Modelling the impact of policy incentives on CO_2 emissions from passenger light duty vehicles in five major economies with a dynamic model of technological change

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This dissertation is submitted for the degree of

Doctor of Philosophy

Oct 2018

Declaration

This dissertation 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 dissertation 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.

Acknowledgement

Firstly, I would like to express my sincere gratitude to my supervisor, Dr Jean-Franois Mercure, for his tremendous support during my PhD study, for his guidance, patience and motivations. It has been an honour to work with him and to be the first undergraduate, and master's and PhD student he supervised in Cambridge. I feel extremely grateful for the time he spent on teaching and inspiring me, even after he started a new career in the Netherlands. I want to express my special appreciation and thanks to my supervisor, Professor Andreas Kontoleon, for his huge support throughout my PhD study. His advice on both research and career has been invaluable. I am grateful to Prof David Reiner and Prof Brian O Gallachoir for their detailed and insightful comments on my dissertation.

I must also express my gratitude to my family, especially my parents, for their continuous support and unparalleled love. I am grateful for my mum, who calls me everyday just to make sure I am well and happy. I am forever indebted to my parents for giving me the opportunities and support to study in this country for the past ten years. My journey here would not have been possible without their selfless encouragement.

I want to thank everyone I met in Cambridge, especially people in the 4CMR, C-EENRG and the Department of Land Economy. In particular, I thank Professor Douglas Crawford-Brown for his encouragement during my stay in 4CMR and Professor Jorge Viuales for inviting me to join C-EENRG, where I met some of my lifelong friends. I thank Chunghan, Aiora, Terry, Pablo, Ida, Pierre, Pau and Leslie-Anne for making our office in DAB an extremely friendly and warm place.

I wish to thank my dearest friend Charles for his love, support and companionship in life. I also want to thank my friends Karolis, Ziyou, Xiyan, Lun, Mao, Mo and Philip for making the PhD life in Cambridge an unforgettable experience.

Finally, I am very grateful for help from people at the Cambridge Econometrics, in particular Unnada, Sophie and Hector for their continuous support throughout my PhD study. I also want to thank Dr Charlie Wilson and Dr Hazel Pettifor for their advice and help with the research.

Abstract

Low-emission vehicle technologies are needed to mitigate rising greenhouse gas emissions from passenger light-duty vehicles (PLDVs). Policy incentives send a signal to consumers and car manufacturers to influence purchasing decisions and the adoption of low-emission vehicles. In this thesis, an innovative model formulation is developed to represent consumer group diversity by capturing different vehicle technologies and engine types. This thesis contributes to the existing literature by modelling and quantifying the impact of different policy measures across five countries, the US, the UK, Japan, China and India. I first explore how policy instruments, such as the annual registration tax, EV subsidy, fuel tax, EV mandate and fuel economy regulations, impact the diffusion of various PLDV technologies and CO_2 emissions at different levels. Subsequently, by studying the interactions between policy instruments, I uncover the trade-off effect and reinforcement effect between the different policy incentives, and how the interactions between policy incentives influence the effectiveness and efficiency of policy instruments in reducing PLDV CO_2 emissions in different countries. This research explores how income changes in different countries impact PLDV choice and the effectiveness of each policy instrument in reducing PLDV emissions.

The findings of this research indicate that policy instrument effectiveness varies between countries and specifically depends on the levels of incentive, the design of the policy incentives and the existing markets for low emission vehicles. Financial incentives such as taxes and EV subsidies are more effective in China and the UK. Fuel economy regulation is more effective in the US, where, on average, engine sizes for conventional cars are large. While I find that there is a general trade-off effect between the financial incentives (i.e. the annual registration tax, fuel tax and EV subsidies), there is also a reinforcement effect between the EV mandate programme and all other policy incentives. Overall, I find that the income effect leads to a small increase in cumulative emissions from PLDVs in the UK, the US, Japan and India, due to the diffusion of luxury vehicles at the expense of small vehicles. In the case of China, I find that cumulative emissions from PLDVs decrease as income increases due to EV diffusion.

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Chapter 1

Introduction

1.1 Motivation

1.1.1 Paris Agreement and the role of the transport sector

In 2015, the Paris Agreement was adopted under the United Nations Framework Convention on Climate Change (UNFCCC). The overarching climate goal of the Paris Agreement is to hold 'the increase in the global average temperature to well below 2°C above the pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels'. Existing climate studies find that about two-thirds of the available carbon budgets for keeping the warming to below 2°C has already been emitted (Millar et al., 2017). A decline in global emissions is urgently required to keep within a 2°C-compatible budget (Rogelj et al., 2016, 2018; Grubler et al., 2018).

To achieve the goals set out by the Paris Agreement, all parties are required to undertake efforts towards reaching global peaking of greenhouse-gas (GHG) emissions as soon as possible. Under the agreement, all governments that have ratified, including the US, China, India and the EU, carry an obligation to achieve the goals that are determined by their country individually and called 'nationally determined contributions' (NDC). Each country sets its own emissions-reduction targets 'with the view to achieving the goal of the Paris Agreement'. For example, the EU committed to a target of 'at least 40%' domestic emissions reduction below 1990 levels by the year 2030 (EC, 2014*a*). China agreed to cut the overall CO_2 emissions per unit of GDP by 40%-45% below 2005 levels by the year 2020, and to peak its CO_2 emissions by 2030 at the latest (Climate Tracker, 2016).

Participating countries will have to adopt different pathways and determine the exact climate policies that will achieve the NDC goals. Transport accounts for a significant share of global fossil fuel combustion-related emissions, producing 7 Gt CO_2 eq of direct GHG emissions in 2010, and was responsible for around 23% of total energy-related CO_2 emissions (IPCC, 2014, p426). Today, among the end-use sectors, transport is the largest CO_2 emitter and the most heavily reliant on fossil fuels. If unabated, the sector's emissions will grow faster than emissions in other energy-related sectors. The large contribution to emissions from the transport sector justifies its important role in significantly reducing emissions and meeting the ambitious climate change goal set by the Paris Agreement, especially in countries where the demand for passenger transport is growing rapidly.

The rapid growth in the transport sector is driven by emissions from the road sector, which have increased by 52% since 1990. In particular, the Passenger Light-Duty Vehicle (PLDV) fleet is projected to expand from 900 million in 2012, to over 1.7 billion in 2035 (IEA, 2012). Following the definitions found in IEA (2017*b*), this thesis includes among PLDVs passenger cars, SUVs and passenger light trucks, but excludes two-wheelers, three-wheelers and low-speed/low-power four-wheeled vehicles, despite India and China being two of the largest two-wheeler markets in the world.

Following the Paris Agreement, some countries have proposed a policy framework or a target to cut emissions from the transport sector, particularly concerning PLDVs. For example, EU legislation sets mandatory emission-reduction targets for new cars. The European Strategy for low-emissions mobility suggests a number of measures aimed at reducing emissions from the transport sector by 60% below 1990 levels by the year 2050 (CarbonBrief, 2015), and PLDV contributions play an important role in emissions reduction from the transport sector. By 2021, phased in from 2020, the EU regulations stipulate that the fleet average that all new cars must achieve is 95 grams of CO_2 per kilometre (EC, 2015). China has announced that it will finalise next-stage fuel-efficiency standards for passenger vehicles and implement them in 2019; thus, the new standards represent an improvement in fuel economy of 6.2% per year between 2016 and 2020 (Feng, 2016).

Policy incentives send consumers and car manufacturers a signal intended to influence purchasing decisions and the adoption of low-emissions vehicles. The levels and the structure of incentives could be used to influence the adoption and development of new-car technologies. The design, level and structure of the instruments determine the effectiveness of the policies and achieving the emissions-reduction targets in the long run. The objective of this thesis is to find the effectiveness and efficiency of several existing, commonly used policy incentives, including the vehicle-registration tax, fuel tax, electric-vehicle (EV) subsidies, fuel-economy regulation and the EV mandate at different levels of stringency in the UK, the US, Japan, China and India, until 2050.

Because policies are almost always introduced simultaneously, this research analyses the interactions between policy incentives. The inclusion of more effective policies in the policy mix allows a less stringent policy to be set than would otherwise be the case to achieve a given level of abatement. Alternatively, the effectiveness would be greater for a given tax level (IEA, 2011*b*). The aim is to find the reinforcement effect and the trade-off effect between policy incentives when they are introduced in different countries.

1.1.2 Fossil fuel dependency and energy security

The transport sector was responsible for over 60% of global oil consumption in 2012 (GlobalPetrolPrices, 2015). Fossil fuel dependency and high demand for oil raise significant concerns for national energy security. Historically, volatile oil prices have been responsible for economic downturns and recessions. For example, in the US, of the 11 post-war recessions, 10 were preceded by sharp increases in oil prices (Grubb, 2014). Conversely, a low oil price may lead to stranded fossil fuel assets (SFFA) in oil-producing countries. Historically, the high prices of fossil fuels have damaged the economy of oil-consuming countries by raising the price of transporting people and goods, while the economy for the oil-producing countries suffers from low oil prices. With much of the world's petroleum reserves located in politically volatile countries, most major oil-consuming countries, such as the US and China, are vulnerable to price spikes and face energy security concerns. This provides incentives for governments to encourage energy efficient vehicles to reduce reliance on oil.

1.1.3 Technological transitions

The diffusion of new energy technology vehicles (e.g. electric vehicles) into the marketplace, and the improvement in fuel economy of the existing petrol cars, determine technological trajectories that are critical in emissions reductions and combating climate change (Kemp, 2000). As stated in IPCC (2014) (p 647), 'understanding how low-carbon transport and energy technologies will evolve (via experience curves and innovation processes) is not well developed', and assessing this gap remains challenging for the PLDV sector.

Technological transitions (TT) are defined as major technological transformations in the way societal functions are fulfilled (Geels, 2002). TT involves both changes in technologies and changes in user practices, regulations, infrastructure, and symbolic meaning and culture (Geels, 2002). Regarding the PLDV sector, auto-mobility is embedded in lifestyles and stabilised through sunk investments and existing practices. Although new energy technologies, such as hybrid vehicles and EVs, are more fuel efficient and generate lower emissions, these technologies have barriers to deployment, including vehicle cost, the electric driving range, long battery-charging times and the restricted choice of vehicle models. Compared with EV, the incumbent technologies have a distinct advantage because they are more widely used and dominant, causing a technological lock-in.

The barrier to technological innovation and transitions in the automotive sector is that there are lock-ins in the process of technological diffusion. A technological lock-in can be defined as positive feedback or increasing returns for the adoption of selected technologies, as a result of social influence and the economies of scale in the car manufacturing sector (Arthur, 1994; Unruh, 2000). Regarding the PLDV sector, the main lock-in mechanisms are learning effects, economies of scale, network externalities and collective action (Klitkou et al., 2015). On the production side, through technological breakthroughs and learning, manufacturers improve vehicle features, increase fuel efficiency and reduce costs of the car technologies. In a co-evolutionary framework, as vehicles become more popular, producers use their profits to expand their production capacity and encourage further purchases by the consumers of PLDV technologies.

On the demand side, consumer choices and their behaviours drive the demand process for transport technologies. Consumer heterogeneity partly determines the rate of adoption of clean technologies. Rogers (2010) illustrates that the diversity of consumers (early adopters, early majority, late majority and laggards) determines the scaling of the typical S-shape profile of diffusion. In terms of the diffusion for zero-emissions vehicles, in contrast to the late adopters, the first group of consumers willing to adopt new technologies is often willing to pay a premium for innovations and may be less risk averse (Carley et al., 2013). The diversity of consumers determines the elasticities of technology substitution (Mercure and Lam, 2015).

1.1.4 The role of the passenger light-duty vehicle (PLDV) technologies

Technology innovation is a major driving force behind the improvements in transport fuel economy to reach emission-reduction targets. For instance, advanced technology, such as the start-stop system, reduces average fuel consumption and has been incorporated into many new vehicles by manufacturers to meet the stringent policy regulations. The use of radical technologies, such as electric vehicles, would make it possible to reduce dependency on fossil fuels, as well as decarbonise and reduce emissions in the transport sectors (ETP, 2012)(p102). This section sets the historical context for the present research on the process of technological diffusion for passenger vehicles.

Petrol cars

By the end of the 19th century, the automobile had emerged as a radically new transport option. Since steam engines and electric motors had been developed, early automobiles were constructed by adding electric engines and steam engines to existing coaches to replace horses. The problem with the early EV of that period was that compared with petrol cars, EVs were limited by the energy content of the lead-acid battery, and hence could not offer a long range or high speed, which were already established as prominent performance criteria for automobiles (Geels, 2005*b*). These criteria led to the development by Karl Benz, in 1886, of the world's first purpose-built car powered by an Internal-combustion engine. However, the Benz model was not affordable for the general public. In 1908, Ford's Model T was introduced as the first affordable car model that was sufficiently robust, built with a speed of up to 40 miles an hour. Ford's Model T established a large market for automobiles, and the sales of petrol cars increased rapidly, overtaking EVs.

As a result of strong technological lock-in and path dependence, petrol cars have continued to gain market share, and the shares of other alternative-fuel vehicles (e.g. hybrid cars, EVs) have remained low, although several historical incidents have sparked interest in developing and facilitating the take-up of alternative-fuel vehicles. For instance, the interest in EVs re-emerged in the 1960s and 1970s, triggered by the 1965 Clean Air Act in the US. However, due to poor performance and price compared with their gasoline counterparts, less than 4,000 EVs had been produced worldwide by the end of the 1970s (Dijk et al., 2012).

The continued reliance on petroleum as the main fuel for vehicles has raised concerns regarding national energy security and global climate change. For instance, in the case of China, between 2000 and 2014, the dependence rate on oil imports increased from 30.2% to 59.6% as a result of the increased demand for private passenger vehicles (BP, 2016). This heavy dependence on oil imports causes concerns over national energy security and impedes economic growth when oil prices are high. Thus, China has been looking to diversify its energy resources, and encourage the growth of alternative-fuel cars. Besides national energy security concerns, under the Paris Agreement, several countries (e.g. China, EU) are taking steps to strengthen the existing fuel economy standards. The fuel efficiency of new gasoline vehicles has continued to improve with advanced engine technologies, such as Start-Stop and Variable Valve Timing, which have been incorporated into the latest car models.

Diesel cars

The first diesel cars were made by Citroen in 1933. However, compared with petrol cars, diesel cars have been less popular for passenger vehicle use but more popular for heavy-duty vehicles. During the oil crisis, the market shares for diesel cars increased significantly in Europe. In particular, after the second oil crisis in 1979, car companies started to develop diesel versions of gasoline engines. In the 1990s, with the purpose of cutting GHG emissions, the EU nations promoted low CO_2 emission diesel cars by imposing a heavier tax on petrol cars, subsidising diesel cars and improving diesel car technologies.

However, diesel cars generate more pollution than petrol cars through the production of particulate matter and nitrogen oxides. Several cities, including Madrid, Paris, Mexico City and Athens are implementing a ban on diesel cars to improve air quality. Starting in 2019, diesel car owners will be required to pay an extra GBP 12.50 to enter central London. Thus, the future sales of diesel cars will be affected by global air pollution concerns.

Battery electric vehicles (BEV)

Since 2005, there has been a revived interest and momentum for EV as a result of climate change concerns, urban pollution concerns and fossil fuel dependency for national governments. Without technological advancement, EVs had previously faced several barriers, such as high cost and range anxiety (i.e. consumers' concern about the shorter driving range), making it difficult for EVs to compete with petrol cars in the marketplace. High risk and cost of investment in EVs mean that car manufacturers have been reluctant to invest in EVs unless they believe there is a market for them. Tesla was the first company to produced automobiles with a lithium-ion battery. To overcome range anxiety, the company produced EVs with a range of over 270 miles (Straubel, 2014). Other car manufacturers, such as General Motors (GM) and BYD, have also invested in EV battery improvement and manufacturing, making EV more affordable, more durable and capable of longer ranges (up to 250 miles) than the previous EV models.

Some policymakers have used climate concerns to develop regulatory frameworks and promote the diffusion of EVs. Concerns about climate and air pollution have motivated some governments (e.g. UK, China) to demand that the car industry decrease emissions. Policies have also been established in some countries to encourage consumers to purchase cleaner and lower-emission vehicles in some countries. These incentives motivate car manufacturers to invest in EV production and development, which will create a more competitive environment that drives the cost of EVs down through learning. Doing so makes EVs more accessible to the market.

As a result of the incentives to support the penetration of EVs, globally, there were more than one million EVs worldwide in 2015 (IEA, 2012). In some countries, the market shares for EVs are very high, such as Norway and the Netherlands. Market shares for new EVs have reached 23% in Norway and nearly 10% in the Netherlands (IEA, 2012).

Fuel cell electric vehicles (FCEVs)

A fuel-cell vehicle is a type of electric vehicle that uses electricity generated from the electrochemical reactions of hydrogen and oxygen, with water being the by-product. Unlike petroleum, hydrogen is not an energy resource by itself but is produced from natural resources, such as gas wells or by electrolysis of water. Around the world, Japan is the leading country for commercialising fuel-cell electric vehicles (FCEVs), with Toyota and Honda both having put FCEVs on the road. FCEVs have a significant barrier to entry due to their high purchase prices and the high cost of fuel cells, hydrogen tanks and hydrogen filling stations. For example, a Mirai car costs twice the price of a comparable EV (59,000 USD), and therefore, there were only around 2,000 FCEVs in Japan (until 2017) (Chasan, 2018).

So far, the body of research on consumer perceptions and the future diffusion of FCEVs is very limited. Because of a lack of historical data and the very niche status of the FCEV, it is not included the FCEV in this analysis.

Ethanol cars

In 1973, global oil prices doubled when oil-producing countries created a cartel and restricted oil supplies (Grubb, 2014). The oil-price shock encouraged the production of more efficient smaller vehicles and gave rise to flex-fuel cars in Brazil. First-generation bioethanol is produced from renewable resources, such as sugar cane, corn, rice and other grains. Although the biofuel produced from renewable resources could help minimise burning fossil fuel and CO_2 production, it is been argued that there may be substantial conflict between the production of biofuel and food production (Searchinger et al., 2015). Second-generation biofuel is made from lignocellulosic biomass (plant matter that is not food), woody crops or waste, and thus, has a lower impact on food prices. Compared with first-generation biofuel, second-generation biofuel can be grown on marginal lands instead of in direct competition with food for land use. However, presently, second-generation biofuels are much less efficient, and large-scale production is not economically feasible, although lignocellulosic ethanol production from biomass may become more promising in the future.

Brazil introduced a pioneering programme for the introduction of ethanol as a fuel for automobiles in the 1970s. The programme involved supply infrastructure, and developed technologies for ethanol-fuelled vehicles by government research centres and Brazilian automakers (Seraphim, 2009). The demand for ethanol collapsed during the 1980s when oil prices fell and the price of sugar increased (Grubler and Nemet, 2013). In 2003, the creation of flex-fuel vehicles that can run on any combination of ethanol and gasoline gave consumers the flexibility of choosing between fuels, especially when prices for the commodities fluctuated. The Brazilian government encouraged the diffusion of flex-fuel cars by introducing a lower tax rate on car purchases of 14% for flex-fuel cars, compared with 16% for petrol cars. Beginning in 2003, the number of flex-fuel cars in Brazil continued to increase, and by 2016, more than 80% of new cars sold in Brazil were flex-fuel vehicles. The fuelling infrastructure for ethanol is very well developed in Brazil, and flex-fuel vehicles allow consumers to choose between petrol fuel and ethanol fuel.

Outside Brazil, the US has the second largest flex-fuel fleet in the world, with around 20 million flex fuel vehicles in use in 2018 (EIA, 2018). However, in reality, the use of ethanol fuel is limited in the US due to a lack of E85 refuelling infrastructure. Up to 2013, about 2,800 of the 110,000 fuel stations in the US reported offering E85, with a great concentration of E85 stations in the Corn Belt states (Seraphim, 2018). The scarcity of fuel stations offering E85 is a major obstacle to the expansion of ethanol consumption through E85 (Pouliot and Babcock, 2017). Hence, despite the fact that around 5% of the fleet in the US are flex-fuel cars, the actual usage of these flex-fuel cars remains much lower because only 2.5% of fuelling stations in the US have an ethanol filling facility (Seraphim, 2018).

Hybrid cars

Hybrid cars started to gain market share in several developed countries, such as the US, the UK and Japan. Niche innovations do not necessarily compete with existing technologies, but may enter into a 'new combination' with them (Geels, 2002). Hybrid cars consist of a combination of a battery and an internal-combustion engine. The Prius I was launched in 1997 in Japan and the Prius II in 2000 in California. Toyota managed to sell more than one million units of the Prius worldwide between 1997 and 2007. In countries such as Japan, there are already five million hybrid cars on the road, accounting for around 25% of the market share.

For consumers, the advantages of hybrid cars over EVs is that they do not need to be plugged in with a charging station and do not require a change in driving habits. Compared with conventional petrol cars, hybrid cars use less gasoline and have lower CO_2 emissions. Depending on the model, hybrid cars have the potential to cut emissions by more than 50% compared with conventional petrol cars. Therefore, hybrid cars will cut fossil fuel consumption and reduce emissions from passenger vehicles.

Natural gas vehicles (NGV)

An alternative fuel to petrol and diesel fuel is natural gas, which has certain advantages over oil as a transportation fuel. Natural-gas vehicles (NGVs) are considered an alternative that produces lower levels of CO_2 emissions (around 25% lower than gasoline) and emissions of other pollutants, such as carbon monoxide, when compared with most oil-fuelled vehicles. In terms of price, natural gas is generally less costly than petroleum fuels on an energy equivalent basis, with less price volatility (Nersesian, 2016).

Liquid petroleum gas (LPG) provides 8% more energy per unit weight than petrol (Ristovski et al., 2005). LPG cars are purposely built or converted from petroleum cars. The fuel system for compressed natural gas (CNG) cars is very similar to the LPG systems. Further, CNG cars can be converted from petrol cars with an average cost range from 1,640 USD to 2,190 USD (ETSAP, 2010). The number of NGVs has increased significantly in China, from 6,000 in 2000 to 3 million NGVs by 2013 [1]. NGVs emit 20% fewer GHG emissions than conventional cars and have been popular with long-distance drivers and taxi drivers. Moreover, NGVs provide an opportunity for China to achieve its air pollution mitigation and carbon emissions targets under the Paris Agreement in the near and medium term within the transport sector.

Despite their advantages, concerns surrounding CNG cars include fuel storage and the availability of fuelling infrastructure. Compared with conventional gasoline vehicles, the availability of CNG cars for purchase is much less than the conventional PLDVs. Because the performance of CNG cars is lower than that of conventional cars, CNG car models mostly offer small to mid-size engines (less than 2000 cc) worldwide.

Autonomous vehicles (AV)

Automated vehicles are defined as those in which at least some of the safety critical control functions (e.g. steering, braking) occur without direct driver input (NHTSA, 2013). Although there are no fully automated fleets at the moment, new car models have increasingly included partial automation and conditional automation, which allow cars to drive themselves on the road in the presence of a human driver. AVs represent a potentially disruptive technology that changes the transportation system in various dimensions, including road safety, congestion and travel behaviour (Fagnant and Kockelman, 2015). Around the world, several countries (or states) have taken steps to legalise AVs, including California, Singapore, the UK and the Netherlands. Some manufacturers (e.g. Nissan, Volvo) have also announced their intentions to have commercially viable autonomous-driving capabilities by 2020 in several vehicle models. Some studies have suggested that vehicles would be capable of full automation on urban and highways by 2025-2030 (Underwood, 2014).

However, there are still several barriers to the large-scale adoption of autonomous vehicles, including the costs of AV platforms and consumer acceptance of this driverless technology. Several studies have examined the possible implications of autonomous vehicles on future energy consumption and emissions, but very few

[1] Many NGVs are used for public transportation such as buses, not PLDVs.

studies were able to quantify the potential carbon impact of AVs in the long run. For example, Anderson et al. (2014) and Grubler et al. (2018) suggest that the AV reduces energy consumption and emissions per kilometre by smoothing traffic, while the annual distance per vehicle may increase as a result. Wadud et al. (2016) finds that a shift over time from privately owned vehicles to a shared-use system with some automation might decrease energy, vehicle travel and emissions; however, the extent to which that could occur depends on the levels of automation. When the vehicles are fully automated, they can offer on-demand mobility services and would allow shared vehicle ownership based on the drivers' preferred travel patterns (Wadud et al., 2016).

Because AVs are mostly still in the testing phase, this means it is very challenging to predict the exact outcomes and implications of AVs on future travel demand, energy consumptions and emissions. This thesis excludes the autonomous vehicles from its scenario analysis.

Summary

Historically, the technological transitions of automobiles have been characterised by social and technical regimes, such as changes in consumer preferences, technological breakthroughs, cost of technologies, cost of commodities and policy incentives (Geels, 2005*a*). Over the past 100 years, alternative-fuel vehicles have elicited public interest and led to interest in the stability of the auto-mobility regime. Nonetheless, the strong lock-in mechanism has meant that unless there is a significant technological breakthrough and a continued interest from consumers and governments in favour of alternative-fuel cars, novel technologies will keep facing significant barriers to entry.

1.1.5 Other transport technologies and the scope of the thesis

This study only focuses on the policy incentives and the technological diffusion of Passenger Light Duty Vehicles (PLDV). However, motorcycles are popular in India and China, with nearly 14 million units in India and more than 90 million units in China in 2019 (Marklines, 2017). The large number of motorcycles in India and China could result in fuel consumption and CO_2 emissions from motorcycles in developing countries potentially contributing significantly to CO_2 emissions. However, this is outside the scope of this thesis, due to availability of data on the market shares for different motorcycle technologies.

On the other hand, in the more developed countries, Heavy Duty Vehicles (HDVs) will increasingly play a role in transport-sector emissions. In fact, emissions growth from the HDVs is higher than from any other transport sector, with a 2.4% increase annually since 2000, mainly due to trucks that account for more than 90% of the growth in energy consumption (IEA, 2017*a*). Since studying the freight sector requires a radically different behaviour analysis, it is outside the scope of this thesis.

Within the passenger transport sector, the aviation sector is one of the largest global CO_2 emitters, with emissions expected to rise dramatically by mid-century. Emissions from the international aviation sector rose 54% from 1990 to 2015 and are projected to increase as much as 4.3% annually over the next 20 years (ICSA, 2010). Policy measures that address emissions from aviation are an important area of study, but one that requires a completely different field of research.

Globally, maritime transportation plays an important role in international shipping, connecting roads and inland waterways through ocean routes (Eyring et al., 2010). As a complement to other modes of transportation, maritime transportation plays an important role in international shipping that connects roads, railways, and inland waterways through ocean and coastal routes (Eyring et al., 2010). Globally, maritime transport emits around 1,000 million tonnes of CO_2 annually and is responsible for about 2.5% of global GHG. International maritime shipping is not included in the Paris Agreement, but regulations that limit the sector′s CO_2 emissions have been established and implemented. This PhD thesis excludes the maritime sector from analysis.

1.1.6 The role of policy incentives

Particular challenges accompany designing successful and effective policies for reducing PLDV emissions, because of the dynamics of technological transition and consumer behaviour. Designing effective policy instruments requires improved knowledge of the mechanisms that facilitate the diffusion of new car technologies. Despite the need to meet the legislated GHG targets, there is a gap in predicting the carbon-emissions reduction effects of individual policy instruments and their costs. It is important to determine the relationship between policy instruments and the rate of adoption for low- or zero-emissions vehicles.

Niche automotive technologies, such as EVs, have several disadvantages in the marketplace, including their additional monetary cost, range anxiety, lack of charging infrastructure and consumer risk aversion. In other words, without policy incentives to support the niche technology, EVs will have a higher monetary cost and non-monetary cost (e.g. risk aversion) than petrol cars, which have higher average emissions than EVs (McCollum et al., 2016). However, the negative perceptions and risk aversion may change over time as the technology becomes more wide spread. Government policies will be critical in the development and adoption of new car technologies. Under the Paris Agreement, some countries (e.g. Japan) have elaborated the breakdown targets based on the energy mix with concrete policies and measures.

These policy choices, levels and combinations are necessary to achieve the CO_2 emissions target, while considering the economic goals (e.g. costs of subsidies and taxation revenues). Fiscal incentives for reducing emissions from PLDVs can be broadly divided into two categories: policies that affect the choice of vehicles (e.g. size of the vehicle fleet, vehicle engine efficiency and shifts to new energy technology PLDVs) and policies that influence vehicle usage. The former includes policies such as vehicle purchase tax, EV subsidies, annual registration taxes, fuel consumption regulations and EV mandates. The latter includes charges based on distance (e.g. tolls), although fuel taxes affect both the choice of vehicles and the vehicle usage.

For this thesis, we focus on the analysis of policies that affect vehicle choices for two reasons. First, the tool developed for this thesis (the FTT-Transport model, see section 1.2) is a model of technological diffusion that is useful in studying how policy instruments affect the dynamical change of vehicle technologies based on market price competition and technological competition. Second, while existing studies have examined or evaluated the impact of various policy instruments on affecting the uptake of technologies in different countries in the short run or as a case study, there is a lack of understanding of how various policy instruments affect the rate of technological diffusion and the medium- to long-term impact of the policy instruments on the cumulative CO_2 emissions.

The following sections review the key policies for reducing PLDV emissions that exist in the UK, the US, Japan, China and India. We have excluded vehicle purchase tax from the analysis, and included EV subsidies and the annual registration tax. This is because the EV subsidies are regarded as a negative vehicle purchase tax, and the annual registration tax is charged on ownership (like vehicle purchase tax) but imposed annually (with EVs paying a lower rate of annual registration tax). Note that we only discuss policies that we have included in the analysis, and policies that are excluded from the analysis, such as toll charges, driving privileges and exemptions to parking restrictions, cannot be easily modelled with the FTT-Transport model and are outside the scope of this PhD thesis.

Annual registration tax

Annual registration tax or annual circulation tax, commonly known as road tax in the UK, is an annual tax imposed on PLDVs for a vehicle to be allowed on the registry. Typically, the levels of annual registration tax are charged based on vehicle characteristics, such as engine sizes, weight, power or fuel consumption. In many countries, the annual registration tax is reduced or exempt for high-efficiency cars.

The effectiveness of the annual registration tax is largely dependent on the level of the charge required to influence the consumer's decision (Brand et al., 2013). Past studies have used surveys to understand the levels of annual registration tax required to change consumer behaviour in the UK, Denmark and Austria (Lane, 2005; Mabit and Fosgerau, 2011; Gass et al., 2014). However, these studies have not examined the long-term effect of the annual registration tax on technological adoption and CO_2 emissions. In addition, while annual registration tax exists in some developing countries, such as China, its effect on the adoption of low-emissions vehicles has not been examined. It is also important to highlight the differences in the effectiveness of the annual registration tax due to varying tax levels and vehicle markets between countries (Mercure and Lam, 2015).

EV subsidies

EV subsidies are a one-off payment to EV purchasers when the vehicle is registered. The EV subsidy is not only used to reward buyers of vehicles that produce zero emissions but also to compensate for the price difference between petrol car models and comparable EV models. At comparable performance, EVs tend to have much higher upfront costs due to the price of lithium-ion batteries. Moreover, in most countries, EV charging stations are still scarce and the EV range is generally lower than that of the range of petrol cars at a comparable price.

In reality, EV subsidies have existed in many countries, including the UK, the US, Japan and China, to support the diffusion of EVs. For example, in the UK, an EV subsidy is offered in the amount of up to 35% of the purchase price, or up to a maximum of 4,500 GBP (5,900 USD) (UK Government, 2017*a*). For the US, the Federal Internal Revenue Service (IRS) tax credit is from 2,500 USD to 7,500 USD per new EV purchased, with the level of credit depending on battery capacity (IRS, 2015). However, the EV subsidy has proved very expensive in countries such as Norway, where the EV subsidy cost 1.07 billion USD over the period of 2010 through the first quarter of 2017 (Brooks, 2018). For less wealthy countries, this makes ensuring budget neutrality difficult, so other policy measures may be required until EVs gain a substantial market share.

Fuel tax

Fuel taxes are imposed upon fuel purchase, the cost of which is linked to the amount of fuel consumed while driving a vehicle. The levels of fuel tax affect the fuel costs of driving and, therefore, could achieve significant emissions reduction by reducing fuel consumption. Fuel prices vary substantially across countries due to the large differences in taxes and subsidies levied on gasoline. For example, after fuel tax, countries such as Norway and Hong Kong have the highest prices for gasoline in the world, at a price of more than 1.7 USD per litre (April 2018 prices), while the gasoline price in the US stands at around 0.7 USD (IRS, 2016).

Studies have found that countries with higher gasoline prices tend to consume less gasoline within their road sectors, and vice versa (Sterner, 2007; Soltani-Sobh et al., 2015). The higher fuel efficiency of PLDVs reduces emissions from PLDV transport by reducing demand for PLDV services and shifting consumers to more fuel-efficient PLDVs. Even when gasoline prices are similar, gasoline consumption varies between countries, depending on income and population density (Burke and Nishitateno, 2013). An econometric analysis is required to find out the relationship between the sociodemographic variations and fuel consumption, given the oil prices. The effectiveness of the fuel tax on total CO_2 emissions from PLDVs depends on the fuel efficiency of vehicles and the price elasticity of gasoline demand in each country.

Fuel consumption regulations

Fuel economy regulations are among the most common types of environmental regulations in the PLDV sector. These fuel economy standards require manufacturers to report the fuel economy of the car models and regulate the average fuel efficiency of vehicles on sale by imposing a penalty on the manufacturers if they fail to meet the standards. Doing so creates incentives to improve vehicle fuel efficiency and reduce

CO_2 emissions from PLDVs. Fuel economy standards have been implemented in many developed nations, including the UK, the US, Japan and China. For example, in the US, the Corporate Average Fuel Economy (CAFE) standards are regulations set by the National Highway Traffic Safety Administration (NHTSA) and the US Environmental Protection Agency (EPA) to improve the average fuel economy of cars and light trucks (NHTSA, 2018). The EU requires the fleet average, to be achieved by all new cars, of 95 grams of CO_2 per kilometre by 2021 (EC, 2014*b*). Although fuel-economy regulations encourage the production of more efficient vehicles, manufacturers have been caught manipulating their reported fuel-economy values, which led to an important court case (McGee, 2018). The effectiveness of fuel economy standards over the long term depends on several factors, including the extent to which the fuel-economy regulations affect driver's travel demands and car turnover rates.

EV mandate

Electric vehicle mandates (EV mandates) include direct requirements for automakers to sell zero-emissions vehicles, thus incentivising automakers to make EVs more appealing to consumers (Sykes and Axsen, 2017). Most notably, the California Zero Emission Vehicle mandate sets mandatory targets for EV sales. Similarly, Chinese policymakers have established a new energy vehicle (NEV) credit system that targets 10% of the conventional passenger vehicle market in 2019 and 12% in 2020 (ICCT, 2018). These supply-focused policies stimulate automakers to increase the availability of zero-emissions vehicles. Furthermore, this type of technology-forcing regulation has been widely adopted across the US and Canada.

The advantage of EV mandates is that they force firms to be innovative and reach a certain sales target. Then, as the number of fleet EVs increases, the rate of diffusion increases faster based on the technological diffusion theory and social influence (McShane et al., 2012). On the other hand, claims have been made that firms will not simply comply with mandates through innovation or investment in the new technologies; instead, they actively prevent the regulation through lobbying activities (Wesseling et al., 2015).

1.1.7 Energy models

Energy models have emerged as a useful methodology, which are aimed at evaluating future energy options and generating insights for policy design (Giannakidis et al., 2015). Although arguably all energy models indicate large quantitative uncertainty, models are critical for supporting policy decisions in PLDV sector, where the interdependence of consumers, producers and social institutions is the main determinant for technological transitions. In particular, the energy models can be used to assess the effectiveness of policy strategies and the possible impact of the policy incentives before they are implemented. In typical policy cycles (e.g. at the European Commission), quantitative analysis of the effectiveness of policy strategy using models will be carried out at the impact assessment stage.

Many national energy models exist for the purpose of analysing transport emissions within their own countries. The global Integrated Assessment Models (IAMs) that can be used to advise on policies for many countries have several advantages over the national energy models. First, the global IAMs are useful for calculating global emissions and assessing whether emissions targets are met globally (i.e. staying within the 2° C target). Second, the global IAMs can be used by many countries for advising on policies in the transport sector. In particular, the global IAMs are useful for assessing the effectiveness of policies across countries and carrying out comparative studies. By covering 59 global regions, the E3ME-FTT-GENIE1 model has been used to assess policy proposals of many governments, notably the European Commission [1].

System dynamics (SD) and agent-based modelling (ABM) overcome some of the shortcomings of the optimisation model by allowing agent heterogeneity. However, both methods have scalability challenges to integrating them into IAM analysis. For example, while ABMs have clear advantages in terms of modelling consumer decisions and agent diversity, ABMs typically apply only to one particular study area, or to only a few cities, due to the limitations of the input data for ABMs at national levels or above.

The FTT-Transport models technological diffusion dynamically based on market price competition and technological competition. Instead of taking a representative agent approach, the FTT-Transport model assumes the presence of a diverse market with heterogeneous agents and PLDV technologies. This is done with a probabilistic treatment of consumer decision-making by using a distribution of cost values for each technology category and establishing three technological subcategories for each car technology. In the FTT-Transport model, we model technological diffusion with a set of logistic differential equations of the Lotka-Volterra family, which

[1] The E3ME-FTT has been used by the EC and soon will be used by East Asia (i.e. Japan, Korea, China and Taiwan) for policy analysis

represent gradual technological substitution processes. Consistent with the theory of technological diffusion and replicator dynamics, in the FTT-Transport model, consumers are more likely to choose a technology that has a higher market share as a result of social influence and path dependence theory.

1.1.8 The E3ME-FTT-Transport model

During my PhD, a model of technological transition for simulating the evolution of PLDV for 59 countries has been developed, in collaboration with my supervisor, Dr Jean-Franois Mercure (see work division in the Appendix B). As a sub-module of the E3ME-FTT-GENIE1 integrated assessment model, the FTT-Transport model calculates global emissions and is coupled with the climate model GENIE 1 (Holden et al., 2013, 2018), making it a fully detailed IAM. E3ME is a non-equilibrium macroeconometric simulation model based on a demand-led Post-Keynesian structure (Pollitt et al., 2007; Pollitt and Mercure, 2017).

The FTT-Transport model is fully integrated into E3ME with a dynamic feedback to global macroeconomic simulation. E3ME calculates global fuel use and combustion emissions, where fuel use for electricity generation is simulated using the FTT-Power model (Mercure et al., 2014). The E3ME model (integrated with the FTT-Transport model and the FTT-Power model) can be used by policymakers as a tool to answer important questions related to climate policy and energy dependency in the transport sector. For example, the model has been used to calculate the macroeconomic implications of future Stranded Fossil Fuel Assets under the projected technological trajectory and under climate policies pursuing the 2 °C target (Pollitt et al., 2018). The model has been used by policymakers to examine the effect of EV diffusion on the demand for electricity and its implications for the climate policies required to achieve the target set by the Paris Agreement.

FTT is a family of models consisting of FTT-Power, FTT-Transport and FTT-Heat. The FTT model makes use of a dynamic set of coupled logistic equations, similar to replicative dynamics and Lotka–Volterra equations (Lotka, 1956; Volterra, 1939), which were originally used to study biological systems, and have been commonly used in evolutionary economics that are representative of market competition and technological transition in energy sectors (Safarzyńska and van den Bergh, 2013). The Lotka-Volterra competition equations are known to produce S-shaped diffusion curves, consistent with the behaviour of the technological diffusion curve.

For the purpose of the thesis, the FTT-Transport model is decoupled from the

E3ME model to analyse the impact of each individual policy incentive on the diffusion of PLDV technologies, for three reasons. First, the E3ME is a top-down model that covers 59 regions, and it is less accurate in terms of the estimation of the PLDV demand for individual countries. Second, to use the E3ME-FTT model, it would have been necessary to update the data to 2016 for all 59 regions, and this was not possible within the time frame of this thesis. Rather, it would be more productive to focus on five countries, including the USA, the UK, Japan, China and India, with more up-to-date data.

The five selected countries are all unique in representing major car markets in different global regions. China and the USA are selected because they have the largest vehicle fleet numbers in the world. With the second largest car fleet in Asia, Japan also has the largest number of hybrid vehicles in the world (Rutherford, 2014). With only 20 people out of 1,000 owning a car and the second largest population worldwide (after China), India enjoys the largest increment in future PLDV stock (Antich, 2015). More than one million plug-in EVs had been registered in Europe by June 2018. Within Europe, the UK has the largest number of plug in EVs among the European countries and the highest market shares of EVs besides Norway and Sweden (EC, 2018). Arguably, Brazil is one of the largest vehicle markets in the world, with the largest alternative-fuel fleet in the world (as of 2018). We exclude Brazil from the current studies because of limited data availability for a Brazilian flex-fuel PLDV market.

Third, as discussed above, as an integrated assessment model, the E3ME model covers many other energy sectors, including the power sector and the heating sector. Although the changes in oil prices in the future may be linked to the demand in other sectors, such as the power sector, it is impossible to present all the assumptions behind such a complicated model in this thesis. Lastly, as a large and complex IAM, the E3ME-FTT model involves work that was done by others, so it is more practical and clearer for the PhD thesis to use a model created entirely by myself.

1.2 The contribution of the PhD thesis

1.2.1 Research question and contributions

During my PhD, I built a simulation model of technological change for PLDVs (FTT-Transport model) for 59 regions of the world. The model was built as a sub-module of a global IAM, the E3ME-FTT-GENIE model. Because policies for the PLDVs emissions are national, it is not necessary to apply the global analysis capacity of the E3ME-FTT-GENIE IAM, even though it is useful for other purposes, such as assessing the impact of the PLDV sector on global climate change (see recent publications using the E3ME-FTT-GENIE IAM (Pollitt et al., 2018; Holden et al., 2018).

For the purpose of policy analysis in this PhD thesis, I will focus on five major countries, namely, the UK, the US, Japan, China and India. The FTT-Transport model was built within the Future Technology Transformation (FTT) framework, which uses a dynamic set of coupled logistic equations similar to those used in ecology for simulating competing species to simulate the diffusion of PLDV technologies (Safarzyńska and van den Bergh, 2013). The demand for PLDV services is estimated with regressions for each country and coupled with the FTT-Transport model to calculate the cumulative emissions from the PLDVs (2016-2050).

Financial incentives such as EV subsidies, road tax and fuel tax have been adopted by all the countries in this study (i.e. the UK, the US, Japan, China and India). A large amount of research on the incentives for low emissions vehicles relates to financial incentives and taxation (Holtsmark and Skonhoft, 2014; Sierzchula et al., 2014; Gass et al., 2014), typically employ a consumer choice model to simulate the effect of the cost factors on the choice of new low emissions vehicles. Besides financial incentives, fuel economy standards require automakers to design more efficient vehicles or to shift sales toward more efficient models. To boost the population of zero emissions vehicles, a cap-and-trade EV mandate has been introduced in some states in the US and China, and this has the potential to rapidly scale EV manufacturing and adoption (Chen et al., 2018; Axsen and Wolinetz, 2018).

Hence, using the FTT-Transport model, I ran several scenario analyses with five policy instruments, namely, annual registration tax, fuel tax, EV subsidy, EV mandate programmes and fuel economy regulations for each country, to address four key research questions:

1) How will each of these policy measures at different levels impact the diffusion of various PLDV technologies and emissions from the PLDVs in the UK, the US, Japan, China and India?

2) What is the cost for each policy incentive at different levels of stringency, and how does the efficiency of each policy instrument vary as it becomes more stringent?

3) Are there trade-off or reinforcement effects between any two policy instruments related to the diffusion of PLDVs in each of the five countries?

4) How will the changes in income impact the effectiveness of the individual

policy instruments for reducing emissions from PLDVs?

1.3 Scenario analysis and summary of the main results

Using the FTT-Transport model, we have developed a methodology that examines the effectiveness and efficiency [1] of five policy incentives and the interactions between any two policy mixes. In this thesis, policy formulations take five possible forms: fuel economy standards, road taxes, vehicle subsidies, fuel tax and EV mandate. In the first part of the analysis, there are four scenarios for policy incentives, at four different levels of stringency. For example, in the baseline scenario, we assume that there is no policy incentive in place. In the current scenario, we assume that tax levels are consistent with the current levels of incentives. In the high fuel tax scenario, we assume that fuel tax is 50% higher than the current fuel-tax level in each country, and in the very-high-fuel-tax scenario, we assume that the fuel tax is 100% higher than the current fuel-tax levels.

