., 2013) with a long tail where a minority of vehicles have particularly high mileages. Diesel vehicles have, on average, higher mileages than Petrol vehicles.

Monthly weather data (average temperatures and rainfall) for 2006-2017 is sourced from the Met Office (2018) as a 12km resolution raster and then aggregated to postcode level using shapefiles (Open Door Logistics, 2017). Postcode temperature data is used to calculate heating degree months for each postcode (HDM, see appendix B.4). The national average HDM and rain are shown in figure 4.2 (right). Fuel price, GDP and weather variables are averaged at monthly level and associated with the driving period of each vehicle. Median income data for the year 2011 is sourced from Experian (2011) and aggregated to postcode level. A consistent time series of income by postcode for the period studied is unfortunately not available.

Using the dataset of vehicles sold between 2001 and 2018 created in chapter 3, a size segment (e.g. Small Sedan, SUV) could be attributed to 91% of vehicles in the MOT data, based on the vehicle manufacturer (e.g. BMW) and generic model (e.g. 3 series). Some vehicles in the MOT data could not be assigned a size segment because they are either old, with model names that were no longer sold after the year 2000 (e.g. Jaguar E-Type), or have erroneous name entries.

For vehicles registered after the year 2000, a 'real-world' fuel consumption estimate is matched using the fuzzy matching algorithms by vehicle manufacturer, model, engine size, fuel type and year of first registration. Since no data on transmission type (Manual/Auto) or drivetrain (AWD) are available in the MOT data, the sales-weighted average data for each group of matched vehicles is used. A real-world fuel consumption estimate is matched to 82% of vehicles registered after the year 2000.

	Mean	Std.	Min.	Max.
Annual VMT	7,421	5,807	400	99,998
Age (years)	7.94	3.55	3	19
Fuel Price (£ 2017)	1.30	0.13	1.01	1.56
GDP (£ 2016)$\times 10^9$	1,821	52.6	1,735	1,937
HDM in Pcd.	5.37	1.09	1.38	16.1
Rain in Pcd.(mm)	72.1	26.8	14.3	379
Pcd. Population $\times 10^3$	676.1	356.2	2.2	2,045.1

Table 4.1 Summary statistics of main variables from 23,016,519 observations. Pcd.=Postcode

Summary statistics of the data are presented in table 4.1 and for three example driving periods in table 4.2. This shows the shares of vehicles in each size segment in the data have remained broadly constant over time with a slight shift to larger SUVs. On average, vehicles on the road have become older and are driven fewer miles every year.

	2006/7	2011/12	2016/17
City %	31.4	30.7	32.5
Medium %	28.4	25.6	25.3
Small Sedan %	14.4	17.1	16.4
Small SUV %	0.6	0.6	1.6
Large Sedan %	13.8	11.3	9.6
SUV/MPV %	11.1	14.4	14.4
Sports %	0.2	0.3	0.3
Tested L/100km*	7.16	6.89	6.33
Real world L/100km*	7.38	7.32	7.15
Age (Years)	7.68	8.34	9.39
Mileage	7556	7297	6971

Table 4.2 Summary statistics of three test periods showing share of vehicles by size segment, average vehicle age and annual mileage as well as average Type-approval (Tested) and 'Real-world' fuel consumption expressed in litres of gasoline equivalent per 100km. *note only vehicles registered after the year 2000 could be attributed fuel consumption estimates.

The average mileage of a group of vehicles between two test years can be determined simply by dividing the sum of the mileages of each vehicle by the number of vehicles. However, this approach has flaws as explained by Wilson et al. (2013). The average mileage of all vehicles tested between 2006 and 2007 for example will include some vehicles tested in January 2006 and January 2007 as well as vehicles tested between December 2006 and December 2007. This means the driving period covered in the averaging process covers almost 2 years of driving (Jan 2006 - Dec 2007). This results in locally time averaged data effectively smoothing out short term perturbations which may be of interest. This averaging process can be useful to show general cross-sectional differences in mileage between geographic areas and types of vehicles, but is inappropriate for estimating short term responses to fuel price changes. For this reason a panel data approach is necessary. The full MOT dataset comprises 275,866,597 rows of data. For computational reasons, two large samples of the data are used:

The first sample is used purely for the descriptive results presented in section 4.5.1. This consists of a random sample of 3 million cars from each year of test data 2006-2016. These are matched with their respective entries in the subsequent test year to create sets of observations of driving periods. This sample is averaged between test years (e.g. 2006 to

2007) to give an important overview of driving trends in Great Britain and the cross-sectional differences between types of vehicles. However, the trends suffer from the smoothing effect (outlined above) and are therefore only appropriate for comparing cross-sectional differences between vehicles and not for analysing responses to fuel price changes.

To estimate fuel price changes using panel methods with fixed effects, individual vehicles need to be tracked over time. The data used in the regressions in section 4.5.2 is created by taking a random sample of 10 million unique vehicle_ids from the full dataset across all years. These 10 million cars are then tracked through time to obtain all driving periods available for this sample of vehicles. After data cleaning and matching procedures this leaves a total of 23,016,519 observations with an average of 3.8 observations for each vehicle_id.

4.5 Results and Discussion

This section presents an overview of driving trends in Great Britain from the MOT data. The differences in mileage between size segments and age groups gives greater context to the regression model results presented in section 4.5.2, which investigate how drivers reacted to changes in fuel prices between 2006 and 2017.

4.5.1 Overview of driving trends in Great Britain

Figure 4.3 shows how the average annual mileage of vehicles varies by size segment. Larger size segments tend to have higher mileage than smaller vehicles, they also have a higher share of diesel engines explaining the differences in figure 4.2 (left). For most segments, vehicles are used less intensively over time. This is likely due to increasing vehicle age over the time period (table 4.1) and a 10% increase in national vehicles per household (DfT, 2020c). The 'small SUV' segment of 'crossover' type vehicles became more popular over time (as shown in figure 3.3), taking market share from Medium cars in particular. This increase in popularity was also associated with a change in the use of this type of vehicle. New small SUVs sold after 2013 are driven more on average than the fewer older models that once made up this size segment.

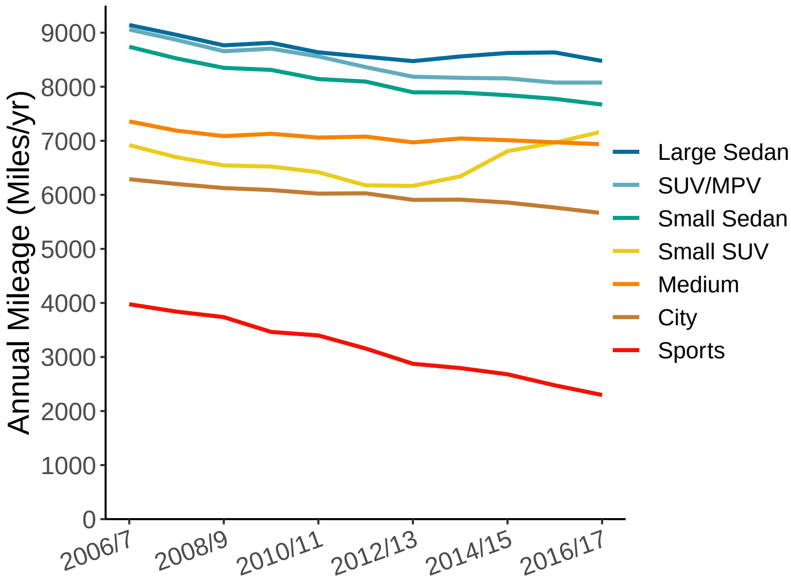

Fig. 4.3 Average annual mileage by size segment.

Figure 4.4 shows that the average mileage of vehicles drops with age across all vintages. For every year a car ages, it's average annual mileage drops by approximately 330 miles per year. Similar findings have been shown using national travel survey data by Serrenho et al. (2017). Importantly, these graphs show average mileage per year between two test years and are therefore subject to the smoothing effect detailed in section 4.4. This means short term fluctuations in mileage due to fuel price changes are averaged out.

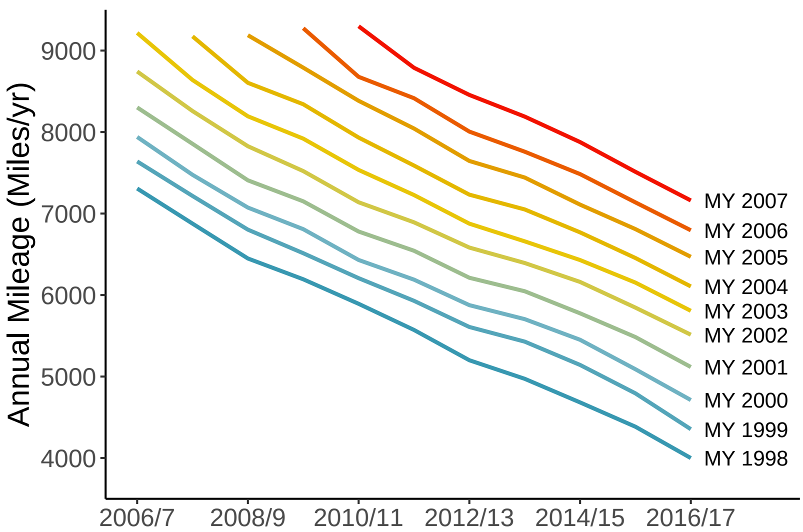

Fig. 4.4 Average annual mileage by model year.

4.5.2 Fuel price elasticities of vehicle mileage

Regression results are presented in table 4.3 for four different regression models. In the first model (1) Base, the effects of fuel price, GDP and vehicle age on mileage are estimated. The sensitivity of these effects to the addition of controls is then investigated. The second model (2) adds controls for the month of each MOT test and the length of the driving period between tests for each vehicle. These controls are performed by means of dummy variables. The third model (3) additionally controls for weather effects in each postcode using heating degree months (HDM) and total rainfall. Cold weather (increasing HDMs) has a small negative coefficient suggesting vehicle mileage is lower during cold periods. A period with increased rain has a small positive effect on mileage. This effect may be larger with data at a higher degree of temporal resolution.

Parameter	(1) Base	(2) Time Effects	(3) Weather Effects	(4) IV 2SLS
lnPrice	-0.045 (0.002)***	-0.048 (0.002)***	-0.046 (0.002)***	-0.04 (0.001)***
lnGDP	0.12 (0.006)***	0.15 (0.006)***	0.089 (0.006)***	0.15 (0.007)***
Age	-0.035 (1e-04)***	-0.035 (1e-04)***	-0.035 (1e-04)***	-0.036 (1e-04)***
lnHDM			-0.021 (0.001)***	-0.018 (0.001)***
lnRain			0.004 (7e-04)***	0.004 (7e-04)***
Month Effects		X	X	X
Period Effects		X	X	X
Vehicle Effects	X	X	X	X
Observations	23,016,519	23,016,519	23,016,519	23,016,519
R^2	0.03	0.03	0.03	0.03

Table 4.3 Regression results for various model formulations. Dependent variable is the natural logarithm of vehicle mileage. Standard errors in parentheses. X indicates effects are included in a model. Statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The low R^2 values highlight the difficulty in predicting changes in the mileage of individual vehicles with such noisy data. There are an innumerable number of factors that could affect the mileage of individual drivers year-on-year that are not possible to explain with the given data (or perhaps any data). When using data with such a large number of observations, it becomes increasingly possible to obtain statistically significant results ($p<0.05$) on variables of interest, as p-values and standard errors are inversely proportional to the number of observations (Nuzzo, 2014; Smith, 2018). For this reason, particular emphasis is placed upon checking that the findings remain robust to the addition/removal of different variables and subsetting data. Appendix B details further investigations including controls for the effects of population growth and removing the effects of GDP. Over all the model formulations, the coefficients of the main variables remain relatively constant suggesting the results are robust. The preferred model specification is Model (3).

To ensure that the UK fuel price is exogenous (independent of vehicle mileage in the UK), the Europe Brent spot price is used as an instrumental variable using 2 stage least-squares regression (2SLS). Model (4) in table 4.3 shows β_{Price} and other coefficients are similar to the results of previous model specifications, thereby confirming that changes in British vehicle mileage are unlikely to influence British fuel prices or government fuel duties. The first stage results are presented in appendix B.7.

The average response to fuel prices across all vehicles in the dataset is $\eta_{P_E}(S) \approx -0.046$. This is lower than the estimate of $\eta_{P_E}(S) = -0.152$ reported by Stapleton et al. (2016) using British aggregate data for years 1970-2011. There are two likely reasons for this difference. Firstly, the later period investigated in this study likely entails a greater degree of satiation for driving and consequently a lower elasticity (as seen in the USA (Hughes et al., 2008)). Secondly, this study estimates changes on an annual level (a short-run effect), the estimates of Stapleton et al. (2016) are a long-run effect. The elasticity estimate is similarly smaller than that found by Gillingham and Munk-Nielsen (2019) of $\approx$ -0.3 for Denmark which may again be due to their estimate using data on driving periods over 2-4 years.

Following equation 2.6, the short-run estimate of $\eta_{P_E}(S) = -0.046$ is likely to be similar in magnitude to the short-run rebound effect $\eta_{\varepsilon}(S)$. The elasticities of GDP (which can be considered to be a measure of income) on vehicle mileage are in the range 0.089-0.15. Goodwin et al. (2004) report an average income effect on per vehicle VMT of 0.06 from studies using static models. Stapleton et al. (2016) report an average long-run estimate of 0.51. Whilst the estimates of this study lie within this range, caution is required as firstly, this study uses national average GDP data, which is only a rough measure of real income data and secondly, GDP had relatively low variance over the short time period studied.

Although the average response to fuel prices is small, this may differ between drivers based on their type of vehicle or socio-economic circumstances. To investigate possible heterogeneity in β_{Price} by vehicle type and geographical region, regressions are run with dummy variable interactions on fuel price in the following sections.

4.5.3 Heterogeneity by vehicle size segment

Parameter	Coefficient
lnPrice: City	0.11 (0.003)***
lnPrice: Medium	-0.038 (0.003)***
lnPrice: Small SUV	-0.077 (0.02)***
lnPrice: Small Sedan	-0.12 (0.004)***
lnPrice: SUV/MPV	-0.19 (0.004)***
lnPrice: Large Sedan	-0.22 (0.005)***
lnPrice: Sports	-0.7 (0.04)***
lnGDP	0.081 (0.007)***
Age	-0.033 (1e-04)***
lnHDM	-0.021 (0.001)***
lnRain	0.0042 (7e-04)***
Month Effects	X
Period Effects	X
Vehicle Effects	X
Observations	20,873,256
R^2	0.03

Table 4.4 Regression results for by vehicle fuel type and size segment. Dependent variable is the natural logarithm of vehicle miles travelled. Standard errors in parentheses. Statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

In table 4.4 and figure 4.5, the sensitivity of different vehicle size segments to fuel price (β_{Price}) is presented using dummy variable interactions. The results show the responsiveness to fuel price increases for larger vehicle size segments and sports cars. These findings are robust to alternative specifications including subsetting the data based on size segment. Only 91% of vehicles in the data could be attributed a size segment, meaning the number of observations is less than those used in table 4.3. Interestingly, the fuel price elasticity of City cars (the smallest vehicle segment) is positive implying they are driven more when fuel prices increase. This may be due to drivers switching between multiple vehicles they own and choosing the more efficient, cheaper vehicle when prices are high. This hypothesis cannot be tested explicitly, as there is no information in the dataset about the number of vehicles owned by each driver. However, Knittel and Sandler (2013) found that drivers in California with a more efficient vehicle in their household appear more responsive to changes in fuel price than those without, suggesting that vehicle switching does occur. If this were true in Great

Britain it would suggest the assumption of the rebound effect being equal in magnitude to the price elasticity is flawed, a point discussed in greater depth in section 4.5.6.

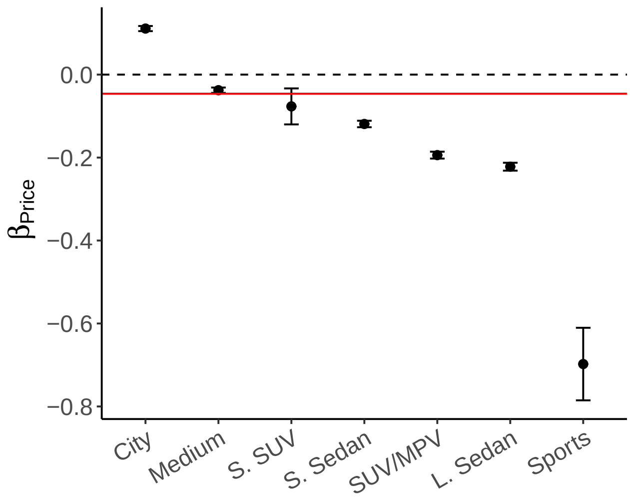

Fig. 4.5 Heterogeneity of the price elasticity of vehicle mileage by vehicle size segment with $\pm 1.96 \times$SE confidence intervals. The red line is the average β_{Price} from model (3) in table 4.3.

The results show that increasing fuel taxation may have a greater effect at reducing mileage of larger vehicles than that of smaller vehicles, leading to energy savings. However, it is not clear from the outset whether these findings are due to (i) larger vehicles being less fuel efficient, (ii) larger vehicles being driven a higher annual mileage than other size segments (seen in fig. 4.3), or (iii) the owners of large vehicles being more likely to also own a small vehicle to use in times of high oil price. The larger vehicles in the data are less fuel efficient on a per mile basis and travel a higher annual mileage (Sports cars are the exception to this rule since they have a high fuel consumption but a low annual mileage). Whilst it is not possible to investigate (iii) further, the importance of mileage and fuel consumption on β_{Price} is investigated in section 4.5.4.

4.5.4 Heterogeneity by vehicle fuel efficiency

This section investigates how the response to fuel price changes may change for vehicles of different fuel consumption (L/100km). Table 4.5 reports regression results from interacting the fuel price with a 'real-world' fuel consumption range. The β_{Price} elasticities for each fuel consumption range are plotted graphically in figure 4.6. These findings show β_{Price} increases in magnitude for higher fuel consumption vehicles suggesting they are the most responsive to fuel price.

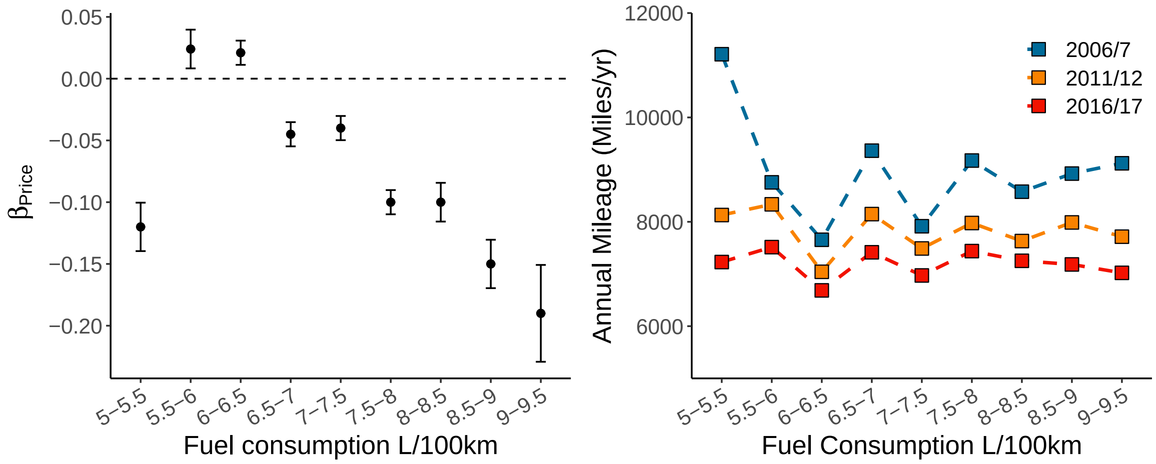

Fig. 4.6 Heterogeneity of the price elasticity of vehicle mileage by real world fuel consumption group with ±1.96×SE confidence intervals.

Parameter	Coefficient
lnPrice: 5-5.5 L/100km	-0.12 (0.01)***
lnPrice: 5.5-6 L/100km	0.024 (0.008)**
lnPrice: 6-6.5 L/100km	0.021 (0.005)***
lnPrice: 6.5-7 L/100km	-0.045 (0.005)***
lnPrice: 7-7.5 L/100km	-0.04 (0.005)***
lnPrice: 7.5-8 L/100km	-0.1 (0.005)***
lnPrice: 8-8.5 L/100km	-0.1 (0.008)***
lnPrice: 8.5-9 L/100km	-0.15 (0.01)***
lnPrice: 9-9.5 L/100km	-0.19 (0.02)***
lnGDP	0.14 (0.009)***
Age	-0.034 (1e-04)***
lnHDM	-0.021 (0.001)***
lnRain	0.006 (9e-04)***
Month Effects	X
Period Effects	X
Vehicle Effects	X
Observations	12200570
R^2	0.03

Table 4.5 Regression results by real world fuel consumption of vehicles. Dependent variable is the natural logarithm of vehicle miles travelled. Fuel consumption in litres of gasoline equivalent. Standard errors in parentheses. Statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Data on the real world fuel consumption of cars is only available for cars sold after the year 2000, which reduces the number of cars in the sample. However, this is unlikely to bias the estimates (see appendix table B.7) given the age of the car is already controlled for and vehicle fixed effects are included.

To determine the effect that average annual mileage may have, Figure 4.6 (right) shows the average mileage of vehicles in each fuel consumption range for three different driving periods. This shows that the annual mileage of vehicles in each range of fuel consumption is broadly similar and suggests that the differences in β_{Price} shown in Figure 4.6 (left) are predominantly due to differences in fuel consumption rather than mileage rates.

The most efficient vehicles (5.0-5.5L/100km) are also more responsive than average. However, caution is required when attributing particular significance to this finding; in the early years of 2006/7 this bin had relatively high mileage (fig.4.6, right) suggesting the usage and types of these vehicles in this group has changed over the time period studied. This is not the case for other bins of vehicle efficiency. These findings complement those presented in section 4.5.3 and suggest that drivers of larger vehicles appear more responsive to changes in fuel prices due to worse fuel efficiency.

4.5.5 Heterogeneity by income and population density of postcode

It is possible that the rebound effect/fuel price elasticity may differ based on levels of income, annual mileage or other geographical and social factors. This is investigated by interacting the fuel price with each of the 118 postcodes in the data. To aid the interpretation of these results, figure 4.7 shows a map in which the colour of the postcode is proportional to the magnitude of β_{Price}. Scatter plots (right) are also presented, where the estimated β_{Price} for each postcode is plotted against the average vehicle mileage, income and population density of each postcode in year 2011. Only statistically significant results are plotted (all others are dark grey, no data is available for Northern Ireland since the MOT dataset covers only Great Britain).

The responsiveness to fuel price changes is loosely related to the average income in each postcode (fig. 4.7, right), while stronger relationships are found between the average annual mileage of vehicles and the population density in each postcode. These scatter plots would suggest drivers living in more urban areas with lower annual vehicle mileage are more responsive to fuel price changes. It is possible this is due to a greater availability of public transport modes. A driver with high annual mileage and living in a more rural postcode may display less responsiveness in fuel price changes if they have no alternative but to drive. It is possible that these trends could be affected by the types of vehicles present in each postcode. However, there is no obvious correlation between the share of large vehicles in each postcode and the responsiveness to fuel price, making any significant bias unlikely (fig. B.9). The results can be compared to the findings of Gillingham (2014) and Gillingham and Munk-Nielsen (2019) who similarly find β_{Price} becomes more negative (i.e. larger magnitude) for drivers in higher income, urban areas in both California and Denmark.

These findings suggest that drivers in some rural, low income areas of Great Britain may be unable to moderate their mileage in response to short term fuel price changes, leading to financial burdens. These insights from the use of the MOT micro-data can therefore be used to aid policy decisions on the social equity effects of fuel taxation and fuel price changes.

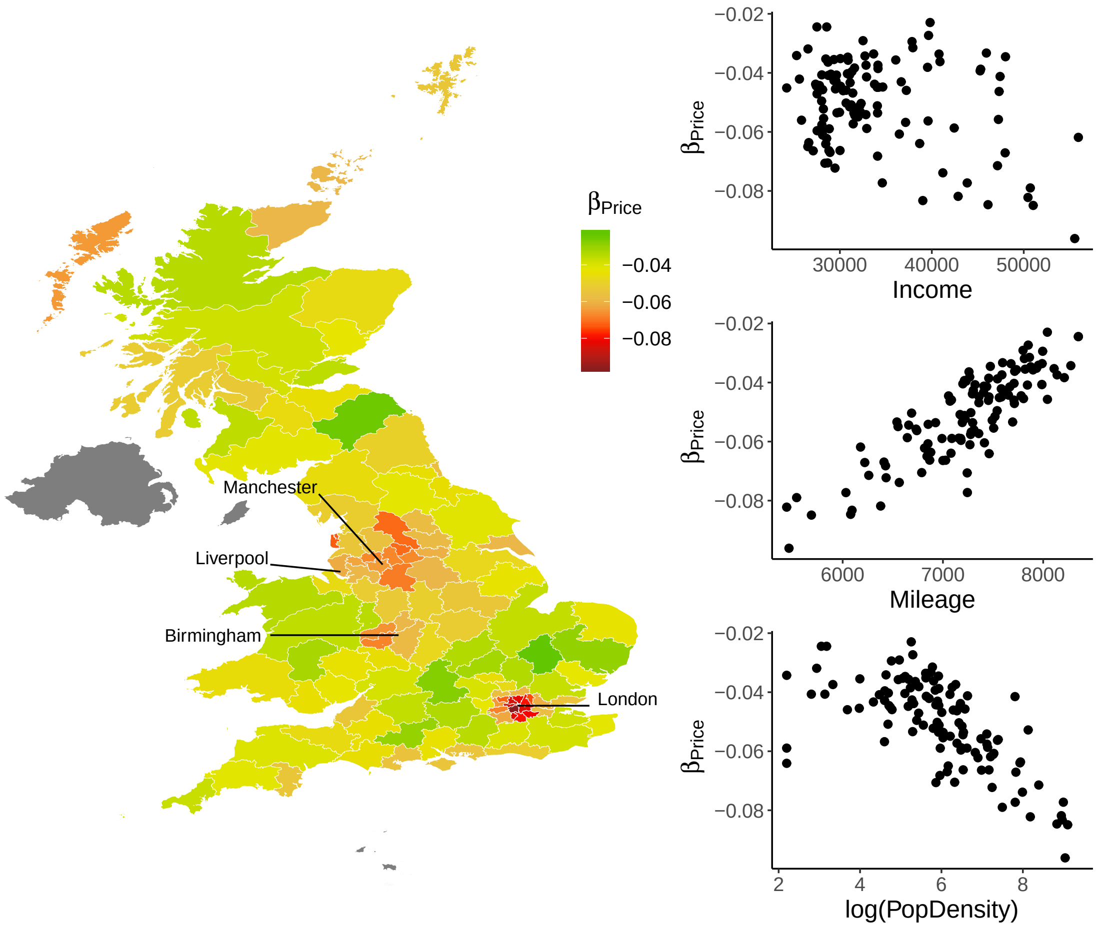

Fig. 4.7 Heterogeneity of the price elasticity of vehicle mileage. Left= map of β_{Price} by postcode. Postcodes where elasticities are not significant at the p=0.05 level are coloured grey. Right= scatters of β_{Price} by postcode vs. average mileage, median income and natural log population density pp/km^2 (2011 levels).

4.5.6 Limitations and future work

The model used in this study could be used in future research to examine the effects of local policy interventions such as congestion charges on vehicle mileage. It might also be used to investigate the effects of changes in public transport provision over time. Doing so would require data at a higher level of geographical detail than the postcode area data provided in the publicly available MOT dataset used in this study (see appendix B.10). One limitation in the data used is the size of postcodes, which are somewhat socially and geographically heterogeneous. The ideal data would have the geographical resolution to better distinguish between urban and rural areas as public transport and environmental policies are predominantly present in urban contexts. The effects of local policies could be investigated using dummy variables on the year of introduction in each city and public transport trips could be introduced as an additional time series continuous variable. More granular geographical resolution may also identify even higher 'hot spots' of price elasticity and may be able to better control for average income and other socio-economic factors.

If public service provision is indeed a factor determining the fuel price elasticity of mileage it would draw into question the convention of assuming rebound effects are of equal magnitude to fuel price elasticities and thus merits further research. Similarly, possible vehicle switching (discussed in section 4.5.3) would also mean $\eta_{P_E}(S)$ may not equal -$\eta_{\varepsilon}(S)$, though would likely still remain a similar order of magnitude at the aggregate level across all vehicles.

Additional considerations cover possible non-linearities in the response to fuel prices. The average fuel price across driving periods changed by a maximum of $\pm$20% over the time period investigated (see table B.2). Changes outside this range may lead to larger elasticities. This could have implications for rebound effects as shifting to an electric vehicle can lead to marginal travel cost savings in the order of 50-70%.

4.6 Policy Considerations

This chapter investigates the effect that vehicle efficiency improvements might have on stimulating higher mileage, known as the rebound effect. The magnitude of this effect in Great Britain between 2006 and 2017 is estimated by quantifying the response of vehicle mileage to fuel price changes. The findings show that vehicle efficiency improvements are unlikely to trigger short-term increases in vehicle mileage. This means the direct rebound effect is likely to be small $\approx$0.046 and any additional mileage stimulated by efficiency improvements is unlikely to significantly reduce energy savings in the short-term.

British drivers' mileage is shown to be inelastic to fuel price changes. A 10% increase in fuel price would lead to a 0.46% decrease in mileage; for the average vehicle travelling ≈7400 miles per year, this is equivalent to a decrease of just 34 miles. Fuel taxes are therefore unlikely to have an important short-term effect on vehicle mileage.

Whilst these effects are small, the findings show that drivers of larger and less fuel efficient vehicles are more responsive to fuel price changes than average. Drivers in rural areas with relatively high annual mileage are also found to be less responsive to fuel price changes than drivers in more populous areas, which are possibly less dependent upon the private vehicle. Since a number of these rural areas have lower than average income, this raises social equity concerns. If car dependent drivers are unable to adjust their mileage in response to changes in fuel price (whether from changes in fuel tax or from market fluctuations) they may have to absorb the additional costs of travel.

Chapter 5

The future potential energy savings of efficiency improvements

5.1 Estimating future transport emissions

This PhD thesis aims to understand how much technical changes in vehicles, be they incremental efficiency improvements or sales shifts to new technologies, might impact future energy use and emissions. The findings of chapter 3 showed that sales shifts between petrol, diesel and hybrid vehicles played a relatively minor role in determining the energy intensity of vehicles between 2001 and 2018, though this is likely to change in future.

Chapter 3's findings show that 65% of the past technical improvements were offset by the increasing size and power of vehicles. This means for every unit of technical improvement, the energy intensity of vehicles improved by just 0.35 units. In chapter 4, the direct rebound effect is shown to be $\approx$0.046. This means for every unit of energy intensity improvements, the energy savings will be 0.964. Bringing the findings from these two chapters together shows that in the past two decades the majority of lost potential energy savings are likely to have been from increasing vehicle size and power rather than any increased mileage from the rebound effect (summarised in figure 5.1). Even if the rebound effect is larger in the long-term, it would in all likelihood still remain far less significant than the effect of vehicle attributes. This result shows that 66% of the energy saving potential of technical improvements has been offset by driving slightly more, in larger and more powerful vehicles.

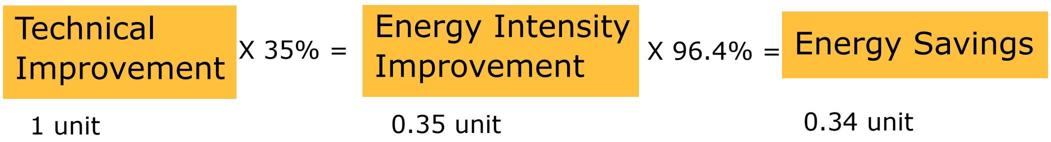

Fig. 5.1 Summary of findings from chapters 3 & 4. For every unit of technical improvement, energy intensity improved by 0.4 units due to increasing size and power. Energy savings then improve by 96.4% of this due to the rebound effect.

The aim of chapters 3 & 4 was to estimate the magnitude of these effects historically. This chapter builds on these historical findings and investigates the impact of incremental technical efficiency improvements, changes in vehicle attributes, technology switching and rebound effects on future energy use and CO_2 emissions.

Estimating future emissions is imperative to make informed decisions about limiting the damaging effects of climate change. To determine the impacts of emissions reduction measures, and prioritise between them, it is important to quantify their likely impact. As discussed in chapter 2.3, past work has predominately relied on scenario analysis to prioritise policies. Analyses of this type can be useful, but they are hampered by the uncertainty of future trends and are particularly dependent upon subjective assumptions of parameter values. This constraint is overcome using formal sensitivity analysis techniques that have not yet been applied to study future emissions from the transport sector.

The aim of this chapter is to explore the likely range of possible futures for the passenger vehicle fleet in the UK, quantifying the CO_2 emissions in each using a vehicle stock model. For the first time, Sobol sensitivity analysis is used to rank the importance of input variables on future transport CO_2 emissions. The use of this novel method can evaluate the relative importance of input variables and thereby help to prioritize interventions to reduce emissions and highlight critical variables to consider in future work.

5.2 Methods

Future carbon emissions from passenger cars are determined by the current and future stock of vehicles on the road. These are estimated using numerical models that predict the turnover of the vehicle stock (via new car sales and scrappage of old vehicles) and the emissions intensities of vehicles on the road. The input variables to vehicle stock models influence the predicted number of vehicles on the road and the emissions they generate. The sensitivity of future emissions projections to each input variable is assessed using Sobol indices, described in section 5.2.1. The equations governing the structure of the stock model and the forecasting of carbon emissions from vehicles are explained in section 5.2.2. Finally, the variance/uncertainty of important, user-defined input variables in the stock model are discussed in section 5.2.3.

5.2.1 Sobol Indices

A vehicle stock model may be expressed as a function f that maps k inputs X_i (such as uptake of electric vehicles, rate of future efficiency improvements...), to produce an output Y (e.g. annual life-cycle emissions):

$$Y = f(X_1, X_2, ...X_k)$$

Sobol indices are used to decompose the variance of an output Y, due to various model inputs X_i. 'If a particular input variable X_i were set to a certain defined value x_i^*, how might that change the output Y?' The expected values of the output Y from setting X_i to x_i^* can be written as:

$$E_{X_{\sim i}}(Y|X_i = x_i^*)$$

These are the range of Y output values obtained by changing all variables to all of their possible values but holding the ith variable constant at $X_i = x_i^*$. The $X_{\sim i}$ subscript denotes that the set of values are calculated across all input variables besides the ith. If we now calculate the variance of this value, for every possible value of X_i we get:

$$V_{X_i}(E_{X_{\sim i}}(Y|X_i))$$

This term can be interpreted as the variance in the output of the model that is dependent upon input variable X_i. The total variance of Y can be decomposed into two terms:

$$V(Y) = \underbrace{V_{X_i}(E_{X_{\sim i}}(Y|X_i))}_{\text{Variance from } X_i} + \underbrace{E_{X_i}(V_{X_{\sim i}}(Y|X_i))}_{\text{Residual variance}} \tag{5.1}$$

The second term in equation 5.1 is known as the residual (Saltelli et al., 2010) and describes the variance in Y that is independent of X_i. If the input variable X_i has a large effect on the variance of Y then the first term in equation 5.1 will be relatively large. Sobol (2001) proposed a measure of sensitivity S_i, as the ratio between the variance explained by variable X_i and the total output variance $V(Y)$:

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y|X_i))}{V(Y)} \tag{5.2}$$

The closer S_i is to 1, the more important the variable X_i is at explaining the variance in the output Y ($S_i \leq 1$). Interactions between variables can add to their importance. To account for this, Sobol (2001) developed the following decomposition, which sums the Sobol indices of all possible parameter interactions:

$$\sum_{i=1}^{k} S_i + \sum_{i=1}^{k} \sum_{j>i} S_{ij} + ... + S_{12...k} = 1 \tag{5.3}$$

The first term is the same as that in equation 5.2 and defines the share of output variance $V(Y)$ due to input X_i. Subsequent terms denote the share of output variance $V(Y)$ due to combinations of input variables e.g. X_i and X_j. The cumulative effect that an input variable X_i has upon $V(Y)$, accounting for all interactions, is therefore the sum of all terms in equation 5.3 with subscript i. Calculating all of the terms in equation 5.3 can be labour/computationally expensive. To address this challenge, Homma and Saltelli (1996) proposed a similar, widely used sensitivity metric, called the 'total effect Sobol index' S_{Ti}, which accounts for all higher order interactions between variables.

$$S_{Ti} = \frac{E_{X_{\sim i}}(V_{X_i}(Y|X_{\sim i}))}{V(Y)} = 1 - \frac{V_{X_{\sim i}}(E_{X_i}(Y|X_{\sim i}))}{V(Y)} \tag{5.4}$$

Empirically, both Sobol indices are estimated using Monte Carlo methods. Each variable X_i is set to a random value x_i^* from a given distribution and the function f is evaluated to give an output Y, holding all other variables $X_{\sim i}$ constant. This is performed iteratively until all the parameters in equations 5.2 and 5.4 can be determined.

The present work uses 'total effect Sobol indices' S_{Ti} to capture all interactions between variables, thereby addressing the main limitations of regression and OAT methods. Sobol indices are calculated for each input variable in order to determine its relative importance on the future of transport emissions. Knowledge of the relative importance of variables aids in the prioritisation of actions to reduce emissions by accounting for uncertainty. The range of input variables and the structure of the stock model used to estimate future transport emissions are detailed in the next section.

5.2.2 Building a vehicle stock model for Great Britain

This analysis focuses on light-duty passenger vehicles. This section will firstly describe how the turnover of the fleet is modelled. Next, the methods used to predict future travel demand is detailed. Subsequent sections explain how the fuel efficiency of new vehicles is estimated and how these are incorporated into estimates of total CO_2 emissions from British vehicles each year.

Model Structure

Figure 5.2 shows the composition of the model. Exogenously defined, stochastic input variables are iteratively fed into the model giving a range of CO_2 emissions estimates for different combinations of input parameters. The equations that govern the model are explained in the following section.

Modelling fleet turnover

Estimates of vehicle scrappage rates are generally not publicly available and require creating a stock model to estimate the age distribution of vehicles on the road. Vehicle stock models have been used in past work (Brand, 2010; Martin et al., 2017; Serrenho et al., 2017) and generally require knowledge of the age of vehicles in a given base year (DfT, 2019c). This information can be used with new vehicle registrations data (DfT, 2019d) to determine curves which describe the probability of scrappage as a function of vehicle age. These curves generally take the form of a modified Weibull distribution as first proposed Romanowicz and Owsiński (1988) and subsequently built upon by Zachariadis et al. (1995):

$$\phi_a = exp\Big[-\Big(\frac{a+b}{T}\Big)^b\Big] \tag{5.5}$$

where a is the vehicle age in years, ϕ_a is the share of vehicles of age a that are still on the road, b is the failure steepness of the curve and T is the characteristic service life. This curve can be used to determine the probability γ that a vehicle of age a is still registered on the road:

$$\gamma_a = \phi_a/\phi_{a-1} \tag{5.6}$$

The number of registered vehicles V of age a in a given year y can therefore be calculated with knowledge of the number of registered vehicles in the previous year according to:

$$V_{y,a} = V_{y-1,a-1} \times \gamma_a \tag{5.7}$$

The total number of vehicles leaving the stock as scrap in any given year is calculated from:

$$\text{Scrap}_y = \sum_a V_{y-1,a-1} \times (1-\gamma_a) \tag{5.8}$$

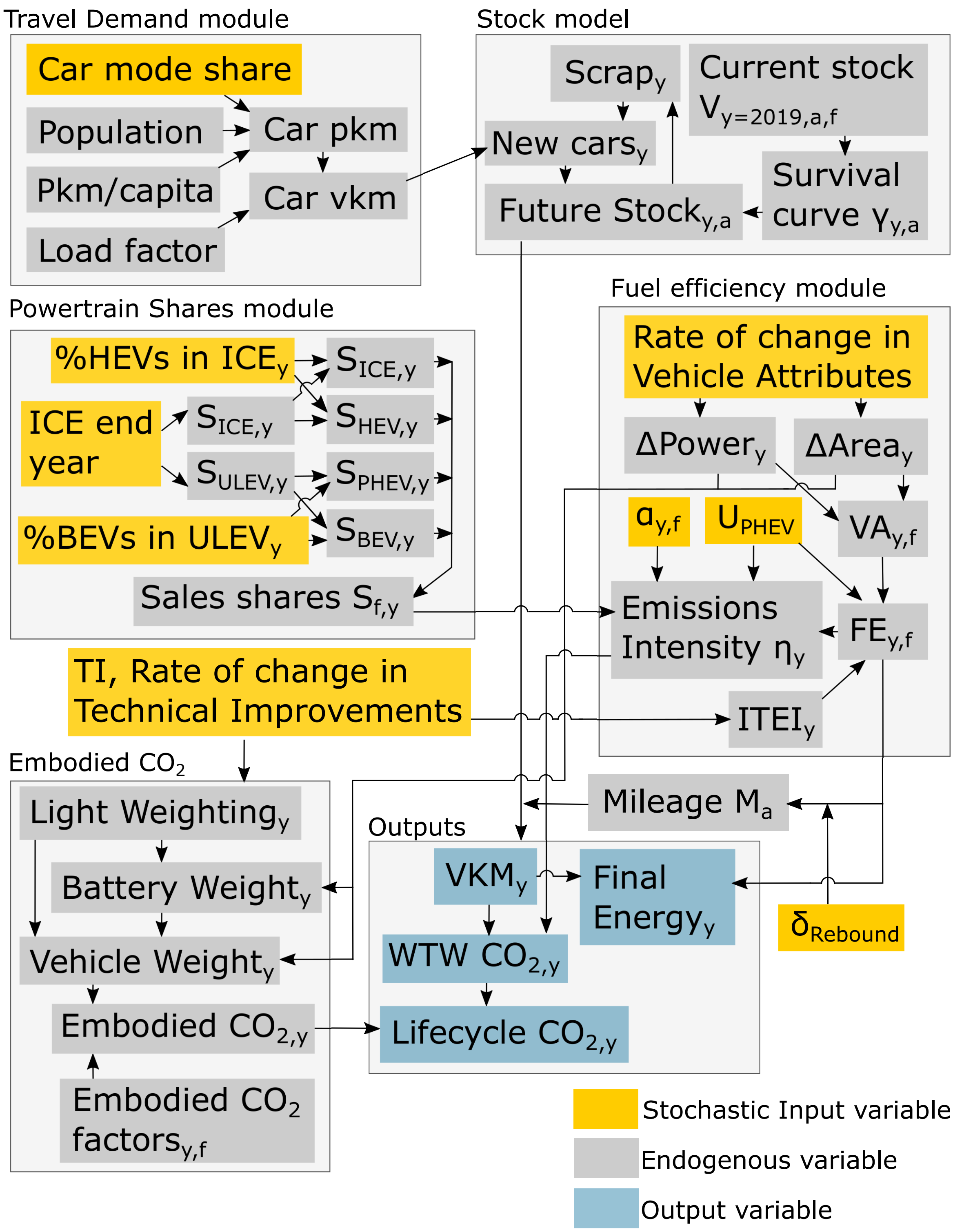

Fig. 5.2 Flow chart of emissions model. Input variables are introduced stochastically producing a range of outputs. Acronyms are as follows: passenger kilometer (pkm), vehicle kilometer (vkm), hybrid electric vehicle (HEV), internal combustion engine vehicle (ICE), sales shares (S), battery electric vehicle (BEV), ultra low emission vehicle (ULEV), plug-in hybrid electric vehicle (PHEV), electricity grid carbon intensity (α), utilisation factor (U), vehicle attributes (VA), fuel efficiency (FE), incremental technical efficiency improvement (ITEI), well-to-wheel (WTW).

In the present work ϕ_a (and consequently the expected vehicle lifetime) is assumed constant over time, in line with past literature (set at 2018 values T=22.5,b=6.5 determined using registration data from (DfT, 2019c)). This is a simplification, as the characteristic lifetime T of vehicles has been increasing slowly over time (Dunant et al., 2020). However, including a dynamic $\phi_{y,a}$ greatly increases the computational burden of running a stock model (as the stock needs to be recalculated in each model run), which is impractical when using the Monte Carlo based methods required to produce Sobol indices. This means changes to the lifetime of vehicles (e.g. via scrappage schemes or vehicle manufacturer design changes) are not considered.

Modelling future travel demand

Demand for Passenger miles travelled (PMT) per capita is initially assumed to remain constant into the future; meaning total demand for PMT increases proportionately to population forecasts sourced from the ONS (2019b). This assumption is then changed in section 5.3.6. The share of PMT by car is an exogenous input into the model with a range of uncertainty into the future. Vehicle occupancy data from the DfT (2019a) is used to calculate total demand for vehicle miles travelled by car (VMT) in every year. This is divided by average vehicle mileage M to calculate V_y the total number of vehicles required in any given year y to satisfy travel demand.

The stock model iteratively determines the vehicles scrapped each year. The annual number of new vehicles is calculated according to equation 5.9, which ensures there are adequate numbers of new vehicles to satisfy demand. The implication of this model structure is that modal shift assumptions affect the choice of when to purchase a vehicle rather than changing the mileage of existing vehicles.

$$\text{New cars}_y = (V_y - V_{y-1}) + \text{Scrap}_y \tag{5.9}$$

The present analysis refrains from explicitly estimating the effect that future fuel prices or future GDP trajectories could have on travel demand, instead a range of future travel demand is investigated in section 5.3.6. However, the influence that fuel efficiency improvements (which reduce the cost of driving) may have on stimulating greater mileage is included. This effect, known as the rebound effect, is calculated each year based on the change in the average fuel consumption of the vehicle stock and is included into the model in a similar fashion to Daly and O Gallachoir (2011). The prices of fuel and electricity are assumed to remain constant at 2018 levels (fuel $\approx$ £1.3/L, electricity $\approx$ £0.12/kWh). These are used to determine the energy cost of driving P (£/mile) for the average vehicle each year. The percentage change in P each year is multiplied by the elasticity of travel demand δ_{Rebound} and thereby modify future average vehicle mileage M:

$$M_{y+1} = M_y \times \left[1 + \delta_{\text{Rebound}} \times \frac{P_y - P_{y+1}}{P_y}\right] \tag{5.10}$$

Modelling the efficiency of new vehicles

The real-world fuel efficiency of vehicles from model years 2001-2018 is sourced from the analysis of chapter 3. These are linearly extrapolated backwards to 1994 in order to attain the fuel efficiency of all vehicles in use in the base year 2018. The average fuel efficiency of BEVs and PHEVs in 2018 on the WLTP cycle are sourced from (VCA, 2019) and increased by 10% to account for differences between WLTP and on-road driving.

The fuel efficiency of future new vehicles by model year, $\text{FE}_{\text{MY},f}$ (MJ/km) is estimated from equation 5.11, which multiplies the fuel efficiency of new vehicles in 2018, $\text{FE}_{\text{MY}=2018,f}$ by a factor representing incremental technical efficiency improvements (ITEI) in the future.

Between 2001 and 2018, ITEI reduced the fuel consumption of new vehicles, independent of vehicle size and power, by around -1.3% year-on-year across petrol, diesel and hybrid vehicles. The future rate of ITEI is allowed to vary by a factor TI, representing the rate of Technical Improvements. When TI=1 then the historical rate of improvements are assumed to continue into the future. TI=0.5 assumes the historical rate of ITEI halves.

The term $\text{VA\_FE}_{\text{MY},f}$ (MJ/km) is included to account for the change in new vehicle fuel efficiency, compared to base year 2018, due to changing vehicle attributes such as power and size. These could have an effect upon the fuel efficiency of vehicles and could offset technical improvements.

$$\text{FE}_{\text{MY},f} = \left(\text{FE}_{\text{MY}=2018,f} \times \overbrace{(1-0.013)^{\text{TI}\times[\text{MY-2018}]}}^{\text{ITEI}}\right) + \text{VA\_FE}_{\text{MY},f} \tag{5.11}$$

$\text{VA\_FE}_{\text{MY},f}$ (MJ/km) is estimated using equation 5.12, where changes in power (kw) and frontal area (m^2) of vehicles between model year 2018 and future model year MY, are multiplied by sensitivity coefficients β_f of each powertrain type. The coefficients for ICE and HEVs are sourced from the data of chapter 3, shown in table 5.1, and are assumed to remain constant over time. The coefficients for electric vehicles are estimated by regression, based on data from the US EPA Fuel Economy database (EPA, 2020) (full regression results in appendix C.1).

$$\text{VA\_FE}_{\text{MY},f} = \Delta\text{Power}_{\text{MY}} \times \beta_{\text{Power},f} + \Delta\text{Area}_{\text{MY}} \times \beta_{\text{Area},f} \tag{5.12}$$

If vehicle attributes remain constant at 2018 levels (i.e. $\text{VA\_FE}_{\text{MY},f} = 0$), then the energy efficiency of a vehicle of fuel type f in a future model year MY would be adjusted solely by ITEI:

$$\text{FE}_{\text{MY},f} = \text{FE}_{\text{MY=2018},f} \times (1 - 0.013)^{\text{TI}\times[\text{MY-2018}]}$$

Powertrain	f	β_{Power} (MJ/km kW)	β_{Area} (MJ/km m^2)
Internal Combustion Engine	ICE	$8.642\times10^{-}3$	0.653
Hybrid Electric Vehicle	HEV	$6.637\times10^{-}3$	0.632
PHEV driven in ICE mode	PHEV_{ICE}	$5.375\times10^{-}3$	0.571
PHEV driven in EV mode	PHEV_{EV}	$2.181\times10^{-}3$	0.293
Battery Electric Vehicle	BEV	$0.155\times10^{-}3$	0.221

Table 5.1 Sensitivity coefficients between vehicle attributes (frontal area and power) and vehicle energy efficiency. Full regression results in appendix table C.1.

The emissions intensity of a vehicle $\eta_{y,\text{MY},f}$ (gCO_2/km) in year y, with model year MY and powertrain f is determined from equation 5.13. The fuel efficiency of each type of vehicle in each year is multiplied by the carbon intensity of the energy source used $\alpha_{y,f}$ (gCO_2/MJ). For battery electric vehicles and PHEVs driven in EV mode, $\alpha_{y,f}$ is the carbon intensity of grid electricity and is allowed to change over time. For vehicles with an internal combustion engine $\alpha_{y,f}$ is assumed constant at 2018 average levels of petrol and diesel, and scaled by the efficiency of petroleum refining assumed to be 90.4% from GREET (ANL, 2019).

$$\eta_{y,\text{MY},f} = \text{FE}_{\text{MY},f} \times \alpha_{y,f} \tag{5.13}$$

The overall emissions intensity of plug-in hybrid vehicles (PHEV) is estimated using the emissions intensity during ICE and EV operation according to equation 5.14, where U_{PHEV} is the percentage of total driving by PHEVs undertaken in all-electric mode, known as the utilisation factor.

$$\eta_{y,\text{MY,PHEV}} = \eta_{y,\text{MY,PHEV}_{\text{ICE}}} \times (1 - U_{\text{PHEV}}) + \eta_{y,\text{MY,PHEV}_{\text{EV}}} \times U_{\text{PHEV}} \tag{5.14}$$

The annual well-to-wheel emissions (WTW) from the British fleet is calculated by multiplying the number of registered vehicles from each model year remaining in year y $V_{y,\text{MY}}$ by the share of new sales $S_{\text{MY},f}$ of each powertrain f in each model year, an age-dependent mileage $M_{y,\text{MY}}$ and the vehicles' emissions intensity η. The mileage M of vehicles drops by ≈330 miles/year as the vehicle ages, as shown in chapter 4. Base levels of emissions intensities for each powertrain are included in the appendix C.3.

$$\text{WTW CO}_{2,y} = \sum_{\text{MY},f} V_{y,\text{MY}} \times S_{\text{MY},f} \times M_{y,\text{MY}} \times \eta_{y,\text{MY},f} \times 1.6 \tag{5.15}$$

Modelling Embodied emissions

Embodied emissions from vehicle manufacture are based on vehicle weight. The weight of future vehicles is estimated using equation 5.16, in a similar way to equation 5.11, by scaling the average weight in base year 2018 by a factor representing technical weight-saving improvements.

Using the data from chapter 3 historical trends in vehicle lightweighting are estimated. Between 2001 and 2018, the weight of new vehicles, independent of vehicle size and power, reduced by 0.4% year-on-year (for petrol, diesel and hybrid vehicles together, regression results in appendix C.4). This historical rate of weight-saving is allowed to vary in the future by a factor representing the rate of Technical Improvements, TI. This is the same factor used to scale incremental technical efficiency improvements in equation 5.11.

$$\text{Weight}_{\text{MY},f} = \left(\text{Weight}_{\text{MY}=2018,f} \times \overbrace{(1-0.004)^{\text{TI}\times[\text{MY-2018}]}}^{\text{Light-weighting}}\right) + \text{VA\_Weight}_{\text{MY},f} \tag{5.16}$$

The effect of future changes in vehicle attributes on vehicle weight are accounted for with the term $\text{VA\_Weight}_{\text{MY},f}$ calculated using equation 5.17. In general, larger and more powerful vehicles have higher mass. The effects of increasing frontal area and power on vehicle weight are presented in table 5.2. Note, the vehicle weight variable only affects embodied emissions. The impact of increasing vehicle size on WTW emissions is accounted for via vehicle frontal area and power coefficients (table 5.1) and the effect of light-weighting on fuel efficiency is accounted for in ITEI.

$$\text{VA\_Weight}_{\text{MY},f} = \Delta\text{Power}_{\text{MY}} \times \phi_{\text{Power},f} + \Delta\text{Area}_{\text{MY}} \times \phi_{\text{Area},f} \tag{5.17}$$

Powertrain	f	ϕ_{Power} (kg/kW)	ϕ_{Area} (kg/m^2)
Internal Combustion Engine	ICE	2.647	846.74
Hybrid Electric Vehicle	HEV	3.426	859.4
Plug-in Electric Vehicle	PHEV	1.887	581.4
Battery Electric Vehicle	BEV	1.169	670.2

Table 5.2 Sensitivity coefficients between vehicle attributes (frontal area and power) and vehicle weight. Full regression results in appendix table C.2.

One of the most carbon intensive components of electric vehicles is the battery. The weight of the battery is calculated using an energy density of 7 kg/kWh (IEA, 2019a). Future battery weight is estimated according to equation 5.18 in a similar way to equations 5.11 and 5.16. Future battery light-weighting is conservatively assumed to proceed in a similar manner to that of the entire vehicle.

$$\text{BatWeight}_{\text{MY},f} = \left(\text{BatWeight}_{\text{MY=2018},f} \times \overbrace{(1-0.004)^{\text{TI}\times[\text{MY-2018}]}}^{\text{Light-weighting}}\right) + \text{VA\_BatWeight}_{\text{MY},f} \tag{5.18}$$

The battery capacity requirements of an electric vehicle are broadly determined by its size and power, increasing the size and power of future vehicles will likely require additional battery capacity with additional weight ($\text{VA\_BatWeight}_{\text{MY},f}$), this is accounted for in equation 5.19.

$$\text{VA\_BatWeight}_{\text{MY},f} = \Delta\text{Power}_{\text{MY}} \times \lambda_{\text{Power},f} + \Delta\text{Area}_{\text{MY}} \times \lambda_{\text{Area},f} \tag{5.19}$$

Powertrain	f	λ_{Power} (kg/kW)	λ_{Area} (kg/m^2)
Battery Electric Vehicle	BEV	1.079	98.89
Plug-in Electric Vehicle	PHEV	0.039	7.09

Table 5.3 Sensitivity coefficients between vehicle attributes (frontal area and power) and vehicle battery weight. Full regression results in appendix table C.3.

Embodied emissions associated with the manufacture of vehicles (eqn. 5.20) are assumed to be 3.6 kgCO_2e per kg of vehicle mass, similar to recent work (Hoekstra, 2019), and are conservatively assumed to remain constant over time.

$$\text{Embodied CO}_{2,\text{MY},f} = \text{Weight}_{\text{MY},f} \times 3.6 \tag{5.20}$$

For electric vehicles, the embodied emissions associated with the battery are calculated separately from rest of the vehicle, as 65 $kgCO_2e$ per kWh of battery capacity, from the latest literature (Hoekstra, 2019). Embodied emissions for electric vehicles (both PHEV and BEV) are then calculated according to equation 5.21.

$$\text{Embodied } CO_{2,\text{MY},f} = \text{BatWeight}_{\text{MY},f} \times \frac{65}{7} + (\text{Weight}_{\text{MY},f} - \text{BatWeight}_{\text{MY},f}) \times 3.6 \tag{5.21}$$

The total annual embodied emissions associated with the manufacture of new vehicles is calculated according to equation 5.22.

$$\text{Embodied } CO_{2,y} = \sum_f \text{New Cars}_y \times S_{\text{MY},f} \times \text{Embodied } CO_{2,\text{MY},f} \tag{5.22}$$

The total life-cycle emissions from passenger vehicles is then determined by the addition of annual WTW emissions and embodied emissions (equation 5.23). The future variance of each input parameter is detailed in the next section. The stock model is calibrated by setting the mileage of new vehicles in 2019 to avoid discontinuities with aggregate vkm statistics from the Department for Transport (DfT, 2019b). Input variables are iteratively fed into the stock model using Monte Carlo methods to produce a series of outputs. Sobol indices are calculated using the SobolEff function from the 'sensitivity' package in the R coding environment. The stock model is run n=6000 times until convergence is achieved.

$$\text{Life-cycle } CO_{2,y} = \text{WTW } CO_{2,y} + \text{Embodied } CO_{2,y} \tag{5.23}$$

5.2.3 Estimating input variance

A broad range of possible futures are considered in this analysis. These are not *all* possible futures. Instead, an effort is made to consider a wide range of futures that would not require particularly significant changes in lifestyles. In theory, we could immediately stop buying internal combustion engined vehicles, or we all could choose to take public transport, or stop driving altogether. These actions would have significant effects on carbon emissions, however the probability of these actions occurring remains low and politically challenging.