Overall, we find that the effectiveness of policy incentives on PLDV emissions varies between countries, depending on the technology mix in the current passenger car markets and the current tax levels/structure of each country.

Comparing the tax incentives, we find that fuel economy regulation is among the most effective policy incentives in reducing emissions in some countries. For the US, fuel economy regulation is the most effective policy incentive and fuel tax is the least effective in reducing emissions. This is because there is a large number of luxury and high-emissions PLDVs in the US. Similarly, we find that fuel-economy regulation is the most effective policy incentive among the five policy incentives in reducing CO_2 emissions in China, leading to 13% emissions reduction if the current petrol cars are phased out by 2030 and gradually replaced with petrol cars that are 35% more efficient. Different from the US and the UK, as a result of the phase-out mechanism, in Japan we find that emissions fall by less than 1%. This is because Japan is the only country with very low petrol car-fleet shares in the baseline scenario, due to existing large shares of hybrid cars.

In the case of India, we find that the financial incentives (e.g. EV subsidy,

[1] Effectiveness is defined as the extent to which policies are achieving the policy goal. Efficiency is defined as the change in the cumulative emissions as a result of the policy incentive divided by the total cost of the policy incentive (see Chapter 7 for definitions).

annual registration tax and fuel tax) are less effective in reducing the cumulative emissions from PLDVs than the regulatory measures (e.g. EV mandates). This is because the fleet shares for EVs are very low (less than 0.1%) for India. The rates of technological diffusion increase with shares for the technologies (see Chapter 3 for explanations). While financial incentives increase the sales for low emissions vehicles, the rates for EV penetrations increase more rapidly in the presence of the EV mandates in countries where shares for EVs are very low.

After analysing the policy incentives one at a time, we study the interactions between all five policy incentives by carrying out scenario analysis and pairing any two policy incentives in a group (i.e. 10 scenarios). This exercise enables us to understand the complexity and interactions of the policy mix. Overall, we find that the sum of effectiveness of two policies individually can be either smaller (trade-off effect) or larger (reinforcement effect) than two policies implemented at the same time, depending on the structure and levels of policy incentives. As such, we conclude from the scenario analysis two main observations. First, there is a trade-off effect between all the financial incentives under this analysis, as the degree of the trade-off effect depends on the stringency of individual policy incentives in each country. Second, there is a reinforcement effect between EV mandates and other policy incentives.

Considering the income effect (i.e. the effect of income change on PLDV choices), we find that the income effect influences consumers' choices differently in each country, depending on the rate of income increases, the distribution of car engine sizes in the market and the market shares for low-emissions vehicles. Overall, we find that the willingness to pay for cars increases with income. After implementing the income effect in the FTT-Transport model, we find that as income increases, emissions increase slightly (less than 5%) in the baseline scenario for all countries (i.e. the income effect has a small impact on the cumulative emissions) except for China, where an increase in income leads to an increase in the shares for EVs (see Chapter 8). The income effect can be partially mitigated by some policy incentives, in particular, the policy incentives taxing/regulating luxury PLDVs.

1.4 Work division

Given the quantity of work needed for the project, Dr J.-F. Mercure and I have collaborated on some parts of the model development, including coding for the model in

MATLAB and developing a platform for the scenario analysis. Appendix B provides an overview of the collaborative work, with the respective degree of responsibility.

The E3ME model is developed and maintained by Cambridge Econometrics and the connection between the E3ME model and the FTT-Transport model has been accomplished by Dr J.-F. Mercure. The project on the income effect and car emissions was carried out as part of a pilot project funded by the ReCoVER programme, in collaboration with the University of East Anglia (UEA), coordinated by Dr J.-F. Mercure and Dr Charlie Wilson, and carried out by myself in collaboration with Dr Pettifor. Details of the work division for this project can be found in Appendix B.

Chapter 2

Literature Review

2.1 Overview of the chapter

The purpose of this review is to show that
1) The modelling of technological diffusion can be improved in the existing IAMs;
2) Social influence and 'realistic consumer behaviour' are absent in most global IAMs. IAMs typically model aspirational scenarios (optimisation), and have limited information concerning real consumer behaviour;
3) The income effect is absent in the existing global IAMs;
4) There is a gap in understanding the cumulative carbon emission reduction effects of individual vehicle tax policies over the medium and long term, with comparisons between different countries.
5) While interaction is a central feature of the existing policy mix, few studies have explicitly analysed the interactions between vehicle policy incentives.

In light of the Paris Agreement, policy makers need to know the impact of policy options and their effectiveness in significantly reducing emissions in individual countries. The existing IAMs tend to focus on emissions trading and carbon price instruments, while in the Emissions Trading System (ETS), the PLDV sector is never included. In reality, the PLDV sector is normally covered with a number of policy instruments other than carbon pricing, including fuel economy regulations, car purchase tax and car registration tax. Specifically, the policy incentives for the PLDV sector are often introduced at the national or local level, influenced by the political environment and the existing car market in each of the individual countries and regions. The goal of this chapter is to identify gaps in the existing literature and to find the position of this thesis among existing studies.

2.2 Review of integrated assessment models

IAM is defined as any model that combines the scientific and socio-economic aspects of climate change, primarily for the purpose of assessing policy options (Kelly and Kolstad, 1999). IAMs describe many of the complex relations between environmental, social and economic systems that determine the effectiveness of climate policy. They are important tools to compare the costs and benefits of different emissions scenarios (see Hof et al. 2012; Nordhaus 2010; Weyant et al. 1996).

Further, IAMs vary widely according to the policy options available to the modeller, the complexity of the economic and climate sectors and the treatment of uncertainty. Examples of IAM approaches are DICE (Nordhaus, 1992), WIAGEM (Kemfert, 2002), FUND (Tol, 1999) and IMAGE (Bouwman and Kram, 2006). Overviews of the development of IAMs can be found in Dowlatabadi (1995); van Vuuren et al. (2011).

A variety of modelling techniques have been utilised in energy and emission projections in various sectors. They differ in terms of data requirements, technology specifications and computing demands. Following several existing studies (see e.g. Nakata et al. 2011; Grubb et al. 2002; Herbst et al. 2012; Löschel 2002), we divide energy system models into five main categories, including system optimisation, macroeconomic models, system dynamics models and agent based models according to their underlying methodologies. This is summarised in Table 2.1.

2.2.1 System optimisation

Energy-oriented models are designed to consider the energy sector and emissions from energy production and consumption in detail (Grubb et al., 2002). One of the most commonly used approaches in modelling in the energy sector is optimisation.

The most well-known examples that utilise the optimisation approach include MARKAL and MESSAGE. Both have been employed extensively to model transport energy systems (McCollum et al., 2013; Gül et al., 2009; Yeh and McCollum, 2011). MARKAL is a linear programming optimisation model developed by the Energy Technology Systems Analysis (ETSAP) of the IEA (ETSAP, 2015). Related to MARKAL, the TIMES Model (**T**he **I**ntegrated **M**ARKAL-**E**FOM **S**ystem) is a bottom-up technology and rich optimisation model generator (Loulou et al., 2005).

MESSAGE is a dynamic linear programming model that calculates cost minimal supply and demand structures over a given time horizon (Messner, 1995). It provides core inputs for major international assessment and scenario studies, such as the Intergovernmental Panel on Climate Change (IPCC), the World Energy Council (WEC) and the Global Energy Assessment (GEA).

Other examples of energy sector models that operate in an optimisation framework include LEAP (Heaps, 2012), REDGEM70 (Takeshita and Yamaji, 2008), MERGE (Kypreos, 2005), REMIND (Leimbach et al., 2010), BEAP (Grahn et al., 2007), GET (Grahn et al., 2007) and PRIMES (Capros et al., 2009).

The strength of optimisation frameworks and general equilibrium lies in their ability to inform the modellers of feasible and desirable scenarios from a system cost perspective. However, the optimisation frameworks seek to identify desirable configurations of the energy system (e.g. how many wind turbines, how many coal plants, how many power lines, which kinds of cars, according to constraints) rather than seeking to describe actual system behaviour with a high degree of realism as impacts of specific policies.

2.2.2 Macroeconomic models

Macroeconomic models are models that use a macro-economic methodology to focus on the entire economy of a society, considering the energy sector as one part of the economy. Macroeconomic models are usually top-down models that have higher sectoral aggregation and better characterisation of impacts of economic growth (Hourcade, 1993). Although they reflect greater details regarding macroeconomic feedbacks, they have been criticised by Edenhofer et al. (2006) for not providing a detailed description of future technology.

Many macroeconomic models take a general equilibrium approach (CGE), including GEM-E3 (**G**eneral **E**quilibrium **M**odel for **E**nergy-**E**conomy-**E**nvironment interactions, Capros et al. 1997), CIMS (**C**anadian **I**ntegrated **M**odelling **S**ystem, Navius 2010), GREEN (**G**eneral **E**quilibrium **E**nvironmental Model, Burniaux et al. 1992), NEMS (**N**ational **E**nergy **M**odelling **S**ystem, NEMS 2018).

Traditional macroeconomic models used to assume the existence of an autonomous energy efficiency improvement (AEEI), and therefore, technological change was exogenous to the model (Grubb et al., 2002). However, the exogenous technical-growth assumption with AEEI has been criticised for neglecting the interactions between policy options and technological change (see Weyant and Olavson 1999; Köhler et al. 2006; Gillingham et al. 2008). Representations of ETC were explored extensively in the 'Innovation Modelling Comparison Project' (Edenhofer et al., 2006). The authors found that the absence of Endogenous Technical Change (ETC) can significantly bias policy assessments. ETC can be represented by a learning-by-doing curve that generates cost reduction stemming from an increasing return. The concept of learning goes back to the aircraft industry in the 1920s, when it was observed that the number of hours needed to manufacture decreased at a uniform rate as the production quantity increased (Yelle, 1979; Alchian, 1963). This shows that the cost of a product falls by a certain percentage every time the total quantity manufactured doubles. Empirical findings suggest that as more units of a technology are produced, the cost for the technology falls, which triggers further sales and increasing returns to scale.

In the past, the experience-curve concept attracted much attention by determining the future potential of new car energy technologies, and it has become a well-known tool in energy-system modelling (Messner, 1997). In particular, many energy-system models have incorporated features of endogenous technical learning. For example, compared to models where technological change is exogenously determined, a model incorporating endogenous technical learning should generate higher overall technological change if the sectors that expand as a result of a policy intervention enjoy more spillovers or faster increasing returns (as a result of cost reductions) (Köhler et al., 2006). Considering that cost is dynamically linked with the quantity of production, the incorporation of learning curves into modelling creates complexity and a stronger path dependence within the system.

In response to criticisms of modelling technological change, WITCH (**W**orld **I**nduced **T**echnical **C**hange **H**ybrid) accounts for technological change endogenously with a detailed energy input component (bottom-up) and a neoclassical optimal growth structure (top-down) (Bosetti et al., 2006). Several modelling teams have explored the development of hybrid models that draw on both the technological details of a bottom-up model and the macroeconomic top-down models. Hybrid models bridge the gap between conventional top-down and bottom-up modelling approaches (Hourcade et al., 2006). Examples of hybrid models include MESSAGE-MACRO and MARKAL-MACRO, MERGE (Kypreos and Bahn, 2003; Kypreos, 2005) and REMIND-D (Leimbach et al., 2010). Instead of using an optimisation approach, E3ME is a non-equilibrium macro-econometric simulation model based on demand-led post-Keynesian structure. In the post-Keynesian world, models are simulations, and productivity change takes place endogenously through knowledge accumulation, with investment endogenous to the economic context (Mercure et al., 2016).

2.2.3 Simulation models

Simulation models suggest that economic trajectories are in constant transformation shaped by institutions, history and political choices, without a 'preferred equilibrium state' (Mercure et al., 2016). Well known examples of simulation models include POLES (Criqui et al., 1999) and TREMOVE for the transport sector in the EU (Van Herbruggen and Logghe, 2005). This section discusses two major approaches in simulation modelling: system dynamics and agent-based modelling.

Systems dynamics approach

System dynamics (SD) is 'the study of information-feedback characteristics of industrial activity to show how organisational structure, amplification and time delays interact to influence the success of an enterprise' (Forrester, 1961).

SD combines technology and market-behaviour frameworks into one holistic framework to represent the causal structure of the system (Martinsen and Krey, 2008), and it is used to analyse the wider impacts of each policy being tested (Fernandez, 2013). While SD offers clear benefits to modelling energy systems characterised by a large number of interactions between several variables (Armenia et al., 2010), it is not widely applied to energy-system models. With few exceptions, IMAGE/TIMER (The **T**argets **IM**age **E**nervy **R**egional, De Vries et al. 2002) analyses the long-term dynamics of the energy system. With a focus on transport, both ASTRA (**AS**sessment of **TRA**nsport Strategies, Fiorello et al. 2010) and GLADYSTE (Global Scale System Dynamic Simulation Model for Transport Fermi and Territorio 2010) are system-dynamic models on a European scale for the strategic assessment of policy scenarios. Pasaoglu et al. (2016) analysed future technological transitions for passenger transport in Europe with a system-dynamic simulation model.

Also involving systematic feedback, amplification and time delays, the FTT: Transport is a simulation model, and the technology transition pathways are supported by evolutionary theory. While system-dynamics models, such as ASTRA, take into account path dependence and technology variation, they do not take into account the heterogeneity in the reservation price for cars and for sociodemographic heterogeneity within the population.

Agent-based approach

Social science often involves heterogeneous human agents with diverse choices. Agent based modelling (ABM) is a computerised simulation of a number of interacting decision-makers. Each assesses his/her situation and makes decisions on the basis of a set of rules (Bonabeau, 2002). Since an agent-based model treats the heterogeneity of actors well, there are a number of agent-based models for the transport sector. **T**ransportation **A**nd **P**roduction **A**gent-based **S**imulator (TAPAS) is a micro-level model for the assessment of different types of transport-related policies (Holmgren et al., 2012). Eppstein et al. (2011) developed an ABM of vehicle consumers that incorporates spatial and social effects. Further, Köhler et al. (2009) studied the penetration of fuel cell cars in the UK with the ABM.

While ABMs have advantages in terms of modelling consumer decisions and agent diversity, ABMs typically apply only to one particular study area, or to only a few cities. However, like system dynamics models, the agent-based models have not yet been integrated into IAM scale analysis, or into global macro models due to computation and scalability challenges.

2.2.4 Gap in existing energy models

Global-scale energy policy modelling approaches mostly use representative consumers with a cost optimisation framework (McCollum et al., 2013; Takeshita and Yamaji, 2008). In the standard equilibrium and optimisation-based models, agents are assumed to be fully rational and the aggregate behaviour is expressed in terms of individual (i.e. non-interacting) utility-maximising representative agents. However, in the vehicle market, it has been shown empirically that choices are made through visual influence within social groups or geographical areas (McShane et al., 2012; Dahl et al., 2001). Social influence happens when agents interact with each other. Thus, the stock of knowledge for each individual becomes heterogeneous.

System dynamic models and agent based models improved on the traditional optimisation models and GEM in terms of the role of agents and their interactions with each other. These models offer the possibility of modelling individual heterogeneity and allow the gradual adoption of a new technology. However, studies using the system dynamic models and the agent based models have either focused on the transitions of one particular technology or on one region. The reason for this is that agent based models can be extremely computationally intensive and time consuming depending on the size and purpose of the models. Due to the complexity of human behaviour and limitation of data, the models have rarely been built for energy technology transitions at a global scale or integrated into IAM.

Compared to SD models and ABM models, using the differential equations approach is less computationally intensive. Existing studies have argued that technological transitions are closely related to the evolutionary process of species and replicator dynamics. However, currently, no global energy-systems model has used the evolutionary approach (or equivalently, replicator dynamics) to model technological transitions in the energy sector on a global scale. Replicator dynamics (taken by the FTT-Transport model) have the advantage of considering complexity in the process of sociotechnical transitions.

2.3 Applying evolutionary theory to study technology transitions

2.3.1 Theory of technological change

Historically, economic models have incorporated technological change as an important driver for growth (Aghion and Howitt, 1998; Mankiw et al., 1990; Samuelson and Solow, 1956). In neoclassical economics, technology is conceptualised by means of the production function (Birky, 2008). Neoclassical theory assumes that all technological options and alternatives are known perfectly and are perfectly accessible, through the optimisation behaviour of firms. Under this framework, technological change is a shift in the production function, as a result of exogenously determined innovation. The problem of neoclassical economics remains that it has little to say about the process of technological diffusion.

The concepts of technology diffusion provide insights into the key dynamics involved in transitions (Rogers, 2010). Technology diffusion is a process by which an innovation is communicated through certain channels over time among members of a social system (Rogers, 2010). According to Rogers, the four categories of adopters are early adopters, early majority, late majority and laggards. When considering successive groups of consumers adopting new technologies, the technology diffusion is described by the S-shaped logistic (sigmoid) curves.

S-curves illustrate the fact that technology diffusion is gradual, with a slow initial growth rate, followed by accelerated growth as new markets are reached, followed by slower growth again (Barreto and Kemp, 2008). One of the earliest classic studies was conducted by Griliches, who found that the penetration of corn seeds followed S-shape logistic curves (Griliches, 1957). Fisher and Pry then proposed the 'technological substitution model', which describes the penetration of new technologies replacing old ones in S-shaped curves (Fisher and Pry, 1972).

Analysis of the historical replacement of old by new technologies has shown that most of the innovation processes can be described by simple rules that are captured in the logistic substitution model (Marchetti, 1979). Marchetti et al. (1980) expanded the Fisher-Pry model into a model involving more than two technologies, with Nakicenovic (1986) specifically focusing on transport. Empirical analysis found that diffusion and substitution of transport technologies historically follows the S-shaped logistic curves (see e.g. Wilson et al. 2012; Grubler 1990; Bass 1969).

Critically, the traditional Integrated Assessment Models are based on the optimisation approach. While the diversity of the car market is known to strongly influence the rate of adoption of innovation (Rogers, 2010), the standard optimisation models assume that a representative agent who will lead to the instantaneous adoption of attractive innovations; yet, this is not consistent with the 'S-shaped' technology diffusion. Models built for the purpose of informing climate policies need to realistically estimate the impact of the policies by providing a representation of technological diffusion in the IAM. Therefore, it is necessary to build a model that takes into account the diversity and heterogeneity of the car market, linking to a global Integrated Assessment Model (IAM).

2.3.2 Technological transition in the PLDV sector

The socio-technical system describes systems that involve complex interactions between humans, machines and the environment (Baxter and Sommerville, 2011). A transition of socio-technical regime (STT) is a set of processes that lead to a fundamental shift in the social-technical system (Kemp, 1994; Geels and Schot, 2007). STT involves technological changes, user practices, regulations, and industrial networks, with a range of actors and over a period of time (Geels, 2005*c*).

The modern automobile industry is deeply embedded in legal, social, cultural and economic practices. These lock-in mechanisms imply that sociotechnical regimes are extremely rigid in the automobile market. There are substantial sunk investments in plants for internal-combustion (IC) engines, skills and fuel infrastructure. Personal mobility practices have also become dominated by petrol-based cars, in turn shaping urban infrastructure. The majority of cars on the street have IC engines and there are strong path dependencies on automobile consumption (Geels et al., 2011). Thus, consumers do not only optimise cost when they choose a car; they also take into account the social trends, the availability of infrastructure and the models available in the market that match their preferences when they purchase a car (Tanaka et al., 2014).

2.3.3 Evolution theory and technological transitions

Evolutionary theory treats the technology diffusion process as continuous, while changes are path dependent. 'Evolutionary economics' was first proposed by Veblen (1919), who upheld that economics should embody the insights of evolutionary economics. Discussing the foundation of economic theory, Schumpeter argues that economic explanations are not legitimate without the consideration of history (Schumpeter, 1927, 1942*a*). This reasoning was dominated in the change of business cycles, or by an 'industrial mutation' that revolutionised economic structure. He further argues that capitalism is a result of 'creative destruction' (Schumpeter, 1934). One of the first applications in the economics of an evolutionary process has been found in 'An Evolutionary Theory of Economic Change' by Winter and Nelson (1982), which is a pioneering work on the change of economic knowledge as it applies to technology and production.

The evolution paradigm of technological change has its root in Schumpeter's theory, which analyses innovation as a historical process and technological substitution as a process of 'creative destruction' of prior technologies (Schumpeter, 1942*b*; Levinthal, 1998). To use an analogy with biology, when an invasive species proves to be better fitted to the environmental conditions, this species may dominate at the expense of others. Similarly, the growth of any technology depends on its fitness. The intrinsic growth rate is an exponential process, while competition is dependent on the population size of the competing technologies (Saviotti and Mani, 1995). In the context of the vehicle market, through trends and fashion, the diffusion of a product reinforces its own ability to diffuse and interact with other technologies (Mercure, 2017). As we discuss in Chapter 3, this can be shown to be satisfactorily described by the replicator dynamics or Lotka-Volterra systems of equations.

Several studies have shown that the Lotka-Volterra competition (LVC) equations, a set of logistic differential equations, can be applied to model technological transition (Saviotti and Mani, 1995; Grubler, 1990; Marchetti et al., 1980; Bhargava, 1989; Morris and Pratt, 2003) and organisation change (Lee et al., 2009). The LVC equations model the competition between various technologies, proportional to market share, and produce logistic substitution curves. Similar to the evolution of ecosystems, technologies compete in the marketplace, and the growth rate increases as the share of the technology rises, resulting in an S-shaped curve of technological diffusion. This can be derived using the LVC equations. Thus, technology diffuses gradually into the market, with the rate proportional to the market shares for the technology. In the PLDV sector, it has been found empirically that diffusion and substitution of PLDV technologies historically follow the S-shaped logistic curves (Grubler, 1990; Wilson, 2012; Marchetti et al., 1980). Logistic growth describes an initial period of diffusion as a technology is introduced into the system, moving then through a rapid exponential growth before reaching a saturation level (Grübler, 2003). Based on a realistic representation of the technology diffusion model, when a policy incentive is imposed, the effectiveness of policy incentives depends not only on the cost, but also on the dynamic competition between technologies and the rate of technological diffusion endogenously, which is not often absent in the existing IAMs.

2.4 Social influence and consumer choices

Social influences and consumer choices are consistently found to be important in empirical work. Within the PLDV sector, behaviour adaptation, network interactions and diversity of consumer preferences are central to the understanding of technology adoption (Mueller and de Haan, 2009*a*; McShane et al., 2012). As such, the rate of technological update is influenced by the diversity of the agent's perceptions of car purchases. Differences between consumer choices drive competition between product varieties, leading to a selection process that determines the rate of technological change (Basalla, 1988). Based on Rogers (2010), diversity is responsible for the gradual adoption of innovations and technology diffusion.

Within the PLDV sector, consumer choices for certain vehicle technologies take place within contexts of distributed income that span several orders of magnitude (Mercure and Lam, 2015). The fact that consumers are diverse implies that car technologies will not diffuse into the market instantly in the presence of a change in price or policy reform. Instead, car technologies diffuse gradually according to consumers' choices and the heterogeneity within the population.

Behavioural aspects and heterogeneity significantly impact the effectiveness of market-based policies (Knobloch and Mercure, 2016). However, general equilibrium and partial equilibrium (optimisation) models may not sufficiently account for the purpose of modelling the effectiveness of specific policy instruments (Mercure et al., 2016). People and firms are usually represented by an agent with rational expectations and there may be various inherent limits to informing policy making if the model does not take into account agent heterogeneity.

Existing studies have shown the important influence of behavioural assumptions on policy-relevant outcomes in the diffusion of low-emissions vehicles (Mau et al., 2008; Li, 2017). This is because individual decisions are strongly affected by social norms and customs when choosing a car (McShane et al., 2012). Instead of instantaneous change in shares when an incentive is imposed, technology diffusion will be shaped by incentives leading to a new technological trajectory.

Capturing 'behavioural realism' in consumer preferences for passenger cars in global IAM may increase its usefulness to policy makers. Thus, modellers have attempted to incorporate some 'behavioural realism' into the existing global IAMs. For instance, Wilson et al. (2015) and Grubler et al. (2018) represent heterogeneous consumer groups for vehicle choices with varying preferences for vehicle range and variety in the MESSAGE model.

The socio-MARKAL model integrates technological, economic and behavioural contributions to the environment in a few cities (e.g Nyon) (Nguene et al., 2011). Similarly, Daly et al. (2014) incorporate travel behaviour into the TIMES model by accounting for individual travel budget constraints for Canada and Ireland. Ramea et al. (2018) incorporate behavioural content from MA3T (Market Acceptance of Advanced Automotive Technologies) into the TIMES model. The MA3T simulates vehicle market behaviour over time, where the core behavioural model is a nested multinomial logit discrete choice model that yields market shares of competing technologies for a large number of consumer segments.

While the above research does improve the 'behavioural realism' of the global IAMs, it is possible to improve further on the representation of consumer behaviour with the FTT-Transport model. Firstly, the FTT-Transport model is an attempt to model consumer preferences changes over time as a result of changes in trends and social influence. Secondly, in the FTT-Transport model, consumer diversity is captured by including different variants of vehicle type (e.g. economy, mid-sized, luxury), fuels (e.g. gasoline, diesel), and consumer preferences based on PLDV price distributions. Essentially, the model resembles the Rogers dynamics of technology diffusion by considering consumer diversity. Thirdly, with an improved representation of consumer behaviour, the model allows a higher number of policy levers in the model for the analysis of detailed policy incentives.

2.5 Income effect on the choices of passenger cars

Several studies have examined the relationships between vehicle ownership and growth in GDP per capita. For instance, Wu et al. (2014) forecast vehicle ownership in China through 2050 against a background of increasing energy use and CO_2 emissions, based on a Gompertz function of per capita GDP. Gately and Dargay (1999) make projections of the growth in cars and total vehicle stocks to the year 2015, considering the historical patterns in the growth of car and vehicle ownership relative to growth in per capita income.

The income effect is the change in vehicle preferences and consumption habits caused by a change in consumer income. Since income is almost always unevenly distributed, it is one of the most important sources of consumer heterogeneity in many markets. The relationship between income and consumption has been known and discussed in many studies (Hogg and Michell, 1996; Dittmar, 1992; Lunt and Livingstone, 1992; Fine and Leopold, 1993; Piacentini and Mailer, 2004). Douglas and Isherwood (1978) argue that consumers use consumption to give themselves a sense of belonging as well as an affinity with others similar to them. According to Belk (1988), who referred to as the extended self, our possessions are a major contributor to and reflection of our identities. Therefore, it is likely that cars reflect the identity and income of their owners, as demonstrated by McShane et al. (2012).

A large body of marketing research has been carried out on the extent to which identity can be expressed by the consumption of luxury products (Dubois and Duquesne, 1993; Vickers and Renand, 2003; Han et al., 2010). Froud et al. (2005) show how income and space variability are connected with fuel consumption. Sowden and Grimmer (2009) find that individuals engage in the process of social identification based on car ownership to locate themselves in society. They also suggest that individuals who use cars to enact their social identity will purchase cars with symbolic meaning. Hogg and Michell (1996) suggest that image-laden messages communicated by car brands are important. Symbols are used to communicate social identity and establish membership in social groups. In economics and consumer choice theory, a rise in income will induce people to change car models. As car buyers seek to display their social identity, and thus social-group characteristics, the price that one is able to pay for a car may be an indicator of one's income and social identity (Douglas, 1978).

Empirical studies have found that consumers' willingness to buy particular types of cars is determined by their incomes, gender and other social demographic characteristics. For instance, Hidrue et al. (2011) find that both high income and being a multi-car household both reduced the likelihood of purchasing EV in California. Furthermore, Liu et al. (2014) find that the higher the income, the higher the gasoline prices, while living in an urban area increases a consumer's preference for hybrid cars in the US. Potoglou and Kanaroglou (2007) find that interactions between vehicle prices and household income reveal how certain income groups perceive vehicle prices in California. Some studies have witnessed an upward spiral in consumer preferences in purchasing more powerful cars, offsetting fuel efficiency gains from technological advances. For example, Mercure and Lam (2015) find that vehicle prices are related to engine size and power, but in a manner that depends on specific countries, suggesting that income enables one to fulfil a preference for vehicle power.

Shifts in consumer choice from small PLDVs to bigger PLDVs obstruct the improvement of fuel efficiency (Kok, 2015; Kwon, 2006; Cuenot, 2009). Purchasing trends toward larger size cars can considerably offset the improvements in technical efficiency of individual car models (Ó Gallachóir et al., 2009). Therefore, it becomes necessary to introduce stricter fiscal policies (such as a carbon price) that either encourage the shifts to less powerful cars or lower emission (more efficient) cars. Studies suggest that the design of the incentives is an important determinant of behavioural responses toward the effectiveness of tax incentives (Gneezy et al., 2011; Brand et al., 2013; Mueller and de Haan, 2009*b*). Appropriate policy design is crucial in mitigating the shifts of consumer car preferences in the presence of the income effect. However, no existing studies have applied the income effect on car demands to the models of technological transitions or global IAMs.

2.6 PLDV market research and global IAM

The heterogeneity of the car market is known to both researchers and car manufacturers (Mercure and Lam, 2015), and market research methods start from the premise that there is little point in addressing the average consumer (Anable, 2005).

The heterogeneity of the car market implies that consumers will react differently to policy incentives depending on social well-being (e.g. income) and preferences (e.g. brand, engine size, technology). Further, there is a large body of market research on consumer car preferences (Brand et al., 2017; Shende, 2014; Biswas et al., 2014; Raj et al., 2013). Some researchers have looked at the impact of policy incentives on the penetration of vehicles based on marketing segmentation and preferences (Brand et al., 2017; Reynaert, 2014; Rogan et al., 2011), mostly for one country. These studies find that brand effects and differences in consumer preferences lead to car market segmentation in five different countries.

Existing studies show that capital costs and operating costs only represent part of a great variety of determinants that drive consumer energy-related decisions. Thus, the vehicle markets are socially constructed (Bijker et al., 2012) and markets are socially embedded (Rip and Kemp, 1998). For example, vehicle attributes, such as maximum speed, power, image, engine noises and household characteristics, are important determinants of car type choices. Through car market surveys, many studies have looked at the car features that are important for consumer choices (Hoen and Koetse, 2014; Train and Winston, 2007; Tanaka et al., 2014; Liao et al., 2017; Wang and Zhang, 2016; Sierzchula et al., 2014) and their willingness to pay for specific car characteristics (also called intangible costs, Hackbarth and Madlener (2016); Shin et al. (2015); Liu (2014); Hackbarth and Madlener (2013)). For example, using choice experiments, Hoen and Koetse (2014) explore the car attributes that affect willingness to pay for cars in the Netherlands. Further, Train and Winston (2007) examine the influence of vehicle attributes, brand loyalty and product line characteristics on consumer vehicle choice in the US.

Although it appears important to link car market research for individual countries to a global IAM for informing policies, market research has not played a major role in these global IAMs. Since these behavioural parameters are difficult to quantify, few attempts have been made to include intangible costs, such as those included in energy system models. With few exceptions, SOCIO-MARKAL modelled behaviour through sociological surveys is used to capture the perception of the population regarding energy consumption (Nguene et al., 2011). Similarly, the CIMS model user can specify an intangible cost factor to characterise estimated real-world consumer preferences (Jaccard et al., 2003). These models generally focus their study on a particular city or country, since intangibles are usually obtained from surveys, and it is not realistic to perform the surveys across many countries for a global IAM.

2.7 The role of policy incentives in reducing emissions from the PLDV sector

Energy models are useful for policy makers to assess the impact of policy incentives on the emissions from the PLDV sector over the long term. In order for the global IAM to be useful for policy assessment, it is crucial to feature a good part of the full diversity of policy instruments used in climate policy to realistically represent the real world climate policy. While in reality, in the PLDV sector, climate policies feature a wide range of different types of incentives, most IAMs feature a few, or sometimes a single, policy lever for decarbonisation, as well as a carbon price that is applied to all sectors targeted by the climate policy (McCollum et al., 2016). As argued by Grubb (2014), it is likely that carbon price alone will not be sufficient to achieve the climate target. At a national level, a number of models have been applied to analyse the effectiveness of policy incentives other than carbon pricing on emissions reduction in individual countries.

Table 2.2 summarises the studies that analyse the mid to long term impacts of individual policy instruments on the CO_2 emissions from the PLDV sector using energy models. Note that all of the studies have focused on the analysis of the policy instruments in one developed country. Most studies have only examined the impact of various taxes (e.g. carbon tax, fuel tax, vehicle acquisition tax) on long term CO_2 emissions. For instance, Kloess and Müller (2011) investigate the effect of various tax incentives and technological progress on the Austrian passenger car fleet. Using the UK Transport model, Brand et al. (2013) assess the long term scenario of several low carbon fiscal policies, such as vehicle purchase tax, road tax and scrappage program, as well as their effects on CO_2 emissions from the PLDVs.

Since the zero-emissions vehicle (ZEV) mandates have existed only in the US and some regions in Canada, Sykes and Axsen (2017) examine the impact of the ZEV mandate on the long term sales in North America using CIMS-ZEV. Karplus et al. (2013) study the cost and effectiveness of fuel economy standards, alone and in conjunction with economy-wide policies that constrain GHG emissions. Morrow et al. (2010) analyse fuel taxes, continued increases in fuel economy standards, and purchased tax credits for new vehicle purchases, as well as the impact of combining these policies for reducing GHG emissions and oil consumption in the US transportation sector. Outside North America, all studies have only analysed the impact of various financial incentives in developed countries.

While several studies have used logit models to represent consumer choices, almost all have taken the prices of the representative car models instead of considering the distribution of car prices to reflects the diversity of consumers and the willingness of consumers to pay car prices. In the FTT-Transport model, we capture consumer preferences by segmenting consumers into groups based on car engine sizes and prices paid by consumers. This approach improves the behavioural realism of models, which substantially affects the analysis of climate change policies (Mattauch et al., 2016).

Indeed, while it is beneficial to understand why some policies have been effective only in certain countries, very few studies have compared policy effectiveness between countries using simulation models. He and Bandivadekar (2011) evaluate fiscal policies for passenger cars that potentially influence vehicle CO_2 emissions in eight different countries, including the UK, the US, France, Germany, Brazil, India and Japan. He and Bandivadekar (2011) analyse the existing fiscal policies statistically without applying the data to a simulation model. As such, it is not their goal to analyse the long term effectiveness of these fiscal policies on CO_2 mitigation. Both Michielsen et al. (2015) and Tietge et al. (2016) study the impact of fiscal policies related to EV within Europe. Mercure and Lam (2015) examine the effectiveness of policy incentives across six global regions, including the USA, the UK, Japan, China, India and Brazil. However, existing studies have not applied the data to a dynamic model in order to examine the effectiveness of the policies over a long period of time.

Thus, we identify three main gaps in the existing studies for the analysis of policy instruments on long term CO_2 emissions. Firstly, there is a gap in understanding the carbon emission reduction effects of individual policy incentives in many of the developing countries, although many policy incentives have already been implemented. Secondly, while many studies have analysed the effectiveness of various tax instruments, very few studies have compared the effectiveness of tax instruments against regulations or ZEV mandates. Although it is acknowledged that the ZEV mandates exist only in North America and China, it is useful to carry out scenario analysis and assess the potential impact of ZEV on different countries if this were introduced. Thirdly, existing models have not captured the variants of both vehicle size and fuel types for PLDVs, which is essential in representing consumer segments and pace of diffusion. Fourthly, existing studies, as we have illustrated, have focused on studying policies for only one country or region. While this approach is useful in understanding the impact of policy incentives for one country, results cannot be compared across different countries to provide answers as to why and under what conditions (e.g. in what countries) would the policies be effective and cost efficient.

To fill the gaps in the existing literature, this study explores the effectiveness of five policy measures, including the annual registration tax, fuel tax, EV subsidy, fuel economy regulations and the EV mandate on the long term emissions from passenger vehicles for five different countries, including the UK, the US, Japan, China and India. As we have emphasised, this study models technological change using the FTT-Transport model, which is a dynamic simulation model that captures three fuel types (Econ, Mid, Lux) for eight PLDV technologies (petrol, advanced petrol, diesel, advanced diesel, CNG, flex-fuel, hybrid, EV), with the rate of technology diffusion determined by market price competition and technology competition. The model allows interactions between policy intervention, consumer choices and technological diffusion, crucial in analysing policies that facilitate the technological transitions for passenger cars (Mercure and Lam, 2015).

2.7.1 The interactions between policy incentives in mitigating emissions from the PLDV sector

As we have discussed above, many studies on policy instrument analysis tend to focus on studying the impact of one instrument in a particular country (Giblin and McNabola, 2009; Mabit, 2014; McCollum et al., 2018). Even when studies consider the impact of several policy instruments, they tend to focus on the collective impact of the policy instruments on CO_2 emissions (Shafiei et al., 2018; Morrow et al., 2010), but ignore the interactions among the policy instruments on the emissions of PLDVs. While it is important to examine the overall impact of a group of policy incentives, the interactions among the policy instruments are a central feature of any policy mix because of their influence on the effectiveness and efficiency of instruments in the mix (Río, 2009; Mir-Artigues and Del Río, 2014; Rogge and Reichardt, 2015).

When various policy incentives are combined, they can be mutually reinforcing or working against one another, depending on how they are designed and implemented (IEA, 2011*a*). In other words, there are synergies and interferences between instruments that are actually implemented, and it is useful to understand the effect of policy interactions between them. Several studies have discussed the possible impact of policy synergies and policy mixes on the effectiveness and the efficiencies of the policies on emissions reductions in the energy sector (Rogge and Reichardt, 2015; IEA, 2011*a*). As such, few studies go beyond qualitative statements. An exception is Viguié and Hallegatte (2012), which provides a multicriteria analysis on the trade-offs and synergies of various urban climate policies, such as zoning and public transport subsidies. Fischer and Fox (2009) carry out scenario analysis on carbon tax and the rebate on mitigating carbon leakage. However, none of these studies examine the interactions between policy incentives within the PLDV sector. Hence, the interactions among multiple policy instruments are often not well understood, which can lead to policies undermining each other, reducing the effectiveness and efficiency of the policy package (IEA, 2011*a*).

This present study fills the gap in the existing literature by carrying out scenario analysis on the effectiveness of policy combinations in comparison to the effectiveness of policy incentives when they are introduced individually. If the effectiveness of the policy combinations is lower than the sum of the effectiveness of the policies introduced individually, then there is a trade-off effect between policy incentives, because adding one policy incentive essentially undermines the effectiveness of another policy. Otherwise, if the effectiveness of combined policies is greater than their sum, a synergy effect takes place and there is a reinforcement effect between policy incentives occurs.

Table 2.1: Examples of major energy models

Model name	Type	Methodology/tools
MARKAL, TIMES, GET, MESSAGE, REDGEM70, BEAP, REMIND, LEAP	Energy sector model	Linear optimization
PRIMES	Energy sector model	Non-linear optimisation
TREMOVE, WEM	Simulation model	Simulation and optimisation
IMAGE/TIMER, ASTRA, CIMS, GLADSTE	Simulation model	System dynamic and non-optimisation
POLES	Simulation model	Simulation and partial equilibrium
TAPAS	Simulation model	Agent-based model
MESSAGE-MACRO, MARKAL-MACRO, RICE, DICE, GEM-E3	Macroeconomic model	Optimization framework
E3MG	Macroeconomic model	Non-optimizing dynamic simulation approach
CIMS, GREEN, NEMS, GEM-E3, WITCH	Macroeconomic model	Equilibrium structure (CGE), TIAM
MERGE, FUND, CETA, WIAGEM	Integrated assessment model	Optimization hybrid models

Table 2.2: Studies for the impacts of individual policy instruments on the CO_2 emission reductions from the PLDV sector using energy models.

Title	**Authurs**	**Countries**	**Policy instruments considered**	**Model**
Modelling the impacts of a carbon Emission-differentiated vehicle tax system on CO_2 emissions intensity from new vehicle purchases in Ireland.	Giblin and McNabola (2009)	Ireland	Carbon tax	COWI cross-country car choice model
Analysis of policies to reduce oil consumption and greenhouse-gas emissions from the US transportation sector.	Morrow et al. (2010)	US	Fuel economy regulations, purchase tax credits, CO_2 tax	National Energy Modelling System (NEMS)
Simulating the impact of policy, energy prices and technological progress on the passenger car fleet in Austria.	Kloess and Müller (2011)	Austria	Fuel tax, vehicle acquisition tax	Simulation model
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.	Brand et al. (2013)	UK	Vehicle purchase tax, road tax, vehicle scrappage scheme	UK Transport Carbon Model
Should a vehicle fuel economy standard be combined with an economy-wide greenhouse gas emissions constraint? Implications for energy and climate policy in the United States.	Karplus et al. (2013)	US	Fuel economy standard, cap and trade	Emissions Prediction and Policy Analysis (EPPA) model
Vehicle type choice under the influence of a tax reform and rising fuel prices.	Mabit (2014)	Denmark	Vehicle registration tax	Mix logit model
A system dynamics based market agent model simulating future powertrain technology transition: Scenarios in the EU light duty vehicle road transport sector.	Pasaoglu et al. (2016)	EU	EV subsidy, fuel economy standards	the system dynamic approach
The vehicle purchase tax as a climate policy instrument.	Fridstrøm and Østli (2017)	Norway	Vehicle purchase tax	Nested Logit Model
No free ride to zero-emissions: Simulating a region's need to implement its own zero-emissions vehicle (ZEV) mandate to achieve 2050 GHG targets.	Sykes and Axsen (2017)	US, Canada	Zero-emissions vehicle (ZEV) mandate	CIMS-ZEV
Car fleet policy evaluation: The case of bonus-malus schemes in Sweden.	Habibi et al. (2018)	Sweden	Bonus-malus schemes	Nested logit model
Macroeconomic effects of fiscal incentives to promote electric vehicles in Iceland: Implications for government and consumer costs.	Shafiei et al. (2018)	Iceland	Vehicle tax, fuel tax, feebates	System dynamic approach

Chapter 3

Methodology

3.1 Theoretical framework of FTT-Transport

The future technology transformation (FTT) is a framework that models technological diffusion dynamically and is based on market price competition and technological competition. Prior to the FTT-Transport model, the FTT model existed to model decision making by investors in power generation technology. As a member of the FTT framework, the FTT-Transport model aims to model technology diffusion dynamically in the PLDV sector based on a decision making module that represents choices made by diverse agents facing restricted information and access to technology for consumers. Currently, the model is available only for PLDVs, which are the focus of this thesis. Note that Dr. Mercure and myself worked collaboratively during the development of the theoretical framework (details of the collaborative work can be found in Appendix B). The following paragraphs discuss the conceptual framework for the FTT-Transport model.

The modelling of technological transition requires consideration of agent diversity and consumer choices in the transport sector. Meanwhile, economic and cost change (through learning and technological advancements) will interact with consumer decisions, R&D, and long-term technological transitions. This requires a model of technological diffusion that describes consumer decisions, R&D, and macroeconomic conditions endogenously within a model.

Instead of taking a representative agent approach, the FTT-Transport model assumes the presence of a diverse market with heterogeneous agents. This is done using a probabilistic treatment of consumer decision making and using a distribution of cost values. We assume that the cost distribution corresponds to the heterogeneity of consumer choices as a result of revealed preferences. The cost distributions are related to whether the consumers are early adopters, an early majority, a late majority, or laggards, which drives the adoption and diffusion of technology, as suggested by (Rogers, 2010). Agent heterogeneity is represented by introducing a cost distribution over agent perspectives with the discrete choice theory.

As a result of increasing returns to adoption (Arthur, 1989), technologies gains higher market shares as more consumers adopt and use the technology for the following reasons. Firstly, people makes choices based on the visibility and accessibility of a technology. For example, people like to behave in a 'socially desirable way' and purchase low-emissions vehicles in order to boost their images within their own social groups (Liao et al., 2017). Secondly, many studies find that consumers have a 'wait and see' attitude when choosing new technologies, in particular, new automobile technologies (Chanaron, 1998; She et al., 2017). This attitude is prevalent because consumers are risk averse and low-carbon vehicles present uncertainty (e.g., range anxiety, availability of charging stations, and so forth) when users are inexperienced. Thirdly, consumers may have a particular preference towards one range of car models (e.g., brand, engine size, style). If their preferences are not satisfied by the available EV models, the technology (e.g., EV) will not match the preference for this group of consumers. However, when EVs become more popular with consumers, this encourages the manufacturer to boost the number of EV models and charging infrastructure available, which will further boost EV sales.