The range of futures investigated in this chapter are constrained by an upper and lower bound for each input variable into the model. To minimise making arbitrary judgements about the most likely value of a specific parameter, or the shape of an input variables' distribution, a uniform distribution is used for each model input parameter between its upper and lower bound. This allows for a relatively unbiased assessment of the impact of each variable on the model results. The range of the input variables are summarised in table 5.4 and are detailed further in the following sections.

Parameter	**Range**	**Unit/Information**
Rate of Technical Improvements, TI	50% to 150%	Multiples of historical rate
Rate of change in size and power	-100% to 200%	Multiples of historical rate
Grid emissions intensity, α	2DS to CES	Scenarios National Grid ESO (2019)
ICE End Year	2035 to 2050	Year of 100% ULEV sales share
Share HEV-to-ICE	20% to 80%	Ratio of HEVs in ICE sales in 2050
Share BEV-to-ULEV	20% to 80%	Ratio of BEVs in ULEV sales in 2050
Rebound Effect, δ_{Rebound}	4.6% to 30%	Fuel efficiency elasticity of driving
PHEV Utilisation Factor, U_{PHEV}	50% to 90%	% of EV vs. ICE driving in PHEVs
Car travel pkm share	73 to 90%	% total pkm by car in 2050

Table 5.4 Parameters and ranges

Technical improvements, TI

The upper bound for the rate of technical improvements (TI) in new vehicles is assumed to be a 50% increase from the historical rate. This is not outside the physical realms of possibility given the large potential for improvements in both conventional internal combustion engined vehicles (Paoli and Cullen, 2019) and in battery technologies in electric vehicles. In an ambitious scenario with high incremental technical efficiency improvements and coupled with reductions in the size and power of vehicles, the average vehicle on the road in 2050 could have a fuel consumption similar to the Volkswagen XL1 concept car (using just 1 L/100km) (Top Gear, 2017). This could be stimulated by increasingly stringent government policy or via increases in R&D. In a more pessimistic future, the rate of ITEI could decrease by 50% (lower bound), for example if potential improvements become difficult to unlock in practice or if manufacturers have little incentive to apply technologies to vehicles.

Vehicle attributes

The size and power of vehicles have increased over time with each new vehicle generation becoming larger and more powerful than the generation it replaces. Between 2001 and 2018, the average new vehicle had 1.7 kW more power than the previous year and 138 cm^2 more frontal area. Two different futures are envisaged. Firstly, the rate of increase in size and power could double, as manufacturers aim to satisfy consumer demand for increasingly large and powerful vehicles resulting in the average vehicle in 2050 being similar to that of the USA and Canada today. Conversely, the historical rate could be reversed (i.e. reductions of

1.7kW and 138 cm^2 per year), due to a shift in the way manufacturers market vehicles to the general public.

Electricity grid emissions intensity

The uncertainty associated with the carbon intensity of grid electricity is estimated using two scenarios produced by National Grid in their annual Future Energy Scenarios publication (National Grid ESO, 2019). The range of futures (shown in fig. 5.3) is defined by the optimistic 'Two Degrees' scenario, 2DS (consistent with reaching a 2 degrees warming target, largely by rolling out low carbon electricity generation, a high share of electric vehicles and electric and hydrogen home heating) and the more pessimistic 'Consumer Evolution' scenario, CES (in which 'the pace of the low-carbon transition continues at a similar rate to today but then slows towards 2050'(National Grid ESO, 2019)). These scenarios are used as the upper (CES) and lower bounds (2DS) for the range of grid emission intensities (shown highlighted in yellow).

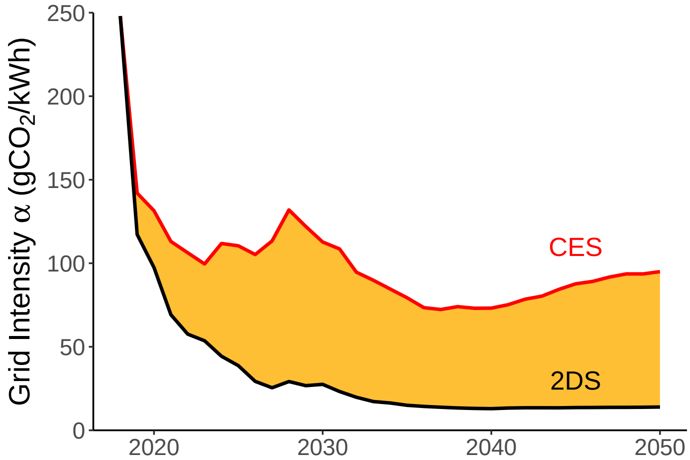

Fig. 5.3 National Grid two degrees (black) and Consumer Evolution (red) scenarios and range used in this analysis (yellow).

Vehicle powertrain technology uptake

The UK government is currently consulting on whether to set a new target for 100% of new car sales in 2035 to be 'Ultra Low Emission Vehicles' (ULEVs) (Campbell, 2020). ULEVs include battery electric (BEV), plug-in hybrid vehicles (PHEV) and hydrogen fuelled vehicles. Such a target will effectively ban the sale of conventional internal combustion engined vehicles (including hybrid electric vehicles) from 2035 onwards. This relatively ambitious goal is used as the upper bound in the range of possible futures. The lower bound for the uptake of ULEV vehicles assumes this target is achieved 15 years later in 2050.

Hydrogen fuelled passenger cars are not considered in this analysis; the latest report by the UK Committee on Climate Change argues ‘battery electric vehicles are now well placed to deliver the bulk of decarbonisation for cars and vans’ (CCC, 2018) and the focus of current government policy documents is on electric vehicles (DfT, 2020a). This is further reinforced by recent manufacturer announcements ending R&D for fuel cell vehicles in favour of electric vehicles (Berman, 2020).

An additional reason for not including hydrogen vehicles is that their market uptake is highly coupled with infrastructure deployment and the carbon intensity of hydrogen. This means the two variables (carbon intensity of hydrogen and uptake of hydrogen vehicles) are highly dependent in ways that are difficult to model. Electricity in comparison is less affected by this relationship given electric generation capacity is widely available today and used across a broad range of sectors.

The ULEVs considered in this analysis are therefore either BEV or PHEV. However, it is not clear which will attain a higher market share in future. The share of BEV within sales of ULEVs in 2050 is allowed to vary between 20% to 80% to examine a range of possible futures. Similarly, the share of hybrid electric vehicles within total ICE vehicle sales is also allowed to vary between 20% to 80% in 2050. Sales trends are assumed to be linear between the base year 2018 and 2050. Finally, the utilisation factor of PHEVs, U_{PHEV}, is allowed to vary between 50% and 90% (for all years).

The Rebound effect

The upper bound of the rebound effect is assumed to be: $\delta_{\mathrm{Rebound}}$=0.3. This is at the high end of the literature (Dimitropoulos et al., 2016; Goodwin et al., 2004) and is calculated using many data points from older years. However, there is some evidence that the rebound effect may have decreased over time with growing vehicle ownership and saturating travel demand in developed economies (Hughes et al., 2008). Thus the lower bound estimate used here is $\delta_{\mathrm{Rebound}} = 0.046$ from chapter 4, based on a short-run calculation of the rebound effect for Great Britain.

Modal shift

In 2018, 83% of total domestic passenger miles travelled (PMT) in the Great Britain were by car (DfT, 2019b). The UK National Travel Survey (NTS, 2019) is used to inform possible futures regarding travel modes. The survey responses for years 2015 to 2017 and covering over 600,000 individual trips, are used to produce figure 5.4, which shows the cumulative percentage share of trips (left) and passenger miles travelled (right) by trip distance. This shows that 50% of trips by car are below 4 miles; these are prime trips to shift to other modes including cycling, walking and public transport. However, they account for just 13% of PMT travelled by car and it may not be possible to shift all of these short distance trips to low carbon modes of transport.

Similarly, 8.25% of trips by car are above 20 miles but these account for 50.5% of PMT by car. If just a small share of these trips could be shifted to alternative modes, the impact on PMT by car would be significant. However, there are fewer modes that can satisfy this demand for longer distance trips, as cycling, underground and walking are not feasible. Just 2.1% of trips by bus are over 20 miles in distance, suggesting significant barriers to growth. On the other hand, longer distance trips are common for rail, as 41% of rail trips are above 20 miles. Increasing rail travel by 100%, a challenging prospect by 2050, would reduce the mode share of car travel by approximately 6%. If an additional 40% of car trips below 4 miles could be shifted to cycling, walking or public transport a further 4% of car PMT could be reduced. The lower bound (high ambition) used for mode shift in this chapter is therefore 10% lower than 2018 levels (73% of total PMT). This is similar to a high mode shift scenario used by the UK Committee on Climate Change (CCC, 2015). An upper bound of 90% mode share is used to account for the potential negative effects of autonomous vehicles reducing public transport demand in the future (Wadud et al., 2016).

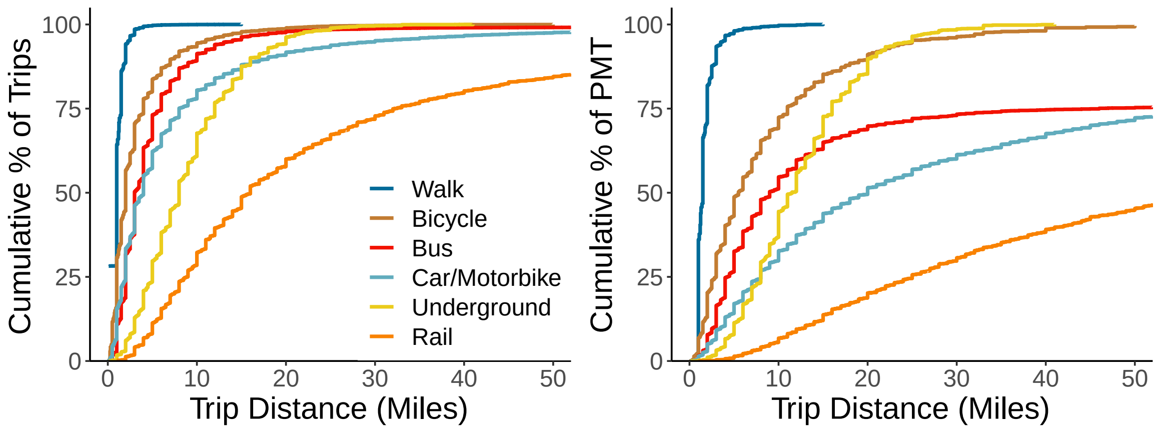

Fig. 5.4 Cumulative % of trips by trips distance (left) and cumulative % of passenger miles travelled (PMT) by trip distance.

Together, these ranges of input variables shown in table 5.4, define a likely solution space for future transport CO_2 emissions in Great Britain. Sobol sensitivity indices are used to determine how much of the variance/uncertainty of future emissions can be attributed to each input variable. Variables are defined as ‘important’ if they cause a large amount of variance in future emissions (and therefore have a relatively large Sobol index). Important variables require particular attention in policy and regulation to ensure their future trajectory is in line with their lower bound, thus reducing emissions. Variables that have a negligible impact upon future variance in transport CO_2 emissions are of lower priority. Tackling climate change requires reducing the total cumulative quantities of greenhouse gases in the atmosphere; Sobol indices are therefore calculated on total cumulative emissions for the 2019-2050 period.

5.2.4 Limitations

The use of Sobol indices provides a transparent approach to rank interventions to reduce emissions accounting for both interactions between variables and their respective uncertainties. However, Sobol indices can not address uncertainty in the structure of a model. For example, in this study the impact of mode shift does not account for the emissions of the alternative mode (bus or rail).

5.3 Results

This section begins by showing the possible variance in each of the input variables and how their uncertainty propagates through the stock model to result in a range of possible futures of transport demand, energy use and CO_2 emissions. The variance of these model outputs is then examined using Sobol indices to highlight the relative importance of input variables.

5.3.1 Model inputs and outputs

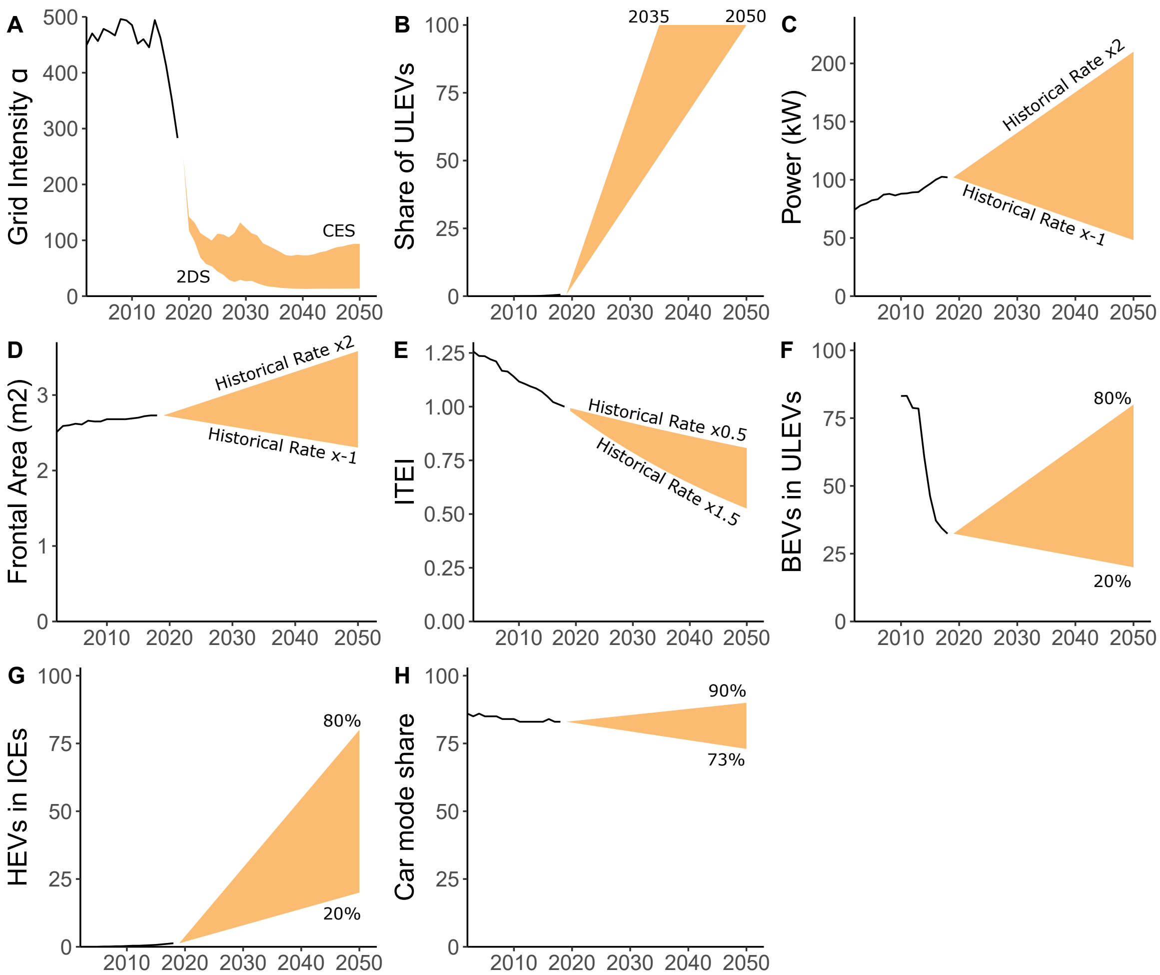

Fig. 5.5 Ranges for each input parameter (yellow) with historical values shown as black lines. From top left to bottom right: (**A**) Carbon intensity of grid electricity (gCO_2/kWh), (**B**) share of ULEVs in new car sales, (**C**) average power of new vehicles (kW), (**D**) average frontal area (m^2), (**E**) incremental technical efficiency improvements (ITEI), (**F**) share of battery electric vehicles (BEVs) in ULEV sales, (**G**) share of hybrid electric vehicles in ICE sales, (**H**) share of total national passenger miles travelled delivered by car.

Figure 5.5 presents the future uncertainty ranges for the model input variables (A-H, shown in yellow) and historical values from the year 2002 (black lines). The input variables are fed into the stock model producing output variables with a range of uncertainty, shown in figure 5.6 (I-K, shown in blue). The energy use of vehicles could drop significantly due to efficiency improvements (fig. 5.6 I) from vehicle light-weighting, technical improvements and reduced size and power. Figures 5.6 J-K show the range of WTW and life-cycle emissions from the British vehicle fleet each year. Life-cycle emissions are larger as they include embodied emissions from vehicle manufacture. Annual emissions are likely to drop in all scenarios by 2050 due to a certain degree of incremental technical efficiency improvements and the eventual uptake of electric vehicles. However, the range of futures varies widely; ambitious futures lead to WTW emissions reaching close to zero by 2050, whilst in the upper bound they drop by just 30% .

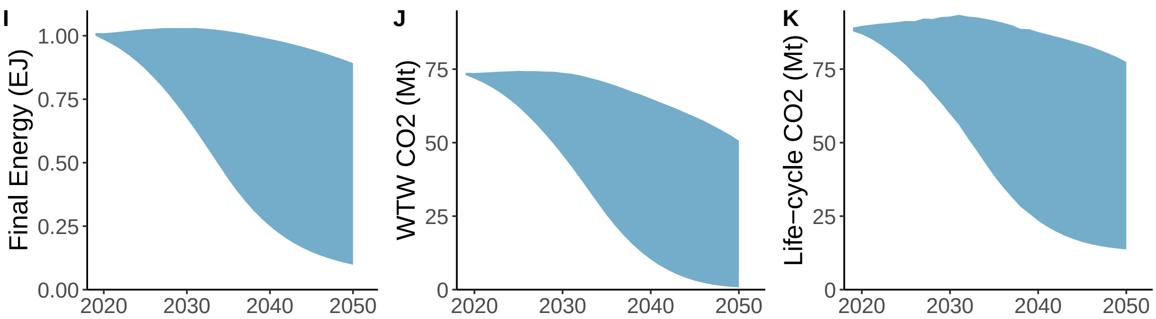

Fig. 5.6 Ranges for output variables (blue), from left to right: (**I**) total annual final energy use (EJ), (**J**) total annual WTW CO_2 emissions and (**K**) total annual life-cycle CO_2 emissions (including manufacturing emissions of new cars).

5.3.2 Important factors for CO_2 emissions

Figure 5.7 (left) presents the range of total cumulative CO_2 emissions between years 2019 and 2050, calculated on both a WTW and a life-cycle basis. The range of future emissions results directly from the uncertainty/variance in the input variables. However, figure 5.7 (left) gives no indication of which variables exert more (or less) influence over the variance in emissions, this requires sensitivity analysis.

The Sobol indices are used to determine which are the most important variables with the greatest impact on cumulative emissions, and are presented in figure 5.7 (right) and table 5.5 for both Well-to-Wheel (WTW) and life-cycle cumulative emissions of the British fleet for the period 2019-2050. A larger Sobol index, indicates that a larger share of the variance is explained by a particular variable, meaning this variable has a greater impact on the future.

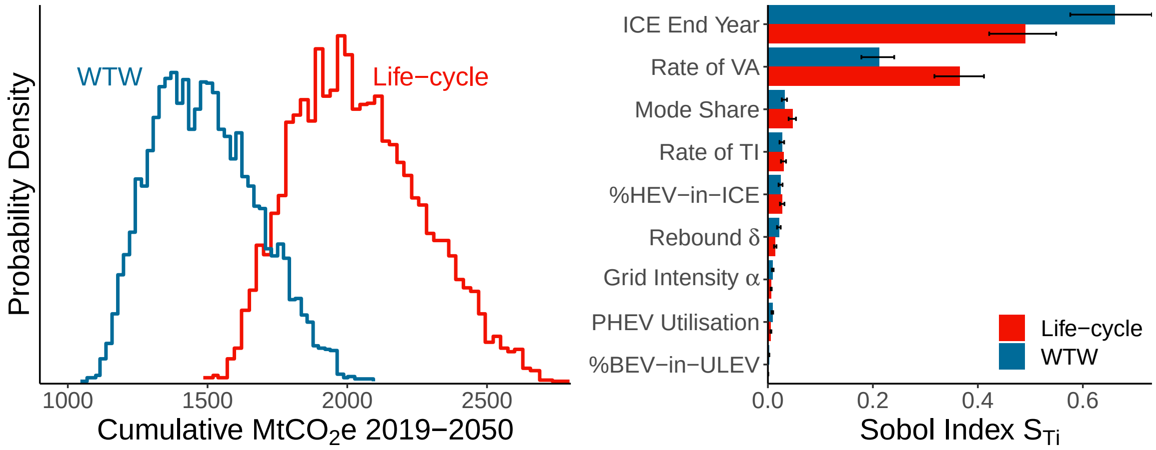

Fig. 5.7 Left= Probability density of cumulative Well-to-Wheel and life-cycle CO_2 emissions (left) for the full British vehicle stock, years 2019-2050. Right= Sobol indices S_{Ti} for each input variable and standard errors (SE) on cumulative CO_2 emissions 2019-2050.

The variable with the largest impact on cumulative Well-to-Wheel emissions is the year that internal combustion engine vehicles are banned (ICE End Year) and replaced with ULEVs in new car sales. This determines the share of ULEVs in the fleet and explains 66% of the variance in cumulative WTW emissions. This is followed by the rate of change of vehicle attributes (Rate of VA) which explains 21%. The majority of travel in Great Britain (both currently and in the likely future) is by private passenger car, meaning efforts to improve the emissions intensity of vehicles, either by electrification or by reducing their size and power, have a significant impact on future cumulative emissions.

The rate of Technical Improvements (TI) explains just 3% of future variance, meaning their role is relatively minor in reducing cumulative emissions, since improvements are relatively small and incremental. Similarly, the share of travel by car, also has a relatively minor impact on future CO_2 emissions as displacing the passenger car, with current levels of travel demand, is challenging. The rebound effect has a negligible impact on cumulative emissions, indicating induced demand is unlikely to greatly offset energy efficiency improvements.

Shifting to ULEV vehicles has the largest impact on cumulative emissions because electric vehicles represent a step change in emissions intensity compared with internal combustion engine vehicles. This is true even under the more conservative grid carbon intensity futures (meaning grid carbon intensity is not a variable of high importance). More incremental improvements such as shifting to HEVs, have a negligible impact on future cumulative emissions. Similarly, the share of BEVs in total ULEV sales makes little difference as plug-in hybrid vehicles still represent a step change in emissions intensity; this also means the Utilisation factor has a negligible impact on emissions (provided it remains between 50-90%).

Input variables have a similar importance when using life-cycle emissions, rather than well-to-wheel. However the importance of the last year ICE vehicles are sold drops from 66.1% down to 49%. There are two main reasons for this change. Including the emissions from vehicle manufacture reduces the difference in emissions intensity of driving an electric vehicle compared with an ICE vehicle, thereby partly reducing the emission benefits of the uptake electric vehicles. Additionally, including the emissions from vehicle manufacture adds importance (from 21.2% to 36.5%) to future trends in vehicle size and power, which can effect embodied emissions through vehicle weight.

Manufacturing emissions were conservatively assumed to remain constant in this study. As industries decarbonise over time the carbon intensity of vehicle manufacture will likely decrease. If embodied emissions were to reduce for all vehicle powertrains equally, this would likely shift the life-cycle Sobol indices towards the magnitudes of the WTW indices (as these don't include emissions from manufacture).

5.3.3 Important factors for Final energy use

The previous section used Sobol indices to highlight the main factors that affect CO_2 emissions. However, Sobol indices can also be used to explain the factors of different model outputs. Figure 5.8 (left) shows the variance of cumulative final energy use (electricity and petroleum fuel) of vehicles between 2019-2050. Figure 5.8 (right) then presents Sobol indices highlighting the input variables that explain the highest share of variance in cumulative energy use.

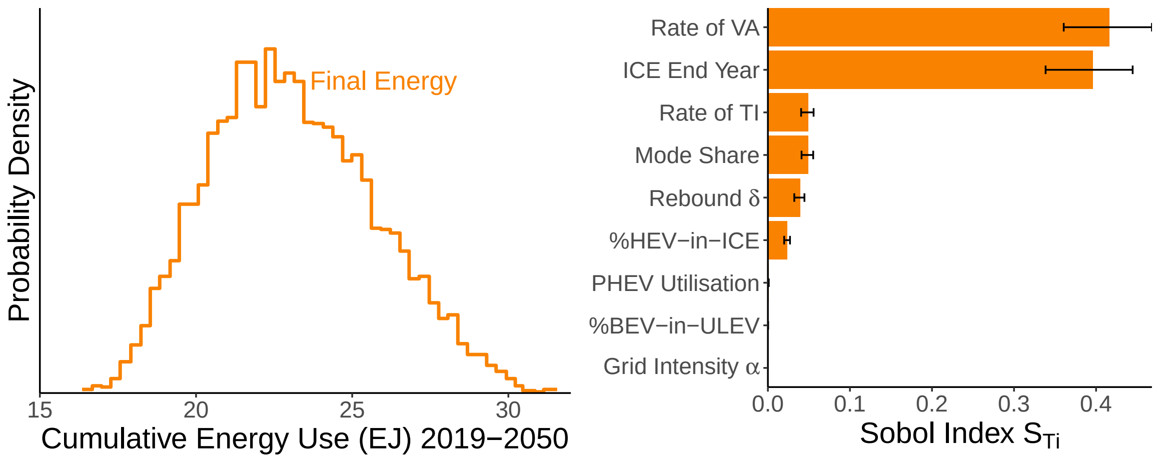

Fig. 5.8 Left= Probability density of cumulative final energy use (right) for the full British vehicle stock, years 2019-2050. Sobol indices S_{Ti} for each input variable and standard errors (SE) on cumulative final energy use 2019-2050.

Vehicle attributes have the highest Sobol index when considering final energy use, as they explain 41% of future variance. The importance of ULEV share on energy use (via ICE end year) is lower than for CO_2 emissions at 39.6%. Electric vehicles have a lower energy intensity than internal combustion engine vehicles (on a final energy basis). However, their emissions intensity is significantly lower than ICE vehicles, meaning the importance of accelerating the shift to EVs is more apparent when considering CO_2 emissions than when solely considering energy use. The importance of shifting to electric vehicles as a measure to reduce energy demand would be further reduced when considering primary energy demand rather than final energy, as the energy conversion efficiencies of power generation are lower than those of petroleum refining (ANL, 2019). Sobol indices on primary energy demand, though not considered here (as they would be dependent upon the types of fuels used in power generation), would likely further increase the relative importance of vehicle size and power, making it the factor with the highest impact at reducing future energy demand. This would be over three times more important than pursuing incremental technical efficiency improvements. Variables primarily associated with the CO_2 emissions intensity of driving, such as the grid carbon intensity α, have no impact on future energy use.

5.3.4 Important factors for Travel demand

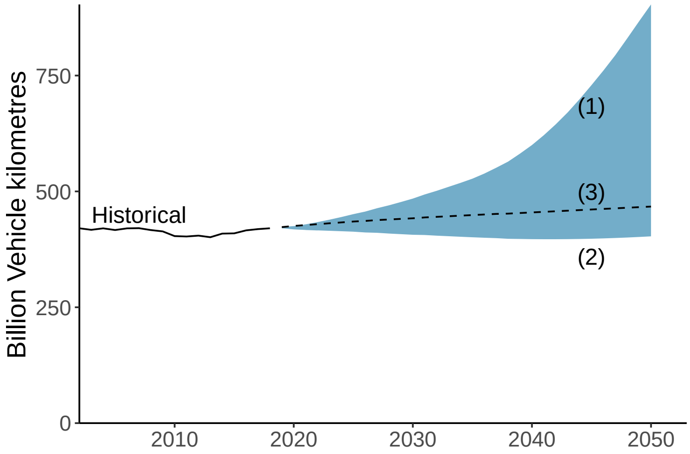

Fig. 5.9 Historical (DfT, 2019b) and future projections of vehicle kilometres (vkm) under extreme scenarios: (1) Large rebound effect coupled with high efficiency improvements and mode shift towards passenger cars, (2) Small rebound effect coupled with low efficiency improvements and mode shift away from passenger cars. (3) shows how vkm would change from population growth alone with no effects of rebound or mode shift.