Thus, the FTT framework is a model designed to reproduce observed S-shaped diffusion curves by modelling competition in the market. The diffusion processes are path dependent and involve positive feedbacks that are captured by the FTT framework. The FTT models of technological diffusion are consistent with the 'bandwagon effect' [1]. It is implied that decisions are recursive and self-reinforcing by assuming that social trends play an important role in the diffusion of technology. In other words, if a group of consumers purchase a new technology through the 'bandwagon effect', it is more likely that people around this group of consumers will follow, leading to path dependence for a technology.

The technological diffusion rate is proportional to the market shares of technologies (i.e. the 'bandwagon effect'). In additional to quantifiable costs (e.g., capital costs, fuel taxes), the model considers the non-quantifiable costs of consumer choices (e.g., comfort, luxury effect) with an empirical factor that is added to the quan-

[1] The bandwagon effect is a phenomenon whereby the rate of uptake of technologies, fads and trends increases as more of them are adopted by others.

tifiable costs (see Section 3.4 for the determination of this value). A learning rate is incorporated in order to take into account the falling cost as production of the technology increases. Differences in the cost distributions is one of the key factors in facilitating future technological diffusion. Further, it is assumed that cost distributions correspond to population heterogeneity, driving technological diffusion through cost comparisons.

In the FTT-Transport model, the transport demand is determined based on econometric analysis, which is presented in Chapter 5.

3.2 Modelling heterogeneity with discrete choice theory

In consumer behaviour theory, consumers are most likely to make purchases according to their own experiences with the technology or the consumption experiences of their peers gained through social interaction (Douglas, 1978) and visual influence (demonstrated by McShane et al. (2012) in the US). It is also likely that the choices of consumers are influenced by their peers through the 'bandwagon effect' (McCollum et al., 2018). The cost distributions reflect the diversity of consumers in terms of choices, taste, and income. The diversity of sales in terms of cost distribution reflects the diversity of agents (Mercure, 2015*a*). The rates of technological diffusion are related to the heterogeneity among the agents who adopt technologies at different times (see the Rogers Adoption Curve, Rogers (2010)).

In the FTT-Transport model, consumer decisions are modelled with chains of binary logits. In discrete choice theory (Ben-Akiva and Lerman, 1985; McFadden, 1973), choices are made in a probabilistic fashion, which means that unobserved factors, such as taste variation and interpersonal heterogeneity, are taken into account in the discrete choice model. In the binary logit model, decision making uses pairwise comparisons of cost distributions, as shown in Figure 3.1. We assume that consumers are choosing between technology i and technology j with cost distributions $f(x)$ and $g(x)$, respectively. The probability that a consumer chooses technology j over technology i depends on the instances in which the cost of technology j falls below the cost of technology i. The comparison of cost distributions captures the heterogeneity of consumer choice in the FTT-Transport model.

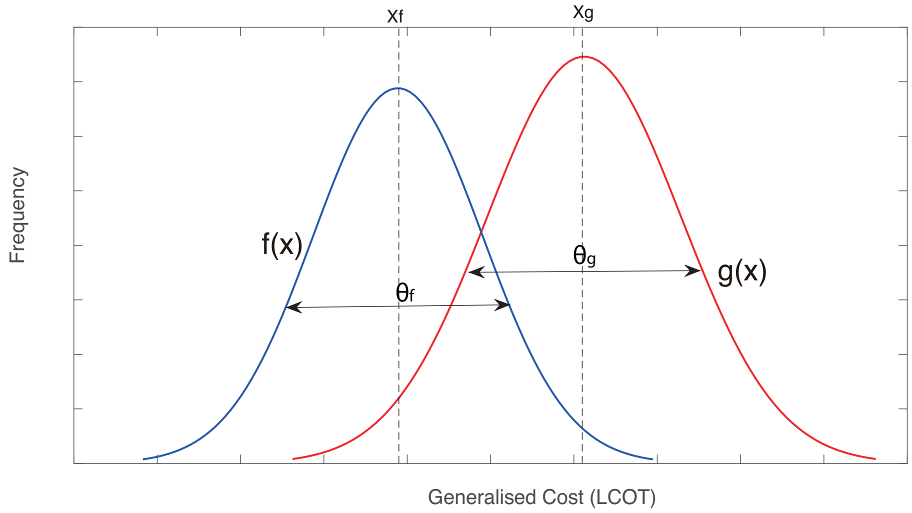

Figure 3.1: The cost distributions f(x) and g(x) for two technologies i and j. The probability that a consumer chooses one technology over another depends on the width of the technology as well as the average cost of the technology.

3.3 Shares equation

3.3.1 Initial market shares

Market shares for vehicle technologies in the FTT-Transport are defined as

$$S_j(t) = N_j(t)/N_{tot}(t)dt, \tag{3.1}$$

where $N_j(t)$ is the number of technology units of technology j at time t, and N_{tot} is the total number of cars on the road, with

$$N_j(t) = \int_{\infty}^{0} \epsilon_j(t-a)l_j(a)da, \tag{3.2}$$

where a is the vehicle age, and l_a is a measure of the survival function [1] for technology j and ϵ_j is the car sales time series.

For vehicles, maintenance costs increases with age. Vehicles come to the end of their useful life through accidents and scrappage decisions. The survival function is typically a monotonically decreasing function that declines from 1 to 0 as age increases and represented by a Weibull distribution (see Zachariadis et al. (1995)).

[1] The survival function is defined as the proportion of vehicles of a given model still in operation at a given age. It provides the fraction of vehicles that survive up to a certain age and is the key parameter used to simulate the dynamics of vehicle turnover (Huo and Wang, 2012).

The determination of vehicle survival rates normally requires substantial historical information about vehicle fleets, and it is also country dependent (as shown in Huo and Wang (2012)). However, it is unrealistic to develop survival functions for all five countries. For this research, the survival function is taken from the existing studies, as will be discussed further in Chapter 4.

3.3.2 Technology diffusion equation

The FTT framework models technology transitions with the Lotka-Volterra competition (LVC) equations. The LVC equations are a set of coupled logistic differential equations that models the interactions of biological species competing for the same resources (Lotka, 1956) and are described by:

$$dN_i/dt = r\alpha_i N_i(1 - N_i/K) \tag{3.3}$$

where N_i is the size of the population, r is the growth rate of the population and K is the maximum population size of the species (i.e., the carrying capacity).

The equation above is equivalent to the replicator dynamic of the evolutionary game theory. A number of studies have shown that L-V equations can be applied to model technological diffusion (Saviotti and Mani, 1995; Grubler, 1990; Marchetti et al., 1980). Furthermore, there is a strong analogy between technology competition and evolution in biology (Safarzyńska and van den Bergh, 2010). In particular, the competition between technologies in the marketplace is analogous to the evolution of genotype frequencies in biology (Hodgson and Huang, 2012).

Considering two technologies, Marchetti et al. (1980) present data with a substitution process in the road transport system over 80 years. The substitution of cars for horse and carriage follows a logistic transition between the two technologies:

$$S_1(t) = 1/(1 + exp(\alpha_{12}(t - t_0)) \tag{3.4}$$

and

$$S_2(t) = 1/(1 + exp(\alpha_{21}(t - t_0)), \tag{3.5}$$

where $S_1(t)$ and $S_2(t)$ are the shares for Technology 1 and Technology 2, respectively. Here, α_{12} and α_{21} determine the rate of technological diffusion.

Thus, we have

$$dS_1/dt = \alpha_{12}S_1S_2 \tag{3.6}$$

and

$$dS_2/dt = \alpha_{21} S_1 S_2 \tag{3.7}$$

In reality, there will always be more than two car technologies competing in the marketplace. Based on the deduction above, we obtain:

$$dS_n/dt = \alpha_{1n} S_n S_1 + \alpha_{2n} S_n S_2 + \alpha_{3n} S_n S_3, \tag{3.8}$$

hence,

$$dS_i/dt = \sum \alpha_{ij} S_i S_j \tag{3.9}$$

The equation suggests that the rate of technology substitutions is dependent on the changes in the shares of the competing technologies i and j, and a constant α_{ij}. This is equivalent to the replicator dynamics in the evolutionary game theory, as stated above. The equation is central to the FTT-Transport model and is referred to as the replicator dynamics equation.

Empirical research has shown that peoples' attitudes and decisions to adopt new technologies are influenced by their social environment and network (see e.g. McShane et al. (2012)). Regarding the PLDV sector, consumers are forced to choose among the available models that fit their preferences. If they are risk averse, they will choose the car models that are widely driven and have infrastructure readily available. Thus, we assume that shares for car technologies replicate at a rate proportional to the shares for that technology in society. In the FTT-Transport model, although the availability of infrastructure is not explicitly modelled, it is assumed that as the shares for EVs increase, the investment in infrastructure will follow; otherwise, consumers will be reluctant to purchase EVs.

The rate of technological diffusion is determined by the gradient of the technology diffusion curve (α_{ij}). Mercure (2015*b*) presents details regarding the α_{ij} constant in the context of technology diffusion. Investments and penetrations of technologies are dependent on the choices of consumers or investors facing a variety of options in the presence of incomplete information or based on the assumption of bounded rationality. This is equivalent to a natural selection carried out by consumers who choose the innovation that matches their tastes, and products that do not win the market competition will be ruled out through the natural selection process. The rate of technological substitution hinges on the relative birth rate, the turnover rate and the death rate of technologies over time. Thus, the birth rate and the death rate determine the timing of the technology diffusion phase.

In the context of the PLDV sector, the decision to buy, substitute or scrap a passenger car is a choice made by each consumer on the basis of various financial, socio-economic, and technological parameters. The diffusion of a car technology is based largely on consumer decisions, which depend on a number of factors, such as family income, car prices, personal preferences, cultural differences, demographics, and lifestyles. We assume that shares flow from technology j to technology i when cars using technology j are 'dead'. The death of a vehicle can be caused by failure or the economic decision to scrap it due to the increased cost of maintenance with time. The turnover rates of cars could be the results of policies that encourage the scrappage of cars or the purchase of new cars for both economic and environmental reasons. The number of cars belonging to technology j, replaced by technology i, depends on the number of cars with technology j being scrapped and the number of consumers that choose car technology i over j after their old cars using technology j are scrapped.

The growth and fall of the share for a technology is determined by the pairwise consumer choice matrix F_{ij} (see discussions in Section 3.4), which specifies the probability of one technology being chosen over another according to perceived costs. The number of units of car technologies flowing from technology j to i is a fraction of its own shares, and thus, proportional to market share S_j times a time constant A_{ij}.

The time constant for technological substitution is determined by a birth and death function. The death function is a strictly decreasing survival function, as we have discussed. . On the other hand, the birth function is defined as the total production from one unit of capital during its lifetime. Mercure (2015*b*) provides a detailed mathematical derivation of the relationships between the birth function, the death function and the constants for technological substitution. The generalised form of the time constant is:

$$A_{ij} = (\bar{\tau}\bar{t}/\tau_i t_j)/\bar{\tau} \tag{3.10}$$

where τ_i is the life expectancy derived from the survival function, and t_j is the fastest possible growth rate in terms of the re-investment rate. In terms of transport, τ_i would be the vehicle survival function, and t_j is the fastest growth rate for vehicles. Note that since t_j and τ_i appear as ratios with their averages $\bar{\tau}$ and $\bar{t}$, respectively, the common scaling factors cancel out (Mercure, 2015*b*). Hence, it is not the absolute value of t_i that determines the rate of technology uptake, but the ratios for the death and birth rates. Thus, the rate of technology substitution is determined by the rate at which a technology is filling the market in comparison with other technologies.

In terms of PLDV technologies, the rate of relative technology turnover rate depends on the frequency of consumer decision making, which is arguably lower than the survival rate of cars. For instance, the rate of technology substitution is related to the payment schedules for cars, ranging from one year to seven years (Montoya, 2018), depending on interest rates and the resale value. Therefore, for vehicle technologies, the turnover rate is determined by:

$$A_{ij} = 1/\bar{\tau} \tag{3.11}$$

The car turnover rate in this model is defined as the number of years before buyers of new cars decide to sell their cars back to the dealer or to the second-hand car markets. In other words, it is the frequency of car-buying decisions by car drivers. In most countries, it is similar to the payback period for new cars. Note that the turnover rate also depends on the income level of a country and the existing policy frameworks that supports the sale of new cars.

For modelling purposes, we have to distinguish between the survival rate/scrappage rate and the turnover rate defined in this section. The survival rate, as its name implies, considers the exit of cars from the market due to car scrappage (death of a technological unit) only, while car turnover rate includes cars that are put onto the second-hand car market. The turnover rate could be much smaller than the scrappage rate, especially if people do not tend to hold onto their new vehicles for very long.

There are a number of reasons behind the differences in turnover rates in different countries as well as the fact that turnover rates tend to vary between years, depending on social economic factors and government policies. Contributing factors include family incomes, depreciation rates, motor vehicle inspection costs, and whether it is legal to export second-hand cars from the country. For instance, in Japan, new cars must be tested three years after purchase and then every two years thereafter. This means that owning and maintaining a car beyond three years is much more costly. On the other hand, if incomes fall after an economic crisis, such as in the US, it becomes less affordable to take out a loan for a car.

Meanwhile, the number of agents choosing technology i is a subset of all agents that have access to information concerning car technology i, which is proportional to the market shares for technology i. This assumption is supported by consumer theory, where choices are made through visual influence within social groups (McShane et al., 2012). Consumers are more likely to choose a technology that has a higher market share as a result of social influence. When given a choice between two technologies i and j, the fraction of consumers that choose technology i is denoted F_{ij}, while the remaining consumers (denoted F_{ji}) choose technology j, with:

$$F_{ij} + F_{ji} = 1 \tag{3.12}$$

The flow of market share from technology j to technology i is

$$\Delta S_{j\to i} = S_i S_j A_{ij} F_{ij} \Delta t \tag{3.13}$$

and the flow of market shares from technology i to technology j is:

$$\Delta S_{i\to j} = S_j S_i A_{ji} F_{ji} \Delta t \tag{3.14}$$

The market shares for technology i as a result of the flow of market shares is:

$$\Delta S_i(t) = \sum_{j=1}^{N} \left(A_{ij}F_{ij} - A_{ji}F_{ji}\right) S_i S_j \Delta t, \tag{3.15}$$

Then we have:

$$\Delta S_i(t) = \sum_{j=1}^{N} \left(F_{ij} - F_{ji}\right) S_i S_j \frac{1}{\bar{\tau}} \Delta t, \tag{3.16}$$

Equation 3.16 is also called a Lotka-Volterra equation, which is strongly path dependent. The rate of technology diffusion is equal to $(F_{ij} - F_{ji})/\bar{\tau}$, which is a logistic diffusion function. This equation is equivalent to the replicator dynamics equation and is central to technological diffusion modelling in the FTT-Transport model.

3.4 Consumer decision matrix

3.4.1 Consumer probabilistic choice

Consumers in the vehicle market are heterogeneous and choices are made in a probabilistic fashion (Mercure and Lam, 2015). We assume that the market heterogeneity can be derived from consumers? 'revealed preferences' (i.e., their vehicle choices) since consumers make purchases based on the availability of car models in the market. As such, the car manufacturers attempt to match consumers? preferences. In discrete choice theory, consumers have heterogeneous taste and place different utility weights on different product characteristics.

In this model, we assumed that consumers make decisions based on a chain of binary logits. Hence, consumers compare two technologies at a time based on generalised costs and preferences. We denote the average generalised cost [1] (see discussions on generalised cost in Section 3.4.2) of technology i as C_i, with a standard deviation σ. The frequency distribution for consumer choices is represented by $f_i(C - C_i)$ and the cumulative distribution $F_i(C - C_i)$. $F_{ij}(\Delta C_{ij})$ denotes the fraction of agents that prefer technology i over j based on the difference in the generalised costs of technologies i and j, and the cost difference between two technologies i and j is denoted as: $\Delta C_{ij}(= C_j - C_i)$.

The F_{ij} can be approximated by the following equation:

$$F_{ij}(\Delta C_{ij}) = \int_{\infty}^{-\infty} F_j(C) f_i(C - \Delta C_{ij}) dC \tag{3.17}$$

and

$$F_{ji}(\Delta C_{ij}) = \int_{\infty}^{-\infty} F_i(C) f_j(C - \Delta C_{ji}) dC \tag{3.18}$$

Then we have:

$$\frac{dF_{ij}}{dC_{ij}} = -\int_{\infty}^{-\infty} f_i(C - \delta C_{ij}) f_j(C) dC = -f_{ij}(\delta C_{ij}) \tag{3.19}$$

Equation 3.19 generates a new frequency distribution. Following the standard discrete choice theory, the f_i is a Gumbel distribution with standard deviation σ_i. We have that $f_i = e^{-e^{(C-C_i)/\sigma_i}}$. Therefore, the convolution of two Gumbel distributions is a logistic equation. Hence, we have:

$$\begin{aligned} F_{ij} &= -\int_{\infty}^{-\infty} (f_i * f_j) dC \\ &= \frac{1}{(1 + e^{\Delta C_{ij}})} \end{aligned}$$

[1] The generalised cost is the sum of quantifiable costs (e.g., car capital costs, fuel costs, taxes) and non-quantifiable costs (e.g., comfort, safety).

We approximate a cumulative distribution by an error function.The consumer choice matrix (F_{ij}) is a logistic function approximated by the error function (erf):

$$
\begin{aligned}
F_{ij} &= \frac{1}{dF_{ij}\sqrt{2\pi}} \int_{\infty}^{C_j} e^{-(x-Ci)^2/(2\sigma^2)} dx \\
&= 0.5 * (1 + erf((C_j - C_i)/dF_{ij})
\end{aligned}
$$

Where

$$
dF_{ij} = 1.414 * \sqrt{\sigma_i^2 + \sigma_j^2} \tag{3.20}
$$

3.4.2 The generalised cost of transportation

It is challenging to determine exactly what quantitative evaluations are carried out by vehicle consumers when choosing vehicles. The generalised cost of the vehicle is defined as the willingness of the consumers to pay for cars. Studies (Baltas and Saridakis, 2013; Shende, 2014; Choo and Mokhtarian, 2004) show that capital and operating costs only represent two of many determinants (e.g., comfort, brand effect, safety) that drive consumer energy-related decisions.

The generalised cost for consumers is therefore defined as the monetary cost paid by the consumers and a personal value assigned by the consumers based on the extent to which cars satisfy their needs. The generalised cost for the car is the price of the car, the cost of driving the car, as well as the cost of comfort and safety that is assigned by individual consumers. Therefore, the generalised cost (C) is distributed and is made up of two components; a quantifiable cost component, such as the capital cost and operating cost, and a non-quantifiable cost component, such as comfort and safety.

Levelised Cost of Transportation

For the quantifiable cost, we assume that vehicle purchasers make decisions using a net present value approach [1]. For modelling purposes, we assume that the econometric equations for car purchases are separated from the costs for the transport services. The purpose of this approach is to find the discounted cost of generating transport services for each car purchase that can then be compared across options.

[1] Since we know that consumers have a time preference, it would be misleading not to include discounting, even if consumers may not calculate a Net Present Value (NPV) every time they make a vehicle purchase.

As such, quantifiable costs should take into account a number of components, including the initial down payment for the vehicle (or loan), the maintenance costs, the fuel costs incurred for the lifetime of the technology, and the costs of policy incentives. We define a levelised cost of transport ($LCOT$), which represents the constant unit cost ($/km) of service and has the same present value as the total cost of running the car over its lifetime. $LCOT$ is the cost of one km of driving when accounting for discounted costs over the lifetime of a PLDV. The $LCOT$ is defined as:

$$LCOT_i = \frac{\frac{I_i}{CF_i} + \sum_t \frac{F_i * FE_i + MR_i + FP_i}{(1+r)^t}}{\sum_t \frac{1}{(1+r)^t}}, \tag{3.21}$$

where I_i, F_i, MR_i and FP_i are the mean capital costs (in USD), fuel cost (in USD/litre), maintenance cost (in USD/km) and fiscal pricing (i.e. tax or subsidy) (in USD/km), respectively. FE_i is the fuel consumption (in litre/km). CF_i is the capacity factor, in km/y. r is the consumer discount rate.

As shown in Mercure and Lam (2015), car prices are distributed due to the heterogeneity of technology and consumer preferences. Maintenance costs are related to car technology and price volatility, so they are distributed as well. Further, the fuel price distribution is determined by its volatility. We define the width of $LCOT$ by $\Delta LCOT$,

$$\Delta LCOT_i = \frac{\sum_t \frac{\sqrt{Dist + FP_i^2}}{(1+r)^t}}{\sum_t \frac{1}{(1+r)^t}}. \tag{3.22}$$

where

$$Dist = \frac{\Delta I_i^2}{CF_i^2} + \frac{I_i^2}{CF_i^4}\Delta CF_i^2 + \Delta F_i^2 FT_i^2 + \frac{\Delta MR_i^2}{FF_i^2} + \frac{MR_i^2}{FF_i^4}\Delta FF_i^2 \tag{3.23}$$

ΔI_i, ΔF_i and ΔMR_i are the widths (standard deviations) for the car price, fuel price, and maintenance cost distributions, respectively. The $\Delta LCOT_i$ represents the cost distributions for cars in real space.

Intangible variable

We define intangible variables as factors that determine the consumer's generalised cost, beyond quantifiable costs. Thus, the intangibles include the components that are valued by consumers to satisfy in terms of personal needs (e.g., comfort, speed). An intangible cost is calculated by minimising the difference in slopes between the projected market shares and the historical market shares. The historical shares for vehicle technologies are calculated by a survival function and new sales for cars across the previous 25 years. In the FTT-Transport, γ_i is defined as the 'difference between generalised cost, which leads to observed diffusion, and the LCOT calculated'. The γ_i represents the factors in the consumer′s decision that cannot be easily quantified. The γ_i parameter accounts for the fact that there could be very large cost differences between engines, which are compensated by benefits to the user that are intangible (e.g., an expensive, powerful engine is compensated by the satisfaction of the user in terms of acceleration). The γ_i adjusts the vehicle price distributions so that the diffusion process is consistent with history, even when large vehicle price differences are observed across categories.

Figure 3.2 shows that when a set of γ_i values are chosen, our projections from 2016 to 2025 follow the trends from 2009 to 2016. The γ_i values are adjusted and fed into the model to calculate the shares for all technologies for the first nine years from 2016. Note that adjusting the γ_i value for one technology will affect the slopes for all other technologies dynamically. Thus, we need to adjust the values for γ_i until the sum of the differences between the projected shares and the historical shares for all technologies is minimised. In the case that other capital costs remain unchanged, γ_i is a constant value, i.e., it only has to be found once, and independent of the scenario assumptions.

3.4.3 Cost comparison

The comparison of costs in the binary logit model is made in logarithmic space. This is because car prices are typically log-normally distributed (as observed in Mercure and Lam (2015)). For simplicity, we compare costs in lognormal space via means and a standard deviations using the following transformation equations (equation 3.25)

$$LGLCOT = log(\frac{LCOT^2}{\sqrt{\Delta LCOT + LCOT^2}}) + \gamma_i \tag{3.24}$$

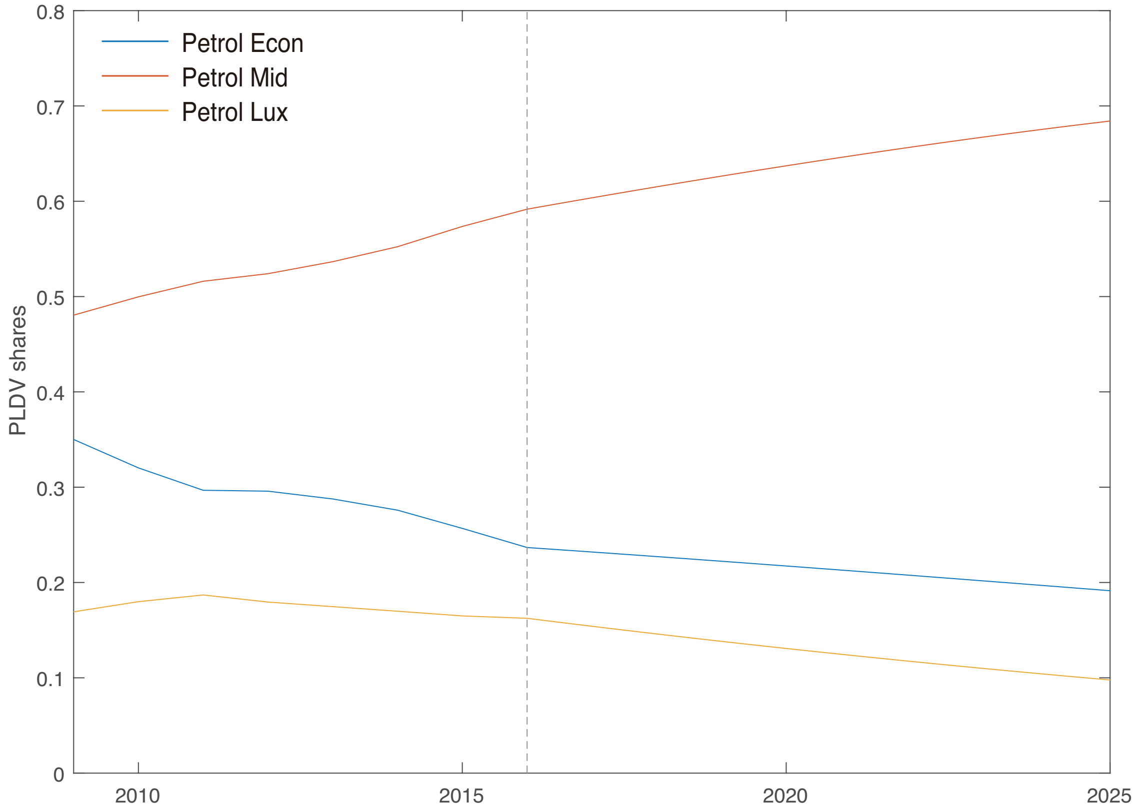

Figure 3.2: Historical and projected shares of petrol cars in China (as a demonstration for how γ_i values are derived). The historical shares of different car technologies are shown on the left side of the black dash lines, with the projected shares of these car technologies shown on the right. The set of constants are adjusted so that the projected shares follow the historical trends.

and

$$dLGLCOT = \sqrt{log(1 + \Delta LCOT_i/(LCOT^2))} \tag{3.25}$$

where LCOT and $\Delta LCOT$ are the mean and standard deviation in the normal dollar (USD) space. The details for the transformation from a standard space to log normal space and can be found in Mathworks. Note that γ_i is found in the lognormal space.

3.4.4 Vehicle prices and learning

The FTT-Transport model uses learning curves and capital costs for vehicle technologies ($I_i(t)$) fall by a certain percentage (learning rate b_i) every time the total quantity manufactured $W_i(t)$ doubles:

$$I_i(t) = I_{0,i} \left(\frac{W_i(t)}{W_{0,i}} \right)^{-b_i}, \tag{3.26}$$

The learning rate is the cost reduction achieved for a doubling of the cumulative installed capacity. For niche technologies, the existence of technological learning implies that prices for the new technologies (e.g., electric cars) will fall as the quantity of production increases. Note that the learning rates for niche technologies are subject to great uncertainty (Tom Hazeldine and Deller, 2010; McDowall, 2012; Weiss et al., 2012) as the result of different methods of estimation. Additionally, for some technologies, specific learning curves and product ratios have been observed in the past, but the ratio may not be applicable in the future since learning rates may change over time (Sagar and Van der Zwaan, 2006). The learning rates are not very different between countries as a result of knowledge diffusion across countries through big car corporations. Mass production has existed for conventional cars since 1910 and the Ford Model T, so the range of learning rates is small and will not have a significant effect on the long-term prices.

To account for the uncertainties regarding learning rates, a sensitivity analysis is presented in the Appendix A, where we examine the extent to which the difference in learning rate creates uncertainties for the model. Future studies may consider using a stochastic model formulation, which can calculate the impact of the learning rate uncertainties in a rigorous manner.

3.4.5 Spillover matrix

Knowledge spillovers occur when investments in knowledge creation by one party produce external benefits via facilitating innovation by other parties (Jafie et al., 2000). In fact, knowledge spillovers happen between firms and technologies. The category of knowledge accumulation does not necessary correspond to vehicle categories, which means that knowledge spillovers take place between categories. This is because learning happens on a component level rather than a technology level and may be used in more than one type of technology; therefore, sales in one technology category may induce learning in other categories. For instance, reductions in the cost of the lithium-ion battery will benefit both hybrid cars and EVs. The lithium battery delivers twice the power compared to similar- sized cells. Further, enlarging the capacity of the battery enables hybrid cars to store energy more efficiently during deceleration. Hence, we have

$$W_i(t) = \sum_j B_{ij} \int_t^0 R_j(x)dx, \tag{3.27}$$

where W_i is the total quantity of technology i manufactured and B_{ij} is the spillover matrix, and R_j(x) is the number of new cars of technology j registered.

3.5 Energy use and emissions calculation for PLDVs

In the FTT-Transport model, the PLDV service demand and the fleet number are estimated and projected with regressions in Chapter 5. The projections for the service demand (in km per year) and the car ownership projections (total car fleet) for each country are used to calculate energy use and emissions as below.

We start with the equation calculating energy use, which is dependent on the fuel consumption factor, in the units MJ/seat-km, and the services provided by all vehicles on the road. The total service generated by a particular technology is equal to the product of PLDV service demand (in km per year multiplied by the occupancy rate) and the transport capacity of the technology, defined as the number of seats in PLDV; thus, we have:

$$G_i = U_i * CF_i * P_i \tag{3.28}$$

where G is the service generated by a PLDV technology, in pkm/year, CF is the km per car in km/fleet, and P_i is the filling factor/occupancy rate (i.e. how many people on average in each car). U is the PLDV fleet number by technology, defined as:

$$U_{k,t} = S_{k,t} * Utot_t \tag{3.29}$$

where $S_{k,t}$ is the share of technology k at time t, and $Utot$ is the size of the PLDV fleet on the road at time t, projected in Chapter 5 and based on the Gompertz function.

For new cars, the fuel consumption factor is obtained from the car manufacturers. Note that the CO_2 emissions from the new cars are lower than those of the car fleet on the road as the result of policy incentives and technological development. However, the data for on- road fleet emissions for each country is not available.

The energy consumption equation is calculated from fuel consumption per kilometre and the services that the vehicles provide while considering the filling factor FF_k [1],

$$J_{k,t} = G_{k,t} * EG_{k,t}/(FF_{k,} * NSeats_k) \tag{3.30}$$

where $NSeats_k$ is the number of seats in cars (i.e., $NSeats_k$=4 in most cases), J is energy consumption in MJ/year, EG is the energy consumption factor in MJ/seat-km as calculated by a fuel consumption factor [2] multiplied by the energy densities [3] for petrol/diesel/ethanol. CO_2 emissions from passenger vehicles are closely related to energy consumption. Emissions are defined as:

$$E_{k,t} = G_{k,t} * CO_{2_{k,t}}/(FF_{k,} * NSeats_k) \tag{3.31}$$

where $E_{k,t}$ is the fleet emissions in $GtCO_2$/yr and $CO_{2k,t}$ is the emissions factor.

In the FTT-Transport model, the fuel consumption factor is collected from the car manufacturers for new cars (see Chapter 5). The indirect fuel consumption of EVs is calculated by dividing battery capacity (in Wh) by the range (in km) provided by the battery, both obtained from the car manufacturers. Note that this is only an estimation of energy consumption factors for EVs because the real energy consumption is associated with trips under consideration. The way in which we obtain the energy consumption of a battery is only accurate in situations in which the battery depletion rate per unit distance is constant across the different levels of the batteries.

In the FTT-Transport model, we account for the indirect emissions from the EVs (i.e., power sector CO_2 emissions due to the electricity demand on the part of EVs). The emission factors for EVs are found by dividing the projected CO_2 emissions of the power sector in each country by the total energy demand in the power sector (Mtoe), which are based on the projections in the New Policy Scenario provided by the IEA (IEA, 2017c). The data for this work is presented in Chapter 4. Note that CO_2 emissions from EVs vary according to decarbonisation scenario in the power sector. However, the scenario analysis on CO_2 emissions from the power

[1]The filling factor is the fraction of seats occupied, on average, when a particular vehicle is in use. We assume that all passenger cars are four-seaters, i.e., FF_i=occupancy/4.

[2]This factor is collected from car manufacturers published as the 'fuel consumption factor' or 'fuel economy', in miles per gallon, litres per km, and so forth. See Chapter 5 for details regarding data collection.

[3]Energy density is defined as energy in MJ per unit of mass of fuel.

sector is outside the scope of this thesis.

Chapter 4

Data

In the context of this research, following the definitions found in IEA (2017*b*), PLDVs include passenger cars, SUVs, and passenger light trucks but exclude two-wheelers, three-wheelers and low-speed/low-power four-wheeled vehicles. In the FTT-Transport model, SUVs and light trucks are treated like other forms of PLDVs (e.g., passenger cars) and are categorised based on their engine sizes. We argue that this is a valid assumption because people choose cars based on their prices and utilities. The SUVs and light trucks in the US differ from the passenger cars only in terms of their sizes (e.g., interiors and engine sizes) and prices. Hence, we assume that the SUVs are one type of PLDVs, with functions and utilities similar to those of normal passenger cars.

Table 4.1 shows the scope of the PLDVs in the context of the five different nations used in this study. The vehicle categories we specified are consistent with car classifications in the dataset provided by each of the national government statistical agencies on automobile fleet numbers. Other than in the US, private passenger vehicles mainly consist of 4-seater passenger cars, SUVs, and light vans, while, in the case of the US, light trucks are included in the analysis.

Table 4.1: The scope of the PLDVs in our research

Country	**Car types**
UK	4-seaters private passenger cars, SUVs
US	4-seaters private passenger cars, SUVs, light trucks
Japan	4-seaters private passenger cars, SUVs
China	4-seaters private passenger cars and SUVs
India	4-seaters private passenger cars, SUVs

4.1 Data requirements

For the present study, an original database detailing the technological profile of cars and populations was built, as required by the methodology. Table 4.3 shows the data required to run the FTT-Transport model. Columns two to four are dedicated primarily to the scope and level of detail required, including the selected time periods and the resolution of the data.

Consistent with the Eurostat definition, PLDVs are divided into three engine sizes categories: Econ ($\leq$1400cc), Mid ($>$1400cc and $<$2000) and Lux ($\geq$2000cc). Eight passenger car technologies are considered in the model, including petrol cars, diesel cars, CNG cars, flex-fuel cars, hybrid cars, electric cars, advanced petrol cars and advanced diesel cars. The advanced categories are defined as cars that use advanced technologies (e.g., variable valve timing, a stop-start system) and are more efficient than the models on the market in 2016.

Electric vehicles were classified according to price (Econ : $\leq$ 20000 USD, Mid: between 20000 USD and 40000 USD, Lux: above 40000 USD). These car technologies are considered to be the most commonly found technologies in the US, the UK, Japan, China, and India.

4.2 Data sources for car prices, engine sizes and fuel economy

As shown in Table 4.4, car prices, engine sizes, and fuel economy data for each car model listed in Marklines were collected from various sources, including car manufacturers, car sales websites, car industry market reports, and government institutions, and matched to the car models listed in the Markines data. Note that the prices obtained are the list prices for 2016. Car fuel economy data was collected from the manufacturers' websites, when available. Otherwise, it was much faster to obtain the car specifications and prices from one single car research website where these data were readily available. To ensure the reliability of the data outside the manufacturer's website, we checked the price, engine sizes and fuel economy data from these car sales research websites and government institutions against the data obtained from the manufacturers.

In many cases, each car model had several car price and fuel economy values, depending on its options. We usually took the mid-value for prices and engine sizes, unless it was known that a particular vehicle option/alternative was very popular. The data sources are listed in Table 4.4.

4.3 Summary statistics

Table 4.5 shows the means, medians and standard deviations (S.D.s) for car price, engine size and fuel economy. The differences in mean and median car price, engine size, and fuel economy show the skewness of the distributions in the consumer market regarding the car price, engine sizes and fuel economy. The S.D.s show the diversity in consumer markets among the five countries.

The summary statistics given in Table 4.5 shows that among the five countries, the average engine sizes are the largest in the US and smallest in India. Regarding the car prices, the UK has the highest average car prices, while India has the lowest car prices. Regarding the fuel economy, on average, cars are the most efficient in Japan compared to the other countries. The S.D.s for car price, engine size, and fuel economy show the width and variation for each of the parameters. We observe that the S.D. for price and engine size S.D.s are the smallest in India and the largest in the US.

4.4 Market shares

We purchased the annual car sales data from the Marklines website, which is an automotive industry portal that consists of motor vehicle market data. Marklines provides the total car sales by car model and brand for 63 countries from 2004 onwards. Hence, it is possible to find the sales for each car model for an individual country. Marklines car sales numbers were checked for reliability against total sales given by a number of data sources (including official data published by the transport departments of various nations). We concluded that the total sales numbers in the Marklines dataset are consistent with the official data. This implies that the Marklines data cover all the models available for sale in each country.

We found the fleet and market shares for different car technologies via a survival function:

$$N(t) = \sum_a Sales(t-a)Surv(a), \tag{4.1}$$

where $N(t)$ is the number of cars, $Sales(t)$ is the number of sales in year t

and $Surv(a)$ is the survival ratio of vehicles at age a. The survival function gives the fraction of vehicles that survive up to a certain age. It is typical represented typically as a monotonically decreasing function that declines from 1 to 0 as the age increases. Specifically, in Zachariadis et al. (1995), the survival rates were simulated using a Weibull distribution, defined as:

$$f(x) = e^{-(\frac{x+b}{T})^b}, \tag{4.2}$$

where T parameterises the vehicle lifetime and b is the parameter that affects the shape of the survival function.

4.4.1 Survival function

The determination of vehicle survival rates requires substantial historical information on stock and scrappage. Three approaches could be used to find the survival function. Firstly, survival functions for some countries (e.g., China, Japan) were taken directly from existing literature (Figure 4.1, see Hao et al. (2011); Goel et al. (2013)). Secondly, when the survival function was not readily available, we could derive a survival function by generating a survival profile based on the survival function derived for the UK (using data obtained from DVLA (2012)). Doing so is based on the assumption that the reliability functions of mechanical systems for vehicles are similar between countries for the first few years of their lifetime. This is a reasonable assumption since the reliability of vehicles is not necessarily related to political borders, since most firms sell internationally. Instead, differences in survival functions between countries are related to weather and traffic contexts. Further, the assumption is largely consistent with existing empirical evidence (Huo et al., 2012). Then we constantly adjusted the survival values until the differences between total sales and total stock became approximately equal.

When neither total sales nor stock were available, we had to borrow survival functions derived for other countries. The variation in survival patterns for cars between countries can be attributed mainly to the differences in scrappage policies in different countries, vehicle management, and improved technologies. For instance, China has mandatory scrappage standards for cars. Survival patterns should be more similar between countries sharing similar scrappage policies. While it could be argued that technology is more advanced in the UK than in India, vehicle makers are largely multinational, so technology spillovers can occur. A sensitivity analysis was carried out to examine the effects of the uncertainties introduced by survival function approximation.

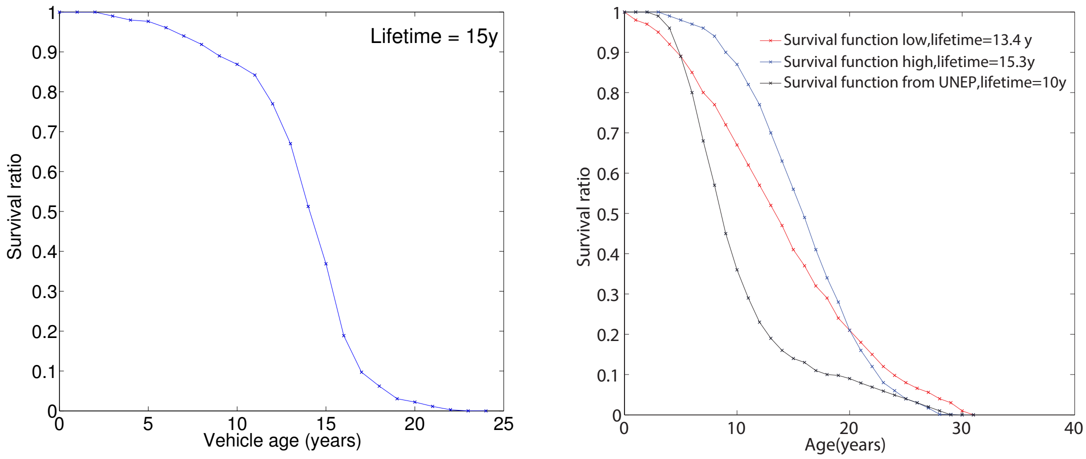

Figure 4.1: *Left* Survival function for cars in China. Data source: Hao et al. (2011). *Right* Survival function for cars in India. Data source: Goel et al. (2013).

4.4.2 The assumptions for fleet shares

As stated in Chapter 3, the intangible value γ_i is derived empirically so that the slopes at the beginning of simulations are consistent with the historical rate of diffusion. In order to find γ_i, it is necessary to find the historical shares of different car technologies. With a survival function and historical market sales obtained from Marklines (using with the method described in Section 4.4), it is possible to find historical shares by a convolution of historical sales and survival functions. The historical sales data is matched to vehicle technologies and engine categories based on car specification data collected from the manufacturers. For new technologies such as EVs and HEVs, the market shares are the sum of historical sales data (from Marklines).

Tables 4.6, 4.7, 4.8, 4.9 and 4.10 present the assumptions for PLDV fleet shares for the UK, the US, Japan, China, and India, respectively. Specifically, in the case of India, petrol cars are predominantly Econ cars, while diesel cars are primarily mid-size. Diesel engines are more efficient and have more torque than gasoline engines. Therefore, diesel engines are more commonly found among larger and mid-sized cars. On the other hand, petrol engines are commonly found among smaller/more fuel efficient cars because of their lower initial costs and relative lower weights.

The historical fleet shares are used to calibrate the γ_i values for each country, and the fleet shares in 2016 are used in the FTT-Transport model as the starting shares to simulate the diffusion of PLDV technologies.

4.5 Fuel economy and emission factor assumptions

In this research, we assume that the fuel economy (in l/100km) is constant over time for one technology. We consider the improvement of a technology over time by assuming the existence of an advanced petrol car or an advanced diesel car (more efficient technology).

The following sections discuss the fuel economy assumptions we have made for all vehicle technologies assumed in the FTT-Transport model and the data sources. Further, this section discusses the assumptions for the emission factors for conventional cars and EVs (indirect emissions) in the five countries.

4.5.1 Fuel economy and fuel prices at the pump for conventional cars

This section presents the assumptions for fuel consumption and fuel prices at the pump for conventional cars in the five countries. The values for fuel economy (in l/100km) were collected from the official manufacturers' websites. The fuel economy values shown in Tables 4.11, 4.12, 4.13, 4.14 and 4.15 are the weighted average fuel economies for a car technology/range in the UK, the US, Japan, China, and India, respectively. Although this approach enables us to consider the fuel economy for the entire PLDV population in a country, the limitation of this approach is that the fuel economy values published on the manufacturers' websites may not reflect the on- road fuel consumption of cars because fuel economy for PLDVs varies according to speed and driving habits. With new technologies that improve the efficiency of petrol/diesel cars (Chatain, 2017), the fuel economy for ?advanced? petrol/diesel cars improves over time. While many countries have adopted mandatory or voluntary standards, the stringency and structure of these standards vary widely across the world. Table 4.2 shows the adopted standards for fuel efficiency in the EU, Japan, the US, China, and India.

The adopted fuel economy standards in the UK, the US, Japan, China, and India are shown in Table 4.2. Following the current fuel economy standards (Yang and

Bandivadekar, 2017*b*), in the FTT-Transport model, the 'advanced' petrol/diesel car categories represent the fuel efficiency improvements by assuming that the fuel economies for the next generation of petrol/diesel cars will be 35% more efficient than the 2016 new cars in China, 30% more efficient than the 2016 new cars in the EU, and 20% more efficient than the 2016 new cars in the US, Japan, and India, with fuel economy regulations introduced in the year 2030 in the 'current phase-out scenario' (see Section 7.4.5 for further details on scenario analysis).