Figure 5.9 shows the future solution space explored for vehicle kilometres by car. The main factors that explain travel demand in the model are the modal share between car travel and alternative modes, the magnitude of the rebound effect and the travel costs of vehicles, which are dictated by their fuel efficiency and fuel type (petroleum or electricity). If the magnitude of δ_{Rebound} is large and coupled with high energy efficiency improvements and a high passenger car modal share, then travel demand more than doubles by 2050 (shown as (1) in fig. 5.9). This is likely an extreme scenario as there are likely to be saturation effects in consumers' willingness to travel. It also assumes travel costs of electric vehicles remain relatively similar to today and no additional government duties (e.g. electricity taxes or road taxes) are introduced.

Conversely, if δ_{Rebound} is small (0.046) and coupled with low energy efficiency improvements and a low passenger car modal share, then travel demand is limited (shown as (2) in fig. 5.9). In (2), a portion of the reduced travel demand from modal shift to alternative modes is offset by population growth (see (3) in fig. 5.9) and induced demand from the rebound effect.

The rebound effect was found to be relatively unimportant on future CO_2 emissions and energy use. However, it is of high importance to future trends in vehicle mileage as shown by the Sobol indices in figure 5.10 (right). Rebound is unimportant for CO_2 and energy use because large increases in travel demand are only stimulated in the presence of large efficiency improvements, which more than offset the impact of increased demand. Interestingly, a common motivation for literature investigating the rebound effect is to better predict future energy use and the effects of energy efficiency policy. However, rebound is of much greater importance to travel demand and associated factors such as congestion.

The second most important variable explaining future variance in travel demand is the mode share, followed by factors which affect the energy efficiency of vehicles (which stimulate rebound). Factors that primarily affect the emissions intensity of travel, such as the carbon intensity of the grid, are of little importance to travel demand.

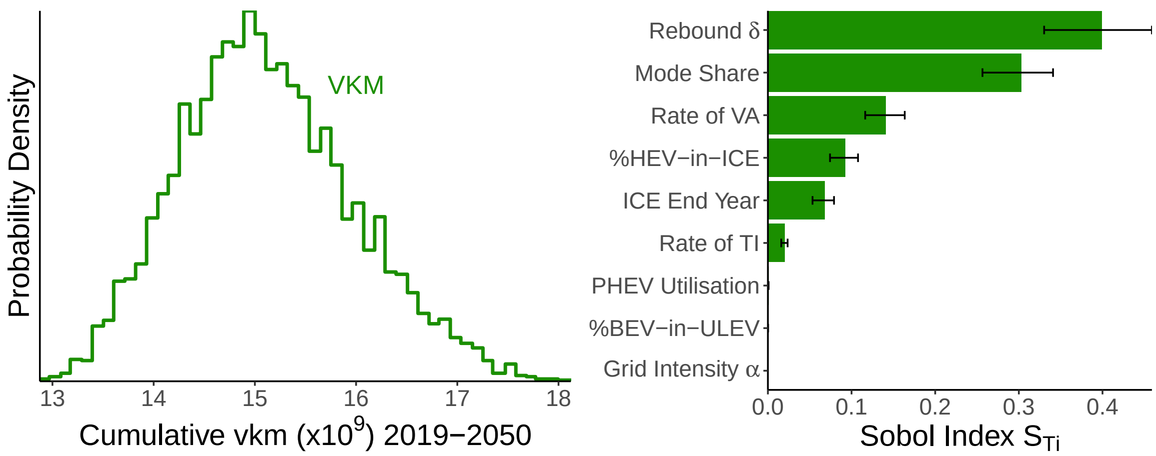

Fig. 5.10 Left= Probability density of cumulative vehicle kilometres (vkm) for the full British vehicle stock, years 2019-2050. Right= Sobol indices S_{Ti} for each input variable and standard errors (SE) on cumulative vehicle kilometres 2019-2050.

To summarise, Sobol indices are a versatile tool for highlighting the relative importance of variables and can be readily applied to a range of output variables of interest such as CO_2 emissions, energy use and travel demand. Figure 5.11 presents the Sobol indices for each different output variable and highlights that the importance of input variables on future passenger car use can differ based on the output variable of interest. Some variables are consistently of low importance to future travel in Great Britain, these include incremental technical efficiency improvements, the utilisation factor of PHEVs, the grid carbon intensity and the share of BEVs in ULEV sales. These can be set to any value within their range without greatly affecting future CO_2 emissions, energy use or travel demand and can therefore be safely excluded from the stochastic analysis.

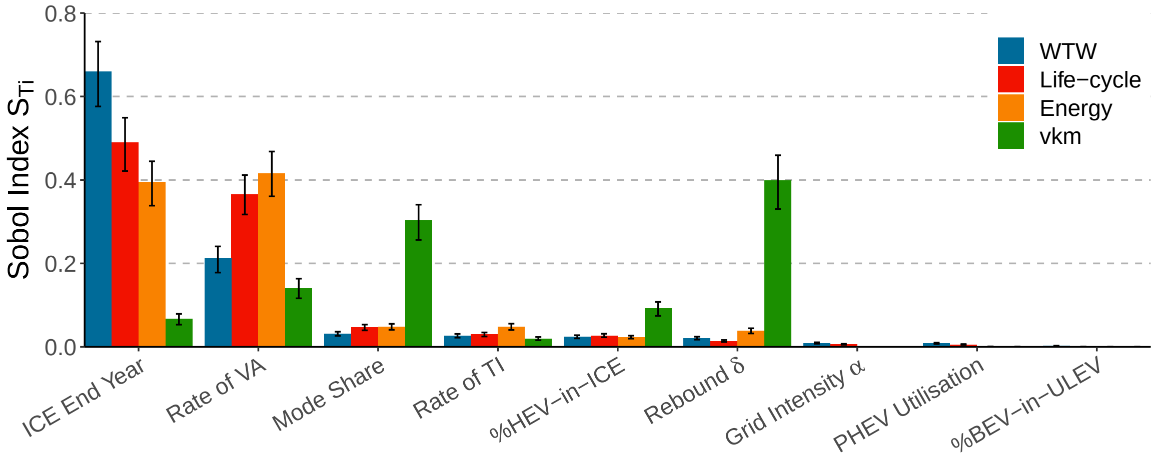

Fig. 5.11 Sobol indices S_{Ti} for each input variable on cumulative WTW and life-cycle CO_2 emissions, final energy use and vehicle kilometres 2019-2050.

5.3.5 The effect of input variance

Knowledge of the precise values to choose for input variables will always be imperfect. The aim of this analysis is to move the assessment of important variables from choosing single deterministic values, to exploring a wide solution space. The choice of upper and lower bounds is of course subjective and has an impact upon the results. For example, halving the variance of the ICE end year variable by modifying its upper bound to 2042 (from 2050), has the impact of reducing its life-cycle emissions Sobol index to 0.23, the vehicle attributes parameter increases to 0.51, but all other parameters continue to explain less than 10% of the variance and thus remain relatively unimportant. If instead the variance in the rate of change of vehicle attributes (size and power) is halved (ranging between -50% and 100%), the life-cycle emissions Sobol index increases to 0.61, the vehicle attributes parameter decreases to 0.14, and all other parameters again continue to explain less than 10% of the variance. These two examples show that the relative importance of variables remain broadly similar. Sobol indices can therefore provide a simple and transparent way to assess the importance of different variables on a future solution space. This can help researchers modelling future demand to eliminate variables of low importance and prioritise critical variables to refine with further analysis or expert elicitation.

Input variable	**WTW**	**Life-cycle**	**Energy**	**VKM**
ICE end year	0.661	0.49	0.396	0.068
Rate of change size and power	0.212	0.365	0.416	0.141
Car mode share	0.032	0.047	0.049	0.303
Rate of Technical Improvements, TI	0.027	0.03	0.049	0.02
Share HEVs-in-ICE	0.024	0.028	0.024	0.093
Rebound Effect, δ_{Rebound}	0.021	0.014	0.039	0.399
Grid emissions intensity, α	0.009	0.006	0	0
PHEV Utilisation U_{PHEV}	0.009	0.006	0.001	0.001
Share BEVs-in-ULEV	0.002	0.001	0	0

Table 5.5 Sobol indices S_{Ti} for each input variable on cumulative WTW and life-cycle CO_2 emissions, final energy use and vehicle kilometres 2019-2050.

5.3.6 Changing travel demand

The previous section assessed plausible upper and lower bounds for different input variables without requiring particularly significant changes in lifestyles. This assumed that the underlying travel demand, the number of desired trips at different distances, remains constant and only the vehicles used to satisfy travel demand are changed (either via modal shift or technical changes to cars). Per capita vehicle kilometres by car were therefore only dependent on endogenous changes in rebound and mode shift. In this section, the effect of an exogenous change in per capita travel demand is investigated.

Figure 5.12 presents the future solution space investigated for travel demand. The upper bound (1) is similar to travel demand projections produced by the Department for Transport DfT (2018a) under scenarios of high GDP growth and low fuel prices, which stimulate future travel demand following historical macroeconomic relationships. According to the ONS (2020), 45% of the British workforce was able to work from home in April and May 2020 during the COVID-19 pandemic. The lower bound (2) assumes future travel demand drops permanently by 20% from 2018 levels as a large share of the population ($\approx$20%) works from home and uses video conferencing software to minimise trips.

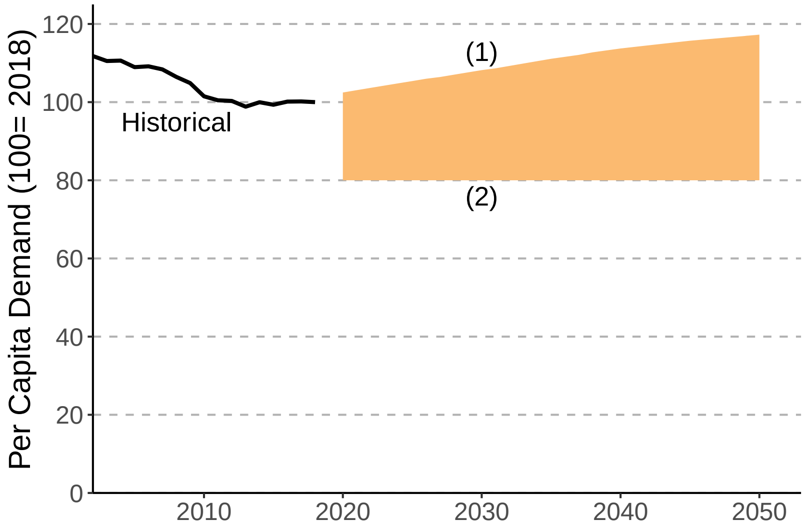

Fig. 5.12 Historical and future projections of travel demand (indexed to 2018 levels) under extreme scenarios: (1) High GDP growth, low fuel prices and otherwise business-as-usual stimulate higher demand, (2) per capita travel demand drops by 20%.

The future range of per capita travel demand is introduced as an additional exogenous stochastic variable to the analysis used in the previous section to account for macro-economic conditions affecting travel. The annual vehicle kilometres by the British fleet output by the model therefore has variance dictated both by rebound effects, modal shift and the macro-economic conditions affecting travel demand. Variables with low Sobol indices in table 5.5 are set to their average values and therefore excluded from further analysis.

The effect of adding in uncertainty of future travel demand is presented in figure 5.13 for WTW emissions (left) and vehicle kilometres (right). A large drop in travel demand has the effect of shifting the likely solution space of future CO_2 emissions and vehicle kilometres to lower values. However, this effect is more pronounced for vkm than it is for WTW emissions showing that changes in per capita demand have a larger effect on total vkm than on CO_2 emissions. This is because futures with low cumulative CO_2 emissions already have efficient, low emission vehicles meaning further reductions in vkm only have slight impacts on cumulative emissions.

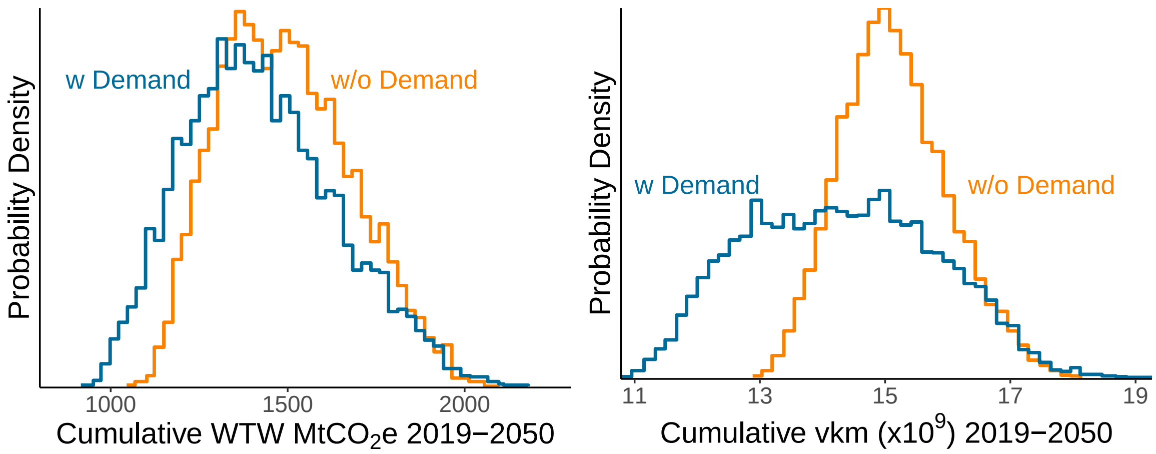

Fig. 5.13 Probability density of cumulative Well-to-Wheel (left) and vehicle kilometres (right)years 2019-2050 split by model runs with (blue) and without (orange) changes in per capita demand. Histograms without demand are the same as those presented in figures 5.7 and 5.10 respectively.

Figure 5.14 and table 5.6 present the Sobol indices for each variable including travel demand. This shows the year that internal combustion engine vehicles are banned remains the most important variable at explaining future variance in CO_2 emissions and that limiting increases in vehicle size and power remains important. However, limiting travel demand can play an equally important role at reducing emissions, energy use and vehicle kilometres since it has the potential to act immediately to limit cumulative travel. Any efforts to avoid travel demand returning to business-as-usual will have significant effects at reducing future transport emissions.

An additional motivation for reducing demand are the serious problems associated with the sourcing and end-of-life treatment of battery materials for electric vehicles. For example, a future with high EV sales could require the production of 7 million vehicles by 2030 and 51 million by 2050. Each EV on average will have a $\approx$400 kg battery, necessitating the extraction and eventual disposal of some 22 million tonnes of battery materials by 2050, rich in critical and difficult to source and recycle elements such as lithium, nickel and cobalt (IEA, 2019a).

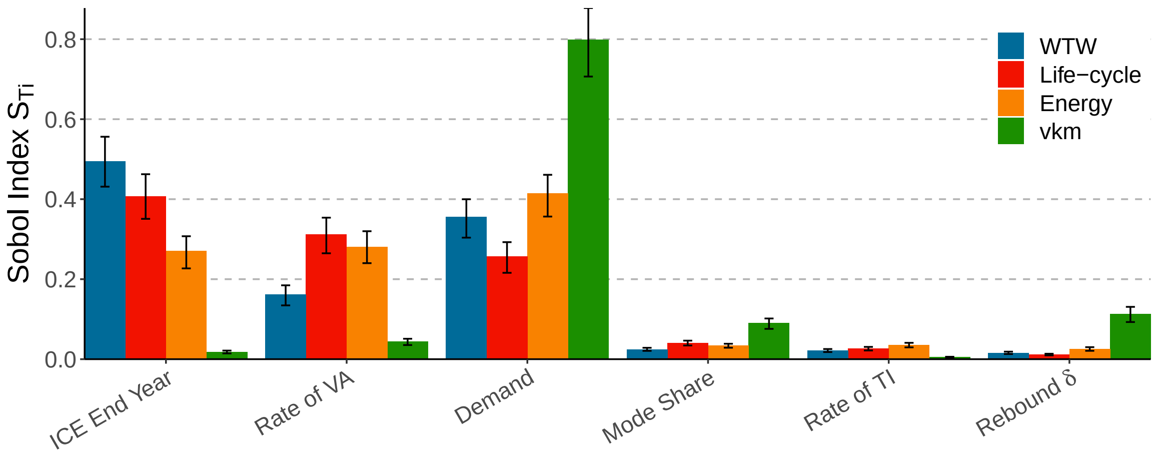

Fig. 5.14 Sobol indices S_{Ti} for each input variable on cumulative WTW and life-cycle CO_2 emissions, final energy use and vehicle kilometres 2019-2050 including changes in underlying travel demand.

Input variable	**WTW**	**Life-cycle**	**Energy**	**VKM**
ICE end year	0.495	0.407	0.27	0.018
Demand	0.356	0.257	0.415	0.8
Rate of change size and power	0.162	0.312	0.281	0.044
Car mode share	0.025	0.041	0.034	0.09
Rate of Technical Improvements, TI	0.022	0.027	0.035	0.005
Rebound Effect, δ_{Rebound}	0.016	0.012	0.026	0.113

Table 5.6 Sobol indices S_{Ti} for each input variable on cumulative WTW and life-cycle CO_2 emissions, final energy use and vehicle kilometres 2019-2050.

5.4 Discussion and Policy Considerations

Having determined the relative importance of variables, this section focuses on the implications of the results and the challenges and opportunities for policy measures to reduce future transport emissions.

Future levels of carbon emissions produced by the transport sector are highly uncertain and difficult to predict. This study estimates a range of possible futures for the British passenger car fleet using a set of plausible ranges for input variables.

Excluding lasting changes in demand, the share of ULEVs and the rate of change in vehicle size and power, together account for over 80% of the uncertainty of future cumulative emissions in both the WTW and life-cycle calculations. The plausible futures investigated in this study suggest two variables must represent the priority for transport policy makers going forward.

The uptake of ULEV sales holds, by some distance, the most importance in limiting future emissions from the British passenger vehicle stock. Recent UK government announcements to ban the sales of ICE engines from 2035 are therefore welcome. It is important for measures to be put in place to attain this goal and accelerate this transition further. Furthermore, it makes little difference whether the market adopts BEVs or PHEVs under current projections of grid carbon intensities.

The leading market for electric vehicles in terms of market share globally is Norway. The share of EVs jumped from 5.8% in 2013 (ICCT, 2019) to 64.4% in January 2020, a rate of 8.4% market share/year. Achieving 100% ULEV market share in the UK by 2035 would require a rate of 6.7% market share/year, so is not outside the realms of possibility. To date, no vehicle market has achieved a market share of ULEVs higher than Norway and there may be particular challenges attaining full market coverage. Similarly, Norway offers significantly larger government subsidies for ULEVs than the UK (Mersky et al., 2016); without these, the uptake of ULEVs in the British market may proceed at a slower pace. In contrast, the increasing market maturity and availability of ULEV models have the potential to increase sales (IEA, 2019a).

The second most important variable, in both the WTW and life-cycle CO_2 calculations, is vehicle size and power, explaining 21% and 36% of future variance respectively. Vehicle size and power are equally influential for future final energy demand. Current government policy only tackles vehicle size and power indirectly, via registration taxes and fuel economy standards; these act upon vehicle fuel efficiency, rather than vehicle attributes directly. This firstly means that if these policy instruments are not sufficiently stringent, then potential emissions savings will continue to be offset by increasing vehicle size and power. Secondly, it means that the life-cycle impacts of increasing vehicle size and power are omitted from policy coverage. Since vehicle size and power increases are the second most important variable at defining future cumulative emissions, addressing vehicle attribute changes directly has the potential to significantly reduce emissions. The large impact that VA has on life-cycle CO_2 emissions could be further mitigated by lowering the carbon intensity of manufacture, which was conservatively assumed to be constant in this analysis.

It is recommended that life-cycle emissions be considered in the formulation of future policy for passenger vehicles. Currently, UK climate change policy is mostly made using WTW emissions criteria (CCC, 2019). The results show that switching to a life-cycle emissions basis does not change the relative importance of the variables, with the ICE end year still dominating. However, using life-cycle emissions amplifies the importance of policies targeting vehicle size and power, as larger vehicles have higher embodied emissions. Beyond emissions, the sourcing and end-of-life treatment of battery materials for electric vehicles poses serious challenges. Policy evidence and instruments which account of life-cycle impacts are therefore clearly needed.

In addition to highlighting the most important variables to direct industry and policy efforts towards, the results also point out lower priority variables. In particular, it is suggested that directing extensive debate and policy efforts towards topics such as the merits of hybrids over traditional internal combustion engines, or battery electric vehicles vs. PHEVs and their utilisation ratio, are not of primary importance. Perhaps surprisingly, incremental technical efficiency improvements are found to be a variable of low importance, such is the emissions intensity improvement from switching to an electric vehicle.

The carbon intensity of the British grid is projected to continue to fall substantially due to the rapid phase-out of coal fired generation and the uptake of renewables. However, the difference between attaining a grid carbon intensity in line with the relatively pessimistic National Grid 'Consumer Evolution' scenario, and meeting the more aggressive 'Two degrees' scenario, has little impact on carbon emissions in passenger transport. This is because the carbon intensity of electricity from the national grid is projected to decrease substantially in coming years, even under relatively pessimistic scenarios (National Grid ESO, 2019). A future low carbon electricity grid is physically possible and compatible with high electric vehicle uptake. According to National Grid, electric vehicles and smart charging can facilitate the integration of renewable electricity generation. Furthermore, the additional peak electricity demand in a high EV uptake scenario would be in the order of 5 GW, just 8% higher than today's levels (National Grid, 2017).

The rebound effect is a relatively unimportant factor for future CO_2 emissions and energy use from transport. However, the difference between assuming δ_{Rebound}=0.046 and δ_{Rebound}=0.3 can have important effects on projections of travel demand. It is therefore crucial to maintain accurate estimates of the rebound effect in numerical models used for policy guidance. The effects of the rebound effect on travel demand could be offset with road pricing measures.

Finally, current government projections assume bus travel will remain constant at 2020 levels to 2050, and that rail passenger miles travelled will increase by 60% from 2019 levels by 2050 (DfT, 2020a). However, total transport demand is also projected to increase, meaning the latter is minor in terms of modal shift from car travel. This means modal shift is a relatively unimportant variable for reducing CO_2 emissions, if the frequency and distance of current travel demand remains unchanged. Meaningfully reducing vehicle kilometres by car therefore requires a fundamental change relying on fewer long distance trips.

Chapter 6

Conclusions and Discussion

This thesis set out to answer the main research question: 'Can technical improvements in passenger cars lead to energy and CO_2 savings?'. This chapter addresses the extent to which this question has been answered. The first section (6.1) summarises the main contributions to knowledge presented in this thesis and the answers to each of the main research questions. The next section (6.2) discusses the wider implications of this work for both academics and decision makers. Section 6.3 will elaborate on potential avenues for future work that could help to overcome some of the limitations of the analysis.

6.1 Contributions to knowledge

The main research question of this thesis was broken down into three sub-questions forming the basis for chapters 3-5. The motivation for chapters 3-4 was to determine the historical extent to which technical improvements have led to energy intensity improvements, and whether these may have stimulated an increase in mileage, thereby reducing energy savings. Informed by the magnitudes of these effects in the past two decades, chapter 5 aimed to determine their potential effects in the future. This section will explore the contributions to knowledge developed in answering the research questions in each chapter.

Have technical improvements led to more efficient vehicles?

The potential efficiency gains from engineering improvements in vehicles may be offset by increasing vehicle size and power. Assessing the magnitude of this effect requires quantifying technical improvements over time and assessing the impact of changing vehicle attributes. Chapter 2 highlighted two main research gaps in past literature exploring this topic. Firstly, past work is not able to adequately distinguish between incremental technical efficiency improvements and the effects of market shifts between powertrain technologies. Secondly, real-world data has not yet been used to quantify technical improvements.

In chapter 3, the first of these research gaps was addressed by presenting a new framework to split changes in the fuel intensity of vehicles over time into three main effects: incremental technical efficiency improvements (ITEI), technology switching (TS) and changes in vehicle attributes (VA) such as size and power. The magnitude of these effects was then quantified for the British vehicle market between 2001 and 2018; firstly using established multivariate regression techniques to determine ITEI and VA for each powertrain type, and then introducing a novel index decomposition technique to determine the technology switching effect.

The second research gap of chapter 3 was addressed by sourcing real-world fuel consumption data and matching them to British vehicle sales data. This allowed for an assessment of trends in the sales-weighted real-world fuel intensity of vehicles between 2001 and 2018. The dataset was then used to determine the magnitudes of real-world ITEI, TS and VA.

The results of chapter 3 show that real technical improvements had the potential to reduce fuel consumption by 1.8 L/100km between 2001 and 2018. Instead 65% of this potential was offset by increasing size and power of vehicles. It is shown that ITEI calculated using real-world data is significantly less than when using type-approval values. Past literature using type-approval data found that the introduction of EU CO_2 emissions standards in 2008/09 increased the rate of ITEI. The results presented in chapter 3 show this was not the case when using real-world data.

Next, the effects of technology switching between powertrains are shown to have been small over the past two decades. This is due to the similar real-world fuel consumption of petrol and diesel vehicles over the time period, meaning sales shifts between them made little difference to the energy intensity of vehicles. New powertrain types such as hybrid vehicles, whilst more efficient than conventional internal combustion engine vehicles, were not present in sufficient volumes to noticeably affect average energy intensity.

To summarise, in the past two decades technical improvements have led to more efficient vehicles, but by far less than their potential. To avoid this continuing, it is essential to avoid further increases in vehicle attributes and to rapidly increase the rate of technical improvements.

Have more efficient vehicles led to energy savings?

If efficiency improvements stimulate travel demand via the rebound effect, there is a risk that potential energy savings from energy efficiency improvements may be lower than expected from engineering calculations. Estimating the magnitude of the rebound is important to evaluate the effects of efficiency improvements and to predict future travel demand. As summarised in Chapter 2, past estimates of the rebound effect have varied widely and have predominantly used aggregate data, which may omit important explanatory factors and relies on data points from historical periods that may no longer be appropriate for current travel demand. Additionally, certain drivers may be more susceptible to fuel price or fuel efficiency changes, than others, based on their ability to pay or their ability to choose alternative modes of transport. It is important to understand these differences to maximise the benefits of policies. However, aggregate data is not able to reveal this heterogeneity.

To overcome this limitation, the analysis of chapter 4 used detailed British 'micro-data', for the first time, to estimate the magnitude of the direct rebound effect between 2006 and 2017. The results show the rebound effect is small, with magnitude $\approx$0.046, meaning efficiency improvements in vehicles are unlikely to stimulate significant increases in mileage. This means more efficient vehicles will lead to energy savings. This short-run estimate of the rebound effect is lower than many literature estimates calculated using aggregate data. However, it is consistent with observed trends in the literature of the rebound effect decreasing over time, potentially due to saturation for travel demand in developed economies.

Have technical improvements led to energy savings?

Having first quantified the degree to which real technical efficiency improvements were offset by the increasing size and power of vehicles, and then quantified the rebound effect, this thesis combined two largely separate bodies of literature for the first time to answer the question: 'Have technical improvements led to energy savings?'.

The findings from chapter 3 show that for every unit of technical improvements in the past two decades, the energy intensity of vehicles improved by just 0.35 units. The findings from chapter 4 show that for every unit of energy intensity improvements, the energy savings will be 0.964. Bringing these two results together, means 66% of the energy saving potential of technical efficiency improvements in the past two decades were lost. Furthermore, the majority of this lost potential was due to the increase in vehicle size and power, rather than any increased mileage from the rebound effect.

Chapters 3 & 4 estimated the magnitude of these effects historically in order to gauge their magnitudes. Chapter 5 then investigated the effects of technical efficiency improvements, changes in vehicle attributes, technology switching and rebound effects on future energy use and CO_2 emissions. The main contributions to knowledge from chapter 5 are summarised in the following section.

What is the likely impact of technical improvements in the future?

Estimating future emissions is important to predict the likely effects of climate change. A range of technology and policy actions can be put in place to reduce carbon emissions, prioritising between them requires quantifying their likely impact. Past work has predominately relied on scenario analyses to quantify the effects of emissions mitigation measures. This is typically achieved by varying individual input variables and using a numerical model to estimate their effects on future emissions. Analyses of this type can be useful, but are hampered by the uncertainty of future trends, which requires subjective assumptions of parameter values. Stochastic methods can reduce the subjectivity of an analysis by focussing on a range of possible futures and exploring a wide solution space. However, both deterministic scenario analysis and stochastic methods alone, are ill-suited to determine the relative importance of variables.