For the FTT-Transport model, we assume that there will be no further improvement for petrol/diesel cars beyond the 'advanced' cars for the following reasons. Firstly, on one hand, in the US, Trump is freezing Obama's fuel economy standards, but, on the other hand, a number of EU countries (e.g., the UK, France, and Germany) seek to ban the sale of new gasoline and diesel cars. We acknowledge that enormous uncertainty remains around the fate of the standards. It is unclear how stringent the fuel economy standards will be beyond 2025 or 2030. Secondly, with further improvements in petrol cars, the fuel economy of petrol/diesel cars will be very close to that of the fuel economy of the hybrid cars.

Some technologies are not readily available in a country. For example, flex-fuel cars are very rarely found in the UK, Japan, China, and India, partly because there are very few E85 fuelling stations in these countries. Similarly, since NGVs are very rare in the UK, the US, and Japan, the weighted average fuel economy for NGVs is not available for these countries.

The data for petrol and diesel prices at the pump were collected from the World Bank Data (World Bank, 2016). The price for E85 ethanol in the US was collected from E85 Prices (E85Prices, 2018), and the price for LPG was collected from Global Petrol Prices (GlobalPetrolPrices, 2017). The last column of Table 4.11, 4.12, 4.13, 4.14 and 4.15 show the fuel prices paid by the consumers, excluding fuel tax, and these are the prices we assumed in the baseline scenario. This assumption was made in order to capture the effect of fuel taxes in the alternative scenarios.

4.5.2 EV fuel economy and emissions factor

An effective mitigation of climate change requires the parallel large-scale diffusion of sustainable technologies in the PLDV sector and power generation. The emissions reduction from EVs depends largely on the carbon intensity of the power sector (i.e., the indirect emissions from EVs). Hence, the decarbonisation challenge lies in the

Table 4.2: Adopted fuel economy standards in selected regions (Yang and Bandivadekar, 2017*b*).

Country	Baseline model year	Implementation period	Reduction in average CO_2 rate (gCO_2/km)
UK	2021	2021-2030	30%
US	2015	2017-2025*	49%
Japan	2010	2020	16%
China	2012	2016-2020	35%
India	2010	2018-2022	18%

*Proposed freezing standards at model year 2020 through 2025

co-evolution of technologies driven by interdependent policies and social dynamics. For example, GHG emissions from electric driving depend directly on the fuel type used in the generation of electricity for charging.

Armed with Marklines's data on EV sales, we selected the most popular EV model in each of the three price ranges and collected their battery pack capacities from official manufacturers′ websites. Table 4.16 shows the battery capacities of the three selected EV models for each country. For modelling purposes, in countries where an EV range is not readily available, we have taken the battery capacities of the most popular model in the given price range. For example, in India, there are a very small number of EVs on the road, so we have used the average battery capacities in China. Similarly, for the US, there is no small EV model on sale, so we have assumed the small EV battery capacity in China for the US. Table 4.17 shows the average fuel energy consumption per kilometre driven assumed in the model, calculated using the published battery capacity and the range achievable. The limitation of this approach is that energy consumption and car range vary if the car is driven under different road conditions and at different speeds. Unfortunately, the average battery fuel consumption is not readily available from the manufacturers' websites.

The average CO_2 emissions from EVs (CO_2/Mtoe) (indirect emissions) were calculated by dividing the projected CO_2 emissions from the power sector by the total energy demand from the power sector (Mtoe). The total CO_2 emissions from the power sector depends on the future renewable energy mix in power generation. Since the analysis of the future power sector evolution is outside the scope of this thesis, we took the projected energy demand and CO_2 emissions in the power sector from the IEA New Policies Scenario (as presented in Table 4.18 and Table 4.19). Since the IEA (2017*c*) report does not have the total emission and energy consumption data for the UK, we have taken the projected EU average values for the UK. Table 4.21 shows the emissions per kilometre driven (gCO_2/km), calculated by multiplying the energy consumption factor (MJ/km) by the CO_2 emissions per unit of energy (gCO_2/Mtoe).

4.6 Cost assumptions

Tables 4.22, 4.23, 4.24, 4.25, 4.26 show the car price, fuel cost per km and operational and maintenance (O&M) cost assumptions used in the FTT-Transport model. Column 1 shows the weighted average car prices, with sales data collected from Marklines, and price data for each car model collected from the car manufacturers. Column 2 shows the fuel cost per kilometre, calculated by multiplying fuel price per litre by the fuel consumption per km. The sensitivity of our results to oil prices is presented in Appendix A. For EVs specifically, the fuel cost per km was calculated by taking the product of fuel consumption per km (see Table 4.17) and the electricity price (2016) for each country (see Table 4.20). Column 3 shows the O&M costs, with data collected from the IEA/ETSAP Energy Technologies Data. Note that since country-specific O&M cost data is not readily available, we have assumed the same O&M costs across different countries. We argue that the assumption will not affect the simulation results significantly because the O&M costs are small compared to fuel costs and car prices.

We assume that the long-term average prices for the conventional cars remain constant over time and that the car prices for EVs and hybrid cars change over time, depending on the learning rates (see Section 4.7 for further discussion on the learning rates). For the developed countries, we do not expect the weighted average car price for the conventional cars to change significantly because the car markets are relatively mature compared to those in the developing countries. On the other hand, in the developing countries, it is possible for the weighted average car prices to change over time as income increases. This is considered in Chapter 8, where we take into account the income effect on the changes in motor vehicle choices over time.

4.7 Assumptions for the baseline parameters

Tables 4.27, 4.28, 4.29, 4.30 and 4.31 present the parameters used in the FTT-Transport model, including lifetimes, car occupancy rates, turnover rates, and learning rates for the five countries. We assume that the discount and learning rates are the same across the five countries for modelling purposes. To consider the uncertainties regarding the discount and the learning rates, we have carried out a number of sensitivity analyses to examine whether the simulations are affected by the uncertainties in these parameters (see Appendix A).

In this research, the turnover rate is different from the mechanical survival rate, as the survival rate considers the exit of cars from the market due to car scrappage (death of a technological unit) only, while the car turnover rate considers average rates at which people purchase new cars. Hence, the average turnover rate is dependent on the economic development/income of a country and the extent to which the car market is mature. For the more developed countries (i.e., the UK, the US and Japan), without specific car scrappage incentives, we assumed that the turnover rate is eight years, consistent with the average turnover rate in Japan (Hancock, 2015). For the developing countries (China and India), we assume that the population-wide turnover rate is much smaller because there are many first-time car buyers. Indeed, consistent with our expectations, we find that the average turnover rate in China was five years in 2017 (California EPA, 2019) and that it is valid to assume that the turnover rate is five years in India (Nandi, 2015).

The last columns of Tables 4.27, 4.28, 4.29, 4.30 and 4.31 show the γ values assumed in the model. The γ value is defined as the non-pecuniary cost found by calculating the difference between the historical fleet share and the projected fleet share in each of the countries. We assume the γ values for the advanced petrol cars and the advanced diesel cars are the same as those for the conventional petrol and diesel cars. This assumption is based on the non-pecuniary costs of the advanced petrol and diesel cars being the same as those for the conventional petrol and diesel cars of the same engine sizes. Note that for PLDV technologies that were not readily available (e.g., NGV and flex-fuel cars in the UK), we assumed that the γ values were zero since there a lack of sufficient data to determine them.

4.8 Assumptions for the biofuel mandate

In this thesis, we assume that under all scenarios, the biofuel mandate increases gradually until it reaches 10% to 20%. Higher volume blends, such as E85, are restricted for use only in a limited number of flex-fuel vehicles. Following the estimations in IEA (2014), Figure 4.2 shows the assumptions for the biofuel mandate in all five countries. Note that, in this study, we have not studied the effect of more stringent biofuel mandates in the five countries for two main reasons. Firstly, except for in the US, there are very few flex-fuel cars and ethanol filling stations available. According to our data, flex-fuel cars are not readily available in the UK, Japan, China, and India. As a result, there are very few E85 filling stations in these countries. Based on the theory of technological diffusion, if the share for a niche technology is nearly zero, the technology will take a very long time to gain a significant market share. In the case of the US, some manufacturers do not advertise their cars as a flex-fuel cars (according to our search of manufacturers' websites); hence, our data for fleet market shares show that there are very few flex-fuel cars (less than 1% of the market share). Although our data may not reflect the true number of flex-fuel vehicles in the US market, most flex-fuel car are not fuelled by ethanol in practice because E85 is distributed to only 1% of the US fuelling stations (Aguilar et al., 2015), leading to a scenario in which the ethanol blend continues to grow in market share until it has met current limits acceptable for ethanol blends in standard vehicle engines (E10, E15), which has been referred to as the 'blend wall' (Aguilar et al., 2015; Zhang et al., 2010).

Secondly, to account for the fuel consumption and emissions under a higher biofuel mandate, a model for biofuel and land-use change is required to account for the true effect of a higher biofuel mandate on global land use and emissions. However, this is beyond the scope of this PhD thesis. Also, the fuel consumption factor advertised on car manufacturers′ websites generally does not take into consideration the use of E85, so there is an uncertainty regarding the average fuel use of a flex-fuel car in the US. Considering the effect of a higher biofuel mandate for the US, therefore, requires a separate study on consumption of E85 in the US and the effect of E85 on land use changes and emissions.

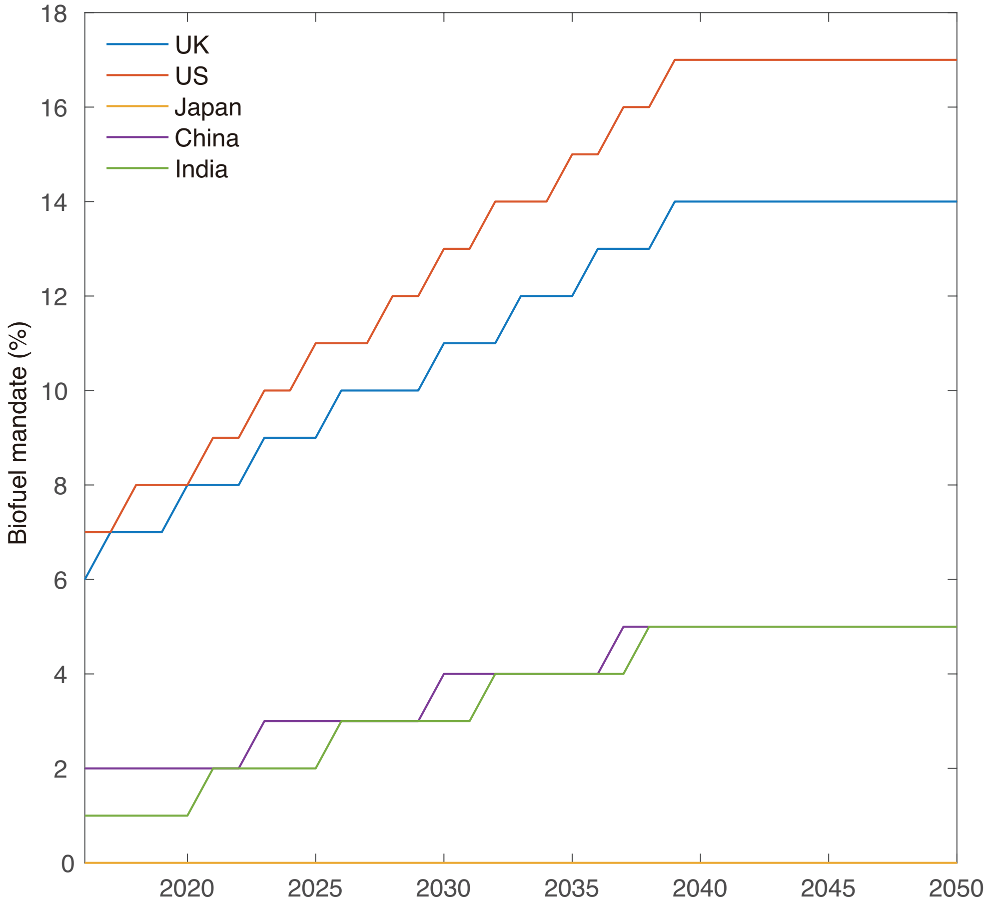

Figure 4.2: Biofuel mandate assumptions in the FTT-Transport model.

Table 4.3: Data sources for the main variables

Variable	Year	Differentiated in 5 countries?	Data source
Car sales (differentiated by engine size and technology)	2016	Yes	MarkLines
Car price	2016	Yes	Car manufacturers′ websites and car sales websites (see details in Table 4.4)
Fuel cost	2016	Yes	Fuel use data are collected from car manufacturers′ websites, and fuel price per litre is collected from the World Bank
Fuel economy	2016	Yes	Car manufacturers′ websites and car sales websites (see details in table 4.4)
Discount rate	2013	No	E.g., Inderwildi and King (2012); Zhuang et al. (2007); Harrison et al. (2010)
Learning rate	2012	No	E.g., Tom Hazeldine and Deller (2010); Weiss et al. (2012); IEA (2013); McDowall (2012)
Mechanical survival rate	2004	No	E.g., DVLA (2012); NHTSA (2008); Hao et al. (2011); Singh et al. (2004)
Car turnover rate	2012	No	IEA-SMP, ARTEMIS
Filling factor	2004	No	IEA-SMP, ARTEMIS

Table 4.4: Summary of data sources.

Country	Car price	Engine size	fuel economy
UK	Car prices are collected from http://www.carpages.co.uk/ for both new models and outdated models.	The car engine sizes are collected from http://www.carpages.co.uk/, along with car prices and fuel economy.	The fuel economy for cars is collected from http://www.carpages.co.uk/, along with car prices and car engine sizes.
US	Official websites of car manufacturers in the US for the existing models. For the old/outdated models, the price data were obtained from car dealers, such as http://www.autonews.com/section/prices	Official websites of car manufacturers in the US. For the outdated/old models, engine size data were obtained from car dealers, such as http://www.autonews.com/section/prices	Official websites of car manufacturers in the US. For the outdated/old models, fuel economy data were excluded from the calculation.
Japan	Official websites of car manufacturers in Japan for the existing models. The price data for cars sold historically were obtained from http://toyota.jp/service/dealer/	Official websites of car manufacturers in Japan for the existing models. The engine size data for cars sold historically were obtained from http://toyota.jp/service/dealer/spt , along with the price data and the fuel economy.	Official websites of car manufacturers in Japan for the existing models. The engine fuel economy data for cars sold historically were obtained from http://toyota.jp/service/, along with the price data and engine size data.
China	Car price data (both new cars and old models) were obtained from commercial dealer websites, such as China Auto Home (http://www.autohome.com.cn/) and Sohu Auto (http://auto.sohu.com/).	Engine size data were collected from http://www.autohome.com.cn/ and http://auto.sohu.com/, along with price and fuel economy data.	Fuel economy data were collected from http://www.autohome.com.cn/ and http://auto.sohu.com/, along with price and engine size data.
India	Car price data were obtained from the official car manufacturers′ websites for India. For old models, we have obtained prices data from http://www.carwale.com/new/ and http://www.zigwheels.com/newcars	Engine size data were obtained from the official car manufacturers′ websites for India, alongside price data. Similarly, for old models, engine size data were obtained from http://www.carwale.com/new/ and http://www.zigwheels.com/newcars	If available, fuel economy data were obtained from the official manufacturers′ websites for India. For some new models (where fuel economy data are not available from the manufacturers) and outdated models, fuel economy data were obtained from http://www.carwale.com/new/ and http://www.zigwheels.com/newcars

Table 4.5: The means, medians and standard deviations for car prices, engine sizes and emissions in the UK, the US, Japan, China, and India.

Country	P(USD)			Engine sizes (cc)			Fuel economy (l/100km)		
	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
UK	28990	30200	10599	1720	1600	594	6.03	5.88	2.03
USA	25953	27339	13090	2880	2400	1332	8.32	8.72	2.28
Japan	19300	14291	12499	1310	1400	733	4.91	5.47	1.88
China	18768	16423	12330	1691	1600	459	6.81	6.5	1.57
India	11312	9748	8985	1260	1200	423	5.05	5.52	1.66

Table 4.6: PLDV fleet shares for the UK (%)

UK		2009	2010	2011	2012	2013	2014	2015	2016
Petrol	Econ	31.23	31.33	30.17	29.83	32.20	32.50	33.24	34.20
	Mid	32.97	31.45	28.64	27.41	29.30	32.18	33.40	36.10
	Lux	6.84	6.49	5.77	5.48	5.56	6.00	5.97	6.50
Adv Petrol	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Diesel	Econ	1.37	1.53	2.16	1.30	1.00	0.80	0.20	0.10
	Mid	19.39	21.93	25.01	25.23	21.60	20.90	19.20	15.60
	Lux	6.59	6.93	7.85	8.32	7.72	6.90	6.00	5.20
Adv Diesel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNG	Econ	0.04	0.04	0.03	0.03	0.00	0.00	0.00	0.00
	Mid	0.04	0.04	0.03	0.03	0.00	0.00	0.00	0.00
	Lux	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00
Flex fuel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hybrid	Econ	0.01	0.02	0.03	0.03	0.05	0.05	0.05	0.04
	Mid	0.12	0.16	0.21	0.28	0.76	1.19	1.22	1.51
	Lux	0.04	0.04	0.04	0.04	0.58	0.60	0.60	0.62
Electric	Econ	0.00	0.00	0.00	0.00	0.01	0.02	0.13	0.21
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.01	0.00	0.02	0.04	0.10

Table 4.7: PLDV fleet shares for the US (%)

US		2009	2010	2011	2012	2013	2014	2015	2016
Petrol	Econ	0.05	1.00	1.29	1.46	1.76	2.17	2.45	2.69
	Mid	8.66	12.00	12.46	13.00	13.43	13.67	14.04	14.23
	Lux	91.29	85.45	84.61	83.54	82.52	81.76	80.92	80.38
Adv Petrol	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Diesel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Adv Diesel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNG	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Flex fuel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.20	0.30	0.30	0.40	0.40
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hybrid	Econ	0.00	0.03	0.04	0.05	0.05	0.05	0.05	0.05
	Mid	0.00	0.98	1.04	1.14	1.23	1.26	1.28	1.32
	Lux	0.00	0.54	0.54	0.57	0.60	0.61	0.62	0.63
Electric	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.01	0.05	0.10	0.15	0.18	0.22
	Lux	0.00	0.00	0.00	0.00	0.01	0.03	0.06	0.10

Table 4.8: PLDV fleet shares for Japan (%)

Japan		2009	2010	2011	2012	2013	2014	2015	2016
Petrol	Econ	33.44	36.23	38.77	41.20	43.35	45.10	46.33	47.36
	Mid	38.97	36.82	34.80	32.37	30.02	28.09	26.64	25.26
	Lux	25.79	24.25	22.85	21.24	19.86	18.43	17.26	16.10
Adv Petrol	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Diesel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.09	0.09	0.10	0.11	0.11	0.12	0.13	0.14
Adv Diesel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNG	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Flex fuel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hybrid	Econ	0.23	0.39	0.65	0.98	1.26	0.00	2.22	2.72
	Mid	1.19	1.77	2.27	3.36	4.38	0.00	5.92	6.72
	Lux	0.30	0.44	0.52	0.67	0.90	0.00	1.31	1.44
Electric	Econ	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.05
	Mid	0.00	0.01	0.03	0.07	0.10	0.00	0.15	0.17
	Lux	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.03

Table 4.9: PLDV fleet shares for China (%)

China		2009	2010	2011	2012	2013	2014	2015	2016
Petrol	Econ	35.00	32.02	29.67	29.48	28.66	27.59	25.68	23.67
	Mid	48.05	49.97	51.61	52.40	53.66	55.23	57.36	59.17
	Lux	16.92	17.89	18.59	17.85	17.47	16.99	16.49	16.24
Adv Petrol	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Diesel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Adv Diesel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNG	Econ	0.00	0.01	0.03	0.08	0.06	0.04	0.03	0.02
	Mid	0.04	0.06	0.10	0.15	0.00	0.01	0.01	0.01
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Flex fuel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hybrid	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.05
	Lux	0.00	0.00	0.00	0.01	0.02	0.02	0.03	0.03
Electric	Econ	0.00	0.00	0.01	0.03	0.04	0.06	0.15	0.19
	Mid	0.00	0.00	0.00	0.02	0.03	0.08	0.22	0.49
	Lux	0.00	0.00	0.00	0.01	0.01	0.02	0.06	0.12

Table 4.10: PLDV fleet shares for India (%)

India		2009	2010	2011	2012	2013	2014	2015	2016
Petrol	Econ	31.13	36.50	40.38	43.85	46.77	49.39	52.05	54.34
	Mid	1.12	1.31	1.53	1.79	1.94	1.96	1.90	1.80
	Lux	1.82	1.79	2.06	2.24	2.37	2.48	2.55	2.60
Adv Petrol	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Diesel	Econ	10.61	9.65	8.99	8.56	8.04	7.48	7.05	6.92
	Mid	52.53	48.21	44.61	41.21	38.58	36.16	33.79	31.53
	Lux	2.79	2.56	2.42	2.34	2.29	2.54	2.67	2.79
Adv Diesel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNG	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Flex fuel	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hybrid	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Electric	Econ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	Lux	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 4.11: Assumptions for fuel consumption for PLDVs in the UK (l/100km) and fuel prices (USD/litre). N/A indicates that the technology is not readily available.

UK		Fuel consumption (l/100km)	Fuel price at the pump (2016) (USD/litre)	Fuel price (without fuel tax) (USD/litre)
Petrol	Econ	4.97	1.46	0.86
	Mid	5.18	1.46	0.86
	Lux	6.27	1.46	0.86
Adv Petrol	Econ	3.98	1.46	0.86
	Mid	4.15	1.46	0.86
	Lux	5.02	1.46	0.86
Diesel	Econ	3.41	1.50	0.90
	Mid	4.55	1.50	0.90
	Lux	5.30	1.50	0.90
Adv Diesel	Econ	2.73	1.50	0.90
	Mid	3.64	1.50	0.90
	Lux	4.24	1.50	0.90
NGV	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Flex fuel	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Hybrid	Econ	1.89	1.46	0.86
	Mid	2.65	1.46	0.86
	Lux	4.28	1.46	0.86

Table 4.12: Fuel consumption for PLDVs in the US (l/100km) and fuel prices (USD/litre). N/A indicates that the technology is not readily available.

US		Fuel consumption (l/100km)	Fuel price at the pump (2016) (USD/litre)	Fuel price (without fuel tax) (USD/litre)
Petrol	Econ	8.00	0.71	0.66
	Mid	8.40	0.71	0.66
	Lux	10.00	0.71	0.66
Adv Petrol	Econ	6.40	0.71	0.66
	Mid	6.72	0.71	0.66
	Lux	8.00	0.71	0.66
Diesel	Econ	7.20	0.65	0.60
	Mid	7.56	0.65	0.60
	Lux	9.00	0.65	0.60
Adv Diesel	Econ	5.76	0.65	0.60
	Mid	6.05	0.65	0.60
	Lux	7.20	0.65	0.60
NGV	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Flex fuel	Econ	9.36	0.42	0.42
	Mid	9.83	0.42	0.42
	Lux	11.70	0.42	0.42
Hybrid	Econ	2.00	0.71	0.66
	Mid	2.40	0.71	0.66
	Lux	2.50	0.71	0.66

Table 4.13: Fuel consumption for PLDVs in Japan (l/100km) and fuel prices (USD/litre). N/A indicates that the technology is not readily available.

Japan		Fuel consumption (l/100km)	Fuel price at the pump (2016) (USD/litre)	Fuel price (without fuel tax) (USD/litre)
Petrol	Econ	5.56	1.10	0.60
	Mid	5.88	1.10	0.60
	Lux	6.67	1.10	0.60
Adv Petrol	Econ	4.88	1.10	0.60
	Mid	5.52	1.10	0.60
	Lux	6.80	1.10	0.60
Diesel	Econ	5.49	0.88	0.38
	Mid	6.21	0.88	0.38
	Lux	7.65	0.88	0.38
Adv Diesel	Econ	4.39	0.88	0.38
	Mid	4.97	0.88	0.38
	Lux	6.12	0.88	0.38
NGV	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Flex fuel	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Hybrid	Econ	2.00	1.10	0.60
	Mid	2.48	1.10	0.60
	Lux	2.70	1.10	0.60

Table 4.14: Fuel consumption for PLDVs in China (l/100km) and fuel prices (USD/litre). N/A indicates that the technology is not readily available.

China		Fuel consumption (l/100km)	Fuel price at the pump (2016) (USD/litre)	Fuel price (without fuel tax) (USD/litre)
Petrol	Econ	6.1	0.96	0.9
	Mid	6.9	0.96	0.9
	Lux	8.5	0.96	0.9
Adv Petrol	Econ	4.88	0.96	0.9
	Mid	5.52	0.96	0.9
	Lux	6.8	0.96	0.9
Diesel	Econ	5.49	0.81	0.75
	Mid	6.21	0.81	0.75
	Lux	7.65	0.81	0.75
Adv Diesel	Econ	4.39	0.81	0.75
	Mid	4.97	0.81	0.75
	Lux	6.12	0.81	0.75
NGV	Econ	4.39	0.40	0.34
	Mid	4.97	0.40	0.34
	Lux	6.12	0.40	0.34
Flex fuel	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Hybrid	Econ	2.00	0.96	0.90
	Mid	2.48	0.96	0.90
	Lux	2.7	0.96	0.90

Table 4.15: Fuel consumption for PLDVs in India (l/100km) and fuel prices (USD/litre). N/A indicates that the technology is not readily available.

India		Fuel consumption (l/100km)	Fuel price at the pump (2016) (USD/litre)	Fuel price (without fuel tax) (USD/litre)
Petrol	Econ	4.55	0.97	0.47
	Mid	6.67	0.97	0.47
	Lux	10.00	0.97	0.47
Adv Petrol	Econ	3.64	0.97	0.47
	Mid	5.33	0.97	0.47
	Lux	8.00	0.97	0.47
Diesel	Econ	4.00	0.81	0.31
	Mid	5.88	0.81	0.31
	Lux	7.14	0.81	0.31
Adv Diesel	Econ	3.20	0.81	0.31
	Mid	4.71	0.81	0.31
	Lux	5.71	0.81	0.31
NGV	Econ	4.392	0.2	0.2
	Mid	4.968	0.2	0.2
	Lux	6.12	0.2	0.2
Flex fuel	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Hybrid	Econ	2	0.97	0.47
	Mid	2.48	0.97	0.47
	Lux	2.7	0.97	0.47

Table 4.16: EV battery capacity (KWh)

	US	UK	Japan	China	India
EV Econ	16	16	16	22	22
EV Mid	30	30	30	30	30
EV Lux	100	100	100	100	100

Table 4.17: EV energy consumption(MJ/km)

	US	UK	Japan	China	India
EV Econ	0.48	0.48	0.48	0.54	0.54
EV Mid	0.79	0.74	0.74	0.76	0.76
EV Lux	0.94	0.94	0.94	0.94	0.94

Table 4.18: Projected CO_2 emissions from power generation ($MtCO_2$) under the IEA New Policy Scenario. Source: IEA (2017*c*)

	2000	**2015**	**2016**	**2025**	**2030**	**2035**	**2040**
US	2433	1967	1855	1755	1733	1705	1664
EU	1692	1454	1403	1168	1049	918	866
China	1449	4395	4394	4478	4544	4493	4337
Japan	460	555	543	394	370	349	330
India	1449	4395	4394	4478	4544	4493	4337

Table 4.19: Projected energy demand in the power sector (Mtoe) under the IEA New Policy Scenario. Source: IEA (2017c)

	2000	**2015**	**2016**	**2025**	**2030**	**2035**	**2040**
US	933	881	868	857	865	873	885
EU	837	836	834	810	795	787	796
China	380	1272	1303	1558	1700	1805	1871
Japan	229	185	186	192	195	198	202
India	459	1065	1149	1449	1656	1843	2009

Table 4.20: Average electricity prices by country under the New Policy Scenario. Source: IEA (2017c)

Dollars per MWh	**2016**	**2040**
EU	240	270
US	120	120
China	70	130
Japan	220	210
India	60	100

Table 4.21: The average indirect CO_2 emissions factor ($gCO_2/100km$) from EVs in the five different countries, derived from the projected CO_2 emissions from power generation ($MtCO_2$) under the New Policy Scenario (Table 4.18) and the estimated average EV energy consumption (Table 4.17).

	2000	**2015**	**2016**	**2025**	**2030**	**2035**	**2040**
US							
EV Econ	34	29	28	26	26	25	24
EV Mid	47	41	39	37	36	35	34
EV Lux	59	50	48	46	45	44	42
UK							
EV Econ	26	22	22	19	17	15	14
EV Mid	37	31	30	26	24	21	20
EV Lux	45	39	38	32	30	26	24
Japan							
EV Econ	26	39	38	26	24	23	21
EV Mid	36	54	53	37	34	32	30
EV Lux	45	67	65	46	42	39	37
China							
EV Econ	49	45	44	37	34	32	30
EV Mid	69	62	61	52	48	45	42
EV Lux	85	77	75	64	60	56	52
India							
EV Econ	41	53	49	40	35	31	28
EV Mid	57	75	69	56	50	44	39
EV Lux	71	92	86	69	61	55	48

Table 4.22: The cost assumptions for the UK. Column 1 shows the average PLDV price assumptions, column 2 shows the fuel cost assumptions (without tax), and column 3 shows the O&M cost assumptions taken in the baseline scenario.

UK		Car price (USD/vehicle)	fuel cost without fuel tax (USD/km)	O&M cost (USD/km)
Petrol	Econ	16927	4.46	0.04
	Mid	31795	4.64	0.05
	Lux	40594	5.62	0.06
Adv Petrol	Econ	20312	3.57	0.04
	Mid	38153	3.72	0.05
	Lux	48712	4.49	0.06
Diesel	Econ	22931	3.68	0.04
	Mid	32758	4.91	0.05
	Lux	38483	5.73	0.06
Adv Diesel	Econ	27517	2.95	0.04
	Mid	39310	3.93	0.05
	Lux	46180	4.58	0.06
CNG	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Flex fuel	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Hybrid	Econ	25224	1.91	0.04
	Mid	36034	2.67	0.05
	Lux	47767	4.31	0.06
Electric	Econ	22931	0.02	0.05
	Mid	32758	0.03	0.06
	Lux	51656	0.04	0.07

Table 4.23: The cost assumptions for the US. Column 1 shows the average PLDV price assumptions, column 2 shows the fuel cost assumptions (without tax), and column 3 shows the O&M cost assumptions taken in the baseline scenario.

US		Car price (USD/vehicle)	fuel cost without fuel tax (USD/km)	O&M cost (USD/km)
Petrol	Econ	17939	5.28	0.04
	Mid	20749	5.54	0.05
	Lux	29744	6.60	0.06
Adv Petrol	Econ	21527	4.22	0.04
	Mid	24899	4.44	0.05
	Lux	35693	5.28	0.06
Diesel	Econ	21527	4.32	0.04
	Mid	24899	4.54	0.05
	Lux	35693	5.40	0.06
Adv Diesel	Econ	30998	3.46	0.04
	Mid	35855	3.63	0.05
	Lux	51398	4.32	0.06
CNG	Econ	17939	NA	NA
	Mid	20749	NA	NA
	Lux	29744	NA	NA
Flex fuel	Econ	17939	3.93	0.04
	Mid	20749	4.13	0.05
	Lux	29744	4.91	0.06
Hybrid	Econ	23958	1.32	0.04
	Mid	28795	1.58	0.05
	Lux	34007	1.65	0.06
Electric	Econ	29744	0.01	0.05
	Mid	30707	0.02	0.06
	Lux	90229	0.02	0.07

Table 4.24: The cost assumptions for Japan. Column 1 shows the average PLDV price assumptions, column 2 shows the fuel cost assumptions (without tax), and column 3 shows the O&M cost assumptions taken in the baseline scenario.

Japan		Car price (USD/vehicle)	fuel cost without fuel tax (USD/km)	O&M cost (USD/km)
Petrol	Econ	12936	2.20	0.04
	Mid	21321	2.48	0.05
	Lux	27991	3.06	0.06
Adv Petrol	Econ	15523	1.76	0.04
	Mid	25585	1.99	0.05
	Lux	33589	2.45	0.06
Diesel	Econ	15523	1.15	0.04
	Mid	25585	1.30	0.05
	Lux	33589	1.61	0.06
Adv Diesel	Econ	18628	0.92	0.04
	Mid	30702	1.04	0.05
	Lux	40307	1.29	0.06
NGV	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Flex fuel	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Hybrid	Econ	19513	0.72	0.04
	Mid	22735	0.89	0.05
	Lux	45303	0.97	0.06
Electric	Econ	18985	0.01	0.03
	Mid	31288	0.02	0.04
	Lux	40200	0.02	0.05

Table 4.25: The cost assumptions for China. Column 1 shows the average PLDV price assumptions, column 2 shows the fuel cost assumptions (without tax), and column 3 shows the O&M cost assumptions taken in the baseline scenario.

China		Car price (USD/vehicle)	fuel cost without fuel tax (USD/km)	O&M cost (USD/km)
	Econ	8901	2.20	0.04
Petrol	Mid	16780	2.48	0.05
	Lux	41177	3.06	0.06
	Econ	10681	1.76	0.04
Adv Petrol	Mid	20135	1.99	0.05
	Lux	49412	2.45	0.06
	Econ	10681	1.15	0.04
Diesel	Mid	20135	1.30	0.05
	Lux	49412	1.61	0.06
	Econ	12817	0.92	0.04
Adv Diesel	Mid	24163	1.04	0.05
	Lux	59295	1.29	0.06
	Econ	8901	1.76	0.03
NGV	Mid	16780	1.99	0.04
	Lux	41177	2.45	0.05
	Econ	N/A	N/A	N/A
Flex fuel	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
	Econ	20000	0.72	0.04
Hybrid	Mid	24019	0.89	0.05
	Lux	39960	0.97	0.06
	Econ	9575	0.01	0.03
Electric	Mid	27073	0.02	0.04
	Lux	42424	0.02	0.05

Table 4.26: The cost assumptions for India. Column 1 shows the average PLDV price assumptions, column 2 shows the fuel cost assumptions (without tax), and column 3 shows the O&M cost assumptions taken in the baseline scenario.

India		Car price (USD/vehicle)	fuel cost without fuel tax (USD/km)	O&M cost (USD/km)
Petrol	Econ	8897	2.14	0.04
	Mid	20545	3.13	0.05
	Lux	30097	4.70	0.06
Adv Petrol	Econ	10676	1.71	0.04
	Mid	24654	2.51	0.05
	Lux	36116	3.76	0.06
Diesel	Econ	12132	1.24	0.04
	Mid	17920	1.82	0.05
	Lux	22743	2.21	0.06
Adv Diesel	Econ	14559	0.99	0.04
	Mid	21504	1.46	0.05
	Lux	27291	1.77	0.06
NGV	Econ	8897	0.88	0.03
	Mid	20545	0.99	0.04
	Lux	30097	1.22	0.05
Flex fuel	Econ	N/A	N/A	N/A
	Mid	N/A	N/A	N/A
	Lux	N/A	N/A	N/A
Hybrid	Econ	10676	0.94	0.04
	Mid	68192	1.17	0.05
	Lux	54189	1.27	0.06
Electric	Econ	9575	0.04	0.03
	Mid	27073	0.04	0.04
	Lux	42424	0.05	0.05

Table 4.27: The parameters used in the FTT-Transport model, including the discount rates, learning rates, turnover rates, and γ values for the UK.

UK	**Car size**	Discount rate	Learning rate	Turnover rate	γ value
Petrol	Econ	0.15	0.01	8	0.45
	Mid	0.15	0.01	8	0.20
	Lux	0.15	0.01	8	0.40
Adv Petrol	Econ	0.15	0.05	8	0.45
	Mid	0.15	0.05	8	0.20
	Lux	0.15	0.05	8	0.40
Diesel	Econ	0.15	0.01	8	0.80
	Mid	0.15	0.01	8	0.90
	Lux	0.15	0.01	8	1.00
Adv Diesel	Econ	0.15	0.05	8	0.80
	Mid	0.15	0.05	8	0.90
	Lux	0.15	0.05	8	1.00
NGV	Econ	0.15	0.01	8	0.00
	Mid	0.15	0.01	8	0.00
	Lux	0.15	0.01	8	0.00
Flex fuel	Econ	0.15	0.01	8	0.00
	Mid	0.15	0.01	8	0.00
	Lux	0.15	0.01	8	0.00
Hybrid	Econ	0.15	0.1	8	1.00
	Mid	0.15	0.1	8	0.30
	Lux	0.15	0.1	8	0.10
Electric	Econ	0.15	0.1	8	0.00
	Mid	0.15	0.1	8	0.00
	Lux	0.15	0.1	8	-0.60

Table 4.28: The parameters used in the FTT-Transport model, including the discount rates, learning rates, turnover rates, and γ values for the US.

US	**Car size**	Discount rate	Learning rate	Turnover rate	γ value
Petrol	Econ	0.15	0.01	8	-0.72
	Mid	0.15	0.01	8	-0.06
	Lux	0.15	0.01	8	0.42
Adv Petrol	Econ	0.15	0.05	8	-0.72
	Mid	0.15	0.05	8	-0.06
	Lux	0.15	0.05	8	0.42
Diesel	Econ	0.15	0.01	8	0.00
	Mid	0.15	0.01	8	0.00
	Lux	0.15	0.01	8	0.00
Adv Diesel	Econ	0.15	0.05	8	0.00
	Mid	0.15	0.05	8	0.00
	Lux	0.15	0.05	8	0.00
CNG	Econ	0.15	0.01	8	0.00
	Mid	0.15	0.01	8	0.00
	Lux	0.15	0.01	8	0.00
Flex fuel	Econ	0.15	0.01	8	0.00
	Mid	0.15	0.01	8	0.00
	Lux	0.15	0.01	8	0.00
Hybrid	Econ	0.15	0.1	8	0.00
	Mid	0.15	0.1	8	-0.12
	Lux	0.15	0.1	8	-0.06
Electric	Econ	0.15	0.1	8	-0.12
	Mid	0.15	0.1	8	-0.40
	Lux	0.15	0.1	8	-1.90

Table 4.29: The parameters used in the FTT-Transport model, including the discount rates, learning rates, turnover rates, and γ values for Japan.

Japan	**Car size**	Discount rate	Learning rate	Turnover rate	γ value
Petrol	Econ	0.15	0.01	8	0.76
	Mid	0.15	0.01	8	0.52
	Lux	0.15	0.01	8	0.40
Adv Petrol	Econ	0.15	0.05	8	0.76
	Mid	0.15	0.05	8	0.52
	Lux	0.15	0.05	8	0.08
Diesel	Econ	0.15	0.01	8	0.00
	Mid	0.15	0.01	8	0.00
	Lux	0.15	0.01	8	0.00
Adv Diesel	Econ	0.15	0.05	8	0.00
	Mid	0.15	0.05	8	0.00
	Lux	0.15	0.05	8	0.00
CNG	Econ	0.15	0.01	8	0.00
	Mid	0.15	0.01	8	0.00
	Lux	0.15	0.01	8	0.00
Flex fuel	Econ	0.15	0.01	8	0.00
	Mid	0.15	0.01	8	0.00
	Lux	0.15	0.01	8	0.00
Hybrid	Econ	0.15	0.1	8	0.00
	Mid	0.15	0.1	8	-0.32
	Lux	0.15	0.1	8	-0.72
Electric	Econ	0.15	0.1	8	0.00
	Mid	0.15	0.1	8	-0.30
	Lux	0.15	0.1	8	-0.60

Table 4.30: The parameters used in the FTT-Transport model, including the discount rate, learning rates, turnover rates, and γ values for China.

China	**Car size**	Discount rate	Learning rate	Turnover rate	γ value
	Econ	0.15	0.01	5	0.78
Petrol	Mid	0.15	0.01	5	0.00
	Lux	0.15	0.01	5	-0.72
	Econ	0.15	0.05	5	0.78
Adv Petrol	Mid	0.15	0.05	5	0.00
	Lux	0.15	0.05	5	-0.72
	Econ	0.15	0.01	5	0.90
Diesel	Mid	0.15	0.01	5	0.90
	Lux	0.15	0.01	5	1.00
	Econ	0.15	0.05	5	0.90
Adv Diesel	Mid	0.15	0.05	5	0.90
	Lux	0.15	0.05	5	0.60
	Econ	0.15	0.01	5	0.00
CNG	Mid	0.15	0.01	5	0.00
	Lux	0.15	0.01	5	0.00
	Econ	0.15	0.01	5	0.00
Flex fuel	Mid	0.15	0.01	5	0.00
	Lux	0.15	0.01	5	0.00
	Econ	0.15	0.1	5	-0.72
Hybrid	Mid	0.15	0.1	5	-1.00
	Lux	0.15	0.1	5	-0.84
	Econ	0.15	0.1	5	-0.60
Electric	Mid	0.15	0.1	5	-0.90
	Lux	0.15	0.1	5	-1.30

Table 4.31: The parameters used in the FTT-Transport model, including including the discount rates, learning rates, turnover rates, and γ values for India.

India	**Car size**	Discount rate	Learning rate	Turnover rate	γ value
Petrol	Econ	0.15	0.01	5	0.38
	Mid	0.15	0.01	5	0.06
	Lux	0.15	0.01	5	-0.48
Adv Petrol	Econ	0.15	0.05	5	0.38
	Mid	0.15	0.05	5	0.06
	Lux	0.15	0.05	5	-0.48
Diesel	Econ	0.15	0.01	5	0.40
	Mid	0.15	0.01	5	0.80
	Lux	0.15	0.01	5	-0.20
Adv Diesel	Econ	0.15	0.05	5	0.40
	Mid	0.15	0.05	5	0.80
	Lux	0.15	0.05	5	-0.20
CNG	Econ	0.15	0.01	5	0.12
	Mid	0.15	0.01	5	-0.08
	Lux	0.15	0.01	5	-0.20
Flex fuel	Econ	0.15	0.01	5	0.00
	Mid	0.15	0.01	5	0.00
	Lux	0.15	0.01	5	0.00
Hybrid	Econ	0.15	0.1	5	0.00
	Mid	0.15	0.1	5	-0.80
	Lux	0.15	0.1	5	-1.10
Electric	Econ	0.15	0.1	5	0.00
	Mid	0.15	0.1	5	-0.08
	Lux	0.15	0.1	5	-0.20

Chapter 5

Demand for PLDV service

5.1 Introduction

The change in the demand is a major factor affecting future energy consumption and GHG emissions in the passenger light-duty vehicle (PLDV) sector globally. In particular, in developing countries, rapid increases in energy demand from the PLDV sector have raised concerns over local air pollution and CO_2 emissions, and there is broad consensus that the PLDV sector will continue to grow in coming decades as incomes rise.

Transport demand is driven by income, population, urban density, family structure and other demographic factors (Karathodorou et al., 2010; Kim and Brownstone, 2013; He et al., 2005; Grote et al., 2016). Studies have also found induced and rebound effects on the demand for passenger car transport (Chai et al., 2016). More specifically, they find that the demand for transport increases with economic and infrastructure development (e.g., road and railway development). For example, Noland and Lem (2002) find that the enhancement of road capacity in the US and Britain impacts traffic demand. Improvements in the infrastructure, such as highway development, generate new consumption of fossil fuels and CO_2 emissions, known as the induced effect. Improvements in energy efficiency in vehicles may lead to an increase in the service demand for PLDVs and thus offset the efficiency gains from technological diffusion, known as the rebound effect. Hence, it is important to consider the elasticity of demand for transport in relation to fuel price, energy efficiency and road accessibility in the estimation and projection for the demand for PLDV services.

This chapter is divided into three sections. The first section involves the econometric analysis of aggregate time-series data on PLDV service demand, GDP per capita, oil prices per litre, road mileage, urbanisation, urban density and fuel economy in the UK, the US, Japan, China and India.

In the second section, we project the future demand for PLDV services using the projections for future oil prices, urban density, urbanisation, fuel economy, road mileage and GDP per capita obtained from government/IEA reports and existing literature. In the third section, we make projections for the growth in the car and total vehicle stock to the year 2050 for the US, the UK, Japan, China and India using an existing car ownership model. A sensitivity analysis is performed to access the effect of uncertainties regarding several parameters, such as oil price and income growth, on the PLDV service demand in the countries used in this analysis.

5.2 Historical pattern in the growth of transport demand

Figure 5.1 shows the total car fleet in use in the UK, US, Japan, China and India between 1970 and 2014. The car fleet data were collected from national transportation bureaus and international data sources, such as US Highway Statistics, Eurostat, the China Statistical Yearbook, the Japan Automobile Manufacturers Association (JAMA), and the Government of India. The total energy consumption from road transportation was collected from IEA energy statistics. As shown in Figure 5.2, total energy consumption from road transport in China and India has been increasing since 1970, while total energy consumption in the UK and Japan has stabilised since 1995.

5.3 PLDV service demand estimation

The demand estimation in this chapter consists of two parts. The first part is the construction of an econometric model which predicts the demand for PLDVs (in km per vehicle) using fuel prices, income, urbanisation, road infrastructure, urban density, and fuel economy. Then we use the econometric model to predict the future private passenger vehicle transport demand (per vehicle). In the second part, we develop a model for vehicle stock and project future car ownership, which is then used to make projections for the total demand for PLDVs.

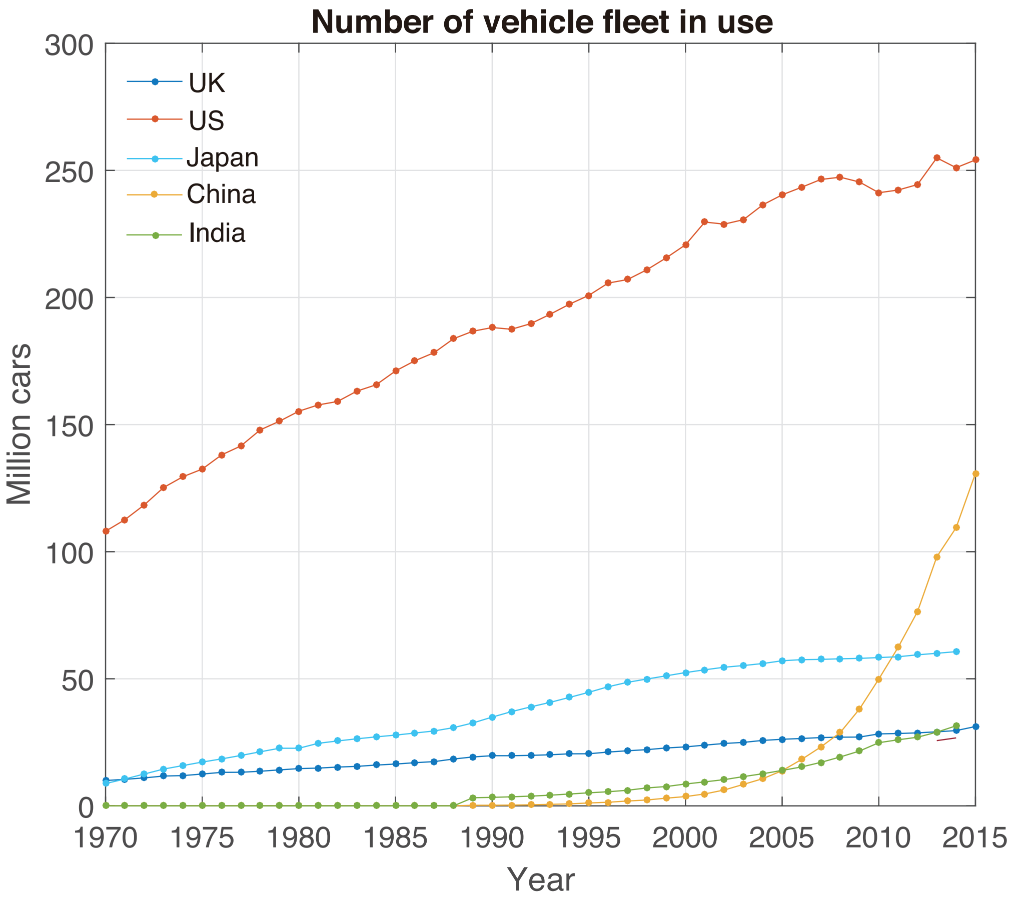

Figure 5.1: Size of the car fleet in use in the UK, the US, Japan, China and India between 1970 and 2015. Source: Eurostat, US Highway Statistics, China Statistical Yearbook, Japan Automobile Manufacturers Association, and the Government of India.

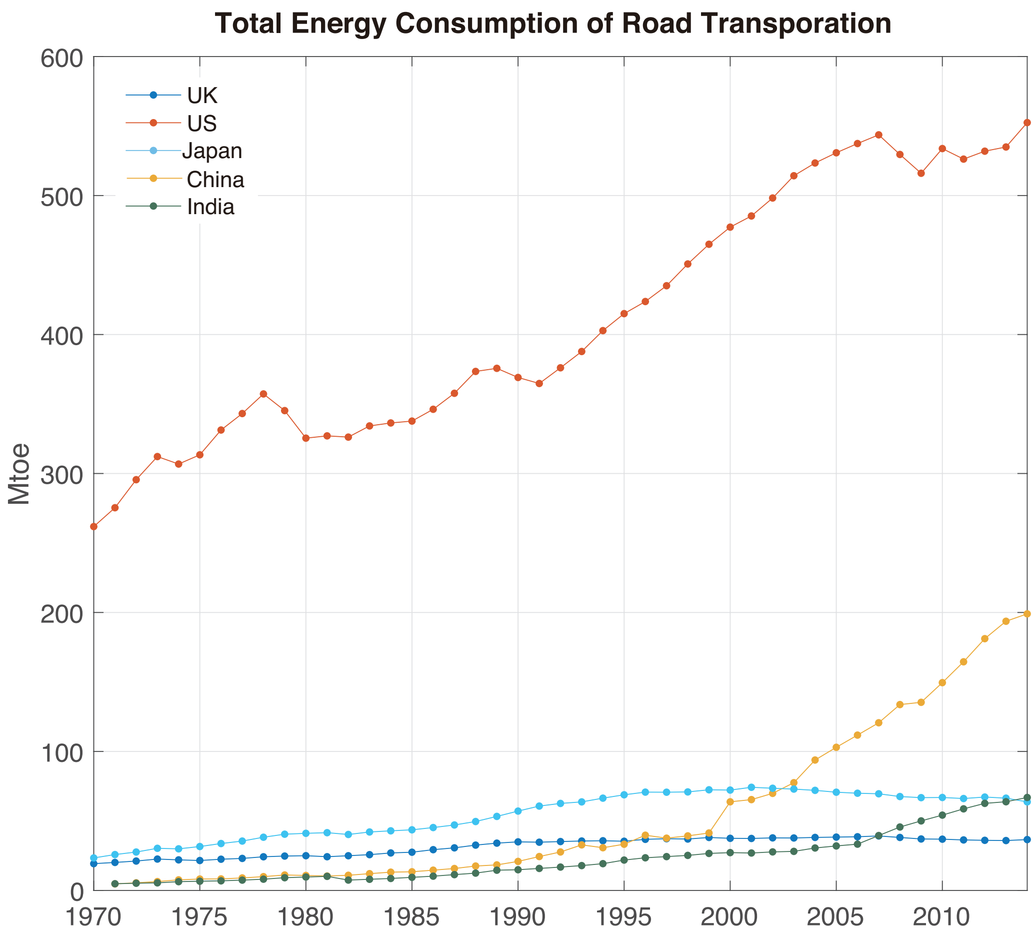

Figure 5.2: Total energy consumption for road transportation in the UK, US, China, Japan, and India between 1970 and 2015. Source: IEA Energy Statistics.

5.3.1 Methodology

Empirical model specification

The empirical model specifies kilometres per PLDV in country i as a function of GDP per capita (Y), fuel cost (in terms of oil price) (FP) and a group of variables, including urbanisation (U), lengths of roads (M), urban density (UD), and fuel economy (FE). We estimate the dynamic model because efficiency improvements and fuel price changes take time, and static models may not capture adequately the long-run adjustments of transport demand. The dynamic model we specify captures the historical trend of passenger vehicle travel demand.

$$\begin{aligned} lnKM_{it} = \beta_0 + \beta_1 lnKM_{it-1} + \beta_2 lnY_{it} + \beta_3 lnFP_{it} \\ + \beta_4 lnM_{it} + \beta_5 lnU_{it} + \beta_6 lnUD_{it} + \beta_7 lnFE_{it} \end{aligned} \tag{5.1}$$

The interpretation for each variable is indicated in Table 5.1. The following section summarises the rationale for each variable in equation 5.1.

Income

Income is known to drive transport demand, and it is recognised as the main driver of transport demand growth per capita income (Small and Van Dender, 2007) since higher incomes allow individuals to spend more on travel. Studies have found that while there exists a positive correlation between income and transport demand, the income elasticity for transport demand may decline as a country becomes richer. For example, Goodwin et al. (2004) surveyed the literature on transport demand elasticities and found that income elasticity declined over the last forty years in the US. Similarly, for the UK, Fouquet (2012) finds that income and price elasticities of passenger transport demand were very large in the mid-nineteenth century and have declined since then. In India, on the other hand, it has been found that gasoline demand is likely to increase significantly for a given increase in income and the effect is larger in the long run than in the short run (Ramanathan, 1999).

Fuel price

Since fuel prices affect the share of fuel costs in the total cost of driving, we expect that a fall in fuel prices will increase the transport distance due to the rebound effect. A large number of studies have examined the elasticities of gasoline prices in transport fuel demand. Price elasticities are almost always negative: an increase in price leads to lower demand, and vice versa. Dahl (2012) examines 240 gasoline demand studies for more than 70 countries. She found that the elasticities of gasoline prices vary significantly between countries and are related to income, infrastructure, and culture. For example, in the US, the price elasticity of gasoline is currently estimated to be in the range of -0.02 to -0.04 in the short term, meaning that it takes a 25% to 50% decrease in the price of gasoline to raise automobile travel by 1%.

Urbanization

With the gradual increase in the proportion of the population living in urban areas and higher urbanisation rates, over half of all people were living in urban areas by 2012 (Chakwizira et al., 2014). With a higher urbanisation level and as a result of economic of agglomeration, it becomes easier for people to access shops and restaurants. As urbanisation progresses, cities become more congested, making it is less convenient to use private cars. With improved public transportation and better accessibility for all the aspects of urban life, the average distance travelled by cars declines. Studies have found that as a region becomes more urbanised, vehicle kilometres per person fall (Karathodorou et al., 2010; Small and Van Dender, 2007).

Urban density

Travel distances are often shorter in cities which have greater density due to congestion and the presence of public transport networks. A number of studies have found that travel demand decreases with increased urban density. Karathodorou et al. (2010) find that there is a negative relationship between passenger car fuel consumption and urban density. Similarly, Newman and Kenworthy (1989) report a strong negative correlation between fuel consumption per capita and urban density.

Road mileage

The relationship between accessibility to destinations and the demand for transport can be measured as an induced effect. In both the UK and US, Nolan and Lem (2001) conclude that the expansion in road capacity has a positive impact on traffic demand. In the case of China, Chai et al. (2016) find that when road accessibility (measured in mileage) is increased by 1%, road traffic demand increases by 1.26%. They also find that the long-term effect of road accessibility on the traffic demand is stronger than the short-term effect. Hence, we expect to find a positive relationship between total road mileage in a country and distance travelled per vehicle.

Fuel intensity and fuel economy standards

As fuel economy improves, the average fuel cost per km falls, and the demand for passenger transport increases as a result of the income effect. The rebound effect is expressed as the percentage of the forecasted reduction in energy use that is lost due to consumer and market responses (Gillingham et al., 2016). Over time, as the cost of travel by cars becomes cheaper, we expect a positive correlation between fuel economy standards and distance travelled per vehicle and a negative correlation between fuel consumption per km and the distance travelled per vehicle per year.

Table 5.1: Interpretation and units of indicators

Type	Variable	Symbol	Unit
Explained	PLDV kilometres per year	$\ln KM_{it}$	km/year
Explanatory	GDP per capita	$\ln Y_{it}$	USD
	Oil price per litre	$\ln FP_{it}$	USD/litre
	Road length	$\ln M_{it}$	km
	Urbanization	$\ln U_{it}$	N/A
	Urban density	$\ln UD_{it}$	population/km^2
	Fuel economy	$\ln FE_{it}$	litre/100km

5.3.2 Data

5.3.3 Data sources

This present study encompasses data obtained from the UK, the US, Japan, China and India. The variables in the dataset consist of the passenger kilometres of PLDVs per annum (km/year), the price of fuel at the gas pump (USD/litre), urbanization

(% of population living in cities), GDP per capita, road length (in km), population density, and fuel efficiency in litres/100km. The data sources and definitions are listed in Table 5.2.

The data were obtained from diverse official sources, including national statistical yearbooks, energy statistics bureaus, car industry yearbooks, the World Bank, and some estimates were obtained from existing literature when data were not readily available. In China and India, the demand for PLDV services in terms of passenger cars is not readily available. The China Statistical Yearbook and the World Bank only provide data for road passenger transport demand, but not passenger cars specifically. Similarly, in the case of India, only data for road passenger transport are readily available from the World Bank. Therefore, it was necessary to find the proportion of passenger vehicle transport attributed to the demand for PLDVs in China and India. For China, we have taken the modal split between cars and buses from the results of Zhang et al. (2007), who build a modal split model maximising spatial welfare constrained by time and travel budgets. Singh (2006) estimates the traffic mobility data from 1950 to 2001 in India based on the assumptions taken from studies such as NTDPC (2014). They build projections of the modal shares from the year 2001 onwards until 2021 based on the Indian mobility trend. For the US and UK, it is possible to obtain passenger car kilometres per year from the National Highway Statistics dataset and Department of Transport Statistics, respectively.

GDP per capita is taken as an indicator for income and collected from the World Bank. The data for urbanisation, urban density and oil price at the pump are readily available from the World Bank. We filled in the missing data with the data collected from national statistics whenever the data were unavailable from the World Bank. For example, in the case of India, there are gaps in the oil price data between 1990-2015. The gaps were filled using the oil price indices collected from the Ministry of Petroleum and Natural Gas.

It is challenging to obtain fuel efficiency data for all countries before 1990 because new car fuel consumption was not routinely recorded in many countries. The fuel economy standard data for all five countries after 2004 was collected from the International Council on Clean transportation (ICCT). In the case of the UK, the US and Japan, new car fuel consumption was taken from official statistics, when available. Otherwise, we have taken the data for new car fuel efficiency from Clerides and Zachariadis (2008), who analyse the evolution of fuel economy and consumption over time (1980-2010) in 18 countries. We extrapolated new car fuel efficiency between 1970 and 1980 based on the evolution of fuel efficiency between 1980 and 1995. [1]. We assumed that average slope for new car fuel efficiency between 1990 and 2005 is flatter than the trend between 2005 and 2012. We argue that this assumption is valid due to two reasons. Firstly, the fuel economy standards for cars did not take effect in India until 2016, so the average fuel efficiency between 2005 and 2012 is related to new technological improvements, but not by any new standards. Secondly, the average fuel efficiency between 2005 and 2012 has improved faster in developed countries (e.g., EU countries) than it did between 1990 and 2005 due to the fuel economy standards introduced in the mid-1990s as a result of the auto industry's voluntary agreement with the European Commission.

Table 5.2: Data definitions and sources

Variables	**US**	**UK**	**Japan**	**China**	**India**
Period	1970-2015	1970-2015	1970-2011	1990-2015	1990-2015
PLDV kilometre per vehicle	US Highway Statistics	Department for Transport Statistics	Japan Statistical Yearbook	China Statistical Yearbook	World Bank and Singh (2006)
GDP per capita	World Bank	World Bank	World Bank	World Bank	World Bank
Oil price per litre	World Bank	Department for Business, Energy and Industrial Strategy	World Bank	World Bank	World Bank
Road length	US Highway Statistics	Department for Transport Statistics	Japan Statistical Yearbook	China Statistical Yearbook	Transport Research Unit, MORTH, India
Urbanization	World Bank	World Bank	World Bank	World Bank	World Bank
Urban density	World Bank	World Bank	World Bank	World Bank	World Bank
Average fuel economy standard	National Highway Traffic Safety Administration	Department for Transport Statistics	ICCT	ICET China	ICCT

[1] Based on the analysis of Clerides and Zachariadis (2008), new car fuel efficiency begins to fall more significantly after 1995 as a result of standards introduced in the late 1990s in the EU and Japan.

5.3.4 Regression results

Pooled OLS results

The results for the pooled OLS estimates are presented in Table 5.3. A country dummy variable is added to account for the unobserved effect. We test whether it is valid to pool the data with the Bresch-Pagan test. The null hypothesis H0 for the Bresch-Pagan test is that the variance of the unobserved fixed effects is zero (i.e., it is possible to use the pooled OLS model). As the test results show, we fail to reject the null hypothesis, meaning that the random effects regression is not appropriate. This implies that a pooled OLS model is superior to the Random Effects Model.

As Table 5.3 shows, the adjusted R-squared indicates that the model has strong explanatory power (R-sq=0.89). Consistent with existing studies, the results show that oil prices, urbanisation, road mileage, population density, and fuel efficiency have a significant effect on the road traffic demand. Income does not significantly affect the distances travelled by car per year, probably because as income increases, people purchase more vehicles instead of travelling more in each car. The coefficient results show that road accessibility has an attractive effect on road traffic demand, while travel demand decreases by 1.5% when the oil price increases by 10%. As countries become more urbanised, people take advantage of the public infrastructure when they are in cities. Hence, we find that distance per car falls as countries become more urbanised and distance per car increases as more roads are built (induced demand). Fuel efficiency improvements will result in a traffic increase, although the effect is small (travel demand increases by 0.3% when fuel efficiency improves by 10%).

The problem with the pooled OLS model is that the outcome variable (travel demand) depends on explanatory variables which are not observable but are correlated with the observed explanatory variables. We conduct the Hausman test to validate the suitability of the Fixed Effects (FE) Model. For the static models, we hypothesise that the best model is the Fixed Effects model and test this with the Hausman test. Table 5.3 shows that fixed effects should be used since the chi-square test statistic is 35.02 and has a p-value of 0.00. Hence, we dismiss the Random Effects Model. However, only three variables are significant in explaining the variability in the traffic demand. Consistent with the findings in the OLS regression, we find that oil prices and urbanisation decrease travel demand, while population density increases travel demand. The total significance of the model is not very strong, with an R^2 of 0.45. There are two main reasons for this. Firstly, unlike what is observed in the OLS model, the FE model removes the non-observable fixed effects. Secondly, there is a significant trend in the time series, which can be captured only with a dynamic panel model.

In order to account for the dynamic effect in the panel data, we use the Arellano-Bond estimator with the General Method of Moments (GMM), which includes the lagged dependent variable as one of the explanatory variables. For dynamic specification, the GMM estimator of Arellano and Bond, which is estimated in the first differences with instruments in levels, is required to remove the unobservable individual specific effects. The Arellano-Bond estimator controls the fixed effects by first differencing and assuming that the idiosyncratic error is serially uncorrelated. We carry out the regressions with the GMM in one step with robust standard errors. Table 5.3 shows the results for the GMM regressions. All variables are significant at either the 5% or 10% levels. Note that the signs for the coefficients of the variables in the GMM estimations are consistent with the OLS pooled estimation and FE model. In order to validate the assumptions of the Arellano-Bond GMM estimator, we carry out the Sargen test, which yields a result of 145 with a p-value of 0.6308. Hence, we cannot reject the null hypothesis of over-identified restrictions.

Table 5.3: Regression results for the Pooled OLS model, the Fixed Effects (FE) model, and the Arellano-Bond GMM model

	OLS			**FE model**			**Arellano-Bond GMM**		
Variable	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat
PKM lag 1	0.56***	0.05	10.46				0.74***	0.06	12.30
Country	0.07***	0.01	6.22						
ln(P)	-0.15***	0.03	-4.55	-0.14***	0.05	-3.17	-0.08**	0.03	-2.46
ln(U)	-0.01**	0.00	-2.42	-0.02***	0.00	-5.37	-0.01***	0.00	-2.93
ln(Y)	0.03**	0.03	2.11	-0.01**	0.03	-2.03	-0.01**	0.02	-2.41
ln(M)	0.02**	0.01	2.15	0.02	0.03	0.90	0.05**	0.02	2.28
ln(UD)	-0.02***	0.03	5.20	-0.04***	0.22	6.69	-0.02**	0.19	2.56
ln(FE)	-0.03***	0.01	-2.86	-0.02	0.14	-0.15	-0.14**	0.10	-2.09
Const	3.46***	0.01	-3.48	3.72	1.24	3.01	0.78	0.96	0.82
Bresch-Pagan test	1.58 (0.21)								
Hausman test				35.02(0.00)					
Sargen test (P-value)							0.63		
N	166			166			158		
Adjusted R-squared	0.93			0.45					

**Means at the 5% significance level

*** Means at the 1% significance level

5.4 Car population projection

Car ownership models are used to forecast transport demand, energy consumption and emission levels. Jong et al. (2004) make a comparison of a number of existing car ownership models. They identify nine model types, including aggregate time series models, aggregate cohort models, aggregate car market models, heuristic simulation models, static disaggregate ownership models, indirect utility models of car ownership, static disaggregate car choice models, panel models, and dynamic car transactions models. Among the different model types, one of the most well-known approaches is an econometric estimation of an income-car stock model based on a logistic function.

Historically, GDP growth and economic development are associated with an increase in vehicle ownership. Past studies have made projections of passenger car ownership based on GDP (Meyer et al., 2012; Bouachera and Mazraati, 2007). Gately and Dargay (1999) examine trends in the growth of vehicle stocks for a large sample of countries and employed the Gompertz function to estimate the relationship between the number of vehicles and per capita income. Meyer et al. (2012) also estimate car stock based on the Gompertz function in 11 world regions. Following the previous studies, we estimated car stock with a Gompertz model:

$$V_{i,t} = V_i^{\star} e^{\alpha e^{\beta EF_{i,t}}} \tag{5.2}$$

which is equivalent to

$$ln(ln(V_{i,t}/V_{i,t}^{\star})) = ln(\alpha) + \beta EF_{i,t} \tag{5.3}$$

where i denotes the country, t denotes the year, $V_{i,t}$ represents the vehicle ownership (vehicles per 1000 people) of country i in year t, $V_i^{\star}$is the saturation level and $EF_{i,t}$ is the per capita income. The parameter α determines car stock demands at zero income levels, and the parameter β determine the shape of the S-shape curve. We find the α and β by regressing $ln(ln(V_{i,t}/V_{i,t}^{\star}))$ against $EF_{i,t}$.

Specification of a saturation level is important for determining future vehicle ownership. A higher urbanisation level and a greater population density would reduce the travel demand as a result of the availability of public transport and a lower need for vehicles (Dargay et al., 2007). In this chapter, the saturation rates for different countries are extracted from existing literature (Huo and Wang, 2012; Dargay et al., 2007; Arora et al., 2011; Meyer et al., 2012; Wu et al., 2014). Note that the saturation levels vary under different scenario and studies. Table 5.4 shows the saturation levels, the data sources and the values for α and β based on GDP per capita and the saturation levels. The stock of road PLDVs is derived from various data sources, such as US Highway Statistics, the UK Department for Transport Statistics, the Japan Statistical Yearbook, the China Statistical Yearbook and the Statistical Yearbook of India. The passenger car stock per 1000 people is derived from the total PLDVs in a country divided by its population, as obtained from the World Bank data.

Table 5.4: The saturation levels, data sources, and values for α and β.

Country	**V***	**Data sources for V***	α	β
UK	550	Dargay et al. (2007)	-3.07	-0.000138
US	800	Dargay et al. (2007)	-17.85	-0.000207
Japan	500	Wu et al. (2014)	-28.30	-0.000177
China	300	Huo and Wang (2012)	-2.05	-0.000735
India	400	Arora et al. (2011)	-5.73	-0.000478

5.5 PLDV demand projections

In this section, we project the PLDV demand using the Arellano-Bond GMM estimations and the projected trends for the explanatory variables are discussed below. The future trends for oil price, GDP per capita, urbanization, road mileage, urban density and fuel economy were projected using government/IEA report, existing literature (Nakicenovic, 2007) and developing trends in the industry (Yang and Bandivadekar, 2017*a*).

5.5.1 Oil price

Figure 5.3 shows the oil price projections until 2040 from the IEA New Policy Scenario. Over half of the pump prices for petrol and diesel are made up of excise duties and value-added tax (VAT). For instance, in the UK, the petrol price at the pump is made up of the cost of oil, government excise duty, and retail/ex-refinery spread (UKPIA, 2017). To find the difference between the oil price and the pump price, we took the pump price from Q3 2016 in the five countries and found the difference between the pump price and the crude oil price in Q3 2016 [1].

To account for uncertainty regarding the oil price, we created 10 oil price scenarios in additional to the baseline scenario (see Figure 5.3), as follows:
Scenario 1: Assumed that the oil price is 5% above the baseline oil price.
Scenario 2: Assumed that the oil price is 10% above the baseline oil price.
Scenario 3: Assumed that the oil price is 15% above the baseline oil price.
Scenario 4: Assumed that the oil price is 20% above the baseline oil price.
Scenario 5: Assumed that the oil price is 25% above the baseline oil price.
Scenario 6: Assumed that the oil price is 10% below the baseline oil price
Scenario 7: Assumed that the oil price is 25% below the baseline oil price.
Scenario 8: Assumed that the oil price is 30% below the baseline oil price.
Scenario 9: Assumed that the oil price is 40% below the baseline oil price.
Scenario 10: Assumed that the oil price is 50% below the baseline oil price.

5.5.2 Population

The World Bank has population simulations and projections from 1960 to 2050. We used the population projection data provided by the World Bank Data Bank (World Bank, 2018).

5.5.3 Urban density

Urban density is calculated by dividing a country's area by its population. The projected urban density up until 2050 is estimated by dividing the country's area by the projected population provided by the World Bank Data Bank (Section 5.5.2).

5.5.4 Fuel economy

The historical trends for fuel economy standards are obtained from the Yang and Bandivadekar (2017*a*) and government transport statistics (as shown in Figure 5.4). The future fuel economy for a car fleet is extrapolated to the future based on the historical trends. For the US, we have taken into account the possibility of weakened fuel economy standards enacted by the Trump administration. The projections for the fuel economy standards for the US are revised based on analyses provided by

[1] The pump price data were collected from the World Bank. Crude Oil prices were collected from NASDAQ (2018).

Plumer and Popovich (2018) and Ingraham (2018). The extrapolation for the fuel economy standards is subject to the introduction of fuel economy standards and the progress of technological breakthroughs in low-emission vehicles in the future.

5.5.5 GDP per capita

The projected GDP data in our study was retrieved from the IIASA's SSP database. The SSP database makes projections based on Shared Socioeconomic Pathways (SSPs). The GDP projections are based on the assumptions used for the interpretation of the SSP storylines in terms of the main drivers of economic growth (Leimbach et al., 2017).

We consider three SSP scenarios obtained from Cuaresma (2017). Table 5.5 shows the world GDP per capita projections by income group. Based on the World Bank definition, the US, the UK, and Japan belong to the high-income countries, while India and China belong to the lower and higher middle-income countries, respectively. As observed in Table 5.5, growth in GDP is higher in the middle-income group than in the high-income group, and the GDP growth slows down after 2040. GDP per capita is calculated by dividing the growth in GDP by the projected population.

Table 5.5: World GDP per capita projections by income group, based on the Shared Socioeconomic Pathways.

	Period	World	High income countries	Middle income countries	Low income countries
SSP1	2010-2040	3.20%	1.70%	4.80%	4.10%
	2040-2100	1.50%	1.30%	1.50%	2.70%
SSP3	2010-2040	1.90%	1.60%	3.90%	1.70%
	2040-2100	0.30%	1.10%	0.50%	0.70%
SSP5	2010-2040	3.50%	1.90%	5.20%	4.60%
	2040-2100	2.20%	1.70%	2.20%	3.50%

5.5.6 Urbanization

The urbanisation from 2016 to 2050 is extrapolated from the historical trend. As shown in Figure 5.5, all the countries have become more urbanised over time. We assume that in countries which are already urbanised, such as Japan, the UK, and the US, urbanisation will stabilise over the next 30 years, while, in China and India, urbanisation will continue to increase following the historical trend until it reaches over 80%.

5.5.7 Projections of the demand for PLDV services

The transport distance for a PLDV per year is estimated with equation 5.1, and the projections for future oil prices, urban density, urbanisation, fuel economy, road mileage, and GDP per capita are based on Arellano-Bond GMM estimation.

To account for the oil price uncertainties, the travelled distance per car each year is estimated under the ten oil price scenarios in additional to the baseline scenario. The baseline scenario oil price is taken from the projection made in the IEA New Policy Scenario. Scenarios 1 to 5 assume that there is a gradual increase in oil price until the oil price is consistent with the IEA′s current policy. Scenarios 6 to 10 assume that there is a gradual decrease in oil price until it is consistent with the IEA′s 450 scenario.

The projections for car distance per year under different oil price scenarios are shown in Figure 5.6. For the US, the UK, China, and India, notice that the car distance projected tends to decrease between 2020 and 2030 but starts to increase between 2040 and 2050. As shown in Figure 5.3, it is assumed that oil prices will increase more steeply between 2020 and 2030 compared to between 2040 and 2050. On the other hand, fuel economy keeps improving for all countries, although the effect is smaller for the US as a result of Trump's decision to freeze the Obama standards. Between 2020 and 2030, when the effect of the increase in oil price is stronger than the effect of fuel economy standards improvements on the car distance travelled, we find the distance travelled by cars falls. Between 2030 and 2040, when the effect of the increase in oil price on the distance travelled is smaller than the effect of fuel economy on the distance travelled, we find that the distance travelled by cars increases. Hence, the projections for car distance per year appear to be U-shaped for all countries except Japan. While the effect of increase in oil prices and the improvement in fuel economy standards are present in Japan, from the historical trend, car distance travelled per year has been falling since 1990, and this trend is reflected in the projections for between 2020 and 2050.

The solid black line is the average distance travelled per car per year, as collected from the national transportation agencies. The dashed blue lines are projections for oil prices assumed in the New Policy Scenario. The dashed black lines represent projections for the average distance travelled by car per year when oil prices increase. The dashed green lines represent the projections for travel distance per year assuming that oil prices decease gradually (scenarios 6 to 10). As expected, the higher the oil price, the lower the average distance is found to be in all countries, and vice versa. We find that as fuel economy improves, the rebound effect leads to an increase in the demand for PLDV services. The rebound effect can be mitigated by the higher oil price scenarios.

5.5.8 Vehicle fleet projections

Figure 5.7 shows the historical fleet sizes for the five countries (solid black lines). Vehicle stock projections were done on the basis of equation 5.2 with the parameters shown in Table 5.4 . The dashed lines in Figure 5.7 show the car fleet size projections between 2016 and 2050 under three GDP assumptions, namely, the SSP1, SSP3, and SSP5 assumptions (see Table 5.5 for details).

For high-income countries, it is assumed that the GDP increases by 1.3% under SSP3 and 1.9% under SSP5 between 2020 and 2040. For the middle-income countries, it is assumed that the GDP increases by 3.9% under SSP3 and 5.2% under SSP5 between 2020 and 2040. For the US, the UK, and Japan, the difference in GDP assumptions does not affect the car fleet size projections significantly. However, in China and India, the size of the car fleet projected under SSP5 is much larger than that under SSP3, reflecting the higher GDP growth projections under SSP5 than SSP3 for China and India.

5.5.9 Discussion

This chapter presents the methodology, data, and projection results for PLDV services. We found that a number of socio-economic factors, such as oil price, urban density, urbanisation, road mileage, and fuel economy are significant for predicting the demand for PLDVs. We used the estimates of the Arellano-Bond model to project the demand for PLDV services and the Gompertz model to project the car populations for the UK, the US, Japan, China, and India. To account for uncertainties in oil prices and GDP per capita, we created ten oil price scenarios for each country. We found that the demand for PLDVs falls as oil prices increase, with the impact varying between countries, depending on the rebound effect (improved fuel economy), induced effect (more roads), and the urbanisation rate. For instance, the rebound effect as the fuel economy improves is largest in the UK and lowest in China among the five countries. Although we find that the fuel economy improves faster in China, the rapid urbanisation rate in China counterbalances the rebound effect of improved fuel economy. The impact of the uncertainty in oil prices is discussed in the sensitivity analysis (see Appendix A).

This section provides regionalised projections of car stocks in the UK, the US, Japan, China, and India. The car stock is a convenient measure of the PLDV demand because consumption activities are based on both the car stock and distance driven by each car. Following the previous studies, we analyse the relationship between car ownership and income until 2050 using the sigmoid Gompertz function. We find that, with the exception of Japan, the car stock increases steadily until 2050, with the rate of increase highest in India under the SSP5 scenario since, in a low income-country like India, income is projected to increase more rapidly compared to in a middle-income country like China. Also, the population projection is greater for India than China (see the World Bank projections in Section 5.5.2). The main limitation of this approach is the uncertainty regarding the car saturation levels, as saturation may well be different for different regions due to population densities, distributions of populations in urban and rural areas, and various transport policies. The uncertainties are more prominent in developing countries, such as China and India, than in developed countries, such as the UK, the US, and Japan, because most studies suggest that as incomes continue to increase, the numbers of vehicles will grow faster. Although the uncertainties regarding the saturation levels are not the focus of this study, for future studies, it is important to look into the impact of fiscal policies on the car saturation levels and emissions.

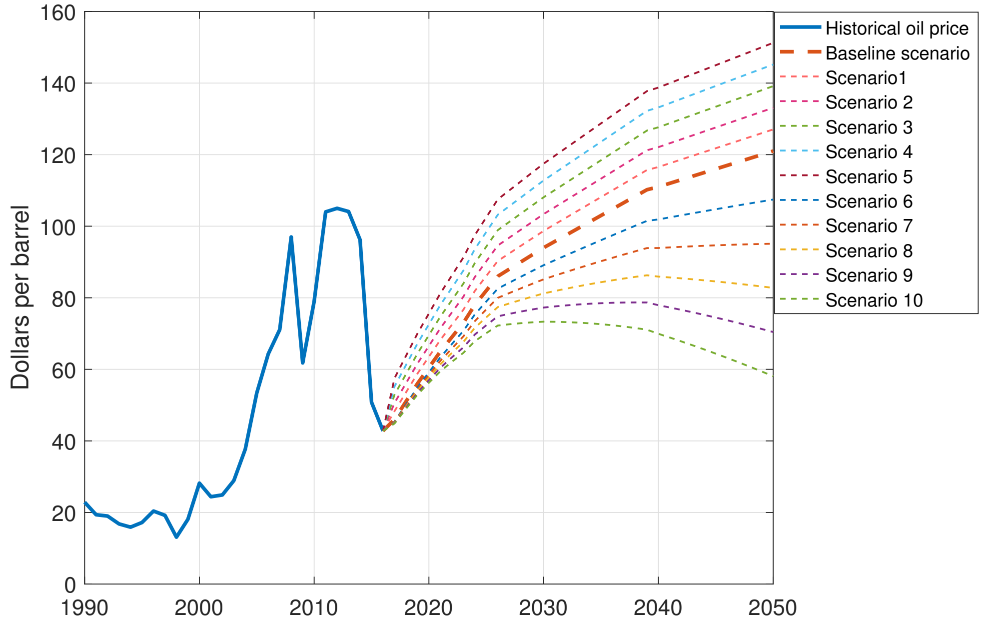

Figure 5.3: World oil price by scenario. The darker red dashed line is the oil price assumed in the New Policy Scenario in (IEA, 2016).

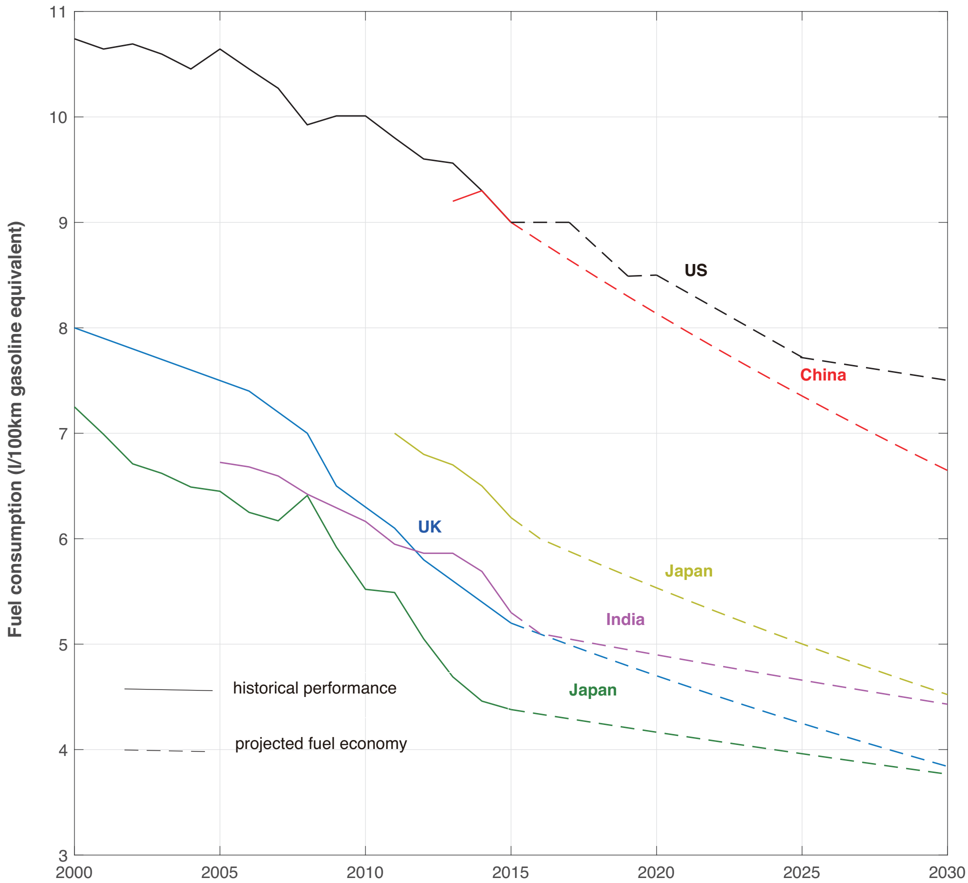

Figure 5.4: Historical and projected fleet fuel economies. Data source: the ICCT, Plumer and Popovich (2018) and Ingraham (2018).

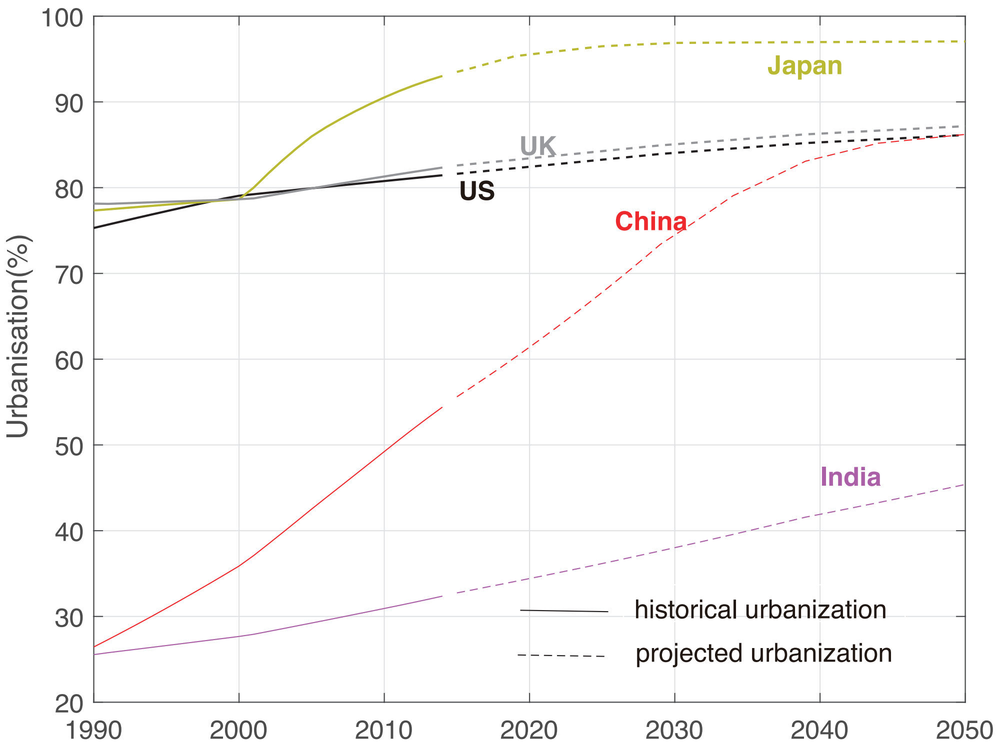

Figure 5.5: Urbanization: historical data and projected trend. Data source for historical data: The World Bank databank.

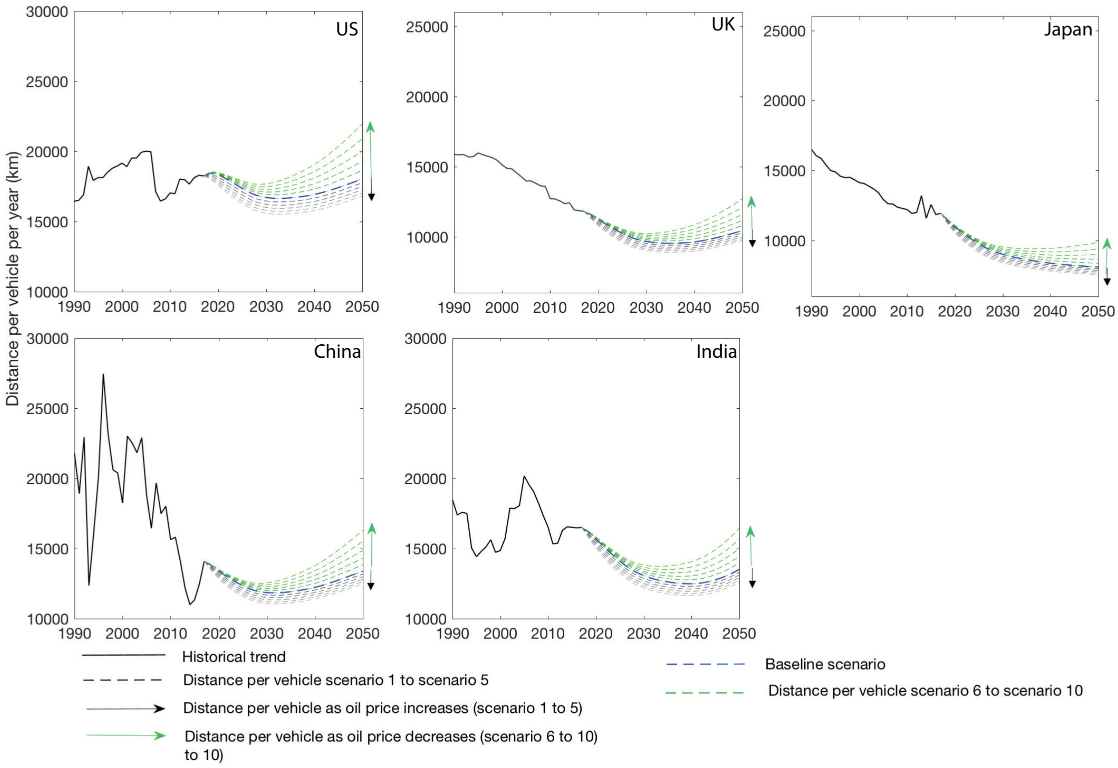

Figure 5.6: Average travel distance travelled by a car per year under GDP per capita assumption SSP1. The solid black lines are the historical trend for the distance travelled by cars. The dashed green lines represent the distance travelled per car as oil prices decrease (i.e., the lower the oil prices, the lighter the dashed green lines). The dashed black lines represent the distance travelled per car as oil prices increase (i.e., the higher the oil prices, the lighter the dashed black lines).