This constraint is overcome in chapter 5 using formal sensitivity analysis techniques that have not yet been applied to study future emissions from the transport sector. Sobol indices are used for the first time to provide a transparent measure of the importance of input variables on future emissions. This analysis therefore uncovers the relative importance of technical improvements, be they incremental technical efficiency improvements or shifts to new powertrain technologies, on future CO_2 emissions, energy use and total travel distance.

The uptake of electric vehicle sales is found to be the most important factor in limiting future emissions from the British passenger vehicle stock. Uncertainty around the uptake of electric vehicles explains 50% of the uncertainty in future transport emissions. Furthermore, under current projections of grid carbon intensities, it makes little difference whether the market adopts BEVs or PHEVs.

Technical improvements in the form of shifts away from traditional internal combustion engine vehicles to new powertrain technologies, will have a large impact on limiting future CO_2 emissions. Conversely, incremental efficiency improvements within powertrain technologies, whilst beneficial, will have a relatively minor effect on future CO_2 emissions from cars.

Potential emissions savings from technical improvements could be limited if consumer trends to larger more powerful vehicles continues. The second most important factor to limit future CO_2 emissions, is the increase in vehicle size and power, which explains between 21%-36% of future uncertainty. Vehicle size and power are equally influential for limiting future final energy demand, explaining 42% of future uncertainty.

The analysis of chapter 5 used Sobol indices for the first time as a tool to cut through future uncertainty and highlight variables of particular importance to direct industry and policy efforts towards. The results also point out lower priority variables that deserve a lower emphasis in future decision making. In particular, extensive discussions on the merits of hybrids over traditional internal combustion engines, or battery electric vehicles vs. PHEVs and their utilisation ratio, are not of primary importance.

The rebound effect is a relatively unimportant factor for future CO_2 emissions and energy use from transport. However, the difference between assuming δ_{Rebound}=0.046 and δ_{Rebound}=0.3 can have important effects on projections of travel demand. It is therefore crucial to maintain accurate estimates of the rebound effect in numerical models used for policy guidance.

With current travel demand, modal shift from car travel is set to only have a minor effect on future CO_2 emissions. This means technical improvements to vehicles in the form of electrification are an inevitable necessity. Meaningfully reducing vehicle kilometres by car requires a more fundamental change by relying on fewer long distance trips.

This thesis has answered the main research questions developed in this thesis, furthering the understanding of the role that technical improvements in vehicles will have in limiting future transport emissions. The following section summarises the implications of the research that are of interest to academics and decision makers.

6.2 Research implications

The findings of this thesis have shown that technical improvements have an important role to play in reducing future carbon emissions from transport and need to be adopted as quickly as possible to limit CO_2 emissions. It is important that policy makers be able to transparently monitor developments in the energy efficiency of passenger cars, to avoid missing future emissions reductions targets and to assess the effectiveness of past policy measures. This thesis showed:

> *Type-approval fuel consumption values need to be sufficiently representative of real-world driving to accurately track fuel efficiency improvements.*

From 2019 onwards, new vehicles undergoing type-approval testing in Europe will use the WLTP test. Early signs show the WLTP is more representative of real-world driving compared with the outgoing NEDC (Dornoff et al., 2020); although the gap between type-approval and real-world driving under WLTP could increase over time, if vehicles are increasingly fitted with auxiliary equipment not included in type-approval testing (Stewart et al., 2015). A new regulation (EU) 2019/631 introduced by the European Commission (2019), requires the introduction of on-board fuel consumption monitoring devices (OBFCM) from 2021, which will hopefully measure real-world fuel consumption and prevent a divergence from the WLTP. If effective, similar regulations will likely need to be adopted in markets outside the EU.

The findings of chapter 3 showed that in the past two decades, the main technical improvements contributing to reducing vehicle emissions were incremental technical efficiency improvements in internal combustion engines, and that the importance of shifting sales between different powertrain technologies (such as hybrids) was minor. However, the conclusions of chapter 5 suggest that incremental improvements will likely play a relatively minor role for future emissions, and that the largest impact can be achieved by rapidly increasing the uptake of electric vehicles. A key finding of this thesis is that we are now at an inflexion point, in which:

> *The majority of future emissions reductions will occur from a shift to new powertrains, rather than incremental improvements within powertrain technologies.*

Achieving 100% electric vehicle market share in the UK by 2035, as recently proposed by the British government (Campbell, 2020), would require an uptake of electric vehicle sales similar to those seen in Norway in the past decade. The adoption of electric vehicles can be stimulated using a variety of policy measures. An example is ‘bonus-malus’ subsidy systems, which have been highly successful in France (Brand et al., 2013) and use the revenues from vehicle taxes on larger vehicles to fund subsidy schemes for low emission vehicles. These can be designed to be revenue generating or revenue neutral. Other policy measures that have proven highly effective at increasing the share of electric vehicles in Norway include VAT exemptions, reduced vehicle parking fees, use of bus lanes and high deployments of charging infrastructure (Holtsmark and Skonhoft, 2014; Mersky et al., 2016).

The ever-present danger is that technical improvements will not result in real energy and emissions savings; this could occur if technical improvements are offset by vehicle size and power. The findings of this thesis showed:

> *In the past two decades, the majority of technical improvements (65%) were offset by increases in vehicle size and power; these consumer trends will remain one of the most important risks to future emissions reductions.*

To limit increases in vehicle size and power, measures could include further increasing registration taxes on larger vehicles. Registration taxes can be highly effective at influencing consumer purchasing patterns (Petrov et al., 2019), but only if they are sufficiently large. Anable et al. (2019) note that 90% of new vehicles purchased in 2018 in the UK, involved some form of financial product or leasing scheme. This had the effect of spreading out registration tax costs over multiple payments, thus diluting their effect.

The true impact of size and power on vehicle emissions is accentuated when including life-cycle emissions criteria. It is therefore recommended that life-cycle emissions be given their due prominence when assessing emissions savings from policy measures. The European Commission (2019) aims to develop a ‘common methodology for the assessment and reporting of the full life-cycle CO_2 emissions of cars or vans’ by 2023. However, it is important these values are also used within the policy making process.

Academics have long argued over the potential of efficiency improvements to lead to energy savings and the degree to which consumers might increase mileage due to the rebound effect. This thesis showed:

> *The magnitude of the rebound effect in recent years is small, at $\approx$4.6%, and will likely have a minor effect on future energy use and CO_2 emissions. However, the rebound effect can have important effects on projections of travel demand.*

The future uptake of vehicles with low running costs could theoretically more than double transport demand from today’s levels, if left unrestrained. It is therefore critical to maintain up-to-date estimates of the rebound effect in numerical models used for policy-making, as well as appropriately calibrating taxation schemes to limit rebound effects.

Fuel taxes have the potential to stimulate a shift to electric vehicles as well as reducing consumer appetite for purchasing high fuel consumption vehicles (Ryan et al., 2009). The results from chapter 4 show that British drivers' mileage is inelastic to fuel price changes, meaning fuel taxes are unlikely to have an important short-term effect on vehicle mileage, but could be used to counterbalance rebound effects. Although the effects of fuel prices on mileage are small, the findings show some variation in how different drivers might respond to increased fuel taxes. Drivers of larger and less fuel efficient vehicles are found to be more responsive to fuel price changes than average. Conversely, drivers in rural areas with relatively high annual mileage are found to be less responsive to fuel price changes than drivers in more populous areas. This may be due to urban drivers being less dependent upon the private vehicle. Some of the areas of the country that are least responsive to fuel price changes are in rural areas, with relatively high annual vehicle mileage and relatively low household income. If car dependent drivers in these areas are unable to adjust their mileage in response to changes in fuel price (whether from changes in fuel tax or from market fluctuations), they may have to absorb the additional costs of travel, which is important to factor into policy design to measure the associated financial burdens.

Controlling total transport demand is important to limit CO_2 emissions and other negative externalities caused by transportation such as congestion and air pollution. Reducing CO_2 emissions in future by simply electrifying vehicles and otherwise continuing as usual, will likely face constraints such as the negative effects associated with battery manufacture and recycling. Therefore, reducing car travel will likely be an important aspect of future transport policy making. Shifting travel mode from cars to cycling, walking and public transport is important for tackling congestion and air pollution. However, modal shift is a relatively unimportant variable for reducing CO_2 emissions, if the frequency and distance of current travel demand remains unchanged. This leads to the conclusion that:

> *Meaningfully reducing vehicle kilometres by car requires a fundamental change relying on fewer long distance trips.*

This could be instilled in the short-term with a greater reliance on tele-working and online shopping delivery used with great effect during the COVID-19 pandemic (ONS, 2020). In the longer-term, town planning will likely play an important role for reducing long commutes and a reliance upon the private car.

6.3 Future work

The analysis undertaken in this thesis spurred further research questions and avenues for future work. These are summarised in this section firstly building from the analysis of the three main chapters and then outlining additional areas of work that fell outside the core scope of this project.

Improving the quantification of technical improvements

Future analysis with more detailed data than used in this thesis, could expand the regression analysis used in chapter 3 by controlling for more variables like air conditioning, vehicle safety equipment and other auxiliaries. Comparing these regression results to engineering estimates would help to further validate these results but data limitations restricted this type of analysis in this thesis.

Future work could aim to disaggregate incremental technical efficiency improvements (ITEI) into its different constituent parts such as engine efficiency improvements, light-weighting and aerodynamics. This would be useful to better understand historical rates of ITEI. When coupled with engineering technical analysis of vehicles (e.g. material composition trends, trends in compression ratios explored for example by Martin et al. (2015)) this could also help to better estimate future rates of ITEI.

An idea briefly investigated in this PhD project was to integrate the estimates of powertrain efficiency presented at the *International Conference of Applied Energy* (Craglia et al., 2017) with estimates of ITEI. However, a visit to the *European Commission Joint Research Centre* in their *Vehicle Emissions Laboratories* (VELA) suggested that coast-down test data was unlikely to be appropriate for assessing trends in engine efficiency due to the increasing divergence between type-approval and real-world data. If real-world, reliable coast-down test data could be produced (perhaps by crowd sourcing) it may allow for engine efficiencies to be better estimated.

Assessing whether fuel economy standards can increase the rate of technical improvements

The work in this thesis used real-world fuel consumption data from the UK, France and Germany and compared it to the type-approval values, all using the NEDC. This showed that the introduction of CO_2 emissions standards in 2008/09 did little to increase the rate of technical improvements. This raises the question, did manufacturers simply choose the least expensive way to meet the target using test flexibilities? Or were they unable to further increase the rate of ITEI? This could be investigated by extending the analysis of chapter 3 to countries such as Japan and the USA, which do not use the NEDC cycle for type-approval testing procedures. It would be of interest to determine whether the rate of real-world technical improvements increased in response to the introduction of fuel economy standards in these markets. This analysis could also include electric and plug-in hybrid vehicles as more data becomes available.

Real-world fuel consumption data for vehicles in the USA is collected by the US EPA in their publicly available 'MyMPG' database. This data has been used in past studies investigating the difference between real-world and type-approval fuel consumption (Greene et al., 2017; Mock et al., 2013; Wali et al., 2018b) but has not yet been used to calculate real-world technical improvements over time. However, one challenge with using this data is the difficulty finding publicly available vehicle registration data in the USA, in order to sales-weight average fuel consumption. This also means that ITEI calculated using the regression techniques of chapter 3 would be on a *model year* basis rather than a *sales year* basis. This would make rates of ITEI non-comparable with the results of chapter 3. Vehicle registration data can be purchased from companies such as *IHS Markit* as carried out by IEA and ICCT (2019).

Improving estimates of the rebound effect and further analysis with odometer data

The analysis of Chapter 4 was partially limited by constraints of the publicly available MOT dataset. In particular, the use of postcode areas as the lowest layer of geographic information presents several limitations, as these are somewhat socially and geographically heterogeneous. More detailed datasets at LSOA level are available from the Department for Transport, but could not be accessed within the time constraints of this project. The use of data at a higher level of geographical detail than the postcode area data, would unlock a large range of interesting avenues for future work. Using more detailed data it would be possible to examine the effects of local policy interventions such as congestion charges on vehicle mileage. It might also be used to investigate the effects of changes in public transport provision over time. Investigating these topics with more detailed data would also help to control for the effects of these variables on vehicle mileage and therefore ensure robust fuel price elasticities.

The ideal data would have the geographical resolution to better distinguish between urban and rural areas as public transport and environmental policies are predominantly present in urban contexts. The effects of local policies could be investigated using dummy variables on the year of introduction in each city and public transport trips could be introduced as an additional time series continuous variable. More granular geographical resolution may also better control for average income and other socio-economic factors.

As future years of MOT tests are added to the dataset published by the UK Department for Transport it may be possible to estimate long-run elasticities which account for how consumers adjust to efficiency improvements and fuel price changes over a longer period of time than the short-run estimates produced in Chapter 4.

The focus of this PhD remained limited to the transport sector, for these reasons only direct rebound effects were estimated, as mentioned in section 2.2.1. However, indirect rebound effects and economy-wide effects may well increase energy use due to efficiency improvements in vehicles and requires further work building upon past studies (Chitnis et al., 2014; Druckman et al., 2011).

The Quality Rebound effect

There is a growing body of academic work which aims to frame the drivers of energy demand in society in terms of 'energy services' (Cullen and Allwood, 2010a). Vehicle miles travelled (VMT) is a measure of the quantity of the transport energy service. However, the energy service of transport also has a qualitative dimension, which is partially dependent upon the attributes of vehicles used. These quality attributes desired by consumers are numerous and range from the easily quantifiable such as performance (measured in terms of power, torque, acceleration, top speed), size (measured as volume or mass), added features (four wheel drive, air conditioning, satnav etc.), to harder to quantify attributes such as aesthetics, social status (potentially quantifiable by cost or brand), comfort and others. Some of these quality attributes can also affect the demand for energy.

Chapter 3 estimated the degree to which technical improvements were offset by vehicle attributes, but did not estimate whether these are coupled. Do greater technical improvements or fuel intensity improvements *stimulate* a shift to larger vehicles?

The effect that lower travel costs might have at stimulating VMT can be considered a 'quantity rebound effect'. This was explored in chapter 4. Considerably less studied in the academic literature are the effects that potential lower travel costs might have at stimulating increases in quality attributes (such as size and power). This effect is defined by Goerlich and Wirl (2012) as the *Quality* Rebound Effect to distinguish it from the *Quantity* Rebound Effect.

As an example, the increasing availability on the market of hybrid vehicles from the year 2012 onwards, meant that a consumer looking to purchase a vehicle, had an option with relatively low running costs. Could this have stimulated some consumers to purchase a larger hybrid vehicle than they might otherwise have chosen? Answering this question is empirically non-trivial as establishing a counter-factual scenario of consumer purchase patterns is challenging. However, estimating this effect could be important in light of the rapid penetration of new powertrains and vehicle technologies that have the *potential* to greatly improve fuel consumption, but may instead be used to offset increases in size and performance.

This effect mostly involves consumer behaviour. A related effect involves the behaviour of vehicle manufacturers. If a manufacturer develops a new technical improvement, with the potential to significantly lower the energy intensity of a vehicle they produce, how much of that potential might they offset by increasing the power, size or other quality attributes of a vehicle to ensure it sells well? Would a greater technical improvement stimulate a manufacturer to increase other vehicle attributes to a greater extent? This is again challenging without a counter-factual and involves marketing decisions and product positioning.

To quantify the effect of efficiency improvements on service quality requires quantifying quality in a single metric. Intuitively, quality is a function of vehicle attributes such as size and power. How can these be reconciled into a single unit? Two options seem the most appealing. The first might be looking at cost, and quantifying consumers' willingness to pay for each attribute. However, the willingness to pay for vehicle attributes is likely subjective to each driver. Similarly, the price that manufacturers charge for a given attribute may change over time. This makes quantifying quality in terms of costs problematic. An alternative is to find the effect of various vehicle attributes on fuel intensity following the methods of chapter 3 and therefore quantify quality as the lost potential improvements in fuel intensity.

The effect that technical improvements may have on stimulating larger and more powerful vehicles was briefly explored during the course of this PhD, with a conference paper presented at the *European Centre for an Energy Efficient Economy* conference in 2019 (Craglia and Cullen, 2019b). Building on some initial findings from Chapter 3 quantifying ITEI using type-approval data, a series of simple regressions were produced aiming to quantify the effect of changes in ITEI on changes in vehicle attributes, VA. The regressions produced elasticities $\eta_{\mathrm{TEI}}(\mathrm{VA}) \approx$ -0.1 meaning that for every unit improvement in technical efficiency, approximately 10% of the potential efficiency gains were lost by stimulating an increase in vehicle attributes. However, empirical limitations resulted in low statistical confidence in these results for several reasons.

Firstly, both average ITEI and vehicle attributes such as size and power, all increased smoothly over the period of investigation (2001-2017) meaning they are all variables which have little year-on-year variance. Secondly, there are likely to be a large number of important omitted variables. The methods of chapter 3 are useful to determine trends in ITEI and VA for the average new vehicle, however when looking to establish causal relationships between ITEI and VA, there are a number of variables that may also affect vehicle attributes such as consumers' willingness to pay and the costs of labour, materials and capital.

Finally, the quality rebound effect is a relatively academic concept that is non-trivial to explain, which hampers its potential usefulness. Given these limitations, further work on this topic was not pursued in this thesis, although there may be future avenues for research in this topic with different data or conceptualisations of this effect.

Improving the prioritisation of actions

Chapter 5 demonstrated how Sobol indices can help to prioritise important variable. The scope of the analysis in chapter 5 could be expanded to the whole transport sector to include alternative modes or expanded to an even greater extent to include sectors outside of transport. This would account for the interaction effects and dependencies between sectors and could reveal how the relative importance of electricity and hydrogen production may change when other sectors are considered.

The future ranges for each variable used in the analysis could be further refined via expert elicitation. The upper and lower bounds of variables were selected to reflect a 'feasible' solution space or action that would generally not require fundamental changes in travel patterns. However, this could be altered to reflect further technical or political constraints.

Assessing limits to vehicle attributes

The potential energy savings from technical improvements can be offset by consumer preferences for larger and more powerful vehicles. This thesis aimed to account for the impacts that future changes in vehicle attributes might have on emissions. One potential area of future work would be to estimate future trends in vehicle size and performance in more depth and determine if the future solution space might be bounded by physical or social constraints to improve emissions forecasts. This topic was briefly explored at the beginning of this PhD project and has also been touched upon by past authors (MacKenzie, 2013). Exploring this topic may be difficult to assess empirically, but studying historical trends in different vehicle attributes may give useful insights.

To explore whether there may be a limit to vehicle acceleration, a dataset of 9145 vehicles with model years between 1997 and 2017 is sourced from a dataset of vehicle technical specifications (McGregor, 2017). Figure 6.1 shows acceleration time (0-100 kph) versus power-to-weight ratio for all vehicles in the dataset. As a means for comparison, the minimum possible acceleration time (theoretical limit) for a given power-to-weight ratio (p/m) is plotted using equation 6.1, where p/m is measured in PS/kg [1].

[1]Derivation: $E = p \times t_{0-100}$, $E = \frac{1}{2}mv^2$

Substituting for E and rearranging: $t_{0-100} = c \times \frac{v^2}{2 \times p/m}$ where c is a constant to equate units and $v = 100$ kph

$$t_{0-100} = \frac{0.525}{p/m} \tag{6.1}$$

Figure 6.1 shows that no vehicle is able to deliver performance equal to the theoretical limit due to difficulties deploying maximum power from rest, gear shifts and other inefficiencies; although for a given p/m certain vehicles are able to get closer to the limit than others. It can also be seen that reducing acceleration times requires ever increasing p/m improvements (thus decreasing margin gains). Other limits to vehicle attributes such as speed, size and may exist and can serve as upper limits to bound future scenarios.

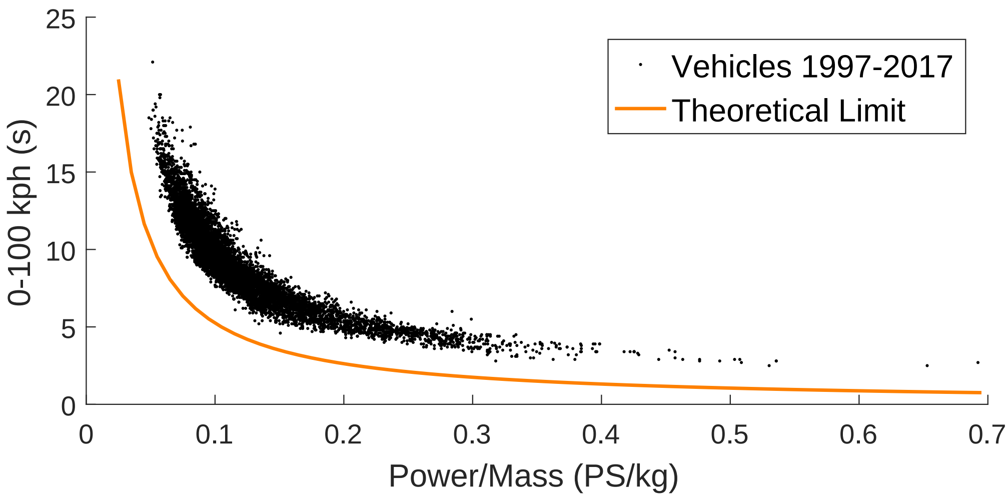

Fig. 6.1 Acceleration time, 0-100 kph (s) of 9145 vehicles with Model Year between 1997-2017 vs. Power to Weight ratio (PS/kg)

References

Allcott, H. and Greenstone, M. (2012). Is There an Energy Efficiency Gap ? *Journal of Economic Perspectives*, 26(1):3–28.

Allcott, H. and Wozny, N. (2014). Gasoline Prices, Fuel Economy, and the Energy Paradox. *Review of Economics and Statistics*, 96(5):779–795.

Anable, J., Brand, C., and Mullen, C. (2019). UKERC Review of Energy Policy 2019: Transport taming of the SUV? Technical report, UKERC.

Ang, B. and Choi, K.-H. (1997). Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method. *The Energy Journal*, 18(3):59–73.

Ang, B. W. (2015). LMDI decomposition approach : A guide for implementation. *Energy Policy*, 86:233–238.

ANL (2019). GREET Fuel Cycle Model. Technical report, Argonne National Laboratories.

Asthana, A. and Taylor, M. (2017). Britain to ban sale of all diesel and petrol cars and vans from 2040.

Bandivadekar, A., Cheah, L., Evans, C., Groode, T., Heywood, J., Kasseris, E., Kromer, M., and Weiss, M. (2008). Reducing the fuel use and greenhouse gas emissions of the US vehicle fleet. *Energy Policy*, 36(7):2754–2760.

Baptista, P. C., Silva, C. M., Farias, T. L., and Heywood, J. B. (2012). Energy and environmental impacts of alternative pathways for the Portuguese road transportation sector. *Energy Policy*, 51:802–815.

Bastani, P., Heywood, J. B., and Hope, C. (2012). The effect of uncertainty on US transport-related GHG emissions and fuel consumption out to 2050. *Transportation Research Part A: Policy and Practice*, 46(3):517–548.

BEIS (2019a). UK Government GHG Conversion Factors for Company Reporting 2002-2019.

BEIS (2019b). Weekly Road Fuel Prices.

Bento, B. A. M., Goulder, L. H., Jacobsen, M. R., and Haefen, R. H. V. (2009). Distributional and Efficiency Impacts of Increased US Gasoline Taxes. *American Economic Association*, 99(3):667–699.

Berman, B. (2020). Daimler ends hydrogen car development because it's too costly.

Blair, R. D., Kaserman, D., and K.L., T. (1984). The Impact of Improved Mileage on Gasoline Consumption. *Economic Inquiry*, 22:209–217.

Bodek, K. and Heywood, J. (2008). Europe's Evolving Passenger Vehicle Fleet : Fuel Use and GHG Emissions Scenarios through 2035. *MIT Laboratory for Energy and the Environment*, (March):78.

Bonilla, D. and Foxon, T. (2009). Demand for new car fuel economy in the UK, 1970-2005. *Journal of Transport Economics and Policy*, 43(1):55–83.

Brand, C. (2010). UK Transport Carbon Model Reference Guide Working Paper. *UKERC*, (January).

Brand, C. (2016). Beyond 'Dieselgate ': Implications of unaccounted and future air pollutant emissions and energy use for cars in the United Kingdom. *Energy Policy*, 97(X):1–12.

Brand, C., Anable, J., and Morton, C. (2019). Lifestyle, efficiency and limits: modelling transport energy and emissions using a socio-technical approach. *Energy Efficiency*, 12(1):187–207.

Brand, C., Anable, J., and Tran, M. (2013). Accelerating the transformation to a low carbon passenger transport system: The role of car purchase taxes, feebates, road taxes and scrappage incentives in the UK. *Transportation Research Part A: Policy and Practice*, 49:132–148.

Brodie, J. (2019). Mercedes sets 2039 target for entirely carbon-neutral line-up.

Brookes, L. (1990). The greenhouse effect : the fallacies in the energy efficiency. *Energy Policy*, (March):199–201.

Cairns, S., Anable, J., Chatterton, T., Wilson, E., and Morton, C. (2017). MOToring along: The lives of cars seen through licensing and test data. Technical Report November, RAC Foundation.

Cairns, S., Harmer, C., Hopkin, J., and Skippon, S. (2014). Sociological perspectives on travel and mobilities: A review. *Transportation Research Part A: Policy and Practice*, 63:107–117.

Campbell, P. (2020). UK plans to ban sale of all polluting cars by 2035.

CCC (2015). Sectoral scenarios for the fifth carbon budget Figure B5.7. Technical report, UK Committee on Climate Change.

CCC (2018). Hydrogen in a low-carbon economy. Technical Report November.

CCC (2019). Net Zero: The UK's contribution to stopping global warming. *Committee on Climate Change*, (May):275.

Chan, N. and Gillingham, K. (2015). The Microeconomic Theory of the Rebound Effect: Nuances, Externalities, and Welfare. *Journal of the Association of Environmental and Resource Economists*, 2(1):133–159.

Chatterton, T., Barnes, J., Wilson, R. E., Anable, J., and Cairns, S. (2015). Use of a novel dataset to explore spatial and social variations in car type, size, usage and emissions. *Transportation Research Part D: Transport and Environment*, 39:151–164.

Chatterton, T. J., Anable, J., Barnes, J., and Yeboah, G. (2016). Mapping household direct energy consumption in the United Kingdom to provide a new perspective on energy justice. *Energy Research & Social Science*, 18:71–87.

Cheah, L., Bandivadekar, A., Bodek, K., Kasseris, E., and Heywood, J. B. (2009). The Trade-off between Automobile Acceleration Performance, Weight, and Fuel Consumption. *SAE Int. J. Fuels Lubr.*, pages 771–777.

Chitnis, M., Sorrell, S., Druckman, A., Firth, S. K., and Jackson, T. (2014). Who rebounds most? Estimating direct and indirect rebound effects for different UK socioeconomic groups. *Ecological Economics*, 106:12–32.

Craglia, M. and Cullen, J. (2019a). Do technical improvements lead to real efficiency gains? Disaggregating changes in transport energy intensity. *Energy Policy*, 134(April):110991.

Craglia, M. and Cullen, J. (2019b). The quality rebound effect in transportation. *ECEEE Summer Study 2019 Proceedings*, pages 1087–1096.

Craglia, M., Paoli, L., and Cullen, J. (2017). Fuel for thought : Powertrain efficiencies of British vehicles. In *Energy Procedia*, volume 142.

Cullen, J. M. and Allwood, J. M. (2010a). The efficient use of energy: Tracing the global flow of energy from fuel to service. *Energy Policy*, 38(1):75–81.

Cullen, J. M. and Allwood, J. M. (2010b). Theoretical efficiency limits for energy conversion devices. *Energy*, 35(5):2059–2069.

Cullen, J. M., Allwood, J. M., and Borgstein, E. H. (2011). Reducing Energy Demand: What Are the Practical Limits? *Environmental Science & Technology*, 45(4):1711–1718.

Daly, H. E. and O Gallachoir, B. P. (2011). Modelling future private car energy demand in Ireland. *Energy Policy*, 39(12):7815–7824.

De Borger, B., Mulalic, I., and Rouwendal, J. (2016). Measuring the rebound effect with micro data: A first difference approach. *Journal of Environmental Economics and Management*, 79:1–17.

DfT (2009). Low Carbon Transport: A Greener Future. Technical Report July, UK Department for Transport.

DfT (2017). Government response to the consultation on proposals to regulate CO2 emission performance standards for new passenger cars and light commercial vehicles in the UK. Technical report, UK Department for Transport.