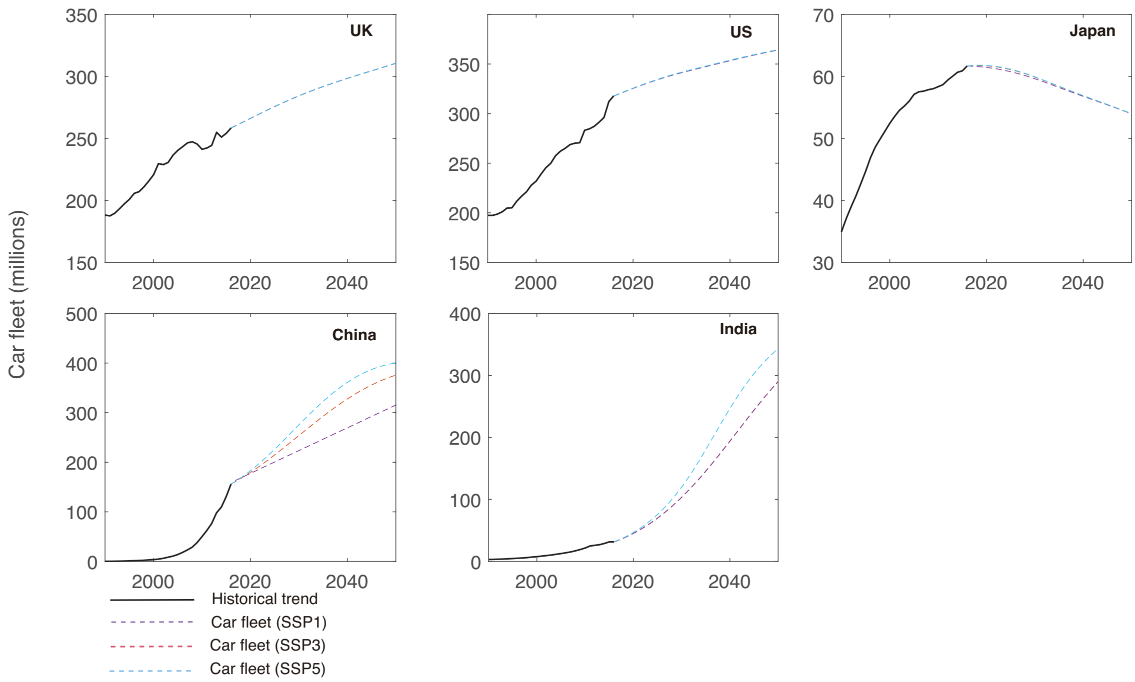

Figure 5.7: Historical and projected car fleets (in millions) under the SSP1, SSP3 and SSP5 assumptions.

Chapter 6

The current policy framework

This chapter reviews existing policy incentives to reduce emissions from PLDVs in five major countries (the US, the UK, Japan, China and India). The purpose for this chapter is threefold. Firstly, the discussions present a background and context for the existing policies that aim to reduce emissions from passenger vehicles. Secondly, to examine policies that reduce emissions further, we design policy scenarios in Chapter 7 and test them in the FTT-Transport model. Studying current policies enables us to design possible scenarios for each country based on existing policy frameworks. Thirdly, the current policy frameworks form the assumptions that underpin the baseline scenario.

6.1 EU and UK

Climate change mitigation and energy security are the UK's primary energy goals. In 2013, the UK greenhouse gas (GHG) emissions covered by the Kyoto Protocol were estimated to be the CO_2 equivalent of 568.3 million tonnes ($MtCO_2$) (DECC, 2013). Domestic transport accounted for 21% of this total in 2013, almost entirely through CO_2 emissions. Road transport is the most important source of emissions in the transport sector passenger cars, in particular.

Existing and planned UK support for low-emission vehicles takes place within the framework of the EU's strategy to reduce CO_2 emissions from new cars (Lane, 2011). The EU has taken three main approaches to encourage the diffusion of low-emission vehicles. The EU first established a law requiring that new cars registered in the EU emit no more than an average of 130 grams of CO_2 per kilometre (gCO_2/km) by 2015 (EC, 2015). By 2021, the average fleet target for new cars is

95 grams of CO_2 per kilometre. Emissions for each car type are set according to mass, using a limit value curve. The limit value curve is set in such a way that the average CO_2 emissions target is achieved in the EU as a whole, with heavier cars allowed higher emissions than lighter cars (EC, 2015). Equation shows the limit value curve displayed in Annex I of the Regulation (EC) No 443/2009.

$$CO_2 = 130 + ax(M - M0) \tag{6.1}$$

where:
M = Mass in kg
M0 = 1290
a = 0.0457 (the slope of the 'limit value curve')

Note that for these targets to be reached, the emissions cap will be phased in over several years. For instance, to reach the 2015 emissions target, 65% of each manufacturer's newly registered cars had to comply by 2012, 75% by 2013, 80% by 2014 and 100% by 2015. As of 2012, if a manufacturer's fleet exceeds its limit value, the company has to pay an excess emissions premium for each car registered. From 2019 onwards, the cost will be 95 EUR (80 GBP) per gCO_2/km for each gCO_2/km above the compliance level (EC, 2015).

The EU's second strategy is to ensure that consumers are armed with the right information about the new cars they purchase. This includes providing fuel consumption and CO_2 emissions data at the point of car sales (Lane, 2011). Along these lines, UK legislation requires the label to be displayed at the point of sale. The third strategy consists of fiscal measures designed to influence purchasing behaviour and car use. These measures can be implemented through various taxation schemes, as discussed in the following paragraphs.

In the UK, the 2008 Climate Change Act established a legally binding target to reduce the UK's GHG emissions by at least 80% below base year levels by 2050 (HMGovernment, 2011). The UK has a long history of demand- and supply-side policies that have affected new vehicle fuel economy. Starting from 1993, the fuel duty escalator was introduced with the mitigation of CO_2 as a major objective. Then, in 1999, the vehicle excise duty was structured to include environmental considerations and set based on car engine sizes.

The Vehicle Excise Duty (VED) is an annual tax levied on vehicles to use public roads. Typically, it is levied based on vehicle characteristics such as engine size, weight or power. The VED was restructured in 2001 when new cars were divided into four VED bands depending on their carbon intensity. More recently, the CO_2-graded VED was recalibrated with higher band resolution and slightly higher duties as well as the introduction in 2010 of a high first-year VED rate for more heavily polluting cars, akin to a purchase tax (Brand et al., 2013). For cars registered since 1 March 2001, tax rates have increased with CO_2 emissions, and all cars with CO_2 emissions up to 100 g/km pay no tax in the first year and standard rate car tax thereafter. For vehicles registered after 1 April 2017, CO_2 emissions levels are divided into 13 bands (see Table 6.1) and applied to the first-year tax cost. As Table 6.1 shows, zero-emission cars pay no VED unless the car costs more than 40,000 GBP. Thus, from 2017 onwards, only zero-emission cars will be VED tax free.

Although the rate of the VED depends on CO_2 emissions in the UK, some evidence suggests that the VED is not a sufficiently strong price signal to incentivise the purchase of lower CO_2 cars (Lane, 2011). The band differential and the tax levels have a relatively small impact on purchasing behaviour.

In addition to the exemption from the VED, in the UK, the electric car (plug-in car) grant intends to incentivise electric car purchases by using a subsidy. The grant offers 35% towards the purchase cost of an electric car (plug-in car) on a given list, up to a maximum of either 3662 GBP for cars or 6592 USD for cars with CO_2 emissions below (UK Government, 2015). Table 6.2 shows the criteria for the subsidy.

Many company cars are on the road. The figures reveal that 950,000 employees paid the company car benefit-in-kind (BIK) tax in 2011 (Robers, 2017). Prior to 2002, employees were taxed at a rate of 35% of the price of the car for having the vehicle for personal use. Since 2002, company and employee company car taxes have been based on a percentage of the official price of the car, the percentage being primarily determined by the car's CO_2 emissions (Lane, 2015). Given that company cars make up a large share in the new vehicle market, variations in the company car tax depending on CO_2 emissions could have an impact on carbon emissions and fuel economy. Table 6.3 shows the BIK rates for 2015-2020. Notice that the tax rate increases over a number of years, depending on the car's fuel economy and fuel use.

Other than fiscal policies, a vehicle scrappage scheme was established in 2009 (for one year). New car purchasers receive a subsidy of 2,000 GBP if the car to be replaced is older than 10 years. The scrappage scheme was introduced relatively late, and the UK government only allocated 300 million GBP to the scheme. The fact that the scrappage scheme is weak in the UK may be a result of the relatively weaker position of the UK motor industry (Aldred and Tepe, 2011), so the government does not have the incentive to encourage fast turnover rates for cars because many cars are imported. Also, unlike other EU countries, such as Spain and Italy where there are emissions criteria linked to the scrappage scheme, in the UK, the primary purpose of the scrappage scheme is to stimulate new car sales, i.e., emissions were not the main concern when it was written (Aldred and Tepe, 2011).

Besides the direct financial benefits, as in the other countries, there have been indirect financial incentives for BEVs. For instance, BEVs are exempted from the London Congestion Charge and, by owning electric cars, a saving of over 2,000 GBP per year can be realised by regular commuters driving in the charging zone (Lane, 2011). Owners will also benefit from free street parking and will be entitled to a 'free residential parking permit' in major London areas. In addition, EVs can access on-street recharging points and pay much lower fuel costs compared to petrol cars.

Table 6.1: Vehicle excise duty rate for the UK (in GBP).

CO_2 emissions (g/km)	First-year rate	Standard rate (year two onwards)	Standard rate (year two onwards) for a car costing more than 40,000 - payable for five years
0	0	0	310
1-50	10	140	450
51-75	25	140	450
76-90	100	140	450
91-100	120	140	450
101-110	140	140	450
110-130	160	140	450
131-150	200	140	450
151-170	500	140	450
171-190	800	140	450
191-225	1,200	140	450
226-255	1,700	140	450
More than 255	2,000	140	450

Source: UK Government (2017*b*)

Table 6.2: UK EV grant.

CO_2 emissions	Zero emission range	Grant	Maximum grant (in GBP)
Under 50g/km	At least 70 miles	35% of cost	4,500 (6592 USD)
Under 50g/km	10 to 69 miles	35% of cost	2,500 (3662 USD)
50 to 75g/km	At least 20 miles	35% of cost	2,500 (3662USD)

Source: UK Government (2017*a*)

Table 6.3: UK company car Benefit-in-Kind (BIK). In every column, the figures on the left show the BIK rates (%) for petrol cars, and the figures on the right show the BIK rates (%) for diesel cars.

Vehicle CO_2 g/km	2015-16	2016-17	2017-18	2018-19	2019-20
1-50	5	7	9	13	16
51-75	13 16	15 18	17 20	19 22	22 25
95-99	14 17	16 19	18 21	20 23	23 26
100-104	15 18	17 20	19 22	21 24	24 27
105-109	16 19	18 21	20 23	22 25	25 28
110-114	17 20	19 22	21 24	23 26	26 29
115-119	18 21	20 23	22 25	24 27	27 30
120-124	19 22	21 24	23 26	25 28	28 31
125-129	20 23	22 25	24 27	26 29	29 32
130-134	21 24	23 26	25 28	27 30	30 33
135-139	22 25	24 27	26 29	28 31	31 34
140-144	23 26	25 28	27 30	29 32	32 35
145-149	24 27	26 29	28 31	30 33	33 36
150-154	25 28	27 30	29 32	31 34	34 37
155-159	26 29	28 31	30 33	32 35	35 37
160-164	27 30	29 32	31 34	33 36	36 37
165-169	28 31	30 33	32 35	34 37	37 37
170-174	29 32	31 34	33 36	35 37	37 37
175-179	30 33	32 35	34 37	36 37	37 37
180-184	31 34	33 36	35 37	37 37	37 37
185-189	32 35	34 37	36 37	37 37	37 37
190-194	33 36	35 37	37 37	37 37	37 37
195-199	34 37	36 37	37 37	37 37	37 37
200-204	35 37	37 37	37 37	37 37	37 37
205-209	36 37	37 37	37 37	37 37	37 37
210-214	37 37	37 37	37 37	37 37	37 37
215-219	37 37	37 37	37 37	37 37	37 37
220-224	37 37	37 37	37 37	37 37	37 37
225-229	37 37	37 37	37 37	37 37	37 37
230 or above	37 37	37 37	37 37	37 37	37 37

Source: Lane (2015)

6.2 USA

In the US, more than 1400 $MtCO_2$ are generated from road transport annually, accounting for 20% of global CO_2 emissions from road transport. Within the transport sector, light-duty vehicles (including passenger cars and trucks) were by far the largest contributors to CO_2 emissions, with 61% of GHG emissions. The US is the largest consumer of oil in the world, burning 20.5 million barrels of oil per day (EIA, 2019). Nearly 70% of oil use in the US is for transportation, and more than 65% of that amount is for private passenger transport (Looney, 2012).

The first nationwide US light-duty vehicle emissions standard was implemented in 1968 and has been reviewed every couple of years. Since 2011, the federal government has offered an income tax credit to fuel-efficient vehicles, ranging from \$2,500 to \$7,500 per vehicle. The amount to which income tax credits can be claimed depends on the tax liability of the purchaser. Brought on by the American Recovery and Reinvestment Act of 2009, the incentive provides full tax credits to the first 200,000 eligible plug-in hybrids and electric vehicles sold per manufacturer.

The Energy Tax Act of 1978 requires car companies to pay a 'gas guzzler' tax on the sale of cars (excluding light trucks and SUVs) with exceptionally low fuel economy. Manufacturers of new cars that fail to meet the minimum fuel economy level of 22.5 miles per gallon (mpg) have to pay a gas guzzler tax. Since 1980, passenger vehicles have been subject to the gas guzzler tax if they fail to reach a minimum fuel economy requirement of first 15 mpg and then 22 mpg after two decades. The tax is intended to discourage the production and purchase of fuel inefficient vehicles. However, the gas guzzler tax has remained at the same level for over 20 years. Table 6.4 shows the rate the manufacturer or importer must pay for each vehicle that does not meet the minimum requirements.

The Corporate Average Fuel Economy (CAFE) establishes the minimum average fuel economy limits for each manufacturer's new car fleet nationwide [1]. CAFE standards were enacted to improve the average fuel economy of cars and light trucks in 1975. The original objective of the law was to reduce US dependence on foreign oil during the oil crises of the late 1970s and through the 1980s. Two standards existed when it was first established, one for cars and a less stringent standard for light-duty trucks. Manufacturers are subject to a fine if they have not met the CAFE standards. The stringency of the CAFE standards increased rapidly each

[1] If the average fuel economy of a manufacturer's annual fleet is below the requirement, the manufacturer must pay CAFE credits or pay a penalty.

year through to about 1985 for cars, and then they stayed almost constant for 20 years from 1990 to 2010 (McConnell, 2013). Table 6.5 shows the historical CAFE standards between 1978 and 2014.

During the Obama administration, the NHTSA was required by Congress to set the CAFE standards for no more than five years at a time (McConnell, 2013). The reformed standards were established jointly by the NHTSA and EPA, which issued final standards for model years 2017 to 2021 and presented non-final standards for years 2022-2025. Under Obama's standards, the auto industry is required to double the fuel economy of vehicles to an average of about 54 miles per gallon by 2050. However, more recently, under the Trump administration, the EPA is considering freezing the fuel-efficiency targets at 2020 levels. This proposal would freeze the increase of average fuel economy standards after 2021 at about 37 miles per gallon (Davenport, 2018).

State and local governments offer a wide variety of incentives beyond what the federal government requires. Note that incentives vary substantially by state, model and time (Gallagher and Muehlegger, 2011). The incentives take many forms, including rebates, income tax credits, sales tax exemptions, and fee exemptions. The next sections summarise the incentives for some of the individual states that offer generous incentives. Table 6.6 shows a summary of the levels and timing of the incentives for hybrid cars and electric cars.

As shown in Table 6.6, Colorado is among the states that offer the most generous tax credits for electric cars and plug-in hybrids. In Colorado, the Department of Revenue offers a tax credit for the purchase of a hybrid electric vehicle (HEV) up to 4,713 USD. Between 2012 and 2016, the cap on PHEV conversions increased to 7,500 USD. Colorado uses a formula that multiplies the battery capacity in kilowatt hours by the vehicle purchase price, deducts the federate tax credit amount, and then divides the results by 100 to arrive at the tax credit amount (DeShazo, 2016). Thus, financial incentives vary on the basis of battery capacity and car models.

Instead of offering tax credits to EVs and PHEVs, some states offer rebates to buyers of EVs and PHEVs. The difference between rebates and income tax credits is that the Clean Vehicle Rebate is a single payment to EV/PHEV buyers, while income tax credits depend on the tax liability of purchasers. For example, in Maryland, the rebate is calculated by multiplying $125 by each kilowatt hour. In Delaware, a rebate of $2,200 is offered to purchasers of new EVs.

According to the California Air Resources Board (CARB), California's Zero Emission Vehicle (ZEV) programme requires battery, fuel cell, and plug-in hybrid electric vehicles to account for at least 15% of California's new vehicle sales by 2025. California emission standards have been more stringent than the EPA requirements. For vehicles purchased after 2010, the state gives anyone who buys a zero-emission or plug-in vehicle up to 5,000 USD and will do so until the funding runs out. Plug-in hybrids qualify for rebates of up to 3,000 USD.

Starting in 2015, to encourage low-income consumers to scrap old vehicles, California began issuing rebates based on income to increase access to EVs and HEVs to as many consumers as possible. Thus, the very rich (individuals earning more than $250,000) are not eligible for the Clean Vehicle Rebate Project (CVRP) rebates. Individuals choosing to scrap old vehicles receive 1,500 USD under an existing programme run by the Bureau of Automotive Repair. Rebate amounts for consumers with household incomes less than or equal to 300% of the federal poverty level are $10,000 per rebate, up from $7,500 (Berman, 2010). Table 6.7 shows the EV and HEV rebates for consumers in different income bands.

Several states in the US provide a sales and use tax exemption for ZEVs. Note that in most cases, tax exemptions do not apply to partial emissions reduction vehicles, such as hybrid cars. Car registration and use taxes vary between states and car models, but they are comparatively low relative to the car price (lower than 200 USD) and hence have a limited effect on consumers' purchasing decisions (US Department of Energy, 2015).

Compared to the car registration tax, the sales tax waiver is much more attractive, mainly because sales taxes are far more significant. States such as New Jersey and Washington offer sales tax waivers to EV and PHEV buyers. Vehicle sales taxes vary by state and often vary by counties, cities, municipalities, and localities within each state.

High-Occupancy Vehicle (HOV) lanes manage traffic and encourage more people to share a single car. Thus, these lanes are a way to reduce emissions from cars and traffic congestion. Several states (e.g., Florida, California, New York, and so forth) have allowed low-emission vehicles to be driven in HOV lanes at any time. Although not a monetary benefit, this privilege can result in considerable time savings for commuters who purchase hybrid cars and electric cars. Other non-monetary incentives that encourage the adoption of low- or zero-emission vehicles include an exemption from insurance surcharges, free parking, and free home-charging equipment, as shown in Table 6.6.

Table 6.4: US Gas Guzzler tax (in USD).

Combined fuel economy of	Amount
at least 22.5 mpg	No tax
At least 21.5, but less than 22.5 mpg	\$1000
At least 20.5, but less than 21.5 mpg	\$1300
At least 19.5, but less than 20.5 mpg	\$1700
At least 18.5, but less than 19.5 mpg	\$2100
At least 17.5, but less than 18.5 mpg	\$2600
At least 16.5, but less than 17.5 mpg	\$3000
At least 15.5, but less than 16.5 mpg	\$3700
At least 14.5, but less than 15.5 mpg	\$4500
At least 13.5, but less than 14.5 mpg	\$5400
At least 12.5, but less than 13.5 mpg	\$6400
less than 12.5 mpg	\$7700

Source: National Highway Traffic Administration and Performance (NHTSAP).

Table 6.5: Historical CAFE standards.

Model Year	Passenger cars (combined) in miles per gallon	Light trucks (combined) in miles per gallon
1990	27.5	20
1991	27.5	20.2
1992	27.5	20.2
1993	27.5	20.4
1994	27.5	20.5
1995	27.5	20.6
1996	27.5	20.7
1997	27.5	20.7
1998	27.5	20.7
1999	27.5	20.7
2000	27.5	20.7
2001	27.5	20.7
2002	27.5	20.7
2003	27.5	20.7
2004	27.5	20.7
2005	27.5	21
2006	27.5	21.6
2007	27.5	22.2
2008	27.5	22.4
2009	27.5	23
2010	27.5	23.4
2011	30.2	24.3
2012	30.5	25
2013	32	27
2014	34	28
2015	34.5	28.5
2016	35	29.5

Source: NHTSAP (National Highway Traffic Administration and Performance)

Table 6.6: Existing incentives to encourage the diffusion of alternative-fuel vehicles with year of launch and the expiration date for individual states in the US. N/A indicates that the expiration date is unknown.

State	Incentives	Launch date/ funding limit	Expiration date
California	HOV access for zero-emissions BEVs and PHEVs	2011	2019
	CVRP provides up to $2500 for BEVs and $1500 for PHEVs	N/A	N/A
	Free parking in any metered parking space in Sacramento for max amount of time allowed by that meter	N/A	N/A
Colorado	Income tax credit up to 75% of the cost premium for a BEV or PHEV purchase up to $6000	2014	2021
Connecticut	Up to $3000 per vehicle for battery electric, fuel-cell electric and plug-in-hybrid electric	For the first 325 vehicles	N/A
	Free metered parking for hybrid and EVs	2005	N/A
Florida	HOV incentives	N/A	N/A
	EVs are exempt from insurance surcharges	N/A	N/A
Maryland	Rebates equal to $125 per kilowatt-hour, not to exceed $3000	N/A	N/A
	Rebate for installing EV charging stations up to $900	N/A	N/A
	Excise tax credit up to $1000	N/A	N/A
New York	Emissions test exemption	N/A	N/A
	Free access to HOV lanes	N/A	N/A
	Electric vehicle recharging property tax credit ($5000 for each installation)	N/A	N/A
New Jersey	Zero-emission vehicles are exempt from sales and use taxes	2004	N/A
	Qualify for access to carpool lane	N/A	N/A
Arizona	Lower licensing fees for BEVs	N/A	N/A
	Free carpool lane access	N/A	N/A
	Tax credit up to $75 for EV charging outlet	N/A	N/A
Delaware	A rebate of $2200 toward the purchase or lease of a new EV	2015	N/A
Hawaii	Allows access to HOV lanes	N/A	N/A
	Free parking	N/A	N/A
	Previous rebates have expired	N/A	N/A
Illinois	Covers 80% of cost premium, capped at $4000	N/A	N/A
Washington	BEVs exempt from 6.5% sales tax	N/A	N/A
Louisiana	Tax credit equalling 36% of cost premium for BEV/PHEV purchases	N/A	N/A
Pennsylvania	Offers $2000 rebates for PHEVs (battery 10kWh or over)	N/A	N/A
	$1000 rebate for any PHEV or EV (battery¡10 kwh)	N/A	N/A
Indiana	Offers a credit of up to $1650 to purchase and install residential EVSE	N/A	N/A
	Free plug-in electric vehicle charging during off-peak hours	N/A	N/A

Source: US Department of Energy (2015).

Table 6.7: Income tax rebate for low-emission car purchasers (Clean Vehicle Rebate) in California (in USD).

Eligible vehicles must be less than 8 years old	Hybrid 20 MPG+	Hybrid 35 MPG+	Plug-in Hybrid	EV
Low income (≤ 225% of the federal poverty level)	\$6500	\$7000	\$10000	\$9500
Moderate income (226% - 300% of federal poverty level)		\$5000	\$9000	\$10000
Above Moderate Income (301% - 400% of federal poverty level)			\$6000	\$8000

Source: US Department of Energy (2015)

6.3 Japan

Japan has the third-largest automobile market in the world, and Japan-headquartered automakers account for the vast majority of global hybrid and electric cars sales (ICCT, 2014). Toyota is the largest Japanese car manufacturer, with an approximate 43% market share, and Nissan and Honda are the second and third largest, with 17% and 15% market shares, respectively. More than 90% of cars sold in Japan are Japanese-made (Kitano, 2013). Under the Paris Agreement, the government of Japan pledged to reduce its national GHG emissions by 26% from 2013 levels by 2030.

Japan is one of the very first countries that engaged in research and policies for energy- efficient products. In 1998, Japan initiated the Top Runner Approach to encourage the energy efficiency of end-use products. The scope was reviewed every few years and, by 2012, 23 products had been included. As part of the Energy Conservation Law, the program identifies the most fuel-efficient automobile in each weight class and designates it as the 'top runner'.

The program then sets mandatory efficiency standards or target values for automobiles based on the most efficient standard products ('top runners') in the market. All vehicles are required to exceed the new target values for their weight class within three to ten years. Manufactures need to ensure that in each financial year, the average fuel economy of their vehicles in each weight category meets the standard.

The government of Japan issues warnings to those companies that do not meet their fuel economy standards.

As a result of the Japanese top runner program, Japanese fuel economy for new vehicles has improved significantly over the past 20 years. Overall, the fuel economy has improved by more than 80% since 1995 and has averaged a 6% annual improvement over the past five years (ICCT, 2015). Table 6.8 shows the fuel efficiency target values for 2015 and 2020, respectively.

With increasing concern over the effects of car usage on energy security and the environment, low-energy car buyers are exempted from some fees and taxes charged for conventional cars. In 2009, the Japanese government introduced an eco-car promotion policy as a part of its FY 2009 tax reform legislation (Ministry of Finance, 2015). Around $2.1 billion in tax reductions was granted to 'eco-cars' and around US$3.7 billion dollars in subsidies were granted to consumers who purchased 'eco-cars' during the 2009 fiscal year (Iino and Lim, 2010). The Japanese eco-car policies encourage the diffusion of not only non-conventional electric and hybrid cars, but also conventional petrol cars with low energy use and emissions. Eco-cars could benefit from various tax reductions depending on the emission levels. The lower the emission levels, the higher the tax reduction. The next sections summarise the car tax framework in Japan and the tax reductions for low-emission cars.

There are nine different taxes for owning cars in Japan, including acquisition, consumption, tonnage, automobile, mini-vehicle, gasoline, regional gasoline exercise, diesel handling, LPG and in-use consumption taxes. In addition, the gasoline and diesel oil delivery taxes are imposed when purchasing fuel (Iino and Lim, 2010). Tax breaks are available for three automobile taxes: acquisition, tonnage and ownership. For the acquisition tax (paid once, upon purchase), in the absence of eco-car tax incentives, the tax rate amounts to 5% of the vehicle purchase price. After the FY2015 taxation revision, the fuel efficiency criteria was raised, and the reduction rates were divided into five categories: no tax, 80%-cut, 60%-cut, 40%-cut and 20%-cut (JAIA, 2015). Table 6.9 shows the acquisition tax reductions for eco-cars.

The tonnage tax is assessed for every year of vehicle ownership based on vehicle weight but is imposed only every two years at the time of mandatory vehicle inspection. The tax rate for private vehicles is 2500 Yen/0.5t/year, with a tax cut/exemption for cars meeting certain environmental requirements (see Table 6.10). After the FY 2015 taxation revision, the fuel efficiency criteria were raised (linked to 2020 fuel economy standards instead of 2015 fuel economy standards) and the reduction rates were divided into more categories to support a smooth shift to stricter fuel efficiency standards (JAIA, 2015). Table 6.11 shows the tonnage tax reductions/cuts for eco-cars after the tonnage tax reform.

The automobile tax (during ownership) is imposed as a property tax and road maintenance charge. It is a local tax levied by various prefectures. Depending on whether the car is for personal or company use, it is paid annually and increases with the engine′s displacement. It is not levied in the initial year of a new vehicle purchase. Table 6.12 shows the automobile tax rates for cars with different engine displacements for private and company uses. Table 6.13 shows the automobile tax reductions available for eco-cars.

In addition to tax reductions, the Japanese government passed a green vehicle purchasing promotion measure in 2009. The programme has two features: one for consumers replacing an old passenger car with a new one, and one for those purchasing a new eco-car without an older car to replace. Under the car replacement scheme, a consumer is eligible for a subsidy of 250,000 Yen (USD 2,176) if he or she replaces the old car (registered for the first time at least 13 years previously) with a new, eco-friendly car. The subsidy is 125,000 Yen (USD 1,088) if the car being replaced is a lightweight car (JAMA, 2015). In addition to the provision of tax exemptions/reductions, the Japanese government offers subsidies to purchasers of eco-cars even without old cars to replace. By using a non-replacement programme, the consumer can get up to 100,000 Yen (870 USD) through the subsidy, which is two-thirds of the price difference between an EV and a comparable gasoline car.

Despite the fact that eco-car incentives have increased the sales of new energy technology cars, there are criticisms that the tax reduction and subsidy programmes have led to some larger passenger vehicles qualifying for the benefits despite their lower fuel efficiency rate. Additionally, many cars on the market have cleared the fuel efficiency standards to be eligible for a tax reduction due to the competitive culture of Japanese car manufacturers.

Table 6.8: Fuel efficiency targets for passenger cars.

Kerb weight (kg)	2015 Fuel economy target (km/l)	2020 Fuel economy target (km/l)
$\leq$ 600	22.5	22.5
601-740	21.8	21.8
741-855	21.0	24.5
865-970	20.8	23.7
971-1080	20.5	23.4
1081-1195	18.7	21.8
1196-1310	17.2	20.3
1311-1420	15.8	19
1421-1530	14.4	17.6
1531-1650	13.2	16.5
1651-1760	12.2	15.4
1761-1870	11.1	14.4
1871-1990	10.2	13.5
1991-2100	9.4	12.7
2101-2270	8.7	11.9
$\geq$ 2271	7.4	10.6

Source: JAIA (2015)

Table 6.9: Automobile acquisition tax reductions in Japan.

Compliance	Automobile acqusition tax
EV/FCV/PHV/Clean Diesel Vehicles/Natural Gas Vehicles	Exemption
Compliant +20% (compared to 2015 FES)	Exemption
Compliant +10% (compared to 2015 FES)	80% reduction of tax rate
Compliant with 2015 FES	60% reduction of tax rate

Source: JAIA (2015)

Table 6.10: Automobile tonnage tax before tax reform.

Compliance	Before reform
EVs/FCVs/PHVs/Clean Diesel Vehicles/Natural Gas Vehicles	Exemption
Compliant +20% (compared to 2015 FES)	Exemption
Compliant +10% (compared to 2015 FES)	75% reduction of tax rate
Compliant with 2015 FES	50% reduction of tax rate

Source: Oka (2014)

Table 6.11: Automobile tonnage tax after tax reform.

Compliance	After reform
EVs/FCVs/PHVs/Clean Diesel Vehicles/Natural Gas Vehicles	Exemption
Compliant +20% (compared to 2020 FES)	Exemption
Compliant +10% (compared to 2020 FES)	75% reduction of tax rate
Compliant with 2020 FES	50% reduction of tax rate
Compliant +5% (compared to 2015 FES)	25% reduction of tax rate

Source: Oka (2014)

Table 6.12: Automobile tax rate in Japan.

Engine displacement (ED) (Litre)	Automobile tax for private use (USD)	Automobile tax for company use (USD)
ED ≤ 1	245	62
1$<$ ED$\leq$ 1.5	286	71
1.5$<$ED ≤ 2	328	79
2$<$ED$\leq$ 2.5	374	115
2.5$<$ED$\leq$ 3	423	130
3$<$ED $\leq$ 3.5	481	149
3.5$<$ED $\leq$ 4	552	170
4$<$ED $\leq$ 4.5	635	196
4.5$<$ED $\leq$ 6	730	225
6$<$ED	921	338

Source: JAIA (2015)

Table 6.13: Automobile tonnage tax after tax reform.

	Reductions 1st year
EVs/FCVs/PHVs/Clean Diesel Vehicles/Natural Gas Vehicles	75%
Compliant +20% (compared to 2020 FES)	75%
Compliant +10% (compared to 2020 FES)	50%
Compliant with 2020 FES	Not eligibility

Source: Oka (2014)

6.4 China

Urbanisation and industrialisation have caused increasing pressure in passenger transport demand. From 1991 to 2012, total annual vehicle production grew from about 700,000 units to 9.35 million units, and total sales of passenger cars has grown more than 20 times since 1990 (China Statistical Yearbook, 2012). By the end of 2012, there were more than 116 million cars on the road. In terms of the passenger car fleet per 1,000 people, China was measured at 34 in 2009 (World Bank, 2013), which is still much lower than in the developed countries. Hence, he potential for future growth remains large.

As a result of increased demand from passenger cars, energy demand increased from 25 Mtoe in 1990 to 236 Mtoe in 2013 (WEO, 2017). In the face of volatile oil prices, rapid growth in passenger car demand put pressure on energy security and urban air quality. In terms of GHG emissions, under the Paris Agreement, China has pledged to cut emissions in relationship to GDP to 60%-65% of 2005 levels by 2030 (CarbonBrief, 2015). The central government is taking steps to curb China's oil consumption and GHG emissions by introducing various policy measures and incentives that encourage the diffusion of low- emission vehicles.

At the national level, to reduce its dependency on foreign oil and encourage more fuel-efficient vehicle technologies, China has subjected the passenger vehicle market to fuel economy standards since 2004. Fuel economy limits for passenger cars are divided into 16 categories based on vehicle weight. The phase I and phase II standards require each individual vehicle model to comply with fuel consumption regulations before entering the market. As China continues to reduce fuel consumption limits, Phase III (from 2012 to 2015) standards requires the average fuel consumption level of new Chinese passenger vehicles to be 7l/100km in 2012 (MIIT, 2015).

Phase IV fuel consumption standards for passenger vehicles are currently under development. In 2014, the Chinese Ministry of Industry and Information Technology (MIIT) released a fuel consumption standard for passenger cars. Compared to the Phase III standard, the new consumption standard would fall to 5l/100km, representing an overall reduction of 28% between 2015 and 2020. Table 6.14 shows the fuel consumption targets based on weight class.

Similar to developed countries, in an attempt to increase demand for energy-efficient and environmentally friendly vehicles, energy-efficient cars, such as plug-in hybrid cars and electric cars, are exempt from car exercise duties and annual registration taxes. Before 2010, car exercise duty rates were based on engine size, with small engine cars enjoying a lower tax rate. However, the excise duty is 10% before the value-added-tax (17%) irrespective of car engine sizes. Registration tax is paid annually based on engine sizes and established by individual provinces or cities. Table 6.15 shows the range for the car registration tax in China.

To reduce dependency on foreign oil, a fuel tax was introduced in 2009 to curb oil consumption in the auto sector. Taxes on fuels can be used to encourage car buyers to purchase more fuel-efficient vehicles. After the fuel tax reform in 2009, the new fuel tax replaced existing types of fees that were previously levied for road and waterway maintenance and management. In 2015, the tax on petrol was increased to 1.52 RMB (0.2 USD) per litre from 1.4 RMB (0.25 USD) (Xinhuannet, 2016).

Because EVs offer an opportunity to address oil security, local pollution and GHG emissions, EV deployment is used by the central government as an essential strategy in tackling local pollution. China launched the EV Subsidy Scheme (EVSS) in 2009, followed by an update in 2013. In the beginning, the subsidy was only available for public procurement, mostly of transit buses and taxis. In 2010, the subsidy was extended to include private purchases. The phase I EVSS ended at the end of 2012. Phase II was announced in 2013 and continued through 2015. Under phase I of the EVSS, subsidies for private purchase of PHEVs and BEVs were based on battery capacity, with a subsidy intensity of 3000 RMB/kWh. Under phase II, subsidies for private purchase of PHEV and BEV were based on the vehicle′s electric range. Vehicles with electric ranges of 250 km or higher, between 150-250 km and between 80-150 km qualified for 60,000 RMB (USD 7,647), 50,000 RMB (7,400 USD) and 5,353 RMB (797 USD) subsidies, respectively (Hao et al., 2014).

For both phases of EVSS, there were subsidy phase-out mechanisms (SPM). Under the phase I EVSS, the SPM was never triggered since no vehicle manufacturers sold more than 50,000 PHEVs and BEVs. Under the phase II EVSS, the SPM required that the subsidy for all EVs should be reduced by 10% and 20% in 2014 and 2015, respectively (Hao et al., 2014).

In 2009, the Chinese government initiated the Ten Cities, Thousand Vehicles programme to stimulate electric vehicle development through large-scale pilots in ten cities. The goal was to kick-start the purchase of EVs with public funds. Initially, the programme targeted the deployment of electric vehicles for government fleets. The programme has since expanded to 25 cities and includes consumer incentives in six cities, Beijing, Shanghai, Hanzhou, Hefei, Changchun and Shenzhen (Gong et al., 2013).

By 2015, 40 cities and provinces had also introduced incentives to encourage the sales of low-emission cars. In addition to the central government′s fixed-amount subsidies (EVSS), local governments offer additional incentives or subsidies to EV purchasers. For instance, on top of EVSS, many cities or provinces offer additional subsidies that are equivalent to the central government subsidies. The Shanghai municipal government offers up to 40,000 Yuan (6,500 USD)/vehicle for an EV and 30,000 Yuan (5,000 USD)/vehicle for a PHEV (TynCar, 2014). In addition, some districts in Shanghai offer additional benefits for new energy vehicles [1]. Table 6.16 provides an overview of the local incentives for purchasing new electric vehicles in China.

Many countries worldwide have considered vehicle restriction policies and lotteries to curb air pollution and traffic congestion. For instance, in 1989, Mexico City implemented a driving restriction programme that banned drivers from using their vehicles one weekday per week, based on the last digit of the licence plate (Davis, 2008). In 1990, the vehicle quota system (VQS) was introduced in Singapore. Under this system, prospective owners of new vehicles must bid for a certificate of entitlement that is valid for 10 years (Davis, 2008).

China first implemented driving restrictions during the 2008 Olympic and Paralympic Games in Beijing. The success in improving air quality and easing congestion led to a series of road space rationing policies in Beijing after the games. Major policies that impact on passenger car CO_2 emissions include driving restrictions and a car licence plate lottery. In Beijing, for example, a licence plate lottery has been used since 2011. For example, to control the total vehicle population at six million by the end of 2017, a new vehicle lottery scheme was implemented from 2014 to 2017 (Beijing Government, 2013). The new quota will decrease from 240,000 to 150,000. Sixty-thousand quotas will be released for four years, including 430,000 regular gasoline vehicles and 170,000 full electric vehicles. This implies that the chance of obtaining a licence plate is much larger for electric vehicles compared with regular gasoline vehicles. New energy cars are also exempt from the day-of-use rationing system, and this non-financial incentive encourages the purchase of new energy vehicles.

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[1] New energy vehicles include cars that are battery electric, fuel cell, hybrid and hydrogen cars.

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Six other cities in China that restrict vehicle registration include Shanghai, Guangzhou, Guiyang, Shijiazhuang, Tianjin and Hangzhou, and they have also introduced a licence plate lottery or auction to control air pollution and congestion. For instance, while licence plates for conventional cars in Shanghai are auctioned, Tianjin and Guizhou have a hybrid system. The bidding prices for the licence plates have been very high due to the limited number released for auction. To illustrate, the average bidding price for a licence plate in Shanghai is 80,020 Yuan (12,380 USD), which is more expensive than a small car. The benefit of purchasing new energy vehicles is that these vehicles are allowed to bypass the auction. Given that a vehicle registration plate in Shanghai was worth 12,300 USD in July 2015, the effective subsidy provided to each battery EV consumer in Shanghai could be worth over 12,300 USD (TynCar, 2014).

Although some incentives have been offered to purchasers of new energy cars, many existing policies and incentive programmes create subsidies only for locally produced vehicles, which may be warding off investors from other Chinese regions or international automakers (Masiero et al., 2016). Different cities still take different approaches to favour local automakers and exclude foreign car makers from the list. For instance, until 2014, Shanghai allowed only EV models manufactured in

Shanghai to be eligible to receive local subsidies. Similarly, Beijing excluded plug-in hybrid cars from the list it will support because no Beijing-based company produces plug-in hybrids (until 2014) (Feng, 2016).

Table 6.14: Fuel consumption standards in China.

Kerb mass in kg	Phase I limits in l/100km	Phase II limits in l/100km	Phase III limits in l/100km
CM≤ 750	7.2	6.2	5.2
750<CM≤ 865	7.2	6.5	5.5
865<CM≤ 980	7.7	7.0	5.8
980<CM≤ 1090	8.3	7.5	6.1
1090<CM≤ 1205	8.9	8.1	6.5
1205<CM≤ 1320	9.5	8.6	6.9
1320<CM≤ 1430	10.1	9.2	7.3
1430<CM≤ 1540	10.7	9.7	7.7
1540<CM≤ 1660	11.3	10.2	8.1
1660<CM≤ 1770	11.9	10.7	8.5
1770<CM≤ 1880	12.4	11.1	8.9
1880<CM≤ 2000	12.8	11.5	9.3
2000<CM≤ 2110	13.2	11.9	9.7
2110<CM≤ 2280	13.7	12.3	10.1
2280<CM≤ 2510	14.6	13.1	10.8
CM>2510	15.5	13.9	11.5

Source : Chinese Ministry of Industry and Information Technology (MIIT).

Table 6.15: Annual registration tax in China.

Engine sizes (cc)	Registration tax (USD)
<1000	10-57
1000-1600	48-86
1600-2000	58-106
2000-2500	106-192
2500-3000	192-384
3000-4000	384-576
>4000	576-864

Source: TynCar (2014).

Table 6.16: Subsidies for new energy vehicles in major Chinese cities.

City	Subsidy and incentive (USD)
Shanghai	40000 Yuan/vehicle for BEVs and 30000 Yuan/vehicle for hybrid cars.
Beijing	Local subsidies equivalent to central government EVSS. The sum of national subsidies and local subsidies must not be higher than 60% of the car prices.
Tianjin	Local subsidies equivalent to central government EVSS.
Xian	For a private new energy car purchaser, the government offers a subsidy worth 10000 Yuan/vehicle and covers 100% the cost of compulsory insurance. For purchasers who scrapped their old cars for new energy cars, the government of Xian offers a 3000 Yuan/vehicle subsidy, on top of scrappage subsidy (2000 Yuan-6000 Yuan/vehicle).
Fujian	Local subsidies equivalent to the central government EVSS.
Hunan	Local subsidies equivalent to the national EVSS. The sum of national subsidies and local subsidies must not be higher than 60% of the car prices.
Guangzhou	Local subsidies equivalent to the central government EVSS.
Qingdao	Local subsidies equivalent to the central government EVSS.
Jiangsu	Offers 24000 Yuan/vehicle for BEVs with lengths longer than 2.45 m and 18000 Yuan/vehicle for passenger cars shorter than 2.45m. The subsidy is 11000 Yuan/vehicle for BEVs shorter than 2.2m. For plug-in hybrid cars, the government offers subsidies of up to 14000 Yuan/vehicle.
Shenzhen	Local subsidies are equivalent to the central government EVSS. For purchasers of new energy cars, the subsidies also cover the cost of charging, cost of installation and compulsory insurance.
Chongqing	Local subsidies are equivalent to the central government EVSS.

Source: TynCar (2014)

6.5 India

India has experienced a sustained period of rapid economic growth since 1991, and the economy grew at an average rate of 7.5% in 2015, faster than the 6.9% growth in China (World Bank, 2015). This rapid economic growth has led to significant growth in the motor vehicle population. India has one of the world's fastest growing car markets. New car sales rose impressively from 1.3 million in 2004 to about 3.6 million in 2012. As a result, the population of motor vehicles has increased eight-fold, from 21 million in 1991 to nearly 160 million in 2012 (Chhibber and Shemar, 2012). The growth in the vehicle population is likely to cause a substantial increase in GHG emissions and fossil fuel use unless the fuel economies of future vehicles are enhanced. According to the IEA, India's share of oil imports could grow from 70% of oil demand in 2006 to over 90% in 2030 (IEA, 2015). Early adoption of fuel efficient policies in India will have a direct effect on national energy security and global oil consumption.

Gasoline and diesel are the most common automobile fuels in India. As in many European countries, diesel cars constitute a significant share of Indian passenger vehicles because diesel cars have been taxed at a lower rate than petrol cars historically. The lower fuel costs for diesel cars have resulted in lower per kilometre operating costs, increasing their popularity with respect to petrol cars. However, more recently, the air pollution levels in India have become a serious issue that threatens public health. Greenpeace research noted that India's air pollution level overtook China′s in 2015, with PM 2.5 concentrations exceeding those found in China (Jamrisko, 2017). To control emissions levels and curb serious air pollution, sales of new diesel cars with engine sizes above two litres were banned by the Supreme Court in Delhi.