DfT (2018a). Road Traffic Forecasts 2018. Technical Report July, UK Department for Transport.

DfT (2018b). Table VEH0160: Vehicles registered for the first time by make and model. *Department for Transport Vehicles Statistics*.

DfT (2019a). Table NTS0905 Car/van occupancy and lone drive rate by trip purpose.

DfT (2019b). Table TSGB0101: Passenger transport by mode from 1952.

DfT (2019c). Table Veh0124: Licensed cars by make, model and year of first registration.

DfT (2019d). Table Veh0153: Vehicles registered or the first time by tax class.

DfT (2020a). Decarbonising transport: Setting the Challenge. Technical report, UK Department for Transport.

DfT (2020b). Table BUS0110a Passenger journeys on local bus services per head by local authority.

DfT (2020c). Table NTS9902 Household car ownership by region and Rural-Urban Classification: England.

DfT (2020d). Table Veh0103.

Dimitropoulos, A., Oueslati, W., and Sintek, C. (2016). The Rebound Effect in Road Transport. *OECD Environment Working Papers*.

Dornoff, J., Tietge, U., and Mock, P. (2020). On the way to Real-World CO2 values: The European passenger car market in its first year after introducing the WLTP. Technical Report May, ICCT.

Druckman, A., Chitnis, M., Sorrell, S., and Jackson, T. (2011). Missing carbon reductions? Exploring rebound and backfire effects in UK households. *Energy Policy*, 39(6):3572.

Dunant, C., Shah, T., Drewniok, M., Craglia, M., and Cullen, J. (2020). A new method to estimate the life-time of long life product categories. *Journal of Industrial Ecology*, ((Under review)).

DVSA (2019). Anonymised MOT tests and results.

EC (2009). Regulation (EC) No. 443/2009 of the European Parliament and of the Council of 23 April 2009 Setting Emission Performance Standards for New Passenger Cars as Part of the Community's Integrated Approach to Reduce CO2 Emissions from Light-duty Vehicles. *Official Journal of the European Union*, pages 1–15.

Edwards, K. D., Wagner, R. M., Briggs, T. E., and Theiss, T. J. (2011). Defining Engine Efficiency Limits. *17th Directions in Engine-Efficiency and Emissions Research (DEER) Conference*, (October).

EEA (2018). Monitoring of CO2 emissions from passenger cars – Regulation (EC) No 443/2009.

EIA (2019). Europe Brent Spot Price FOB 1987-2019. *U.S. Energy Information Administration*.

EPA (2016). Light-Duty Automotive Technology, Carbon Dioxide Emissions and Fuel Economy Trends: 1975 Through 2016. Technical report, United States Environmental Protection Agency.

EPA (2020). Fuel economy database.

European Commission (1995). A community strategy to reduce CO2 emissions from passenger cars and improve fuel economy. *Communication from the commission to the council and the european parliament COM(95) 689*.

European Commission (2019). CO2 emission performance standards for cars and vans (2020 onwards).

Experian (2011). UK Household Income 2011 by LSOA.

Fischl, T. (2018). https://www.spritmonitor.de/en/.

Fontaras, G., Zacharof, N. G., and Ciuffo, B. (2017). Fuel consumption and CO2 emissions from passenger cars in Europe – Laboratory versus real-world emissions. *Progress in Energy and Combustion Science*, 60:97–131.

Fouquet, R. (2012). Trends in income and price elasticities of transport demand (1850–2010). *Energy Policy*, 50:62–71.

Frondel, M., Peters, J., and Vance, C. (2008). Identifying the Rebound : Evidence from a German Household Panel. *The Energy Journal*, 29(4):145–163.

Frondel, M., Ritter, N., and Vance, C. (2012). Heterogeneity in the rebound effect: Further evidence for Germany. *Energy Economics*, 34(2):461–467.

Garcia, R. and Freire, F. (2017). A review of fleet-based life-cycle approaches focusing on energy and environmental impacts of vehicles. *Renewable and Sustainable Energy Reviews*, 79(April):935–945.

Garcia, R., Gregory, J., and Freire, F. (2015). Dynamic fleet-based life-cycle greenhouse gas assessment of the introduction of electric vehicles in the Portuguese light-duty fleet. *International Journal of Life Cycle Assessment*, 20(9):1287–1299.

Gately, D. (1990). The U.S. Demand for Highway Travel and Motor Fuel. *The Energy Journal*, 11(3):59–73.

Gillingham, K. (2014). Identifying the elasticity of driving: Evidence from a gasoline price shock in California. *Regional Science and Urban Economics*, 47(1):13–24.

Gillingham, K., Jenn, A., and Azevedo, I. M. L. (2015). Heterogeneity in the response to gasoline prices: Evidence from Pennsylvania and implications for the rebound effect. *Energy Economics*, 52:S41—-S52.

Gillingham, K. and Munk-Nielsen, A. (2019). A Tale Of two tails: Commuting and the fuel price response in driving. *Journal of Urban Economics*, 109(September 2018):27–40.

Goerlich, R. and Wirl, F. (2012). Interdependencies between transport fuel demand, efficiency and quality: An application to Austria. *Energy Policy*, 41:47–58.

Goldberg, P. K. (1996). The effects of the corporate average fuel efficiency standards. *NBER Working Paper Series*, (5673).

González Palencia, J. C., Furubayashi, T., and Nakata, T. (2012). Energy use and CO2 emissions reduction potential in passenger car fleet using zero emission vehicles and lightweight materials. *Energy*, 48(1):548–565.

Goodwin, P., Dargay, J., and Hanly, M. (2004). Elasticities of road traffic and fuel consumption with respect to price and income: A review. *Transport Reviews*, 24(3):275–292.

Greene, D. L. (1992). Vehicle Use and Fuel Economy: How Big is the "Rebound" Effect? *The Energy Journal*, 13(1):117–143.

Greene, D. L., Kahn, J. R., and Gibson, R. C. (1999). Fuel Economy Rebound Effect for US Household Vehicles. *The Energy Journal*, 20(3):1–31.

Greene, D. L., Liu, J., Khattak, A. J., Wali, B., Hopson, J. L., and Goeltz, R. (2017). How does on-road fuel economy vary with vehicle cumulative mileage and daily use? *Transportation Research Part D: Transport and Environment*, 55:142–161.

Greening, L. A., Greene, D. L., Di, C., and Difiglio, C. (2000). Energy efficiency and consumption - the rebound effect - a survey. *Energy Policy*, 28(6-7):389–401.

Harrison, D. and Powell, D. (2018). www.honestjohn.co.uk/real-mpg/.

Haughton, J. and Sarker, S. (1996). Gasoline Tax as a Corrective Tax: Estimates for the United States, 1970-1991. *The Energy Journal*, 17(2):103–126.

Hensher, D. A. and Smith, N. C. (1986). A structural model of the use of automobiles by households: A case study of urban Australia: Foreign summaries. *Transport Reviews*, 6(1):87–111.

Herring, H. (2006). Energy efficiency - A critical view. *Energy*, 31(1 SPEC. ISS.):10–20.

Hoekstra, A. (2019). The Underestimated Potential of Battery Electric Vehicles to Reduce Emissions. *Joule*, 3(6):1412–1414.

Holtsmark, B. and Skonhoft, A. (2014). The Norwegian support and subsidy policy of electric cars. Should it be adopted by other countries? *Environmental Science and Policy*, 42:160–168.

Homma, T. and Saltelli, A. (1996). Importance measures in global sensitivity analysis of nonlinear models. *Reliability Engineering and System Safety*, 52(1):1–17.

Hu, K. and Chen, Y. (2016). Technological growth of fuel efficiency in european automobile market 1975-2015. *Energy Policy*, 98:142–148.

Hughes, J. E., Knittel, C. R., and Sperling, D. (2008). Evidence of a shift in the short-run price elasticity of gasoline demand. *The Energy Journal*, 29(1):113–134.

Hughes, P. S. (1992). *A Strategy For Reducing Emissions Of Greenhouse Gases From Personal Travel In Britain*. PhD thesis, The Open University.

Hymel, K. M. and Small, K. A. (2015). The rebound effect for automobile travel: Asymmetric response to price changes and novel features of the 2000s. *Energy Economics*, 49:93–103.

Hymel, K. M., Small, K. A., and Dender, K. V. (2010). Induced demand and rebound effects in road transport. *Transportation Research Part B: Methodological*, 44(10):1220–1241.

ICCT (2019). European Vehicle Market Statistics. *EU Pocketbook*.

IEA (2017). Energy Technology Perspectives. Technical report, International Energy Agency, Paris.

IEA (2018a). Energy Efficiency Market Report. Technical report, International Energy Agency.

IEA (2018b). *World Energy Outlook 2018*. World Energy Outlook. OECD.

IEA (2019a). Global EV Outlook 2019. Technical report, International Energy Agency.

IEA (2019b). Tracking Transport.

IEA (2019c). World Extended Energy Balances.

IEA (2020). CO2 Emissions from fuel combustion.

IEA and ICCT (2019). Fuel Economy in Major Car Markets: Technology and Policy Drivers 2005-2017. *GFEI - Global Fuel Economy Initiative Working Paper 19*.

IPCC (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. *IPCC*, page 151.

Jahanshahi, K. (2018). DFT T-TEAR National Transport Model Development: NTMv2R Demand Model Calibration and Validation. Technical report, RAND Europe.

Jensen, M. (1999). Passion and heart in transport - a sociological analysis on transport behaviour. *Transport Policy*, 6(1):19–33.

Jevons, W. S. (1865). *The Coal Question: An Inquiry Concerning the Progress of the Nation, and the Probable Exhaustion of Our Coal Mines*.

Johansson and Schipper (1997). Measuring the Long-run Fuel demand for cars. *Journal of Transport Economics and Policy*.

Jones, C. (1993). Another Look at U.S. Passenger Vehicle Use and the Rebound Effect from Improved Fuel Efficiency. *The Energy Journal*, 14(4):99–110.

Kadijk, G., Verbeek, M., Smokers, R., Spreen, J., Patuleia, A., Van, M., Aea, R., Norris, J., Johnson, R. A., O'brien, S., Wrigley, S., Pagnac, J., Seban, M., and Buttigieg, D. (2012). Supporting Analysis on Test Cycle and Technology Deployment for Reviews of Light Duty Vehicle CO 2 Regulations. *TNO*.

Kagawa, S., Hubacek, K., Nansai, K., Kataoka, M., Managi, S., Suh, S., and Kudoh, Y. (2013). Better cars or older cars?: Assessing CO2 emission reduction potential of passenger vehicle replacement programs. *Global Environmental Change*, 23(6):1807–1818.

Kennedy, R. (1913). *The Book of the Motor Car*. Caxton, 1st edition.

Khazzoom, J. D. (1980). Economic Implications of Mandated Efficiency in Standards for Household Appliances. *The Energy Journal*, 1(4):21–40.

Kirsch, D. A. (1998). *The Electric car and the burden of history: studies in automotive systems rivalry in america 1890-1996*. PhD thesis, Stanford University.

Kleinbaum, D. G. (1998). *Applied regression analysis and other multivariable methods*. Duxbury, 3rd edition.

Klier, T. and Linn, J. (2016). The effect of vehicle fuel economy standards on technology adoption. *Journal of Public Economics*, 133:41–63.

Knittel, B. C. R. (2011). Automobiles on Steroids : Product Attribute Trade-Offs and Technological Progress in the Automobile Sector. *The American Economic Review*, 101(7):3368–3399.

Knittel, C. and Sandler, R. (2013). The Welfare Impact of Indirect Pigouvian Taxation. *NBER working paper series 18849*.

Knobloch, F., Hanssen, S. V., Lam, A., Pollitt, H., Salas, P., Chewpreecha, U., Huijbregts, M. A. J., and Mercure, J.-f. (2020). Net emission reductions from electric cars and heat pumps in 59 world regions over time. *Nature Sustainability*.

Kühlwein, J. (2016). The impact of official versus real-world road loads on CO2 emissions and fuel consumption of European passenger cars. *ICCT White Paper*, (May):1–54.

Kwon, T. H. (2006). The determinants of the changes in car fuel efficiency in Great Britain (1978-2000). *Energy Policy*, 34(15):2405–2412.

Langer, A., Maheshri, V., and Winston, C. (2017). From gallons to miles: A disaggregate analysis of automobile travel and externality taxes. *Journal of Public Economics*, 152:34–46.

Li, S., Timmins, C., von Haefen, R. H., and Haefen, R. H. V. (2009). How Do Gasoline Prices Affect Fleet Fuel Economy? *American Economic Journal: Economic Policy*, 1(2):113–137.

Ligterink, N. and Smokers, R. (2016). Real-world fuel consumption of passenger cars based on monitoring of Dutch fuel-pass data. (October 2016).

Ligterink, N. E., Smokers, R. T. M., and Spreen, J. (2016). Supporting analysis on real-world light-duty vehicle CO 2 emissions.

Liu, F. L. and Ang, B. W. (2003). Eight methods for decomposing the aggregate energy-intensity of industry. *Applied Energy*, 76:15–23.

Long, J. S. and Ervin, L. H. (2000). Using Heteroscedasticity Consistent Standard Errors in the Linear Regression Model. *The American Statistician*, 54(3):217–224.

Lutsey, N. (2012). Regulatory and technology lead-time: The case of US automobile greenhouse gas emission standards. *Transport Policy*, 21:179–190.

Lutsey, N. and Sperling, D. (2005). Energy Efficiency, Fuel Economy and Policy Implications.

MacKenzie, D. (2013). *Fuel Economy Regulations and Efficiency Technology Improvements in U.S. Cars Since 1975*. Phd thesis, MIT.

MacKenzie, D. and Heywood, J. B. (2015). Quantifying efficiency technology improvements in U.S. cars from 1975-2009. *Applied Energy*, 157(2015):918–928.

Martin, N. P. D., Bishop, J. D. K., and Boies, A. M. (2017). How Well Do We Know the Future of CO 2 Emissions? Projecting Fleet Emissions from Light Duty Vehicle Technology Drivers. *Environmental Science & Technology*, page acs.est.6b04746.

Martin, N. P. D., Bishop, J. D. K., Choudhary, R., and Boies, A. M. (2015). Can UK passenger vehicles be designed to meet 2020 emissions targets? A novel methodology to forecast fuel consumption with uncertainty analysis. *Applied Energy*, 157:929–939.

Matas, A., Raymond, J. L., and Dominguez, A. (2017). Changes in fuel economy: An analysis of the Spanish car market. *Transportation Research Part D: Transport and Environment*, 55:175–201.

Mattioli, G., Philips, I., Anable, J., and Chatterton, T. (2017). Developing an index of vulnerability to motor fuel price increases in England. *UTSG Conference Proceedings*, (January).

Maxwell, D., Owen, P., McAndrew, L., Muehmel, K., and Neubauer, A. (2011). Addressing the Rebound Effect. *A report for the European Commission DG Environment*, pages 1–133.

Mayo, J. and Mathis, J. (1988). The Effectiveness of Mandatory fuel efficiency standards in Reducing the Demand for Gasoline. *Applied Economics*, 20:211–219.

McCollum, D. and Yang, C. (2009). Achieving deep reductions in US transport greenhouse gas emissions: Scenario analysis and policy implications. *Energy Policy*, 37(12):5580–5596.

McGregor, Z. (2017). www.carfolio.com.

Melaina, M. and Webster, K. (2011). Role of fuel carbon intensity in achieving 2050 greenhouse gas reduction goals within the light-duty vehicle sector. *Environmental Science and Technology*, 45(9):3865–3871.

Mellios, G., Hausberger, S., Keller, M., Samaras, C., and Ntziachristos, L. (2011). Parameterisation of fuel consumption and CO2 emissions of passenger cars and light commercial vehicles for modelling purposes. Technical report, EU Joint Research Centre.

Mersky, A. C., Sprei, F., Samaras, C., and Qian, Z. S. (2016). Effectiveness of incentives on electric vehicle adoption in Norway. *Transportation Research Part D: Transport and Environment*, 46:56–68.

Met Office (2018). HadUK-Grid Gridded Climate Observations on a 12km grid over the UK for 1862-2017. Centre for Environmental Data Analysis.

Mock, P. (2018). The role of standards in reducing CO 2 emissions of passenger cars in the EU. Technical Report February, ICCT.

Mock, P., German, J., Bandivadekar, A., Riemersma, I., Ligterink, N., and Lambrecht, U. (2013). From laboratory to road. *ICCT White Paper*, 49(May):77.

Modaresi, R., Pauliuk, S., Løvik, A. N., and Müller, D. B. (2014). Global carbon benefits of material substitution in passenger cars until 2050 and the impact on the steel and aluminum industries. *Environmental Science and Technology*, 48(18):10776–10784.

Monod, H., Naud, C., and Makowski, D. (2006). *Uncertainty and sensitivity analysis for crop models in Working with Dynamic Crop Models: Evaluation, Analysis, Parameterization, and Applications*. Elsevier, 1st edition.

National Grid (2017). Our energy insights. Technical Report August, National Grid.

National Grid ESO (2019). Future Energy Scenarios 2019. *Future Energy Scenarios*, (July):162.

Naudot, E. (2018). http://www.fiches-auto.fr/essais-tests/.

NHTSA (2020). Corporate Average Fuel Economy.

Nocera, S. and Cavallaro, F. (2016). The competitiveness of alternative transport fuels for CO2emissions. *Transport Policy*, 50:1–14.

NRS (2019). Population Estimates Time Series Data. *National Records of Scotland*.

NTS (2019). UK National Travel Survey, 2002-2016.

Ntziachristos, L., Mellios, G., Tsokolis, D., Keller, M., Hausberger, S., Ligterink, N. E., and Dilara, P. (2014). In-use vs. type-approval fuel consumption of current passenger cars in Europe. *Energy Policy*, 67(2014):403–411.

Nuzzo, R. (2014). Statistical errors. *Nature*, 506(13):150–152.

OECD (2018). Consumer Price Indicies Database.

Onat, N. C., Kucukvar, M., and Tatari, O. (2016). Uncertainty-embedded dynamic life cycle sustainability assessment framework: An ex-ante perspective on the impacts of alternative vehicle options. *Energy*, 112:715–728.

ONS (2018). Lower Layer Super Output Area population estimates. *Office of National Statistics*.

ONS (2019a). Monthly GDP and main sectors to four decimal places.

ONS (2019b). UK National population projections: 2018-based.

ONS (2020). Coronavirus, the UK economy and society, faster indicators: 7 May 2020.

Open Door Logistics (2017). Postcode Shapefiles.

Pannone, G., Betz, B., Reale, M., and Thomas, J. (2017). Decomposing Fuel Economy and Greenhouse Gas Regulatory Standards in the Energy Conversion Efficiency and Tractive Energy Domain. *SAE International Journal of Fuels and Lubricants*, 10(1):897–2017.

Paoli, L. and Cullen, J. (2019). Technical limits for energy conversion efficiency. *Energy*, page 116228.

Pauliuk, S., Dhaniati, N. M. A., and Müller, D. B. (2012). Reconciling sectoral abatement strategies with global climate targets: The case of the chinese passenger vehicle fleet. *Environmental Science and Technology*, 46(1):140–147.

Pavlovic, J., Marotta, A., and Ciuffo, B. (2016). CO2 emissions and energy demands of vehicles tested under the NEDC and the new WLTP type approval test procedures. *Applied Energy*, 177(2016):661–670.

Pelkmans, L. and Debal, P. (2006). Comparison of on-road emissions with emissions measured on chassis dynamometer test cycles. *Transportation Research Part D: Transport and Environment*, 11(4):233–241.

Petrov, I., Ryan, L., and Monaca, S. L. (2019). Vehicle tax design and car purchase choices: a case study of Ireland. *ECEEE Summer Study 2019 Proceedings Proceedings*.

Pianosi, F., Beven, K., Freer, J., Hall, J. W., Rougier, J., Stephenson, D. B., and Wagener, T. (2016). Sensitivity analysis of environmental models: A systematic review with practical workflow. *Environmental Modelling and Software*, 79:214–232.

Puller, S. and Greening, L. (1996). Household Adjustment to Gasoline Price: An Analysis Using Nine Year of U.S. Survey Data No. LBNL-40015. Technical report, Lawrence Berkeley National Laboratory.

Quaglietta, E. and Punzo, V. (2013). Supporting the design of railway systems by means of a Sobol variance-based sensitivity analysis. *Transportation Research Part C: Emerging Technologies*, 34:38–54.

Reichmuth, D. S., Lutz, A. E., Manley, D. K., and Keller, J. O. (2013). Comparison of the technical potential for hydrogen, battery electric, and conventional light-duty vehicles to reduce greenhouse gas emissions and petroleum consumption in the United States. *International Journal of Hydrogen Energy*, 38(2):1200–1208.

Rice, P. and Parkin, J. (1984). New Car Fuel Consumption 1978-83: A study of the official model year car test results with special reference to the small car. *Working Paper WP84 Transport Group, Department of Civil Engineering, Imperial College London*.

Rohr, C., Fox, J., Glenesk, J., Collins, J., and Whittaker, B. (2018). Latest Evidence on Factors Impacting Road Traffic Growth. *Report by RAND for the Department for Transport*, (May).

Romanowicz, T. M. and Owsiński, J. W. (1988). On dynamic modeling of car populations. Part I. *Technological Forecasting and Social Change*, 34(1):81–94.

Rostow, W. W. (1978). *The World Economy: History and Prospect*. University of Texas Press.

Ryan, L., Ferreira, S., and Convery, F. (2009). The impact of fiscal and other measures on new passenger car sales and CO2 emissions intensity: Evidence from Europe. *Energy Economics*, 31(3):365–374.

Saltelli, A. and Annoni, P. (2010). How to avoid a perfunctory sensitivity analysis. *Environmental Modelling and Software*, 25(12):1508–1517.

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., and Tarantola, S. (2010). Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. *Computer Physics Communications*, 181(2):259–270.

Sato, K. (1976). The Ideal Log-Change Index Number. *The Review of Economics and Statistics*, 58(2):223–228.

Saunders, H. D. (1992). The Khazzoom-Brookes Postulate and Neoclassical Growth. *The Energy Journal*, 13(4).

Schimek, P. (1996). Gasoline and Travel Demand Models Using Time Series and Cross-Section Data from United States. *Transportation Research Record*.

Schipper, L. (2008). Automobile Fuel Economy and CO2 Emissions in Industrialized Countries : Troubling Trends through 2005/6. *University of California Transportation Center Report*.

Schipper, L. and Tax, W. (1994). New car test and actual fuel economy: yet another gap? *Transport Policy*, 1(4):257–265.

Seba, T. (2017). Rethinking Transportation 2020-2030. *RethinkX Report*, (May).

Serrenho, A. C., Norman, J. B., and Allwood, J. M. (2017). The impact of reducing car weight on global emissions: the future fleet in Great Britain. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*.

Sheehan, S. (2017). All Maserati models to use electrified drive from 2019.

Singh, B. and Strømman, A. H. (2013). Environmental assessment of electrification of road transport in Norway: Scenarios and impacts. *Transportation Research Part D: Transport and Environment*, 25(2013):106–111.

Small, K. A. and Dender, K. V. (2007). Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect. *Energy Journal*, 28(1):25–51.

Smith, C. J., Forster, P. M., Allen, M., Fuglestvedt, J., Millar, R. J., Rogelj, J., and Zickfeld, K. (2019). Current fossil fuel infrastructure does not yet commit us to 1.5 C warming. *Nature Communications*, 10(1):1–10.

Smith, R. J. (2018). The continuing misuse of null hypothesis significance testing in biological anthropology. *American Journal of Physical Anthropology*, 166(1):236–245.

SMMT (2018). New Car CO2 Report 2018. *Society of Motor Manufacturers and Traders*.

Sobol, I. M. (2001). Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and Computers in Simulation*, 55(1-3):271–280.

Sorrell, S. (1992). Fuel efficiency in the UK vehicle stock. *Energy Policy*, 20(8):766–780.

Sorrell, S. (2009). Jevons' Paradox revisited: The evidence for backfire from improved energy efficiency. *Energy Policy*, 37(4):1456–1469.

Sorrell, S. and Dimitropoulos, J. (2007). The rebound effect: Microeconomic definitions, limitations and extensions. *Ecological Economics*, 65(3):636–649.

Sorrell, S., Dimitropoulos, J., and Sommerville, M. (2009). Empirical estimates of the direct rebound effect: A review. *Energy Policy*, 37(4):1356–1371.

Sorrell, S., Gatersleben, B., and Druckman, A. (2018). Energy sufficiency and the rebound effects. *Concept paper for the European Council for an Energy Efficient Economy*.

Sovran, G. and Blaser, D. (2003). A Contribution to Understanding Automotive Fuel Economy and its Limits. *SAE International 2003-01-2070*.

Sprei, F. and Karlsson, S. (2010). New Sold Cars in Sweden 2007 – Is a New Trend Materializing ? *Proceedings to the 12th World Conference for Transportation Research July 11-15 Lisbon Portugal*.

Stapleton, L., Sorrell, S., and Schwanen, T. (2016). Estimating direct rebound effects for personal automotive travel in Great Britain. *Energy Economics*, 54:313–325.

Stapleton, L., Sorrell, S., and Schwanen, T. (2017). Peak car and increasing rebound: A closer look at car travel trends in Great Britain. *Transportation Research Part D: Transport and Environment*, 53(May):217–233.

Stewart, A., Hope-Morley, A., Mock, P., and Tietge, U. (2015). Quantifying the impact of real-world driving on total CO2 emissions from UK cars and vans. Technical report.

Thomas, J. (2014). Drive Cycle Powertrain Efficiencies and Trends Derived from EPA Vehicle Dynamometer Results. *SA International Journal of Passenger Cars - Mechanical Systems 7(4)*, pages 1374–1384.

Tietge, U., Díaz, S., Mock, P., Bandivadekar, A., Dornoff, J., and Ligterink, N. (2019). From Laboratory to Road 2018 Update. *ICCT White Paper*, (January).

Tietge, U., Mock, P., Franco, V., and Zacharof, N. (2017a). From laboratory to road: Modeling the divergence between official and real-world fuel consumption and CO2 emission values in the German passenger car market for the years 2001–2014. *Energy Policy*, 103(May 2016):212–222.

Tietge, U., Mock, P., German, J., Bandivadekar, A., and Ligterink, N. (2017b). From Laboratory To Road a 2017 Update of Official and Real-World Cars in Europe. *ICCT White Paper*, (November).

Top Gear (2017). Volkswagen XL1 Review.

Train, K. (1986). Qualitative Choice Analysis: Theory, Econometrics and Application to Automobile Demand. *MIT Press*.

Turrentine, T. S. and Kurani, K. S. (2007). Car buyers and fuel economy? *Energy Policy*, 35(2):1213–1223.

US EPA (2015). Notice of Violation on Clean Air Act to Volkswagen AG Sep 18.

Vartia, Y. O. (1976). Ideal Log-Change Index Numbers. *Scandinavian Journal of Statistics*, 3(3):121–126.

Vaughan, A. (2017). All Volvo cars to be electric or hybrid from 2019.

VCA (2019). Car fuel and emissions information.

Wadud, Z., MacKenzie, D., and Leiby, P. (2016). Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice*, 86:1–18.

Wagner, D. V., An, F., and Wang, C. (2009). Structure and impacts of fuel economy standards for passenger cars in China. *Energy Policy*, 37(10):3803–3811.

Waldmeir, P. (2018). Saudi Aramco aims for cleaner car engines.

Wali, B., Greene, D. L., Khattak, A. J., and Liu, J. (2018a). Analyzing within garage fuel economy gaps to support vehicle purchasing decisions – A copula-based modeling & forecasting approach. *Transportation Research Part D: Transport and Environment*, 63(May):186–208.

Wali, B., Khattak, A. J., Greene, D. L., and Liu, J. (2018b). Fuel economy gaps within and across garages: A bivariate random parameters seemingly unrelated regression approach. *International Journal of Sustainable Transportation*, 13(5):324–339.

Watson, L. (1989). Car Fuel Consumption: Its relationship to official list consumptions. *Transport and Road Research Laboratory*.

Wei, T. (2013). A review of sensitivity analysis methods in building energy analysis. *Renewable and Sustainable Energy Reviews*, 20:411–419.

Weiss, M., Irrgang, L., Kiefer, A. T., Roth, J. R., and Helmers, E. (2019). Mass- and power-related efficiency trade-offs and CO2 emissions of compact passenger cars. *Journal of Cleaner Production*, 243:118326.

Wheaton, W. C. (1982). The Long-Run Structure of Transportation and Gasoline Demand. *The Bell Journal of Economics*, 13(2):439–454.

Wilson, R. E., Cairns, S., Notley, S., Anable, J., Chatterton, T., and McLeod, F. (2013). Techniques for the inference of mileage rates from MOT data. *Transportation Planning & Technology*, 36(1):130–143.