Low-emission cars, such as hybrid and electric cars, are still facing major obstacles in India. The country has taken some steps over the last few years to promote EVs, mainly in the form of subsidies. For instance, in 2008, the Ambient Air Fund account was opened by the Delhi Pollution Control Committee (DPCC). This programme aims to provide subsidies for battery-powered cars by allowing a 30% cost reduction for battery-powered vehicle buyers. In 2010, the Indian government announced a subsidy scheme for vehicle manufacturers for the production of BEVs and HEVs. Through 2012, the scheme subsidised up to Rs. 4,000 (USD 60) for low-speed two-wheelers, Rs. 5,000 (USD 76) for high-speed two-wheelers and Rs. 100,000 (USD 1,523) for four-wheeled vehicles. The production cap was set at

300,000 two-wheelers and 140 electric cars (Bansal and Bandivadekar, 2013).

To promote eco-friendly vehicles, the Indian government launched the Faster Adoption and Manufacturing of Hybrid and Electric vehicles (FAME) to incentivise HEV and EV purchases. Under FAME India, the Indian government will provide incentives from Rs. 1,800 (USD 25) to Rs. 29,000 (USD 440) for two-wheelers and Rs. 1.38 Lakh (USD 2,000) for every electric car sold. For passenger cars shorter than four metres in length, incentives start at Rs. 13,000 (USD 198) for a mid-HEV with conventional battery in Level 1, and go up to Rs. 124,000 (USD 1,888) for a BEV with an advanced battery in Level 2, as shown in Table 6.17.

In addition to subsidies for new energy technologies, excise duties are levied depending on the sizes, engine types, and whether the vehicles are new energy technology vehicles. For cars shorter than four metres, the excise duty is set at 8% for conventional cars, and the excise duty increases for cars longer than four metres and with larger engine sizes, going up to 24% for cars with engine sizes more than 1,500 cc (as shown in Table 6.18). For EVs, India has reduced the excise duty from 8% for conventional cars to 4% for EVs (Bansal and Bandivadekar, 2013).

Different states also have their own incentives for energy-efficient vehicles. For example, Delhi, Rajasthan, Uttarakhand, and Lakshadweep do not levy taxes on EV sales. Delhi also offers subsidies and rebates adding up to nearly 29.5% of the cost of EV purchases (Bansal and Bandivadekar, 2013). More recently, in 2015, the New Delhi government began to introduce a round of two-week car restrictions, and cars will be allowed on streets only on alternate days, in response to the rise in public health concerns.

India has not introduced a fuel economy standard for passenger cars, although that will change in the next few years. However, before the formal announcement by the government of India, it is unclear what exact standard will be set in the next few years.

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In 2001, India began a 5% ethanol blending pilot programme, and, in 2003, nine states in India made E5 gasoline available for the first time in India (Bansal and Bandivadekar, 2013). In 2006, the mandate was expanded to include almost the entire country (except for a few northern states). In 2008, E10 was mandated throughout India. At the same time, the government of India approved a policy that seeks to mandate 20% blending of ethanol throughout the country by 2017 (Abdi, 2019).

As discussed in this section, although some incentives are in place in India, the incentive programme comes very late compared to those of other countries. Also, there is no fuel economy standard yet in India, which implies that the government of India has not had a clear policy framework and a road map for reductions in CO_2 emissions.

Table 6.17: Incentives for passenger cars.

Length not exceeding 4 metres	Level 1 (Rs)	Level 2 (Rs)
Mid HEV (Conventional Battery)	13,000 (USD194)	16,000 (244USD)
Mid HEV (Advanced Battery)	19,000 (USD284)	23,000 (350USD)
Strong HEV (Advanced Battery)	59,000 (USD881)	71,000 (1081USD)
Plug-in HEV (Advanced Battery)	98,000 (USD1463)	118,000 (1797USD)
BEV (Advanced Battery)	76,000 (USD1135)	124,000 (1889USD)

Source: Batra (2015)

Table 6.18: Excise duty for passenger cars.

Condition 1	Less than 4 metres and	More than 4 metres and	More than 4 metres and	More than 4 metres and
Condition 2	Less than 1,200 cc (petrol cars)/ Less than 1,500 cc (diesel cars)	Less than 1,200 cc (petrol cars)/ Less than 1,500 cc (diesel cars)	More than 1,500 cc (petrol cars) / more than 1,500 cc (diesel cars)	More than 1,500 cc and ground clearance more than 170 mm
Excise Duty on such cars	8%	20%	24%	24%

Source: Batra (2015).

Chapter 7

Scenario analysis

This chapter explores the effectiveness and efficiency of various policy instruments in cutting global emissions from passenger transport in five nations, namely, the UK, US, Japan, China and India. Fiscal incentives such as EV subsidy, if sufficiently high to offset cost differences between EVs and conventional cars, are the most important reason to buy an EV in Norway (Bjerkan et al., 2016). Fuel tax is effective in decreasing fuel consumption and demand for more efficient vehicles in some countries (Xiao and Ju, 2014; Antweiler and Gulati, 2016). Moreover, regulatory instruments such as fuel economy standards and EV mandates have been widely implemented. It is also worth studying the impacts and efficiency of such regulatory instruments and comparing them to the three most commonly used financial instruments-fuel tax, EV subsidies and road tax.

Therefore, in this thesis, policy formulations take five possible forms: annual registration taxes, EV subsidies, fuel tax, EV mandate and fuel economy standards. With a diversity of instruments, we analysed the policy interactions and synergies of policies explicitly. By analysing the efficiency and effectiveness of individual policy instruments or combinations of policy instruments, this chapter aims to answer three main research questions:

1. How will policy measures at different levels impact the diffusion of various PLDV technologies and emissions from the PLDVs in each of the individual countries, including the UK, US, Japan, China and India? (Section 7.4)

2. What is the cost for each policy incentive at different levels of stringencies, and how does the efficiency for each policy instrument vary as it becomes more stringent? (Section 7.4 and Section 7.5)

3. Are there trade-off or reinforcement effects between any two policy instruments

on the diffusion of PLDVs in each of the five countries? (Section 7.5)

7.1 Definition of policy instruments

This section defines the policy instruments discussed in the chapter. Table 7.1 provides the definition for each policy, how these incentives were modelled and examples of the policy in real terms. As we have discussed in Chapter 6, these policy incentives represent some of the most commonly found existing policy instruments in the UK, the US, Japan, China and India.

Table 7.1: Definition of policy incentives

Policy incentives	Model representation	Examples of the real-world policy
Annual registration tax	Added to the annual costs summed to get the *LCOT*	UK Road tax
EV subsidies	Subtracted from the capital cost at the time of car purchases	EV rebates
Fuel tax	Added to the fuel cost	Fuel tax (e.g. petrol tax, diesel tax)
EV mandate	A certain percentage of sales (and hence fleet shares) must be EV	The Zero Emission Vehicle (ZEV) program in California
Fuel economy standards	Fuel economy of cars is improved	US CAFE standards

7.2 Modelling of policy instruments in the FTT-Transport model

In this section, we present how we model the five policy instruments identified in the FTT-Transport model. We divide the policy incentives into two major types: policies that take the form of financial incentives (applied either at the time of car purchase or throughout car ownership) and policies that do not (e.g. fuel economy regulation and EV mandate). The pecuniary incentives can be described by looking at the equation of the $LCOT$, while regulation and EV mandates are related to the fleet share values instead of $LCOT$.

7.2.1 Pecuniary incentives

Here, we reproduce the $LCOT$ (see equations 7.1 in Chapter 3) , with added policy parameters:

$$LCOT_i = \frac{\dfrac{I_i - EVS_i}{CF_i} + \sum_t \dfrac{\dfrac{RT_i(t)}{CF_i} + (F_i(t) + FT_i(t)) * (FE_i(t)) + MR_i(t)}{(1+r)^t}}{\sum_t \dfrac{1}{(1+r)^t}}, \quad (7.1)$$

where I_i, F_i, MR_i are the mean capital costs (in USD), fuel cost (in USD/litre) and maintenance cost (in USD/km), respectively. EVS_i represents EV subsidies, paid to car purchasers (and therefore, negative cost) at purchase. FT_i is the fuel tax in USD/litre. The fuel cost depends on the fuel consumption ($FE_i(t)$) and the distance travelled each year ($Dist_t$). $RT_i(t)$ is the annual registration tax, vehicle/class-specific, paid by car owners once per year. CF_i is the capacity factor, km/y.

The policy incentives fall into two types: those that are paid once (e.g. EV subsidy), and those that are paid yearly (annual registration tax, fuel tax). The difference in impact is that the yearly policies are discounted, while the one-off policies are not. It is possible to model other financial incentives (e.g. vehicle purchase tax, parking fee exemption) by adding the cost to the $LCOT$ equation for future studies.

We assume that fuel tax affects the demand for PLDV in the FTT-Transport model, as well as the $LCOT$. According to our analysis in Chapter 4, we find that a 10% increase in oil price leads to a 0.8% fall in average distance driven by PLDV per year.

7.2.2 Fuel economy regulation and EV mandates

Many policies in the real world (as we discussed in Chapter 6) do not take the form of financial incentives. This can be regulatory in nature and apply to manufacturers. In the FTT-Transport model, this is modelled by influencing the flow of value of shares, in particular, in the technology category. In the presence of a fuel economy regulation, we assume that there are no new market shares gained in the categories being phased out. In the FTT-Transport model, the flow of market shares from technology j to technology i is

$$\Delta S_{j\to i} = S_i S_j A_{ij} F_{ij} \Delta t \tag{7.2}$$

In the case when conventional petrol cars are phased out, we assume that F_{ij} is 0, so there no longer can be any gain in market share for conventional petrol cars. Instead, there can be a gain in market share for advanced petrol cars and any other technologies (such as hybrid cars or EVs). Existing conventional petrol cars live to the end of their lifetimes.

For the EV mandate, in the FTT-Transport model, it is assumed that the policies exogenously change the shares of vehicle types at a specific point in time.

We assume that market shares flow from conventional cars j to EVs i by assigning exogenous shares to $\Delta SE_{j\to i}$. For example, if we assume that $x\%$ of the new car sales have to be EVs, then

$$\Delta SE_{j\to i} = x\% * NewSales/Fleet \tag{7.3}$$

Then $\Delta SE_{j\to i}$ is added to the shares of EVs (i) and removed from shares of conventional cars (j). Essentially, in this way, we model the exogenous change in market share in terms of sales.

This approach models mandates with targets that require certain percentages of EV sales. However, this approach is not exactly the same as some of the real-world EV mandates, in which the government sets an EV production quota (e.g. China New Energy Vehicle (NEV) mandate and the California ZEV mandate programme) or assigns a NEV credit, under which each NEV is assigned a specific number of credits depending on metrics, including electric range and energy efficiency (ICCT, 2018). While companies are required to make a certain number of EVs, this does not mean that car manufacturers are able to sell all of their EV productions.

7.3 Definition of policy effectiveness and policy efficiency

7.3.1 Policy effectiveness

By definition, the effectiveness of public policies is defined as the extent to which policies are achieving the policy goal. In this context, the effectiveness of a given policy on CO_2 emissions is defined as the amount of abatement achieved by a given policy.

$$Effectiveness = \sum_i \int_{2016}^{2050} (E_{t,i} - E_{0,i})dt \tag{7.4}$$

where $E_{t,i}$ is the sum of the emissions over all technologies between the year 2016 and 2050 when policy incentives are imposed. $E_{0,i}$ is the sum of the emissions over all technologies between the year 2016 and 2050, without any policy incentives in the baseline scenario. The effectiveness index captures the possible effect of a policy incentive across technologies and the cumulative emissions reduction achieved by a particular policy incentive.

7.3.2 The cost of policies and policy efficiency

In practice, while it is important to have an effective policy that reduces emissions significantly, a policy needs to be efficient so that it is cost effective and feasible. The efficiency of a policy option is defined as the cumulative CO_2 abatement divided by the cost of the options. We consider the cost as the cost to the consumers ($ConsumerCost$) as a result of taxes, the cost to the Exchequer (i.e. EV subsidies) ($ExchequerCost$) and the cost to manufacturers ($MCost$), such as the fuel economy standards and EV mandates. We assume that the costs are positive to individual parties/groups. For example, we assume that annual registration tax is a positive cost to car owners and not a negative cost to the government. This approach captures how the costs of policies vary as a result of the different levels of policy incentives. Hence, we have:

$$TotCost = ConsumerCost + ExchequerCost + MCost$$

We assume the costs of policies are zero in the baseline scenario because we assume that there is no new policy added in the baseline scenario. In the FTT-Transport model, changes in policies are modelled with respect to the baseline scenario.

7.3.3 Policy efficiency

The efficiency of a policy incentive is equal to the change in the cumulative emissions as a result of the policy incentive ($Effectiveness$) divided by the total cost of the policy incentive ($TotCost$). Note that we have not included any discounting in the cost calculation. Hence, we have

$$Efficiency = \frac{\sum_i \int_{2016}^{2050} (E_{i,t} - E0_{i,t})dt}{TotCost}$$

The next sections discuss how the costs for each policy instrument were calculated.

7.3.4 Registration tax

We assume that the registration tax is paid by consumers annually over the lifetime of the car. The total cost of the annual registration tax to the consumers in a country each year is equal to the total fleet number multiplied by the registration tax. In this research, we assume that the rate of the registration tax is dependent on the PLDV technologies and engine sizes.

$$TotalRT = \sum_i \int_{2016}^{2050} (RT_{i,t} * S_{i,t} * Fleet_t)dt$$

where $TotalRT$ is the total annual registration tax paid by the consumers between 2016 and 2050. $RT_{i,t}$ is the annual registration tax (in USD per unit) paid by owners of technology i in year t. $S_{i,t}$ is the share for PLDV technology i in year t, and $Fleet_t$ is the total car fleet at time t.

7.3.5 Fuel tax

We assume that fuel tax is paid by the consumers based on the car's fuel consumption. Hence, the cost of the fuel tax to each consumer is calculated by multiplying the distance travelled by each consumer, the average fuel consumption factor PLDV and the levels of fuel tax in each country. The total cost of fuel tax to consumers in a country is the product of the total fleet number in a country and the cost of the fuel tax for each PLDV.

$$TotalFT = \sum_i \int_{2016}^{2050} (FT_{i,t} * FE_{i,t} * Dist_t * S_{i,t} * Fleet_t)dt \tag{7.5}$$

where $TotalFT$ is the total fuel tax paid by the consumers between 2016 and 2050. $FT_{i,t}$ is the fuel tax (in USD per litre) paid by owners of technology i in year t. FE_i is the average fuel consumption (in litre/km) for each PLDV technology.

$S_{i,t}$ is the shares for technology i in year t, $Fleet_t$ is the total car fleet in at time t and $Dist_t$ is the average distance travelled by average fleet.

7.3.6 EV subsidies

We assume that EV subsidies are paid directly by the government to the new EV purchasers. In reality, the levels of EV subsidies depend on a number of factors, including battery sizes (e.g. China) or as income credits to car buyers (e.g. US). For modelling purposes, we assumed that the levels of EV subsidies increase with prices of EVs (see assumptions in Table 7.20).

$$TotalSub = \sum_i \int_{2016}^{2050} Sub_{i,t} * EV_{i,t} dt \tag{7.6}$$

where $TotalSub$ is the total EV subsidies paid by the government between 2016 and 2050. $Sub_{i,t}$ is the subsidies (in USD per unit) paid by the government to EV car owners. $EV_{i,t}$ is the number of new EVs of size i at time t.

7.3.7 EV mandates

We assume that the costs for the EV mandates are paid by car manufacturers [1] or the consumers. We assume that the total costs of the EV mandates equal the difference in the prices of EVs and conventional cars, multiplied by the number of new EV sales as a result of the EV mandates. For example, if the EV mandate requires 10% of new car sales to be EVs in 2020, then the total cost of the EV mandate programme is the difference between the average price of EV and conventional cars multiplied by the 10% of new car sales.

$$TotalKS = \int_{2016}^{2050} (EVCost_t - AvgCost_t) * NewEV_t dt \tag{7.7}$$

$TotalKS$ is the cost of the EV mandate programme to the manufacturer or to the consumers between the years 2016 and 2050. We assume the cost is equal to the difference between the price of EV ($EVCost_t$) and the price of an average petrol car ($AvgCost_t$) multiplied by the number of new EV sales ($NewEV_t$) under the EV mandate programme.

[1] We assume that the car manufacturers may decide to subsidise EVs to sell them.

7.3.8 Fuel economy standard

While fuel economy standards have the benefit of reducing fuel consumption for consumers, fuel economy standards have imposed costs on car manufacturers and consumers. In this study, we assumed that the costs of fuel economy standards ($FEcost$) are partly absorbed by car manufacturers and the costs are 3% (Siegel, 2017) of the gross car sales with fuel savings enjoyed by the consumers. Consistent with our cost assumptions, we assume that the costs of advanced cars are, on average, 20% [1] more expensive than conventional petrol cars:

$$FEcost = MC - FuelSavings + \int_{t_i}^{2050} (NewCar_t * AvConvPr_t) * 20\% dt \quad (7.8)$$

where

$$MC = 3\% * \int_{2016}^{2050} NewCar_t * AvPrice_{i,t} dt \quad (7.9)$$

and

$$FuelSavings = \int_{2016}^{2050} (FE_{adv} - FE_{conv}) * FP_t * Dist_t dt \quad (7.10)$$

Here, MC is the cost of fuel economy standards ($FEcost$) borne by car manufacturers, which is equal to 3% of the gross sales. $NewCar_{i,t}$ is the number of new cars (advanced petrol cars/advanced diesel cars) sold in time t, $AvPrice_t$ is the average car price at time t, $AvConvPr_t$ is the average price for the conventional cars, FE_{adv} and FE_{conv} are the fuel economy (in litre/km) for the advanced petrol cars and conventional petrol cars. FP_t is the fuel price in $USD/litre$. $Dist_t$ is the average distance travelled per year by car owners. t_i is the time when fuel economy regulation is introduced.

7.4 Scenario analysis

In this section, we present the results for the scenario analysis under various policy assumptions. The scenario analysis consists of two parts. The first part analyses

[1] We find that the price difference between several powertrain specifications (including VVT, turbocharging and direct injection) within one car model ranged from 10% to 30% of the car price (from the official car manufacturer's website). We take 20% to represent the price difference between conventional cars and advanced cars.

the effectiveness of each of the policy incentives when they are imposed one at a time at four different levels. The aim of the exercise is to unveil the impact of each policy incentive on PLDV emission reductions in each country. The second part studies the interactions between policy incentives by grouping two policy incentives and examining the interactions among instruments by highlighting the trade-off effect and the reinforcement effect among the five policy instruments.

While it is important to have an effective policy that significantly reduces emissions, a policy needs to be efficient so that it is cost effective. The costs for the policy incentives to consumers and governments may be significant. The total costs, average costs per year and average efficiency for annual registration tax, EV subsidy, fuel tax, EV mandate and fuel economy regulation are shown in Tables 7.3, 7.5, 7.7, 7.9 and 7.11.

7.4.1 Registration tax (RT)

Consumers are required to pay an ownership tax annually in all five nations. To encourage the purchasing of low emissions PLDVs, there is a reduction or exemption of the annual registration tax for consumers who purchase low emissions PLDVs in many countries. In this section, we study the effect of the annual car registration tax on the future diffusion of low-emissions car technologies.

In the current registration tax (RT) scenario, we assume that the current annual registration tax is consistent with the tax levels stated in Chapter 6. Then, in the high RT scenario and the very high RT scenario, we assume that the registration tax is increased by 50% and by 100% from the current registration tax level for each country, respectively. This approach enables us to understand the effect of the three different levels of annual registration tax on the PLDV technological transition.

We also assume in the high RT scenario and the very high RT scenario that EVs are exempt from the annual registration tax. This enables us to understand the outcome of the annual registration tax in different countries when the incentives are at reasonably high levels. Tables 7.15, 7.16, 7.17, 7.18, 7.19 show the registration tax assumptions for the UK, US, Japan, China and India, respectively, taken in baseline scenario, current RT scenario, high RT scenario and very high RT scenario. We assume that the tax levels will remain the same until 2050 to capture the effect of policy stringency in different scenarios.

Figure 7.1 shows the PLDV services generated in the UK, US, Japan, China and India as a result of different levels of annual registration tax. The total costs, average costs per year and average efficiency for annual registration tax are presented in Table 7.3. Under the baseline scenario, the model projects that the share for hybrid cars will reach around 90% in Japan, while in China, the fleet market share for EVs will reach 30% by 2050. When the current annual registration tax is introduced (current RT scenario), cumulative emissions fall by 7% in the US and more than 6% in China as a result of EV diffusion. Compared with China and the US, cumulative emissions fall only by 2% in Japan as a result of continued penetrations by hybrid cars. As a result of high cost and small effectiveness of the registration tax, under the current scenario, the average costs of emission reductions from the registration tax are the highest for Japan, amounting to over 20,000 USD per tonne CO_2, and the lowest for China, amounting to 855 USD per tonne CO_2. The lack of penetration of EVs and continued penetration of hybrid cars are partly explained by the fact that hybrid cars are already gaining shares in Japan under the baseline scenario and that according to equations of the replicator dynamics, PLDV technologies with larger fleet shares are likely to diffuse faster in the market than PLDV with lower fleet shares (see Chapter 3, Section 3.3).

The current registration tax alone in India has a very small effect on the diffusion of clean energy PLDVs in India, leading to around 2% cumulative emissions reduction in India and costing Indian consumers 11 billion USD annually. There are two reasons for this. First, the shares for EVs and hybrid cars are very small in India. Based on the replicator dynamics equations in the FTT-Transport model (see Chapter 3, Section 3.3), when the shares for PLDV technologies are small, the rate of diffusion for the technology is small because many people do not have access to (or do not have a choice of) the technology, or they do not trust the technology. Second, the registration tax incentives are lower in India compared with the UK, US, Japan and China, as demonstrated in Table 7.19.

When the annual registration tax is increased by 50%, the effect of the tax increment on technological diffusion is small for all countries, as observed in Figure 7.1. Hence, we find that the 50% registration tax increment has a very small effect on the total PLDV emissions. As we observed in Column 4 of Figure 7.1, when the registration tax is twice the current level for conventional cars (and EV is exempt from the registration tax), cumulative emissions from PLDVs do not change significantly for any of the countries. Hence, emissions reductions of 6.7% cost 36 billion USD for Japan, and this is equivalent to 36,000 USD per tonne CO_2. Only by doubling the levels of the annual registration tax do we find that emissions fall significantly for the UK. This is because hybrid cars pay significantly less annual registration

Table 7.2: Cumulative emissions from PLDVs ($MtCO_2$ emissions) as a result of the registration tax (upper section) and change in cumulative emissions as a result of annual registration tax (lower section).

Country	Baseline scenario	Current RT	High RT	Very high RT
UK	1447	1428	1428	1352
US	29873	27749	27740	27441
Japan	1862	1828	1828	1828
China	16346	15290	15398	15246
India	8532	8363	8363	8363
UK		-1.34%	-1.34%	-6.58%
US		-7.14%	-7.14%	-8.14%
Japan		-1.82%	-1.82%	-1.83%
China		-6.47%	-6.73%	-6.73%
India		-1.97%	-1.97%	-1.97%

tax than petrol cars in the UK compared with the US, Japan, China and India (see Table 7.15). However, in the case of the UK, when the annual registration tax is twice the current level, the annual registration tax costs 37 billion USD per year, and this averages to around 14,000 USD per tonne CO_2 emission reductions. For all countries, the more stringent annual registration tax comes at even higher costs per tonne of emissions reduction. Hence, the efficiency of annual registration tax falls as the policy incentives become more stringent.

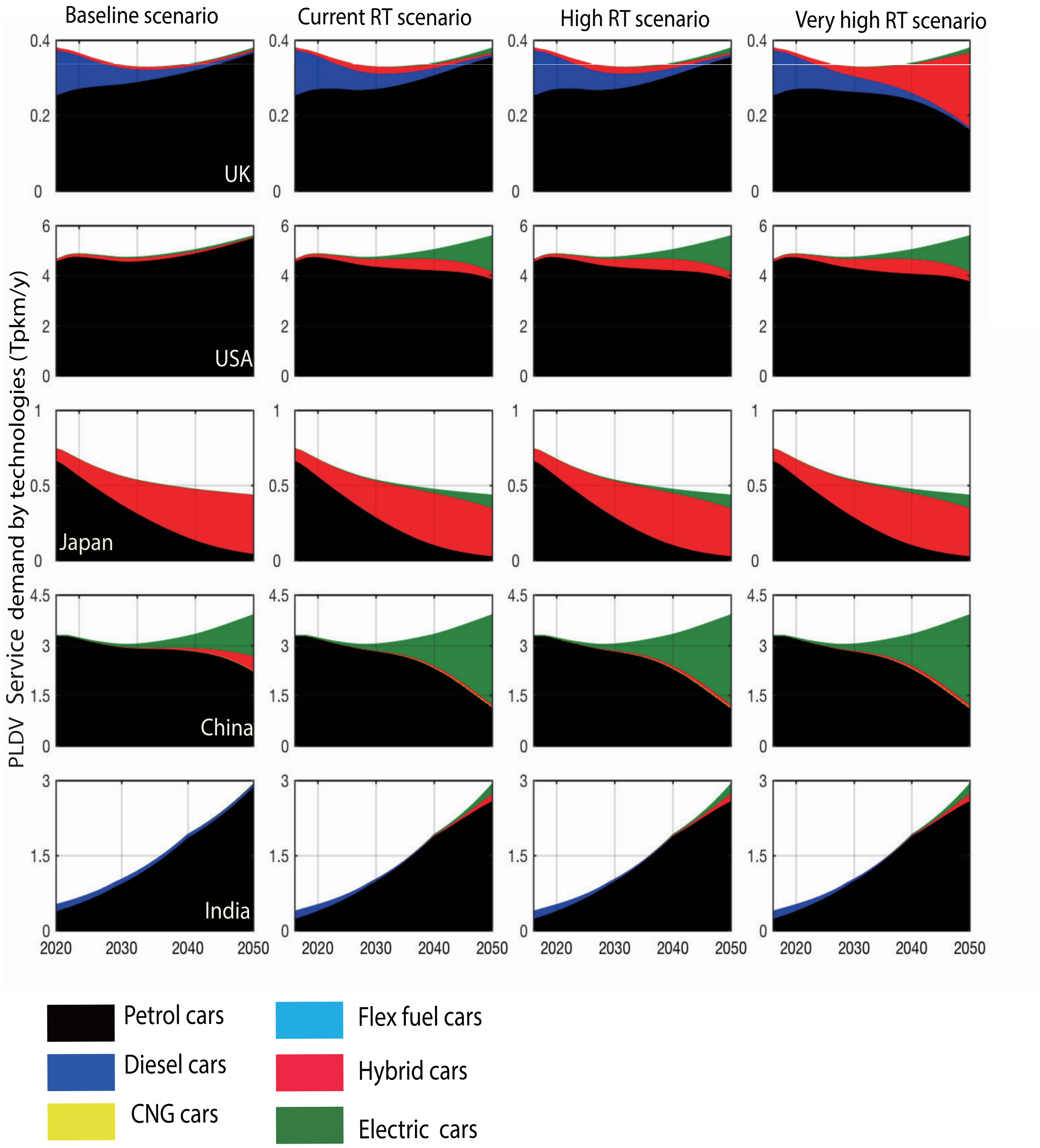

Figure 7.1: PLDV service demand by six energy technologies in Tpkm/year for the following five countries, namely, the UK, US, Japan, China and India. The first column shows the PLDV technology mix in the baseline scenario. Column 2 shows the PLDV technology mix under the current RT scenario. Column 3 shows the PLDV technology mix under the high RT scenario. Column 4 shows the PLDV technology mix under the very high RT scenario.

Table 7.3: The total cost, annual cost and efficiency of the annual registration tax

Total cost (billion USD)	Current scenario	High RT scenario	Very high RT scenario
UK	567	851	1258
US	4189	6283	8064
Japan	683	1025	1222
China	904	1293	1898
India	387	593	703
Average cost per year (USD)			
UK	17	25	37
US	123	185	237
Japan	20	30	36
China	27	38	56
India	11	17	21
Efficiency (USD/tCO_2)			
UK	9019	13470	14158
US	1917	2875	3270
Japan	20118	30155	35950
China	855	1176	1726
India	2301	3525	4175

7.4.2 EV subsidy (EV Sub)

Among the five countries, EV subsidies exist in the UK, US, China and India to encourage the diffusion of EVs. In this section, we first study the effects of current EV subsidies on the future diffusion of low-emissions car technologies. The levels of the EV subsidies for individual countries and states were discussed in Chapter 6. For the US, we have taken the EV income tax rebate in California as an example, and for China, as discussed in Chapter 6, EV subsidies are composed of the Central Government Subsidy (EVSS) and the local government subsidy. For illustration purposes, we have taken the EV subsidy in Shanghai as an example of the local government subsidy. For Japan, where the EV subsidies were absent, we assume the EV subsidies are consistent with the US in the baseline scenario for illustration purposes. Then, in the high EV subsidy and very high EV subsidy scenarios, we assume that the EV subsidies are increased by 50% and by 100% from the current EV subsidy levels.

Table 7.20 shows the EV subsidy assumptions for the UK, US, Japan, China and India, taken in this section. Under the current EV subsidy scenario, we assume that the EV subsidy is introduced for 10 years (between 2020 and 2030), and then the EV subsidy is removed. Under the high EV subsidy and the very high EV subsidy scenarios, we assumed that the subsidy levels will remain the same until the fleet shares for EVs are above 50% to facilitate the diffusion of EVs. Table 7.5 shows the total costs, average costs per year and average efficiency for EV subsidy.

Figure 7.2 and Table 7.4 show the fleet shares for EVs and the total emissions from PLDVs as a result of the EV subsidy. In the baseline scenario, among the five countries, only China has a significant number of EVs projected in 2050, reaching more than 10% of fleet market shares. Furthermore, a very small number of EVs is projected in India in 2050.

Under the current EV subsidy levels, the shares for EVs increase in all five countries, as shown in Figure 7.2. The numbers of EVs increase further when the EV subsidy is increased by 50% and 100%. Under the current EV subsidy scenario, the EV subsidy costs China 3 billion USD per year and the US 630 million USD per year. However, because the fleet shares for EVs in the baseline scenario are very small in all countries except China, the rate of diffusion for EVs remains small, and the shares for EVs remain small (under 15%), as a result of the replicator dynamics equation. If the shares for the EVs are small, the rate of technological diffusion is small because consumers are less exposed to EVs and there are fewer EV models available (see Chapter 3, Section 3.3). Hence, the efficiency for EV subsidy alone remains low, making the average cost of reduction for EVs around 145 USD per tonne CO_2 for China and 217 USD per tonne CO_2 for the US.

The diffusion of EVs as a result of EV subsidies has a small effect on the total emissions in the PLDV sector (Table 7.4). In particular, in Japan and India, we see a negligible effect of the EV subsidies on the total emissions from passenger cars. For India, this is because the shares for EVs are still very small (less than 1.5%) despite the presence of the EV subsidies, which is the lowest among all countries. Hence, the efficiency for EV subsidy is very low in India, costing 145 USD per tonne CO_2 emissions reductions.

For Japan, we find that although the shares for EVs reach 9% when the levels of EV subsidies double, emissions are reduced by less than 0.3%, EVs replace hybrid cars in Japan, and under our assumptions, there is only a 10% difference between EV (indirect) emissions and hybrid car emissions in Japan (see Chapter 4 for fuel economy assumptions). Although EV subsidies alone are insufficient to meet climate

Table 7.4: Cumulative emissions ($MtCO_2$ emissions) from PLDVs as a result of the EV subsidies (upper section) and change in cumulative emissions as a result of the EV subsidies (lower section).

Country	Baseline scenario	Current EV sub	High EV sub	Very high EV sub
UK	1447	1437	1425	1420
US	29873	29721	29657	29550
Japan	1862	1860	1859	1858
China	16346	15605	15432	15382
India	8532	8526	8522	8521
Country				
UK		-0.7%	-1.53%	-1.42%
US		-0.51%	-0.72%	-1.08%
Japan		-0.10%	-0.17%	-0.24%
China		-4.54%	-5.59%	-5.90%
India		-0.07%	-0.11%	-0.12%

targets, this does not mean that an EV subsidy as a policy has no effect. EV subsidies can play an important role in combinations with other policies.

For all countries, if an EV subsidy is introduced alone, as the EV subsidy becomes more stringent, the cost of reduction per tonne CO_2 increases. For example, in the case of China, due to the large amount of EV diffusion, the EV subsidy costs 146 USD per tonne CO_2 reductions and increases up to 1005 USD per tonne CO_2 reductions when the level of EV subsidy doubles. Similarly, for India, the cost of reductions from EV subsidy increases from 174 USD per tonne CO_2 to 546 USD per tone CO_2 reductions when EV subsidy is twice the current level.

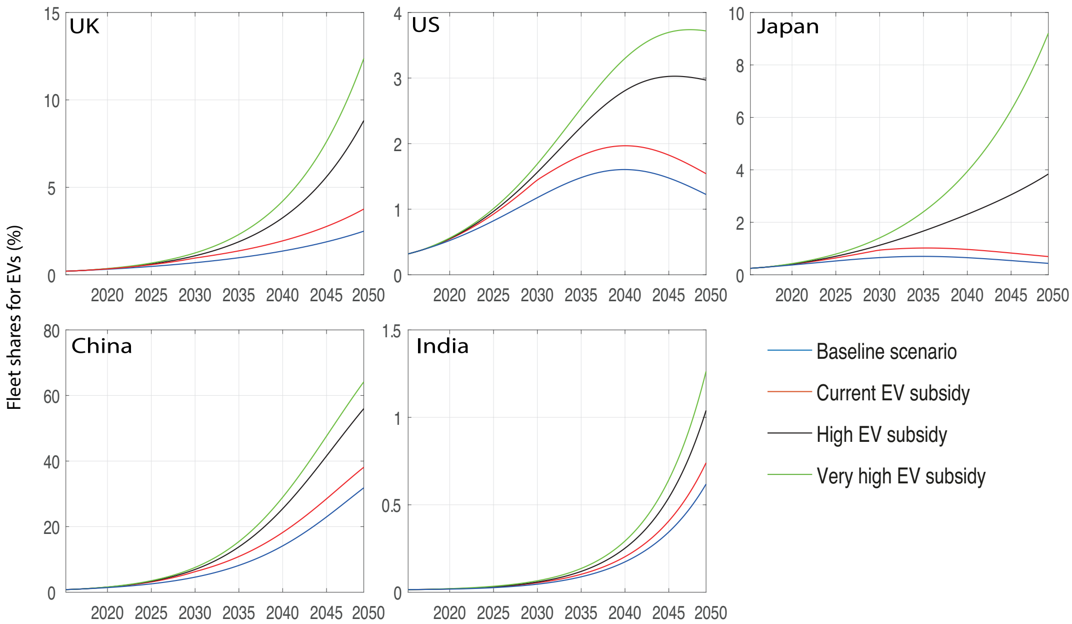

Figure 7.2: The fleet shares for EVs as a result of EV subsidies in the UK, US, Japan, China and India. The blue lines show the fleet shares for EVs in the baseline scenario. The red lines show the fleet shares for EVs under the current subsidy level. The black lines show the fleet shares for EVs when the EV subsidies are increased by 50%. The green lines show fleet shares for EVs when the subsidies level is increased by 100%.

Table 7.5: The total cost, annual cost and efficiency of EV subsidies.

Total cost	Current scenario	High EV Sub scenario	Very high EV Sub scenario
UK	2.21	5.22	6.74
US	21.54	55.44	117.26
Japan	1.97	4.50	9.25
China	108.00	579.37	969.17
India	1.04	3.52	5.60
Average cost per year (billion USD)			
UK	0.07	0.15	0.20
US	0.63	1.63	3.45
Japan	0.06	0.13	0.27
China	3.18	17.04	28.50
India	0.00	0.10	0.16
Efficiency (USD/tCO_2)			
UK	217.12	235.09	247.94
US	136.81	250.01	355.25
Japan	1030.66	1415.79	2072.34
China	145.69	633.82	1005.10
India	173.70	387.19	545.71

7.4.3 Fuel tax (FT)

Table 7.21 shows the fuel tax assumptions for the UK, US, Japan, China and India, respectively. Since petrol cars are the dominant technology, we study the effect of current petrol tax levels on the diffusion of low emissions car technologies. Under the current FT scenario, we assume the current petrol tax level in individual countries. The current fuel levels are obtained from different sources, including government websites and various sources. Then, in 'High FT scenario' and in 'Very High FT scenario', we assume that the fuel tax levels are increased by 50% and by 100% from the current fuel tax levels, respectively. We assume that fuel tax will remain at the same level from 2016 to 2050.

Figure 7.3 and Table 7.21 show the PLDV services generated by PLDVs and the total emissions from PLDVs as a result of the fuel tax assumed in Table 7.21. The total costs, average costs per year and the average efficiency for annual registration tax are presented in Table 7.9.

Our scenario analysis shows that the current fuel tax does not have any significant effect on the technological mix because we find only a small difference in the technology mix by changing the fuel tax levels (Figure 7.3). In fact, as observed in Figure 7.3, we do not see a significant change in the technological mix even when the fuel tax is doubled, largely because the cost of the fuel tax is too small to cause a significant change in technological shares over the long term. To illustrate, typically, a petrol car consumes 5 litres of petroleum per 100 km, assuming that cars are driven an average 10000 km per year. This amounts to 500 litres of petroleum per year and will cost consumers an additional 150 USD per year, assuming that the fuel tax is increased by 0.3 USD/litre. This cost is smaller compared with the levels of annual registration tax for a typical mid-size car. However, because fuel tax is charged on the distance travelled by households, fuel tax costs nearly 4 billion USD per year in Japan and nearly 12 billion USD in China under the baseline scenario. This is equivalent to 885 USD per tonne CO_2 reductions for Japan and 585 USD per tonne CO_2 reductions in China. The efficiency of fuel tax in reducing CO_2 emissions does not necessarily increase or decrease with its stringency, as Table 7.7 shows. The reason is that the costs of policies do not always increase linearly with the effectiveness of policies. For China, the cost per tonne CO_2 emissions reductions falls as fuel tax increases, while for the US, the cost per tonne CO_2 emissions reductions decreases when fuel tax is 50% higher than the baseline scenario and increases when the fuel tax is 100% higher than the baseline scenario.

Table 7.6: Cumulative emissions from PLDVs (MtCO_2 emissions) as a result of fuel tax (upper section) and change in cumulative emissions as a result of fuel tax (lower section).

Country	Baseline scenario	Current FT	High FT	Very high FT
UK	1447	1416	1406	1394
US	29873	29748	29669	29589
Japan	1862	1810	1792	1772
China	16346	16106	15953	15807
India	8532	8336	8271	8232
UK		-2.13%	-2.86%	-3.69%
US		-0.42%	-0.68%	-0.95%
Japan		-2.81%	-3.76%	-4.82%
China		-1.47%	-2.40%	-3.40%
India		-2.29%	-3.06%	-3.51%

Although an increase in fuel tax is not sufficient to change the vehicle′s technological mix over the long term, an increase in fuel cost reduces the PLDV service demand, as we have discussed in Chapter 5. We find that a 10% increase in oil price will lead to 0.8% decrease in driving distance per year in Chapter 5. Depending on the particular countries, under the very high FT scenario, we find that the effectiveness of fuel tax in reducing CO_2 emissions from PLDV is the highest in Japan (4.82%) and the lowest in the US (0.95%) due to low fuel tax in the US and high fuel tax in Japan (see Table 7.21). Typically, the effectiveness of fuel tax in reducing CO_2 emissions depends on consumer discount rates. Fuel tax is less effective at higher discount rates than lower discount rates because agents pay less attention to future costs (such as fuel cost) and more attention to present costs (such as car price).

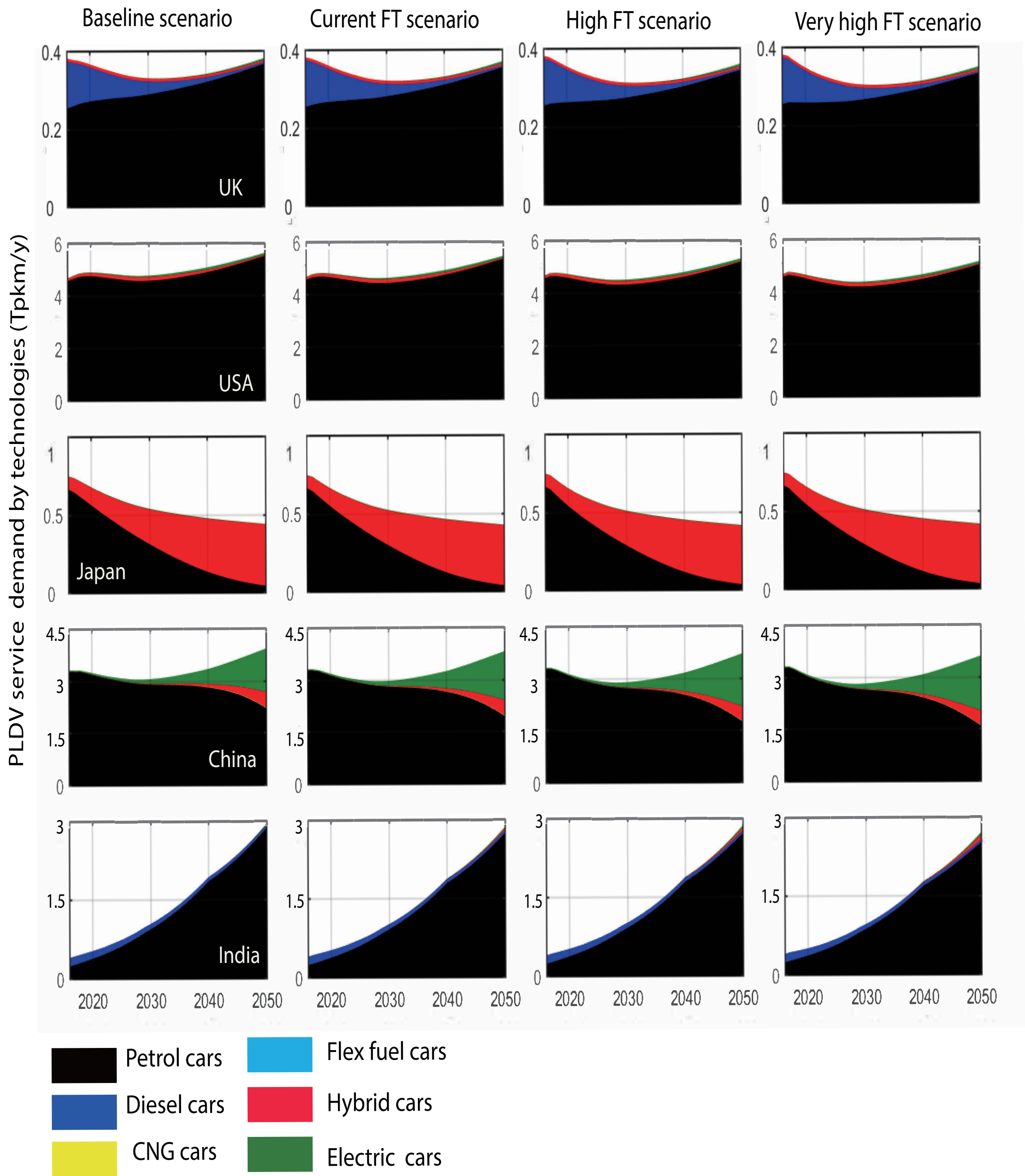

Figure 7.3: PLDV service demand by five energy technologies in Mpkm/year for the five nations, namely, the UK, US, Japan, China and India. The first column shows the transport technology mix in the baseline scenario. Column 2 shows the transport technology mix under the current FT scenario. Column 3 shows the transport technology mix under a high FT scenario. Column 4 shows the transport technology mix under a very high FT scenario.

Table 7.7: The total cost, annual cost and efficiency of fuel tax.