Yang, Z. and Rutherford, D. (2019). Japan 2030 fuel economy standards. Technical Report September, ICCT.

Zachariadis, T., Samaras, Z., and Zierock, K. H. (1995). Dynamic modeling of vehicle populations: An engineering approach for emissions calculations. *Technological Forecasting and Social Change*, 50(2):135–149.

Appendix A

Do technical improvements lead to more efficient vehicles?

A.1 Vehicle Size Segmentation

Vehicles from a single reference year (2013 was chosen) are segmented into size segments with the aid of clustering algorithms based on vehicle dimensions (height, width and length). These vehicles are split into one of seven segments shown in table A.1. Next, the vehicle models are given a model group (e.g. from VW GOLF TSI AUTO to VW GOLF) and the segment that each model group pertains to is used to fill in other years of data (e.g. a BMW 3 series in 2013 is allocated to the small sedan segment, this is used to match a BMW 3 series in year 2001 to the small sedan segment even though it's dimensions may be different to the 2013 version). Any models in a certain year without a segment are allocated one using classification trees on dimensions of vehicles in the same year (e.g. the Rover 25 wasn't sold in 2013 so a model in 2001 wasn't given a segment, however it has similar dimensions to a BMW 3 series in the year 2001 so could be classified into the small sedan segment). Each model group is only allocated to one segment for all years and all model variants (e.g. a BMW 3 series will always be a small sedan in all years). The clustering process was not able to reliably split Sports Utility Vehicles (SUVs) from Multiple Passenger Vehicles (MPVs) using just vehicle dimensions of height, width and length, they are therefore grouped into one size segment.

Size Segment	**Typical Vehicles**
City Car	Smart, Skoda Citigo, Audi A1
Medium Car	Ford Focus, BMW 1 series, Audi A3
Small Sedan	BMW 3 series, Mercedes C class
Large Sedan	Audi A6, BMW 5 series, Mercedes E class
Small SUV	BMW X1, Mini Countryman, Suzuki SW4
SUV/MPV	BMW X3/X5, VW Sharan
Sports	Ferrari, Porsche 911, Lamborghini

Table A.1 Vehicle Segmentation

A.2 Fuzzy matching algorithms

In this thesis a technique to reconcile data from disparate sources was required. A challenge encountered was that vehicle model names differ between datasets, therefore 'fuzzy' matching algorithms are used to find the best match for each vehicle. Vehicles are compared between two different datasets in a series of steps.

Firstly, the manufacturer name is compared by comparing the two character strings. Each string (manufacturer name) is split into the individual words (string split by space). If the two strings are identical then a score of 1 is returned. If not, a score is given based on the number of words that are identical between the two strings. Two long strings are more likely to share words, the score is therefore normalised by the length of the strings. Furthermore, for vehicle names it was found that if the strings were similar at the beginning of the string array, they had a higher chance of being a suitable match. For example comparing an 'AUDI A3 diesel turbo 90PS' to an 'AUDI Q7 petrol turbo 90PS' shows that it is more important for strings to share the initial words than later ones; therefore weights are applied to give a greater score for early matches.

Strings are matched with eachother in two separate steps.

1. In the first instance, the first manufacturer name from the first database, the 'left' database, is compared with the first manufacturer name from the second database, the 'right' database, and a score is returned.

2. In the second instance, the string in the right database is compared with the string in the left.

This is important when strings differ in lengths. For example if the left string is 'VW GOLF' and the right string is 'VW GOLF TDI SPECIAL EDITION' the first comparison of the strings will return a score of 1 because 'VW' and 'GOLF' both appear in the string on the right. Alone, this could give false confidence in the match. Therefore, the second step is necessary as it would give a much lower score (as not all the words in the right string appear in the left string). The scores from the two steps are then averaged and the score is returned from the function. This process is performed for every combination of strings in each database resulting in a table of scores, strings with scores that are below a user defined threshold are discarded, leaving a selection of possible candidate matches.

These candidates are then further screened based on vehicle model names and whether they have the same fuel type and any other known technical details such as engine capacity, power, hybridisation, turbocharging, drivenwheels and transmission (where the data is available). A final 'best' match for each vehicle model in the left database is returned by taking the highest score of the retained candidate matches. All matches are screened for errors by outputting the results and screening by visual inspection.

A.3 Year fixed effects

Tables A.2 and A.3 below show the year fixed effects (T_t) for both type-approval fuel consumption and real-world data and split by powertrain type.

Type-Approval	Petrol	Diesel	Hybrid
(Intercept)	-6.915 (0.11)***	-14.912 (0.127)***	-3.982 (0.84)***
Year 2002	-0.013 (0.002)***	-0.016 (0.007)*	0 (0.142)
Year 2003	-0.066 (0.003)***	-0.076 (0.007)***	-0.069 (0.107)
Year 2004	-0.07 (0.003)***	-0.073 (0.006)***	-0.136 (0.106)
Year 2005	-0.087 (0.003)***	-0.108 (0.006)***	-0.224 (0.11)*
Year 2006	-0.096 (0.003)***	-0.117 (0.006)***	-0.208 (0.112)
Year 2007	-0.132 (0.003)***	-0.156 (0.006)***	-0.156 (0.106)
Year 2008	-0.168 (0.003)***	-0.181 (0.006)***	-0.17 (0.104)
Year 2009	-0.199 (0.003)***	-0.208 (0.006)***	-0.224 (0.102)*
Year 2010	-0.239 (0.003)***	-0.256 (0.005)***	-0.285 (0.102)**
Year 2011	-0.283 (0.003)***	-0.314 (0.005)***	-0.293 (0.102)**
Year 2012	-0.322 (0.003)***	-0.363 (0.005)***	-0.333 (0.101)**
Year 2013	-0.357 (0.003)***	-0.4 (0.005)***	-0.361 (0.101)***
Year 2014	-0.397 (0.003)***	-0.45 (0.006)***	-0.385 (0.101)***
Year 2015	-0.428 (0.003)***	-0.492 (0.006)***	-0.418 (0.101)***
Year 2016	-0.457 (0.003)***	-0.53 (0.006)***	-0.468 (0.101)***
Year 2017	-0.476 (0.003)***	-0.533 (0.005)***	-0.463 (0.101)***
Year 2018	-0.473 (0.003)***	-0.529 (0.006)***	-0.477 (0.101)***

Table A.2 Year fixed effect coefficients and standard errors in parentheses. Base year is 2001. Statistical significance of t-tests: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Real World	Petrol	Diesel	Hybrid
(Intercept)	-8.808 (0.105)***	-13.893 (0.107)***	-9.51 (0.749)***
Year 2002	-0.013 (0.002)***	-0.004 (0.005)	0 (0.118)
Year 2003	-0.047 (0.002)***	-0.044 (0.005)***	0.023 (0.086)
Year 2004	-0.042 (0.003)***	-0.048 (0.005)***	0.019 (0.086)
Year 2005	-0.047 (0.003)***	-0.071 (0.005)***	0.011 (0.088)
Year 2006	-0.051 (0.003)***	-0.086 (0.005)***	0.006 (0.09)
Year 2007	-0.078 (0.003)***	-0.102 (0.005)***	-0.059 (0.086)
Year 2008	-0.082 (0.003)***	-0.107 (0.005)***	-0.059 (0.086)
Year 2009	-0.102 (0.003)***	-0.12 (0.004)***	-0.083 (0.085)
Year 2010	-0.122 (0.003)***	-0.137 (0.004)***	-0.112 (0.085)
Year 2011	-0.14 (0.003)***	-0.148 (0.004)***	-0.111 (0.085)
Year 2012	-0.154 (0.003)***	-0.159 (0.004)***	-0.119 (0.084)
Year 2013	-0.171 (0.003)***	-0.167 (0.004)***	-0.121 (0.084)
Year 2014	-0.183 (0.003)***	-0.179 (0.004)***	-0.138 (0.084)
Year 2015	-0.194 (0.003)***	-0.199 (0.004)***	-0.17 (0.084)*
Year 2016	-0.205 (0.003)***	-0.222 (0.004)***	-0.212 (0.084)*
Year 2017	-0.22 (0.003)***	-0.233 (0.004)***	-0.218 (0.084)**
Year 2018	-0.228 (0.003)***	-0.239 (0.004)***	-0.235 (0.084)**

Table A.3 Year fixed effect coefficients and standard errors in parentheses. Base year is 2001. Statistical significance of t-tests: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

A.4 Real-World Fuel Consumption Data

The real-world fuel consumption of vehicles is inevitably dependent upon a large number of variables such as driving style and external temperature, meaning reported real-world fuel consumption values will always have a considerable degree of uncertainty. For example the effect of vehicle age/mileage could not be accounted for in the real-world reported values. To investigate the real-world fuel consumption data further, vehicles which were present in both the Fiches-Auto dataset as well as the Honest John data were matched together to compare reported real-world fuel consumption between the two datasets (fig. A.1). A simple linear fit gives an R^2 of 0.78.

There are a larger number of real-world fuel consumption entries for smaller, cheaper vehicles in all datasets used than for more expensive large SUVs or sports cars. This is likely due to the users of the websites being more conscious of their fuel consumption than the average driver of a high powered inefficient vehicle. There is therefore a higher uncertainty associated with the larger vehicles in the dataset. This is partly captured in the tests for heteroskedasticity discussed in section 3.2.

Vehicles on the Honest John and Fiches-Auto websites are dated according to the range of years in which each vehicle was sold. Vehicles in the Spritmonitor website are dated by build year.

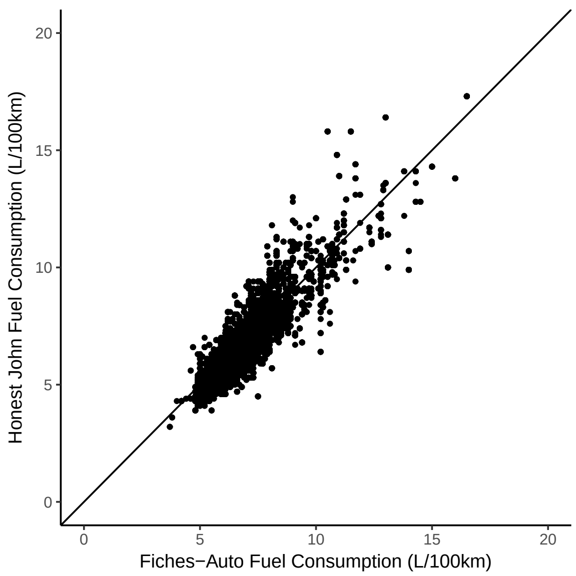

Fig. A.1 Scatter of matched entries between Fiches-Auto and Honest John. Simple linear fit R^2=0.78. Also shown is line of gradient 1 and intercept 0.

Figure A.2 shows the percentage difference between real-world and type-approval fuel consumption for each market segment.

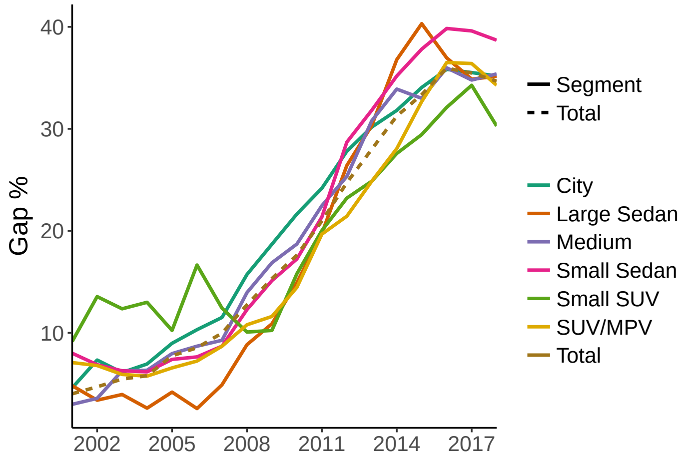

Fig. A.2 Sales-weighted percentage divergence between real-world and type-approval fuel consumption by size segment. Dashed line is average of all vehicles.

Appendix B

Do more efficient vehicles lead to energy savings?

This supplementary material presents the interested reader with insights into the dataset used, summary data, procedures for cleaning and a selection of additional regressions using alternative specifications to those used in the main body of the report.

B.1 Derivation of equation 2.6

If transport demand S (with units VMT) is a function of marginal travel costs P_S (cost per VMT) then:

$$S = f(P_S) \tag{B.1}$$

The cost of travel P_S is a function of both the price of energy P_E and energy efficiency ε. It is also possible that energy efficiency is a function of the price of energy. This means:

$$P_S = P_E/\varepsilon(P_E) \tag{B.2}$$

Taking partial derivatives of equation B.1 gives:

$$\frac{\partial S}{\partial P_S}\frac{P_S}{S} = \frac{\partial S}{\partial (P_E/\varepsilon(P_E))} \times \frac{(P_E/\varepsilon(P_E))}{S} \tag{B.3}$$

Multiplying the right hand side by $\partial P_E/\partial P_E$ we get:

$$\frac{\partial S}{\partial P_S}\frac{P_S}{S} = \frac{\partial S}{\partial P_E} \times \frac{(P_E/\varepsilon(P_E))}{S} \times \frac{\partial P_E}{\partial (P_E/\varepsilon(P_E))} \tag{B.4}$$

The final term on the right hand side can be differentiated using the chain rule:

$$\frac{\partial P_E}{\partial(P_E/\varepsilon(P_E))} = \left[\frac{1}{\varepsilon(P_E)} - \frac{P_E}{\varepsilon(P_E)^2}\frac{\partial\varepsilon}{\partial P_E}\right]^{-1} \tag{B.5}$$

Substituting this back into the previous equation we get:

$$\frac{\partial S}{\partial P_S}\frac{P_S}{S} = \frac{\partial S}{\partial P_E}\frac{P_E}{S} \times \frac{1}{1 - \frac{P_E}{\varepsilon(P_E)}\frac{\partial\varepsilon}{\partial P_E}} \tag{B.6}$$

This can be written as:

$$\eta_{P_S}(S) = \eta_{P_E}(S) \times \frac{1}{1 - \eta_{P_E}(\varepsilon)} \tag{B.7}$$

B.2 Data Cleaning procedures

The postcode 'XX' which is used by the postoffice and army is removed. Vehicles must have an annual mileage above 400 and less than 100,000 between two test dates to remove erroneous entries. Vehicles which are tested at less than 3 years old are omitted, as are vehicles over 20 years old. Vehicles with make or manufacturer set as 'UNCLASSIFIED' are removed. Only vehicles which pass their tests (with pass identifier 'P' are used). Only cars are used (test_class_id=4). Driving periods over 18 months are excluded to ensure β_{Price} represents a short-run elasticity.

B.3 Data Sampling procedures

Running regressions on the full MOT dataset with all observations presented computational difficulties (not enough RAM), for this reason, a smaller sample is used as outlined in section 3.2. To obtain this sample, a full list of all unique vehicle_id's in the dataset (across all test years) was made and then sampled (n=10M). This therefore gives a random selection of vehicles from all registration years and test years. This subset of vehicles is then tracked through time. Each test year is searched for the subset of vehicle_id's. Each vehicle is then matched with it's entry in the subsequent test year by matching by vehicle_id, make, model, fuel_type, postcode_area and engine capacity. Vehicles without matching entries in the subsequent year are dropped. This matching procedure therefore loses a number of observations. The majority of these lost observations are due to no match of vehicle_id in the subsequent year. This is due to a number of reasons: 1. vehicles taking longer than 1 year between MOT tests, 2. a change of vehicle_id in the system, 3. scrappage of the vehicle between two test years. This removes 33% of entries. Errors matching vehicle model names, fuel_types and engine capacities (most likely due to erroneous manual entries) loses a further 5% of observations. Finally, since vehicles are also matched by postcode_area, observations are also lost if a vehicle changes postcodes between test years, this loses a further 14%.

B.4 Weather Data

A heating degree month measures how cold a given location is, by comparing the mean monthly temperature to a standard reference temperature, which is 15.5 degrees Celsius by convention. This is a similar measure to the more common Heating degree days (HDD) measure that is widely used to predict energy use from weather forecasts.

The use of degree months is better suited to tracking trends in cold weather than the average temperature as it avoids particularly hot months cancelling out particularly cool months.

HDMs measure how much the monthly mean temperature exceeds the standard temperature each month over a given driving period (e.g. a period in the summer or the entire year). For example, a month with a mean temperature of 5.5°C, has 10 HDMs (15.5-5.5). If the next month has a mean temperature of 8.5°C, it has 7 HDMs. The total for the two month period is therefore 17 HDMs.

Using month average temperature raster files at 12km resolution from the UK Centre for Environmental Data Analysis (CEDA) Met Office (2018) the HDMs for each 12km x 12km cell are caluclated and aggregated to each postcode to form a time series of HDM for each postcode.

Using monthly precipitation raster files at 12km resolution from the UK Centre for Environmental Data Analysis (CEDA) Met Office (2018), the total rainfall for each 12km x 12km cell is calculated and aggregated to each postcode, to form a time series of rain for each postcode. Examples of weather in a particularly cold and wet postcode (Perth, PH) and a dry and warm postcode (Portsmouth, PO) are shown in figure B.1.

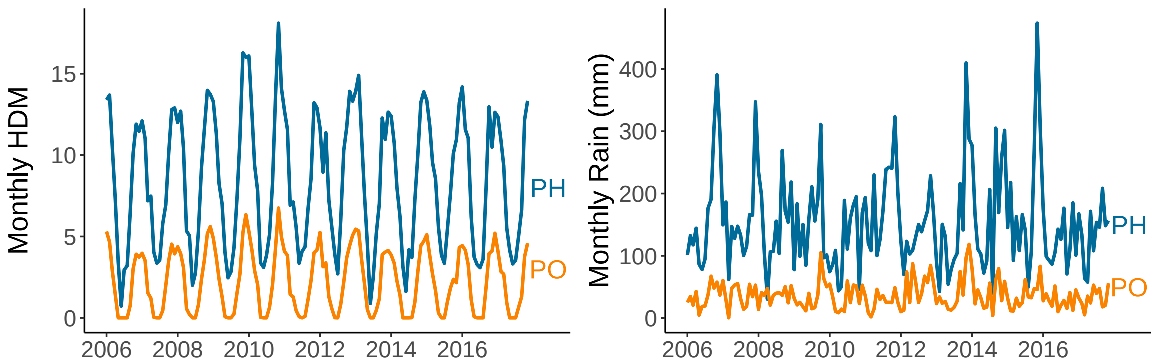

Fig. B.1 Weather trends of heating degree months (HDM) and monthly rain for Perth (PH) and Portsmouth (PO)

B.5 Shares of vehicles by segment and fuel consumption

Vehicle stocks take in the order of 10-15 years to turn over, this means changes in the average characteristics of cars on the road change over long time periods. This is evident in figure B.2 which shows the shares of vehicles tested each year in the data by size segment and ‘real-world’ fuel consumption group. These shares are somewhat representative of the British vehicle stock on the road (though recall vehicles are only tested after their first 3 years of driving). The shares of different vehicle size segments has remained relatively similar over the time period studied, the rapid growth of the SUV segments began around 2014 which is too later to be captured in our data which only extends to 2017. The average fuel consumption of cars has also changed little, this is due to both the slow turn over of the stock of vehicles as well as slow improvements in the 'real-world' fuel consumption of vehicles (see Craglia and Cullen (2019b)).

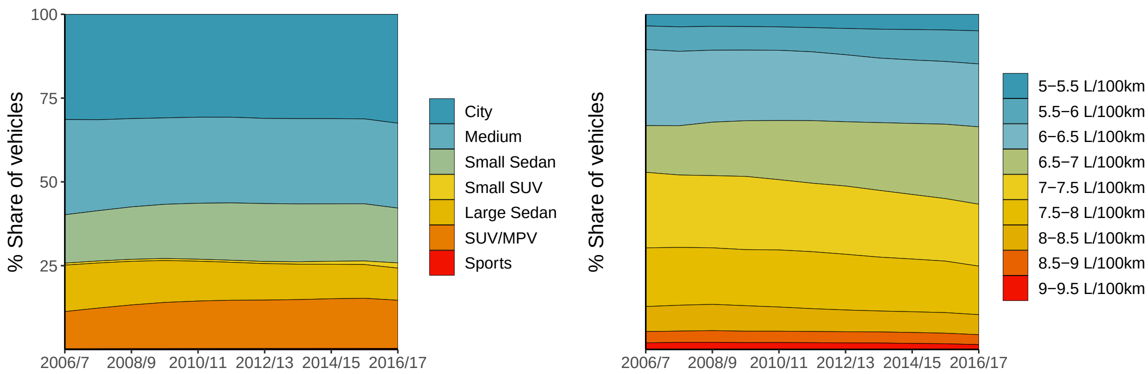

Fig. B.2 Left=Share of vehicles by size segment. Right= Share of vehicles by real world fuel consumption group, note that fuel consumption could only be attributed to vehicles sold after the year 2000.

Figure B.3 shows the shares of vehicle size segments in each bin of 'real-world' fuel consumption. This shows smaller vehicles are more efficient and larger vehicles dominate the higher fuel consumption bins.

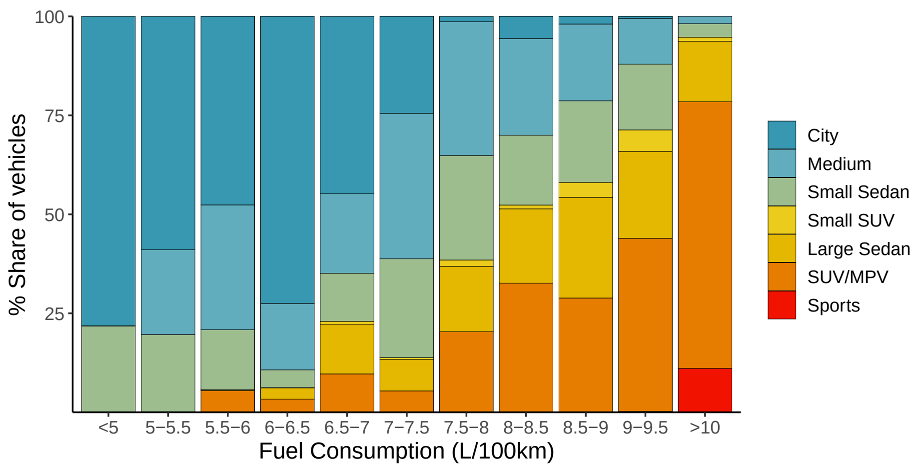

Fig. B.3 Share of vehicles in each size segment across fuel consumption bins. Note that fuel consumption could only be attributed to vehicles sold after the year 2000.

Figure B.4 shows the estimated 'real-world' fuel consumption distribution in each vehicle segment for all years. This shows larger vehicles have higher fuel consumption than smaller vehicles. Figure B.5 similarly shows the distributions of annual vehicle mileage for each size segment for all years.

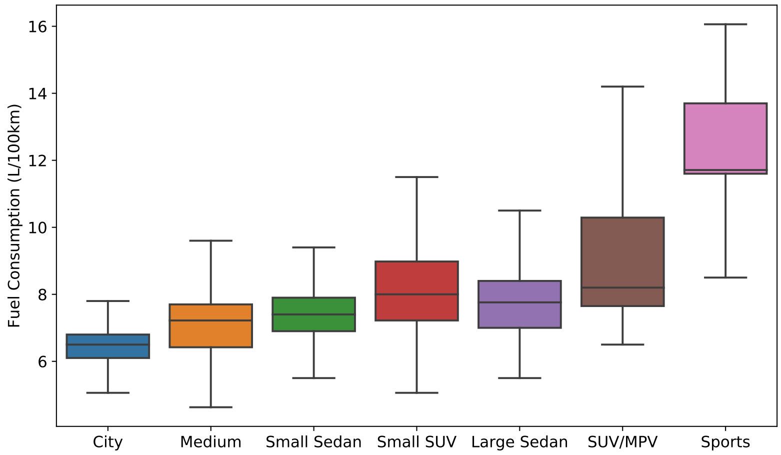

Fig. B.4 Boxplots of 'real-world' fuel consumption (litres of gasoline equivalent per 100km) by vehicle size segment. Boxplots show the median fuel consumption in each size segment, the 25th and 75th percentiles and whiskers show 5th and 95th percentiles.

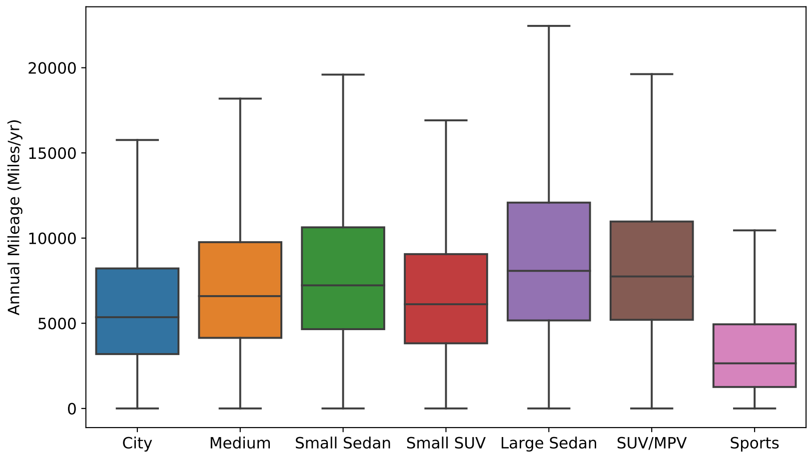

Fig. B.5 Boxplots of annual mileage by vehicle size segment. Boxplots show the median mileage in each size segment, the 25th and 75th percentiles and whiskers show 5th and 95th percentiles.

Figure B.6 shows the mileage distribution in each bin of ‘real-world’ fuel consumption. Vehicles with unknown fuel consumption are principally first registered before the year 2001. Their mileage is slightly lower than other vehicles due to their age (recall fig. 4). The most efficient vehicles within each size segment tend to be driven more than higher fuel consumption vehicles within the segment. This has the effect of ‘smoothing’ out the fuel consumption vs. mileage distribution.

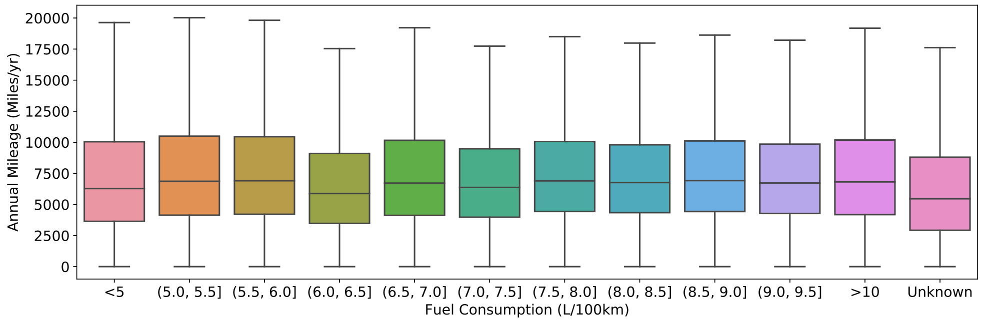

Fig. B.6 Boxplots of annual mileage by bin of ‘real-world’ fuel consumption. Boxplots show the median mileage in each size segment, the 25th and 75th percentiles and whiskers show 5th and 95th percentiles.

B.6 Additional Investigations

B.6.1 The effects of introduction/omission of dependent variables

The effect that population change in each postcode might have upon vehicle mileage was also investigated. Population (Pop_{it}) time series data for each postcode is included to account for increased congestion and other unobserved trends associated with population growth. Population data for each postcode and years 2006-17 are sourced for England and Wales ONS (2018) and Scotland NRS (2019) at local authority level and then aggregated to postcode level and matched by test year. The effect of population growth in each postcode is included in the first column of table B.1. This has a negative effect on mileage as might be explained by increased congestion and urban sprawl leading to longer commutes. In the second column of table B.1 the effects of GDP growth are removed. Neither of these changes affect the magnitude of β_{Price} or the main results shown in the main body of the analysis.

Parameter	(5) Population Growth	(6) No GDP
lnPrice	-0.046 (0.002)***	-0.053 (0.002)***
lnGDP	0.092 (0.006)***	
Age	-0.035 (1e-04)***	-0.034 (9e-05)***
lnHDM	-0.02 (0.001)***	-0.026 (0.001)***
lnRain	0.0037 (7e-04)***	0.0059 (7e-04)***
lnPop	-0.012 (7e-04)***	
Month Effects	X	X
Period Effects	X	X
Vehicle Effects	X	X
Observations	23,016,519	23,016,519
R^2	0.03	0.03

Table B.1 Further regression results, (5) includes population growth in each postcode, (6) omits GDP. Dependent variable is the natural logarithm of vehicle mileage. Data is based on a random sample of 10 million vehicles which are filtered for erroneous entries and then tracked through time. Standard errors clustered at the vehicle level for each coefficient are included in parentheses. Statistical significance: * p<0.05, ** p<0.01, *** p<0.001

Table B.2 shows the percentage changes of key variables between test periods. The population growth effect is omitted from the main results of table 4.3 due to its small variance coupled with its small coefficient, which means its effect size (standardised regression coefficient) is an order of magnitude smaller than other variables.

% Changes	Min.	25%	50%	75%	Max.
GDP	-4.80	0.90	1.50	2.40	3.70
HDM	-69.0	-8.4	1.8	12.5	210.8
Population	-3.50	0.50	0.70	1.00	3.40
Fuel Price	-21.0	-6.6	-1.5	7.4	21.9
Rain	-70.0	-17.0	-4.6	12.1	232.6
Annual VMT	-99.6	-19.6	-3.6	14.1	22724

Table B.2 Summary statistics of main variables: Percentage changes between driving periods for individual vehicles (‘within’): minimum, 25^{th}, 50^{th} and 75^{th} percentiles and maximum. E.g. The median % change in mileage between tests is -3.6%.

B.6.2 An alternative model specification

The main model chosen for the investigations of this analysis (eqn. 6) uses log-log regression with fixed effects. The coefficients of the regression therefore represent an elasticity; the relationship between a percentage change in the independent variable (e.g. Fuel Price) and the dependent variable (e.g. VMT). This section shows the same results can be obtained by running a simple linear OLS regression on the percentage changes in the data. Firstly, the data is manipulated to obtain, for each vehicle_id, the percentage changes in mileage between test periods. For example a vehicle that travelled on average 1000 miles in one test period and 1100 in a subsequent test period would have changed mileage by 10% between the two test periods. Figure B.7 shows a histogram of the percentage changes in mileage between test periods. The median percentage change in mileage is slightly negative (-3.6%) because cars are driven less on average as they age. In general, the majority of vehicles change their mileage by between $\pm$50%.

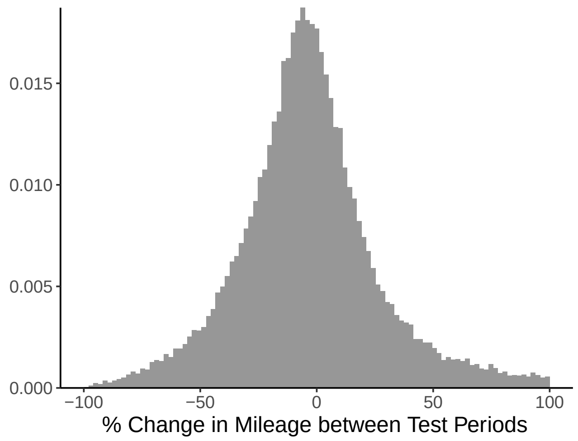

Fig. B.7 Histogram of percentage changes in individual vehicles' mileage between test periods.

Next, table B.3 shows the results of a simple regression following equation B.8. The first column shows the magnitude of the elasticity remains the same to the findings presented in table 4, adding in percentage changes in other variables does not affect the magnitude of β_{Price}. The percentage change in a vehicle's mileage between test periods can drop by a maximum of 100% (aka if the mileage dropped to zero). However, it can increase by more than 100% (e.g. a vehicle changing from 500 miles/year to 50,000 miles/year). The distribution shown in figure B.7 has a long positive tail for a small number of vehicles. In theory this could bias the results. In the second column of table B.3, vehicles whose mileage changes by >100% between test periods are excluded, this does not affect the magnitude of $\beta_{\text{Fuel Price}}$.

$$\%\text{Change Mileage} = \text{Intercept} + \beta\ \%\text{Change Fuel Price} + \varepsilon \tag{B.8}$$

Parameter	All % Changes	% Changes <100%
Intercept	8.05 (0.047)***	-3.59 (0.013)***
% Change Fuel Price	-0.041 (0.005)***	-0.046 (0.002)***
Observations	5,215,164	5,006,679
R^2	0.000	0.000

Table B.3 Regression results of simple linear OLS between % change in mileage between test periods and % change in fuel price between test periods. Statistical significance: * p<0.05, ** p<0.01, *** p<0.001

B.7 Instrumental Variable Regression

To ensure the exogeneity of British fuel price the European Brent spot price (sourced from EIA (2019)) is used as an instrumental variable. This is performed by 2 stage least squares regression (2SLS) and results are presented in the final column of table 4. Table B.4 shows the first stage estimates which regress the European Brent spot price and other controls on the UK fuel price. The high correlation and F statistic shows the Brent spot price is an adequate instrumental variable.

Parameter	1^{st}stage IV estimation
Intercept	8.4 (0.001)***
lnBrent	0.34 (4e-05)***
lnBrent:fuel_type(Petrol)	-0.0034 (5e-05)***
Age	0.019 (3e-06)***
lnGDP	-1.1 (3e-04)***
lnHDM	0.035 (4e-05)***
lnPop	-0.00031 (2e-05)***
lnRain	-0.032 (3e-05)***
Month Effects	X
Period Effects	X
Vehicle Effects	
Observations	23,016,519
R^2	0.95
F stat.	1.15e+07

Table B.4 First stage Instrumental Variable regression results. Dependent variable is the natural logarithm of UK fuel price (both petrol and diesel) at 2017 £ PPP. Independent variables are EU brent spot price (£ 2017 PPP), a dummy variable of fuel type (petrol fuel price) interacted with the brent price and other controls. Statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Bootstrapping could not be used in the 2SLS procedure as there is currently no package in python that allows for both fixed effects and bootstrapping. Equivalent packages in R or Stata are not able to deal with this quantity of data. Given the large size of the sample, there is likely to be little cause for concern.

B.8 Heterogeneity by vehicle size segment and fuel type

Table B.5 shows regression results run on subsets of data (rather than by dummy variable interaction shown in table 5. The results are similar in showing that β_{Price} increases for larger vehicles.

Parameter	1 Petrol	2 Diesel	3 City	4 Medium	5 S Sedan	6 L Sedan	7 SUV/MPV
lnPrice	-0.058***	-0.051***	0.001	-0.05***	-0.076***	-0.096***	-0.1***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
lnGDP	0.069***	0.18***	0.015	0.084***	0.13***	0.16***	0.099***
	(0.008)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Age	-0.03***	-0.043***	-0.023***	-0.032***	-0.037***	-0.044***	-0.043***
	(1e-04)	(2e-04)	(2e-04)	(2e-04)	(2e-04)	(3e-04)	(3e-04)
lnHDM	-0.023***	-0.019***	-0.021***	-0.029***	-0.025***	-0.019***	-0.0069*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
lnRain	0.0065***	-0.0012	0.01***	0.0047***	0.004*	-0.0027	0.0012
	(9e-04)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Month Effect	X	X	X	X	X	X	X
Period Effect	X	X	X	X	X	X	X
Vehicle Effect	X	X	X	X	X	X	X
Observations	15293391	5579865	6506308	5439642	3425238	2487244	2836012
R^2	0.02	0.05	0.01	0.03	0.04	0.05	0.05

Table B.5 Regression results for by vehicle fuel type and size segment. Dependent variable is the natural logarithm of vehicle mileage. Data is based on a random sample of 10 million vehicles which are filtered for erroneous entries and then tracked through time. Standard errors clustered at the vehicle level for each coefficient are included in parentheses. Statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

B.9 Heterogeneity by fuel consumption run on subsets of data

Table B.6 presents results of regressions investigating heterogeneity in the response to fuel price changes with respect fuel efficiency. This is achieved by subsetting the data into vehicle groups of similar fuel consumption. The results show the elasticity of mileage to fuel price changes increases for higher fuel consumption vehicles. These results are similar to the results presented in the main analysis, which use dummy variable interactions.

Table B.7 shows the results of running the regression only on vehicles which could be associated with a real-world fuel consumption estimate. The fact that these vehicles are on average less old (only vehicles sold post 2000 could be allocated a fuel consumption estimate) does not seem to bias the results.

Parameter	5-6 L/100km	6-7 L/100km	7-8 L100km	8-9 L/100km	9-10 L/100km
lnPrice	-0.068***	-0.0023	-0.025***	-0.089***	-0.15***
	(0.003)	(0.006)	(0.003)	(0.006)	(0.01)
lnGDP	0.14***	0.21***	0.15***	0.092***	0.019
	(0.02)	(0.03)	(0.02)	(0.03)	(0.05)
Age	-0.034***	-0.037***	-0.032***	-0.038***	-0.044***
	(2e-04)	(4e-04)	(2e-04)	(4e-04)	(7e-04)
lnHDM	-0.021***	-0.023***	-0.022***	-0.0084*	-0.0091
	(0.002)	(0.004)	(0.002)	(0.004)	(0.007)
lnRain	0.007***	0.011***	0.0053***	-0.0025	0.0075
	(0.001)	(0.003)	(0.001)	(0.003)	(0.005)
Month Effects	X	X	X	X	X
Period Effects	X	X	X	X	X
Vehicle Effects	X	X	X	X	X
Observations	4567699	1411150	4723685	1258264	444424
R^2	0.03	0.03	0.03	0.04	0.06

Table B.6 Regression results by real world fuel consumption of vehicles. Dependent variable is the natural logarithm of vehicle mileage. Data is based on a random sample of 10 million vehicles which are filtered for erroneous entries and then tracked through time. Fuel consumption is based on real world reported values and is quoted in Litres of gasoline equivalent. Standard errors clustered at the vehicle level for each coefficient are included in parentheses. Statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Parameter	FC_sample
lnPrice	-0.048 (0.002)***
lnGDP	0.14 (0.009)***
Age	-0.034 (1e-04)***
lnHDM	-0.022 (0.001)***
lnRain	0.006 (9e-04)***
Month Effects	X
Period Effects	X
Vehicle Effects	X
Observations	12200570
R^2	0.03

Table B.7 Regression results of vehicles attributed an estimated specific fuel consumption. Dependent variable is the natural logarithm of vehicle mileage. Fuel consumption is based on real world reported values and is quoted in Litres of gasoline equivalent. Standard errors clustered at the vehicle level for each coefficient are included in parentheses. Statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

B.10 Public transport provision

Changes in public transport provision could in theory have an impact upon the results. However, there is no publicly available consistent data on public transport at detailed geographical levels. Table BUS0110a DfT (2020b) published by the Department for Transport provides some information but only for England, from 2010 onwards and disaggregated data for London is not provided. However, the main limitation to investigating public transport use further is that the MOT data is at postcode area level. These are relatively large geographical areas that encompass both main cities but also accompanying rural areas. Grouping data for England in 2011 from table BUS0110a DfT (2020b) up to postcode area level and plotting it against the average population density of the postcode (figure B.8, left) shows there is no significant relationship between the two principally because the data is aggregated and any differences between cities and rural areas are merged. Plotting the β_{Price} estimated for each postcode in section 4.5 against this limited set of bus trips data (figure B.8, right) shows no significant correlation. With MOT data at a more granular level of geographical resolution this could be an interesting avenue of further study.

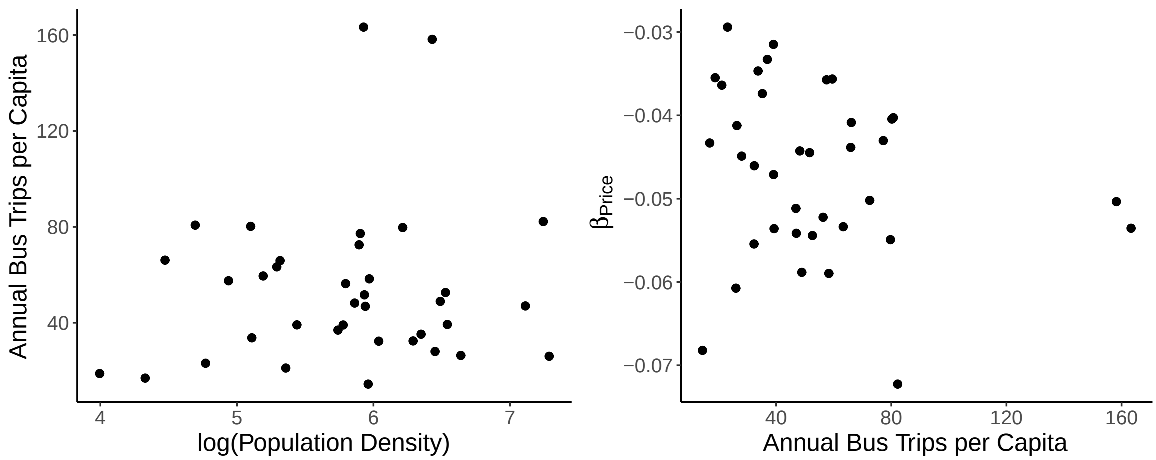

Fig. B.8 Scatter plots of annual bus trips per capita in each postcode (note only England is considered) in year 2011 vs. log(population density) (inhabitants/km^2) (left) and β_{Price} estimates in each postcode vs. bus trips (right).

B.11 Postcode regression results and statistics

It is possible that the β_{Price} elasticities shown in figure 7 could be biased by a different make up of the vehicle fleet in each postcode. This is unlikely to be the case, as shown in fig. B.9 below, which shows scatters of the β_{Price} estimate of each postcode against the share of each vehicle size segment in that postcode. If there were a strong trend between the share of SUVs and the price elasticity in vehicle postcodes it would suggest a possible dependency.

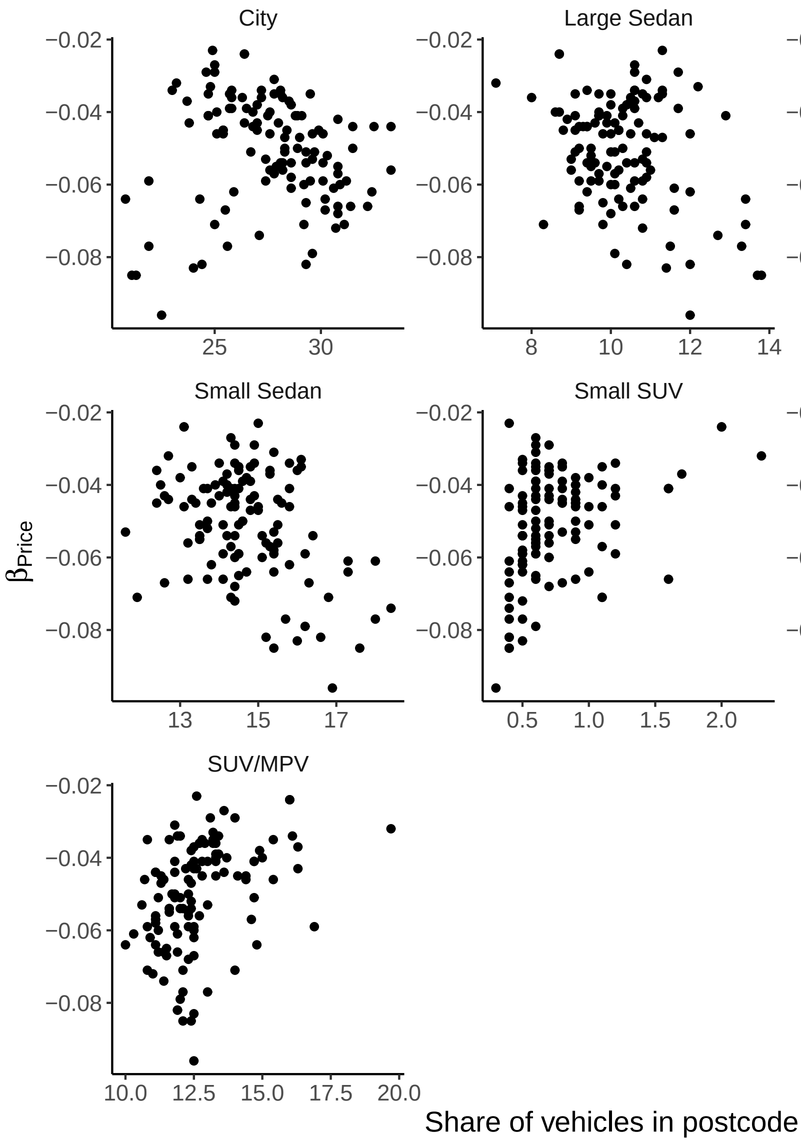

Fig. B.9 Scatter plots of β_{Price} estimates in each postcode vs. the share of each vehicle size segment in each postcode. Shows there is no strong relationship between size segment and β_{Price}.

The regression results of dummy variable interactions between fuel price and postcode area are presented in the following tables alongside postcode summary data.

Table B.8 Postcode statistics (income, population density, average mileage per year) and regression results, (Beta= β_{Price}, pvalue and SE= standard error)

Postcode	Income (£ 2011)	PopDensity (pp/km^2)	Miles/yr	Beta	pvalue	SE
AB	37227	40	7708	-0.046	0.00	0.003
AL	47321	590	7071	-0.046	0.00	0.003
B	28037	1232	7276	-0.058	0.00	0.003
BA	33768	204	7294	-0.044	0.00	0.003
BB	28228	419	7506	-0.055	0.00	0.003
BD	28368	352	7242	-0.071	0.00	0.003
BH	31967	500	6552	-0.055	0.00	0.003
BL	28808	1297	7027	-0.066	0.00	0.003
BN	32309	620	6687	-0.05	0.00	0.003
BR	50713	1799	5541	-0.079	0.00	0.004
BS	34097	693	6926	-0.054	0.00	0.003
CA	29517	54	7804	-0.045	0.00	0.004
CB	39812	192	8042	-0.023	0.00	0.003
CF	27360	643	7640	-0.044	0.00	0.003
CH	30354	539	7453	-0.046	0.00	0.003
CM	40886	333	7716	-0.036	0.00	0.003
CO	32898	278	7436	-0.041	0.00	0.003
CR	43849	2467	6032	-0.077	0.00	0.003
CT	29632	497	7320	-0.041	0.00	0.003
CV	31401	407	7359	-0.047	0.00	0.003
CW	34076	259	7183	-0.051	0.00	0.003
DA	39593	1597	6739	-0.056	0.00	0.003
DD	29223	2457	7667	-0.041	0.00	0.004
DE	30676	363	7279	-0.05	0.00	0.003
DG	31056	16	7987	-0.041	0.00	0.004
DG	28030	23	7987	-0.041	0.00	0.004

Postcode	Income (£ 2011)	PopDensity (pp/km^2)	Miles/yr	Beta	pvalue	SE
DH	27777	352	7654	-0.044	0.00	0.003
DL	28741	88	7843	-0.041	0.00	0.003
DN	27515	230	7713	-0.047	0.00	0.003
DT	30070	111	7056	-0.045	0.00	0.004
DY	28930	464	6412	-0.067	0.00	0.003
E	34614	8060	7244	-0.077	0.00	0.003
EN	42435	1254	6645	-0.059	0.00	0.003
EX	31314	100	7231	-0.04	0.00	0.003
FK	31592	525	8211	-0.038	0.00	0.004
FY	29467	1399	6433	-0.072	0.00	0.004
G	31828	3395	7492	-0.053	0.00	0.003
GL	34144	188	7457	-0.039	0.00	0.003
GU	48014	375	7473	-0.035	0.00	0.003
HA	47143	4404	6260	-0.071	0.00	0.003
HD	30013	688	6868	-0.066	0.00	0.004
HG	37147	99	7282	-0.057	0.00	0.004
HP	45313	378	7544	-0.039	0.00	0.003
HR	31109	76	7405	-0.043	0.00	0.004
HS	28462	9	7461	-0.064	0.00	0.009
HU	28234	391	6990	-0.059	0.00	0.003
HX	28671	558	6788	-0.071	0.00	0.004
IG	41199	2950	6564	-0.074	0.00	0.004
IP	32515	143	7799	-0.029	0.00	0.003
IV	32726	9	8276	-0.034	0.00	0.004
KA	28467	156	8109	-0.035	0.00	0.003
KT	55939	1347	6178	-0.062	0.00	0.003
KW	28842	9	7177	-0.059	0.00	0.006
KY	30051	275	7934	-0.035	0.00	0.003
L	28126	1440	7269	-0.061	0.00	0.003
LA	31237	108	7171	-0.051	0.00	0.004
LD	26529	19	7812	-0.032	0.00	0.006
LE	32165	380	7216	-0.051	0.00	0.003

Postcode	Income (£ 2011)	PopDensity (pp/km^2)	Miles/yr	Beta	pvalue	SE
LL	25293	103	7953	-0.034	0.00	0.003
LN	29576	100	7625	-0.043	0.00	0.003
LS	31447	591	7357	-0.057	0.00	0.003
LU	34057	634	7583	-0.045	0.00	0.003
M	26619	2813	6878	-0.064	0.00	0.003
ME	34138	572	7588	-0.037	0.00	0.003
MK	37937	323	7863	-0.031	0.00	0.003
ML	28121	719	8042	-0.046	0.00	0.003
N	42858	7670	6379	-0.082	0.00	0.003
NE	28010	220	7540	-0.05	0.00	0.003
NG	29682	375	7193	-0.054	0.00	0.003
NN	33668	273	7990	-0.034	0.00	0.003
NP	25598	298	7582	-0.042	0.00	0.003
NR	29358	196	7303	-0.043	0.00	0.003
NW	46111	6875	6079	-0.085	0.00	0.003
OL	27096	1079	7000	-0.066	0.00	0.003
OX	39645	200	7851	-0.027	0.00	0.003
PA	31065	668	7519	-0.051	0.00	0.003
PE	30894	140	7898	-0.036	0.00	0.003
PH	32843	28	8139	-0.037	0.00	0.004
PL	29020	164	7199	-0.04	0.00	0.003
PO	31626	684	6659	-0.054	0.00	0.003
PR	31520	420	7296	-0.054	0.00	0.003
RG	45935	311	7595	-0.033	0.00	0.003
RH	45256	346	7214	-0.039	0.00	0.003
RM	36467	1461	6851	-0.061	0.00	0.003
S	27522	651	7181	-0.06	0.00	0.003
SA	24213	115	7563	-0.045	0.00	0.003
SE	39020	7828	6093	-0.083	0.00	0.003
SG	40784	292	7679	-0.034	0.00	0.003
SK	34099	388	6427	-0.068	0.00	0.003
SL	47426	765	7408	-0.041	0.00	0.003
SM	50458	3577	5441	-0.082	0.00	0.004
SN	36077	180	7733	-0.036	0.00	0.003
SO	36673	366	7303	-0.043	0.00	0.003

Postcode	Income (£ 2011)	PopDensity (pp/km^2)	Miles/yr	Beta	pvalue	SE
SP	37847	118	7995	-0.029	0.00	0.003
SR	25827	1626	7310	-0.056	0.00	0.004
SS	32832	1228	6853	-0.054	0.00	0.003
ST	28206	329	7221	-0.052	0.00	0.003
SW	55544	8418	5464	-0.096	0.00	0.003
SY	29354	54	7820	-0.035	0.00	0.003
TA	30683	120	7085	-0.046	0.00	0.003
TD	27501	21	8351	-0.024	0.00	0.004
TD	28565	24	8351	-0.024	0.00	0.004
TF	30860	166	7876	-0.035	0.00	0.004
TN	39535	231	7267	-0.038	0.00	0.003
TQ	29960	199	6541	-0.053	0.00	0.003
TR	28709	212	7260	-0.036	0.00	0.004
TS	27443	378	7780	-0.044	0.00	0.003
TW	47975	2510	6220	-0.067	0.00	0.003
UB	38679	2774	7080	-0.064	0.00	0.003
W	51028	8960	5688	-0.085	0.00	0.004
WA	32919	658	7158	-0.059	0.00	0.003
WD	47244	1064	6732	-0.056	0.00	0.003
WF	28054	925	7414	-0.06	0.00	0.003
WN	28559	989	6816	-0.062	0.00	0.003
WR	34665	178	7360	-0.045	0.00	0.003
WS	27995	755	7088	-0.059	0.00	0.003
WV	26513	476	6841	-0.065	0.00	0.003
YO	30820	109	7709	-0.04	0.00	0.003
YO	30448	118	7709	-0.038	0.00	0.003
ZE	32150	16	7695	-0.089	0.00	0.013

Appendix C

The future potential of efficiency improvements

C.1 Regression Results

Data on fuel economy/energy efficiency of BEVs and PHEVs used to calculate the sensitivities of efficiency and weight to vehicle attributes are sourced from (EPA, 2020). These are matched with vehicle dimensions and weight data from online databases (McGregor, 2017). ICE and HEV coefficients from Craglia and Cullen (2019a).

MJ/km	**Powertrain** f				
	ICE	HEV	PHEV_{ICE}	PHEV_{EV}	BEV
β_{Power} (MJ/km kW) $\times 10^-3$	8.642 ***	6.637***	5.375***	2.181 ***	0.155 *
β_{Area} (MJ/km m^2)	0.653 ***	0.632***	0.571 ***	0.293 ***	0.221 ***
R^2	0.648	0.872	0.785	0.727	0.351
Observations	94673	852	122	122	118

Table C.1 Sensitivity coefficients between vehicle attributes (frontal area and power) and vehicle energy efficiency. Statistical significance: . $p<0.1$,* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Vehicle Weight	**Powertrain** f			
	ICE	HEV	PHEV	BEV
ϕ_{Power} (kg/kW)	2.647 ***	3.426***	1.887 ***	1.169 ***
ϕ_{Area} (kg/m^2)	846.7 ***	859.4***	581.4***	670.2 ***
R^2	0.835	0.902	0.835	0.625
Observations	94673	852	122	118

Table C.2 Sensitivity coefficients between vehicle attributes (frontal area and power) and vehicle weight. Statistical significance: . $p<0.1$,* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Battery Weight	**Powertrain** f	
	BEV	PHEV
λ_{Power} (kg/kW)	1.079 (0.08) ***	0.039 (0.01) ***
λ_{Area} (kg/m^2)	98.89 (52.3) .	7.09 (3.09) *
R^2	0.745	0.277
Observations	118	102

Table C.3 Sensitivity coefficients between vehicle attributes (frontal area and power) and battery weight. Statistical significance: . $p<0.1$,* $p<0.05$, ** $p<0.01$, *** $p<0.001$

LightWeighting

	Estimate	SE	
(Intercept)	-596.888	6.43475	***
Year2002	1.9211	3.84033	
Year2003	-17.6503	3.97064	***
Year2004	-12.8253	3.91869	**
Year2005	-11.2795	3.81559	**
Year2006	-4.33146	3.92685	
Year2007	-4.14075	3.96475	
Year2008	-12.164	3.97037	**
Year2009	-13.7359	3.84719	***
Year2010	-7.90003	3.78103	*
Year2011	-7.77708	3.85892	*
Year2012	-24.3646	3.78738	***
Year2013	-31.5203	3.76808	***
Year2014	-51.7437	3.75628	***
Year2015	-63.4783	3.62143	***
Year2016	-90.7678	3.73732	***
Year2017	-91.674	3.73152	***
Year2018	-105.288	3.88067	***
kw	2.64712	0.01077	***
Area	846.7431	2.28661	***
R^2	0.708		
Observations	94673		

Table C.4 Regression of vehicle weight vs. engine power (kw) and frontal area with year dummy variables. Statistical significance: . $p<0.1$,* $p<0.05$, ** $p<0.01$, *** $p<0.001$

C.2 Data

The main sources of data used to initialize the stock model are presented in table C.5.

Parameter	Source
Registered vehicles, years 2011-2018	DfT (2019c)
Number of newly registered vehicles	DfT (2019d)
Vehicle Occupancy	DfT (2019a)
New car average power and frontal area	Craglia and Cullen (2019a)
New car average real-world fuel efficiency	Craglia and Cullen (2019a)
BEV, PHEV new car average WLTP fuel efficiency	VCA (2019)
British passenger transport by mode 2002-2018	DfT (2019b)
Electricity and Fuels GHG Conversion factors	BEIS (2019a)
Fuel consumption information for EVs and PHEVs	EPA (2020)

Table C.5 Sources of data

C.3 Powertrain emissions

The table below shows the base level of emissions intensity of vehicles in the year 2018. PHEVs are split by 50% utilisation factor in the upper bound and 90% utilisation in the lower bound. MJ/km is the average energy efficiency of each powertrain, for PHEVs this is a compound of electricity and fuel. gCO_2/MJ is the average emissions produced for each MJ of fuel (again a compound for PHEVs based on the utilisation factor assumed). The carbon intensity of electricity in 2018 was 248 gCO_2/kWh.

Data	Year	MY	MJ/km	gCO_2/MJ	gCO_2km
ICE	2018	2018	2.34	72.99	170.79
HEV	2018	2018	1.75	72.99	127.73
BEV	2018	2018	0.72	68.89	49.6
PHEV (90% U)	2018	2018	0.88	69.3	61.12
PHEV (50% U)	2018	2018	1.53	70.94	108.54