Total cost (billion USD)	Current scenario	High FT scenario	Very high FT scenario
UK	28.60	38.30	51.31
US	33.07.62	45.12	65.07
Japan	46.27	61.98	83.02
China	140.52	188.23	252.13
India	22.73	30.45	40.79
Average cost per year (billion USD)			
UK	2.38	3.19	4.28
US	2.76	3.76	5.42
Japan	3.86	5.17	6.92
China	11.71	15.69	21.01
India	1.89	2.54	3.40
Efficiency (USD/tCO_2)			
UK	928.51	924.06	960.24
US	264.56	221.18	218.56
Japan	884.61	887.12	925.95
China	584.66	479.12	467.75
India	116.14	116.67	144.99

7.4.4 EV mandate programme (EVM)

As we have discussed in the previous sections, countries with low EV shares tend to have a lower EV diffusion rate due to technological path dependency in the replicator dynamics equation (Chapter 3 Section 3.3). In a consumer world, technology diffusion occurs as a result of consumer and social influence (Wood and Hayes, 2012). Because EVs are still relatively new and unfamiliar to most people, consumers' preferences are expected to evolve along with technological progress, familiarity with EVs, market penetration and social influence. The higher the shares, the more dealers sell this type of car, and the more people see them on the streets (assume that dealers do not stock PLDVs that do not sell at all). The more dealers stock these types of cars, the more models are available in the market and the more likely people will buy them. Hence, the adoption rate for a preferred vehicle is proportional to its market share (please see details in Chapter 3 Section 3.1).

The EV mandate programme requires a particular percentage of new sales of PLDVs to be zero-emission PLDVs. An example of this is the Zero Emission Vehicle Mandate (ZEV), which requires 5 million electric cars on California's roads by 2030. China's New Vehicle Energy Mandate (NEV) is a modified version of the ZEV, which establishes that NEV′s credit targets 10% of the conventional passenger vehicle market in 2019 and 12% in 2020. As we have discussed in section 7.2.2, it is not possible for the FTT-Transport model to capture the more complicated mechanisms of the NEV credits, under which range and car efficiency both contribute to NEV credit targets. In the FTT-Transport model, we capture the effect of an EV mandate by assigning exogenous shares (calculated based on sales targets) to a given year (see details in Section 7.2.2) [1].

In the baseline scenario, we assume that no incentives are in place. Under a low EV mandate scenario, we assume that 5% of new car sales are EVs in the year 2025, which are half of the levels that China proposed. Under an EV mandate mid-scenario, we assume that 10% of new car sales are EV, consistent with the level China proposed starting from the year 2019, and this costs China 24 billion USD. Under an EV mandate high scenario, we assume that 15% of new car sales are EV, higher than the level China proposed, and this costs 48 billion USD for China. However, in term of efficiency, we find that the EV mandate is the most efficient.

Since the EV mandate is absent in the UK, India and Japan, we assume that the levels of the EV mandates are the same for other countries as in China, for scenario analysis purposes.

Figure 7.4 and Table 7.8 show the PLDV services generated by EVs and the total emissions from PLDVs as a result of the current 5% kick-start, 10% EV mandate and 15% EV mandate. The EV mandate increases the numbers of EVs in all countries. The total costs, average costs per year and average efficiency for EV mandate at different stringencies are presented in Table 7.7.

As a result of the EV mandate, we find that emissions fall in all countries, with the effect being more significant in India and China than in the UK, US and Japan. For example, we find that the 15% EV mandate programme leads to 4% emissions

[1] According to the equation of replicator dynamics, if a PLDV technology has a share of zero, in the model, it remains zero by definition. Hence, for countries in which we record a very small number of EVs, not using an EV mandate would mean that there would hardly be any EVs. The mandate implies someone somewhere kick-starting the market by buying the first few, with other people following suit afterwards. It also implies that someone is investing in the infrastructure, because otherwise, no one would buy EVs without infrastructure.

Table 7.8: Cumulative emissions ($MtCO_2$ emissions) from PLDVs as a result of EV mandate (upper section) and change in cumulative emissions as a result of EV mandate.

Country	Baseline scenario	EV mandate low	EV mandate mid	EV mandate high
UK	1447	1435	1423	1413
US	29873	29774	29714	29338
Japan	1862	1853	1850	1841
China	16346	16045	15890	15681
India	8532	8408	8415	8215
UK		-0.86%	-1.70%	-2.35%
US		-0.33%	-0.53%	-1.70%
Japan		-0.47%	-0.66%	-1.12%
China		-1.84%	-2.79%	-4.07%
India		-1.45%	-2.54%	-3.71%

reduction in China and 3.7% emissions reduction in India, compared with 2.35% and 1.7% emissions reduction in the UK and the US, respectively. Compared with other policy incentives, we find that the EV mandates are the most effective policy incentives in reducing emissions and encouraging the diffusion of EVs in India. Because there are more first-time car buyers in India, we assume that there are more new cars in India, and the average lifetime (or what we call the turnover rate) in India is, therefore, shorter than in the developed countries (see the turnover rate assumptions in Chapter 5). We expect the process of technological diffusion to happen faster with a lower turnover rate. As a result, the cost of EV mandate is generally lower annual registration tax and EV subsidy for most countries. For example, under the baseline scenario, the average cost of reductions is equivalent to around 138 USD/tonne CO_2 reductions and only 80 USD per tonne CO_2 reductions for China. As an EV mandate becomes more stringent, the efficiency of an EV mandate can either increase or decrease, depending on specific countries/policy levels. For instance, in the case of China and Japan, efficiency falls as the EV mandate becomes more stringent, while in the case of US, the cost per tonne of CO_2 reductions is lower (139 USD/tCO_2 reductions) under the high EV mandate scenario, compared with the current scenario (82 USD/tCO_2 reductions).

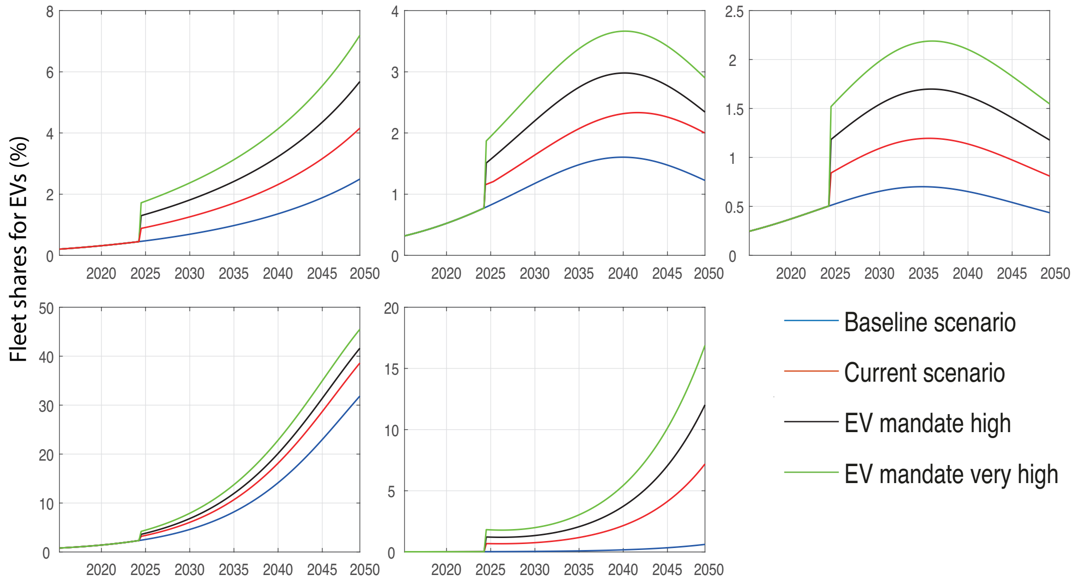

Figure 7.4: Transport demand by six energy technologies in Mpkm/year for five countries, namely, the UK, US, Japan, China and India. The first column shows the transport technology mix in the baseline scenario. Column 2 shows the transport technology mix under the current FT scenario. Column 3 shows the transport technology mix under a high FT scenario. Column 4 shows the transport technology mix under a very high FT scenario.

Table 7.9: The total cost, annual cost and efficiency of EV mandate.

Total cost (billion USD)	Current scenario	EV mandate high	EV mandate very high
UK	1.72	3.58	5.16
US	14.25	25.91	42.75
Japan	3.88	7.77	11.65
China	24.09	48.19	72.28
India	10.50	21.00	31.50
Efficiency (USD/tCO_2)			
UK	138.32	145.36	151.82
US	139.09	158.33	82.39
Japan	447.39	634.85	561.02
China	80.10	105.57	108.70
India	84.96	215.18	99.50

7.4.5 Fuel economy regulations (Reg)

As we discussed in Chapter 4, several countries and regions, such as the EU, US, Japan and China, have introduced mechanisms that phase out less efficient car models. Following COP24 in Poland, which reiterated the urgent progress needed to cut emissions from the transport sector, the European Parliament proposed setting a fuel economy target for reducing EU fleet-wide emissions for new cars by 2030 of 40% (year of reference 2021) (Mihov, 2018). On the other hand, for the US, while the Obama Administration and Environmental Protection Agency (EPA) set out to raise the average fleet's fuel economy to 54.5 mpg in 2025 (from 35.5 mpg in 2016), the Trump Administration proposed to freeze the mpg standards for cars and light trucks after the 2020 model year. Following the proposals by the EU and US, in the 'current phase-out scenario', we assume that the current petrol cars and diesel cars are phased out in 2030, replaced by advanced petrol cars and advanced diesel cars. We assume that the fuel economy for the advanced petrol and diesel cars is 40% higher than the current petrol cars in the UK and 20% higher in the US.

Because the long-term fuel economy standards (up to 2030) for Japan, China and India have not been published, we take the historical fuel economy assumptions in our analysis. The adopted fuel economy standards (2010-2020) are presented in Table 4.2 in Chapter 4. Following the adopted fuel economy standards, in the 'current phase-out scenario', we assume that the current petrol cars and diesel cars for China, India and Japan are phased out in 2030, replaced by advanced petrol and diesel cars that are 35% more efficient than the current petrol cars in China, and 20% more efficient in Japan and India. We assume that the penetration of advanced petrol and diesel cars starts (from the beginning of the simulation) before the implementation of the phase-out regulations because manufacturers respond to fuel economy regulations by introducing more efficient cars gradually.

In the 'stringent phase-out scenario', we assume that current petrol cars and diesel cars are phased out in 2025, and the fuel economy standards are consistent with the the 'current phase-out scenario', for comparison purposes. Table 7.24 shows the assumptions for fuel economy standards under the 'baseline phase-out scenario', 'current phase-out scenario' and 'stringent phase-out scenario'.

Figure 7.5 and Table 7.10 show the mixes of car technologies and the total emissions from PLDVs under the baseline scenario, the 'current phase-out scenario' and the 'stringent phase-out scenario'. The total costs, average costs per year and the average efficiency for 'current phase-out scenario' and the 'stringent phase-out scenario' are presented in Table 7.11.

We observe that the advanced petrol cars and the advanced diesel cars penetrate into the market as we expected, replacing the conventional petrol cars and diesel cars. In the 'current phase-out scenario', emissions fall by 13% in China and 9% in the UK. As a result of the 'stringent phase-out scenario', we find that emissions fall by more than 17% in China and around 11% for the UK. This costs China 1.2 billion per year and the UK 50 millions USD per year.

For China and the US, fuel economy regulations lead to increases in the shares for advanced petrol cars and higher EV shares. For the UK, Japan and India, fuel economy regulations lead to increases in the shares for advanced petrol cars. By phasing out the conventional petrol cars, it becomes more expensive to purchase petrol cars (prices for advanced petrol cars are 20% higher), so the price differences between advanced petrol cars and electric cars/hybrid cars are lower after the introduction of fuel economy regulations. This leads to higher EV fleet shares or hybrid car fleet shares in the US, China, UK and Japan.

The effectiveness of fuel economy regulations in China and the UK is stronger than the US, Japan and India because the current fuel economy regulations are assumed to be more stringent in China and the UK (see Table 7.24). Among the US, Japan and India, we find that the fuel economy regulation is more effective in the US. This is because there are a large number of Lux petrol cars (i.e. engine size

$\geq$ 2000cc) in the baseline scenario in the US. However, the fuel economy regulation costs the US 1.36 billion USD per year under the 'current phase-out scenario' and 1.92 billion USD under the 'stringent phase-out scenario'.

On the other hand, the effectiveness of fuel economy regulation is the lowest in Japan (emissions are reduced by less than 3% as a result of fuel economy regulation). This is because Japan has the lowest petrol car fleet shares projected in the baseline scenario, with less than 10% petrol fleet shares projected in 2050 in the baseline scenario. Hence, fuel economy standard is least efficient in Japan, costing 27 USD per tonne CO_2 reductions under the 'baseline phase-out scenario' and increasing to 29 USD per tonne CO_2 reductions under 'stringent phase-out scenario'. The efficiency of fuel economy standard is the highest in the UK, equivalent to around 9 USD per tonne CO_2 reductions under the 'current regulation scenario'. However, as the policy becomes more stringent, the tighter EV mandate comes at ever-higher costs per tonne of emissions reductions, although the effect of the more stringent fuel economy regulations on the efficiency of the fuel economy regulation is not significant. Compared with other policy incentives such as the annual registration tax, EV subsidy, fuel tax and EV mandate, we find that the efficiency of the fuel economy standard is among the highest.

Table 7.10: Cumulative emissions from PLDVs ($MtCO_2$) as a result of fuel economy regulation (upper section) and change in cumulative emissions as a result of fuel economy regulation (lower section).

Country	Baseline scenario	Current phase-out scenario	Stringent phase-out scenario
UK	1447	1316	1287
US	29873	28090	27379
Japan	1832	1761	1747
China	16346	14158	13553
India	8532	8169	7882
Country			
UK		-9.05%	-11.06%
US		-5.97%	-8.35%
Japan		-3.88%	-4.64%
China		-13.39%	-17.09%
India		-4.25%	-7.62%

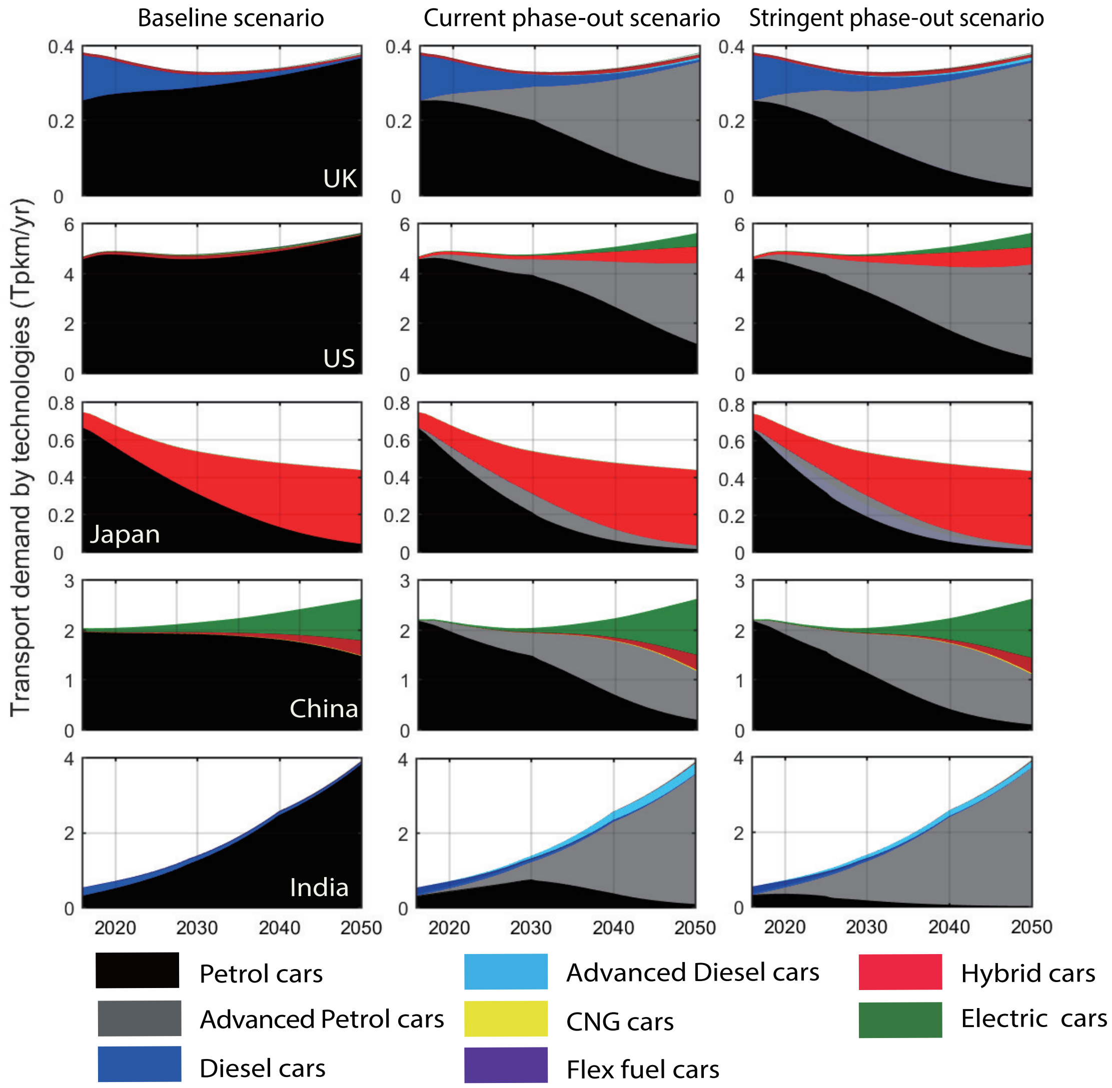

Figure 7.5: PLDV service demand by eight energy technologies in Tpkm/year for five countries, namely, the UK, US, Japan, China and India with fuel economy regulation. The first column shows the PLDV technology mix in the baseline scenario, with fuel economy regulation. Column 2 shows the transport technology mix in the 'current phase-out scenario' and the third column shows the PLDV technology mix in the 'stringent phase-out scenario'.

Table 7.11: The total cost, annual cost and efficiency of fuel economy regulation.

Total cost (billion USD)	Current regulation scenario	Stringent regulation scenario
UK	1.14	1.86
US	46.10	65.33
Japan	1.94	2.50
China	31.50	40.39
India	17.86	23.77
Average cost per year (billion USD)		
UK	0.03	0.05
US	1.36	1.92
Japan	0.06	0.07
China	0.93	1.19
India	0.53	0.70
Efficiency (USD/tCO_2)		
UK	8.70	11.61
US	25.27	25.57
Japan	27.23	29.38
China	14.40	14.46
India	16.80	17.61

7.4.6 Summary and discussions

This section discusses the policy implications derived from our simulation results in the previous sections. For the UK, we find that the annual registration tax is comparatively more effective than the other financial incentives, while the EV subsidy is less effective than other financial incentives and policy incentives in reducing CO_2 emissions. This is due to the structure of the annual registration tax in the UK, where annual registration tax is much lower for hybrid cars than for conventional cars (hybrid cars pay around 50% of the annual registration tax in the UK). However, the cost of annual registration tax is very high in the UK. Under the 'very high RT scenario', the annual registration tax costs around 240 billion USD per year, and this is equivalent to 3270 USD per tonne CO_2 emissions reductions in the baseline scenario.

On the other hand, the EV subsidy alone is not sufficient to cut emissions significantly. This is because the fleet shares for EVs are still very low (less than 0.5% in 2016) for the UK and the rate of technological diffusion is slow when the fleet shares are low as a result of the replicator dynamics equation. Hence, the efficiency of the EV subsidy is around 217 USD per tonne CO_2 emissions reductions in the current scenario, and this increases to around 250 USD per tonne CO_2.

For the US, fuel economy regulation is comparatively more effective than other policy incentives, and fuel tax is less effective than other policy incentives in reducing CO_2 emissions. This is because there is a large number of luxury and high emissions PLDVs in the US. By introducing fuel economy standards, consumers shift from conventional luxury PLDVs to more fuel efficient luxury PLDVs. Compared with other policy incentives, fuel economy standard is also the most efficient policy incentives in the US. Under the 'stringent regulation scenario', the marginal cost of emissions reduction is 26 USD per tonne CO_2 emissions reductions. Although fuel tax can potentially reduce service demand by households, the current fuel tax levels in the US are very low (at 0.05 USD in 2016), and hence, are comparatively less effective policy incentives in reducing CO_2 emissions under the'very high EV sub scenario'.

Similarly, for China, fuel economy regulation is a more effective policy incentive in reducing CO_2 emissions compared with the other incentives, while fuel tax is relatively weak in reducing CO_2 emissions. Under the FTT-Transport model, fuel economy regulation in China encourages consumers to either choose more expensive and more fuel-efficient advanced petrol/diesel cars or EVs and reduce CO_2 emissions subsequently, at a cost of 14 USD per tonne CO_2 under the current regulation scenario. Similarly to the US, fuel tax in China is comparatively low (at 0.06 USD in 2016), and hence, fuel tax is less effective in reducing emissions than other policy incentives. For 540 megatons of cumulative CO_2 emissions reductions, the marginal cost of emissions reduction is 468 USD per tonne CO_2 emissions reductions in China.

Unlike China and the US, compared with other policy incentives, we find that fuel tax is a more effective policy incentive in Japan. This is because, consistent with the current fuel tax levels, the current fuel tax in Japan is around 10 times higher than the levels in the US and China (at 0.5 USD at 2016). However, the efficiency for fuel tax in Japan remains low. For 5% of emissions reductions in Japan (equivalent to 90 Mega tonne of cumulative CO_2 emissions reductions), marginal cost of emissions reduction is 926 USD per tonne CO_2 emissions reductions. On the other hand, like the UK, an EV subsidy is a relatively lesser policy incentive in reducing CO_2 emissions in Japan. This is because the fleet shares in Japan are relatively low (at 0.3% in 2016), while the fleet shares for hybrid cars are much larger (at 11% in 2016). As a result of the replicator dynamics equation in the FTT-Transport model, consumers are more willing to adopt hybrid cars than EVs when the fleet shares for EVs are still much lower. This implies that the efficiency for EV subsidy is low in the Japan, costing more than 2000 USD per tonne CO_2 emissions reductions as a result of EV subsidy alone, under the 'very high EV Sub scenario'.

Unlike other countries, an EV mandate is more effective in reducing CO_2 emissions than other policy incentives in India. This is because the rate of technological diffusion increases as the fleet shares for the technology increase, based on replicator dynamics equation in the FTT-Transport model. Thus, it takes longer for the new energy technologies to diffuse when fleet shares are low. Using the EV mandate, our calculation suggests that to reduce emissions from PLDVs by about 317 Mt cumulative emissions would cost around 100 USD per tonne CO_2 emissions. We find that EV subsidy is less effective than other policy incentives in India when it is introduced alone. This is because the fleet shares in India are very low (less than 0.03% in 2016). In addition, the current levels of EV subsidy are among the lowest in the five countries. Without enough financial incentives and availability of car models and infrastructures for EV, we find that even when the EV subsidy is twice the current level, the fleet shares for EVs remain very low in India. Hence, we find that the efficiency of CO_2 emissions from PLDVs as a result of EV subsidy falls as policy incentives become more stringent. To reduce emissions from PLDVs by 6 Mt, the marginal cost of emissions reduction is around 174 USD per tonne CO_2 emissions reductions in India. To reduce CO_2 emissions further by 11 Mt CO_2 emissions, the marginal cost of emissions reduction is around 546 USD per tonne CO_2 emissions reductions in India.

To summarise, the effectiveness of policy incentives varies between countries, depending on the levels of the incentives, structure of the incentives, and the current market shares for certain PLDV technologies (e.g. the shares for hybrid cars or EVs). Financial incentives are more effective in countries where the levels of incentives are high and the shares for niche technologies (e.g. EVs or hybrid cars) are also relatively high. Fuel economy regulation is more effective in countries where on average, engine sizes for conventional cars are large. When the shares for niche technologies are low, based on the theory of technological diffusion and the replicator dynamics equation in the FTT-Transport model, the rates of diffusion for niche technologies will remain low unless some parties (e.g. government or consumers) kick-start the market by buying certain numbers of EVs and thus, EV mandates will be effective in the countries where shares for EVs are very low. Hence, the efficiency for the EV mandate is higher than the financial incentives in the countries where the shares for EVs are low, such as in India.

Overall, in terms of cost, we find that for some policies such as the annual registration tax and EV subsidy, the costs of emissions reduction increase further when policies become stricter (i.e. cost per tonne CO2 reductions increases as the tax levels increase), consistent with existing findings (Rivers et al., 2018; McCollum et al., 2018). The efficiency of the annual registration tax and EV subsidy varies between countries, depending on the rate and effectiveness of the policy incentive. Our research also reflects that the cost of CO_2 emissions reductions can be extremely high (equivalent to 10,000 USD per tonne CO_2 emissions reductions) if the policy incentive is not effective in cutting emissions. Although carbon tax in the transport sector has not been introduced in many countries, existing policy incentives such as EV subsidy, fuel tax and annual registration tax all play a role in reducing CO_2 emissions from the transport sector. However, if not sufficiently effective, these policy incentives could result in a very high cost per tonne CO_2 emission reductions. Among the policy incentives, if introduced individually, fuel economy regulation is among the most efficient policy incentives in all countries, costing only around 26 USD per tonne CO_2 emissions reductions for the US. However, the efficiency of fuel economy falls as the regulation becomes stringent. For other policies, such as fuel tax and EV mandates, we find that as policies become more stringent, the efficiencies of policies could either increase or decrease, depending on the individual countries/policy levels. This is because the costs of policies do not always increase linearly with the effectiveness of policies.

7.5 Policy interaction analysis

The previous sections examine the effectiveness of each of the policy incentives of different stringencies while encouraging the diffusion of low emissions PLDVs. However, in reality, there are several policies in force at the same time. Because the FTT-Transport model is a non-linear diffusion model, we found that strong policy interactions arise in the model (i.e. each policy influences the effectiveness of the others) (Mercure et al., 2018). For example, as we have illustrated, the effectiveness of EV subsidies is different between countries, not only as a result of the levels of the subsidies but also due to the current market shares for EVs (see discussion in section 7.4.6).

In this section, we study the effectiveness and the efficiency of all possible combinations of the five policy incentives. However, it is not necessary to study the policies of all stringencies stated above and each of their interactions and synergies. We picked the most stringent scenario for each policy incentive as an example (e.g. we analyse the interactions between 'a very high RT scenario' and 'a very high FT scenario'). Table 7.12 provides the definitions and assumptions for the 10 scenarios.

Table 7.12: Definitions of the scenarios and the assumptions taken in the scenarios.

Scenario		Assumptions
1	Registration tax (RT), Fuel tax (FT)	Very high RT, Very High FT
2	Fuel tax (FT), EV subsidy (EV sub)	Very high EV sub, Very high FT
3	Regulation (Reg), Registration tax (RT)	Very high RT, With regulation
4	Fuel tax (FT), Regulation (Reg)	Very high FT, With regulation
5	EV subsidy (EV sub), Regulation (Reg)	With regulation, With regulation scenario
6	Registration tax (RT), EV mandate (EVM)	Very high RT, EV mandate high
7	Fuel tax (FT), EV mandate (EVM)	Very High FT, EV mandate high
8	EV subsidy (EV sub), EV mandate (EVM)	Very high EV sub, EV mandate high
9	Regulation (Reg), EV mandate (EVM)	With regulation, EV mandate high
10	EV subsidy (EV sub), Registration tax (RT)	Very high RT, Very high EV sub

7.5.1 Two policy interaction

In this section, we study how the effectiveness of policy incentives changes when two policy incentives are combined. Here, we define the interactions between policies in terms of the total effectiveness (of the two policies) minus the effectiveness of individual policies:

$$Int(x1, x2) = Eff(x1, x2) - Eff(x1) - Eff(x2) \tag{7.11}$$

where $Int(x1, x2)$ is the interaction between two policy incentives, $Eff(x1, x2)$ is the total effectiveness of two policy incentives, $Eff(x1)$ and $Eff(x2)$ are the effectiveness of policy incentives $x1$ and $x2$ that are introduced independently. Because the policy incentives interact non-linearly in the FTT-Transport model, there could be interactions between policy incentives (i.e. $Int(x1, x2)$ does not necessarily equal zero). $Int(x1, x2)$ is positive if there is a reinforcement effect between two policy incentives, and $Int(x1, x2)$ is negative if there is a trade-off effect between two policy incentives. If policies do not interact, $int(x1, x2)$=0 and $Eff(x1, x2)$=$Eff(x1)$+$Eff(x2)$. Figure 7.6 shows the effectiveness of each of the policy incentives and the interactions between pairs of policy incentives. The red areas and green areas in Figure 7.6 are the differences between the total effectiveness and the effectiveness of individual policies (i.e. the interactions between two policies). The red areas indicate that there are reinforcement effects between two policy incentives, and the green areas indicate that there are trade-off effects between two policy incentives. Table 7.14 shows the total cost of policies and their efficiencies when two policies are combined.

Overall, we find that the sum of the effectiveness of two policies can be either smaller (trade-off effect) or larger (reinforcement effect) than two policies implemented on their own, depending on the structure and levels of policy incentives. Thus, we conclude three main observations from the scenario analysis. First, there is a trade-off effect between the financial incentives under this analysis (as shown in the green bars of Figure 7.6), while the degree of the trade-off effect depends on the stringency of individual policy incentives in each country. The reason is that financial incentives are charged based on fuel economy (e.g. fuel tax) or engine size (e.g. annual registration tax). If consumers are incentivised to buy more energy efficient PLDVs because of one of the incentives, the effectiveness of pairing incentives will be lower because the costs (of pairing incentives) for consumers of more efficient cars are less than for those consumers of less efficient cars. For instance, when a car buyer chooses a more efficient vehicle (as a result of the annual registration tax), the effectiveness of a fuel tax falls as the fuel economy improves. Hence, we find that in all countries, there is a trade-off effect between annual registration tax, fuel tax and EV subsidies. As a result of the trade-off effect between two policy incentives, the efficiency of two financial incentives when these are introduced simultaneously is generally lower than when they are introduced independently. For instance, when fuel tax is combined with the annual registration tax, the costs for the UK are 39 billion, and equivalent to around 11700 USD per tonne CO_2 emissions reductions. Although the efficiency is higher when EV subsidy is combined with fuel tax in all countries, it can still cost up to 1300 USD per tonne CO_2 emissions reductions for China.

Second, there is a reinforcement effect between EV mandates and other policy incentives, as shown in the red bars in Figure 7.6. The size of the reinforcement effect depends on specific countries and the sizes of the policy incentives. The EV mandate increases the model′s availability and the visibility of EVs. The higher availability of EVs enables the other policies to have more of an effect by giving a broader range of choices to consumers. In particular, we find that there is a strong reinforcement effect between fuel economy regulation and EV mandates. This is because consumers are more likely to shift from buying conventional petrol/diesel cars to EVs when conventional cars are banned and when more EV models are available in the market. In particular, we find that efficiencies are the highest when an EV mandate is combined with fuel economy regulations. Hence, when fuel economy standard is introduced with the EV mandate, we find that the combination only costs China around 16 USD per tonne CO_2 emissions reductions and 33 USD per tonne CO_2 emissions for the US.

Third, the policy effectiveness is lower among countries with a dominant technology or that have very low market shares of low emissions PLDVs compared with countries with relatively larger EV fleet shares. For example, without the EV mandate, we find that the effectiveness of policy combinations is among the lowest in India due to the very small number of low-emission PLDVs (see Table 7.13). This is a result of the technological lock-in effect. Hence, an EV mandate is necessary to reduce the technological lock-in effect by increasing the rate of technological diffusion for EV and to create a reinforcement effect between EV mandates and other policy incentives. Without EV mandates, in the case of Japan, where hybrid cars dominate the market, we find that the cost of abatement goes up to 35900 USD per tonne CO_2 emissions reduction if EV subsidy is imposed with the annual registration tax. Overall, we find that the cost of abatement can vary significantly for one single country. For example, in the case of Japan, the cost of CO2 emissions abatement ranges from 78 USD per tonne CO_2 emissions reduction when fuel economy is combined with EV mandate up to more than 30,000 USD per tonne CO_2 emissions reduction when EV subsidy is combined with the annual registration tax.

In reality, there are likely to be more than two policies combined (i.e. policy framework includes more than two policies), although this is outside the scope of this study. It is possible to extend our conclusions for two policy interactions to the scenarios with more than two policies. Essentially, in the framework of more than two policy incentives, we are likely to find that there is a trade-off effect between all financial incentives and a reinforcement effect between EV mandates and other policy incentives. This is because policies that encourage the uptake of more efficient PLDVs weaken the effectiveness of other financial incentives. However, if EV mandates increase the shares for EVs, this increases the models available for consumers and further incentivises consumers to choose EVs if they are required to pay higher taxes for higher emissions PLDVs. As we find in this research, as a result of the trade-off effect and reinforcement effect between policy incentives, the cost of abatement can range significantly for one country, depending on the combinations of policy incentives. In reality, when several policy incentives are introduced simultaneously, it is possible that the trade-off effect between incentives will lead to the very high cost of CO_2 emissions reductions (as in the case of Japan), although policy incentives often have multiple objectives.

Although our analysis reveals that the marginal cost of abatement is unique for each country under different levels of policy measures, certain trends are robust across scenarios/countries. If policy measures supporting the diffusion of low emissions vehicles fail to materialise (i.e. the effectiveness of the policy measure is low), then the mitigation potentials of the policy measures for the country are poor, and we observe a steep curves for CO_2 mitigation and emissions are 'inelastic' to the stringency of policy measure. On the other hand, certain policy measures (or combination of policy measures) are more 'elastic' to the stringency of policy measures.

Table 7.13: Upper section: the total effectiveness ($Eff(x1, x2)$) of policy $x1$ and $x2$. Lower section: the interaction effect between two policy incentives ($Int(x1, x2)$). When the interaction effect is positive, there is a reinforcement effect between the two policy incentives. When the interaction effect is negative, there is a trade-off effect between the two policy incentives.

The combined effectiveness ($MtCO_2$)					
Scenario	UK	US	Japan	China	India
1. FT+RT	-7.74%	-8.14%	-5.42%	-8.08%	-2.24%
2. FT+ EV sub	-3.59%	-1.26%	-4.89%	-5.51%	-3.28%
3. Reg + RT	-13.52%	-9.36%	-5.67%	-17.81%	-8.53%
4. FT + Reg	-11.91%	-8.82%	-4.72%	-17.46%	-8.05%
5. EV sub + Reg	-11.81%	-8.91%	-4.72%	-18.33%	-7.68%
6. RT + EVM	-9.54%	-11.29%	-5.69%	-14.07%	-7.10%
7. FT + EVM	-7.53%	-2.03%	-8.75%	-10.40%	-7.27%
8. EV sub + EVM	-4.42%	-3.52%	-1.99%	-13.03%	-4.81%
9. Reg + EVM	-15.20%	-12.69%	-8.11%	-29.98%	-11.60%
10. EV sub + RT	-5.32%	-8.83%	-1.84%	-9.79%	-2.04%
The interaction effect ($MtCO_2$)					
Scenario	UK	US	Japan	China	India
1. FT+RT	-31	-227	-23	-319	-258
2. FT+ EV sub	-21	-9	-3	-603	-11
3. Reg + RT	-60	-2180	-13	-982	-91
4. FT + Reg	-41	-86	-87	-478	-297
5. EV sub + Reg	-16	-159	-2	-762	-5
6. RT + EVM	15	445	51	535	225
7. FT + EVM	22	38	52	496	126
8. EV sub + EVM	27	229	12	501	187
9. Reg + EVM	26	810	45	1442	23
10. EV sub + RT	-15	-117	-4	-464	-5

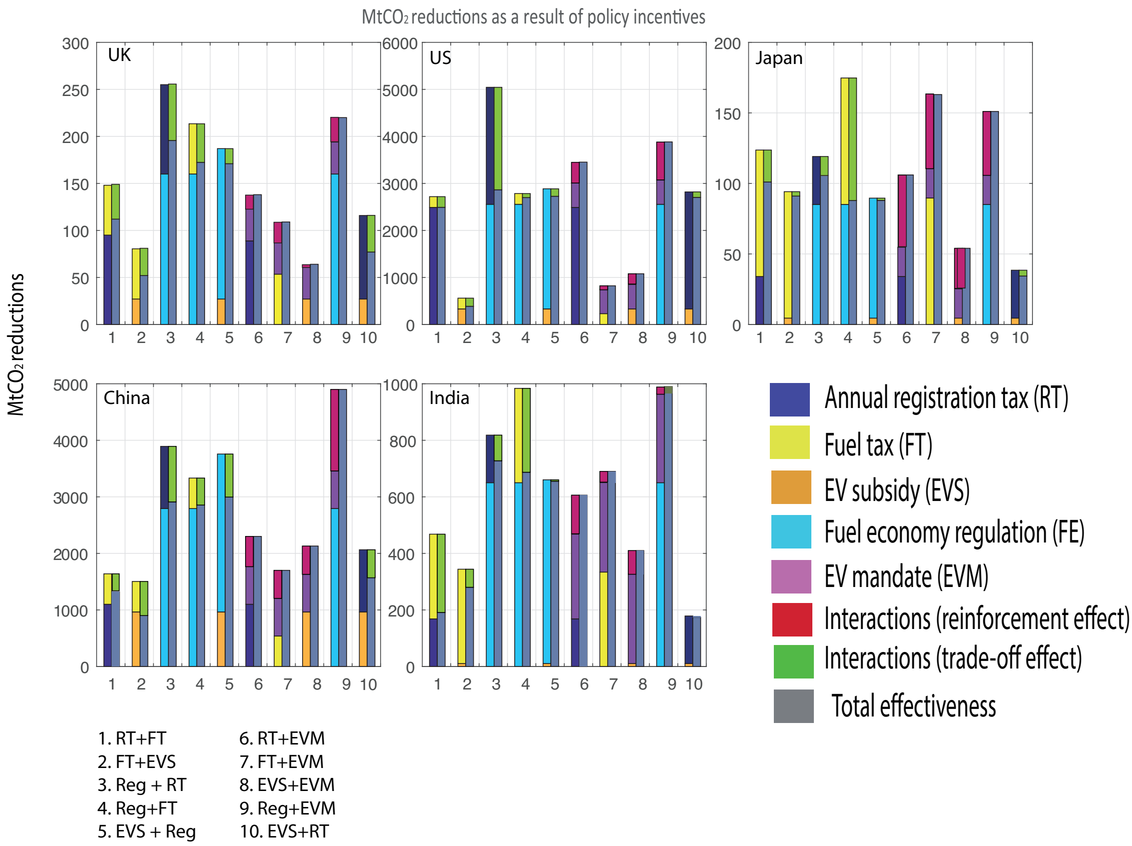

Figure 7.6: Policy effectiveness (in absolute values) and interactions between policy incentives. Policy effectiveness is defined as cumulative emissions reductions (between 2016 and 2050) achieved by a given policy or set of policies. The bar diagram shows the effectiveness of policy incentives in absolute terms (i.e. CO_2 emissions reductions achieved by the policy incentive(s)). The grey bars show the total effectiveness of two policy incentives of the corresponding scenarios. The green bar shows the trade-off effect between the policy incentives in the corresponding scenarios. The red bars show the reinforcement effect between two policy incentives in the corresponding scenarios.

Table 7.14: The total cost, annual cost and efficiency of combinations of policy incentives.

Total cost (Billion USD)	**UK**	**US**	**Japan**	**China**	**India**
1. FT+RT	1310	8212	1305	2150	743
2. FT + EV sub	58	179	92	1221	46
3. Reg + RT	1508	6972	1103	1426	692
4. FT + Reg	61	168	78	214	57
5. EV sub + Reg	9	195	10	804	23
6. RT + EVM	1263	8107	1233	1971	734
7. FT + EVM	56	103	95	324	72
8. EV sub + EVM	12	160	21	1041	37
9. Reg + EVM	6	128	12	80	46
10. EV sub + RT	1265	8182	1231	2867	708
Average cost per year (Billion USD)					
1. FT+RT	38.52	241.53	38.38	63.25	21.87
2. FT + EV sub	1.71	5.26	2.71	35.92	1.36
3. Reg + RT	44.34	205.07	32.45	41.95	20.34
4. FT + Reg	1.78	4.94	2.30	6.30	1.68
5. EV sub + Reg	0.27	5.74	0.31	23.65	0.67
6. RT + EVM	37.16	238.45	36.28	57.96	21.59
7. FT + EVM	1.66	3.02	2.78	9.54	2.13
8. EV sub + EVM	0.35	4.71	0.61	30.63	1.09
9. Reg + EVM	0.19	3.77	0.35	2.37	1.36
10. EV sub + RT	37.20	240.64	36.21	84.34	20.83
Efficiency (USD/tCO_2)					
1. FT+RT	11692	3377	12919	1629	3895
2. FT + EV sub	1116	476	1014	1357	141
3. Reg + RT	7706	2435	10448	490	950
4. FT + Reg	352	62	890	75	83
5. EV sub + Reg	53	72	119	268	35
6. RT + EVM	9155	2348	11636	857	1212
7. FT + EVM	518	170	581	191	100
8. EV sub + EVM	205	122	387	534	90
9. Reg + EVM	29	33	78	16	47
10. EV sub + RT	16428	3027	35878	1792	4071

Table 7.15: Registration tax assumptions for the UK (in USD). We assumed that there is no policy instruments introduced in the baseline scenario. The current RT scenario represents the current registration tax level in the UK. We assumed that the registration tax is 50% higher than the current level in the High RT scenario and 100% higher in the very high RT scenario

UK	Baseline	Current RT	High RT	Very high RT
Econ Petrol	0	120	180	240
Mid Petrol	0	200	300	400
Lux Petrol	0	1200	1800	2400
Econ Diesel	0	120	180	240
Mid Diesel	0	200	300	400
Lux Diesel	0	1200	1800	2400
Econ CNG	0	120	180	240
Mid CNG	0	200	300	400
Lux CNG	0	1200	1800	2400
Econ FFV	0	120	180	240
Mid FFV	0	200	300	400
Lux FFV	0	1200	1800	2400
Econ Hybrid	0	100	150	200
Mid Hybrid	0	140	210	280
Lux Hybrid	0	500	750	1000
Econ EV	0	60	0	0
Mid EV	0	100	0	0
Lux EV	0	600	0	0

Table 7.16: Registration tax assumptions for the US (in USD). We assumed that there is no policy instruments introduced in the baseline scenario. The current RT scenario represents the current registration tax level in California (taken as a representative state) . We assumed that the registration tax is 50% higher than the current level in the high RT scenario and 100% higher in the very high RT scenario.

US	Baseline	Current RT	High RT	Very high RT
Econ Petrol	0	290	435	580
Mid Petrol	0	400	600	800
Lux Petrol	0	600	900	1200
Econ Diesel	0	290	435	580
Mid Diesel	0	400	600	800
Lux Diesel	0	600	900	1200
Econ CNG	0	290	435	580
Mid CNG	0	400	600	800
Lux CNG	0	600	900	1200
Econ FFV	0	290	435	580
Mid FFV	0	400	600	800
Lux FFV	0	600	900	1200
Econ Hybrid	0	290	435	580
Mid Hybrid	0	400	600	800
Lux Hybrid	0	600	900	1200
Econ EV	0	0	0	0
Mid EV	0	0	0	0
Lux EV	0	0	0	0

Table 7.17: Registration tax assumptions for Japan (in USD). We assumed that there is no policy instruments introduced in the baseline scenario. The current RT scenario represents the current registration tax level in Japan. We assumed that the registration tax is 50% higher than the current level in the high RT scenario and 100% higher in the very high RT scenario. We also assumed that EVs are exempt from the annual registration tax in the high RT scenario and the very high RT scenario.

Japan	Baseline	Current RT	High RT	Very high RT
Econ Petrol	0	325	488	650
Mid Petrol	0	372	558	744
Lux Petrol	0	480	720	960
Econ Diesel	0	325	488	650
Mid Diesel	0	372	558	744
Lux Diesel	0	480	720	960
Econ CNG	0	325	488	650
Mid CNG	0	372	558	744
Lux CNG	0	480	720	960
Econ FFV	0	325	488	650
Mid FFV	0	372	558	744
Lux FFV	0	480	720	960
Econ Hybrid	0	260	390	520
Mid Hybrid	0	298	446	595
Lux Hybrid	0	384	576	768
Econ EV	0	81	0	0
Mid EV	0	93	0	0
Lux EV	0	120	0	0

Table 7.18: Registration tax assumptions for China (in USD). We assumed that there is no policy instruments introduced in the baseline scenario. The current RT scenario represents the current registration tax level in China. We assumed that the registration tax is 50% higher than the current level in the high RT scenario and 100% higher in the very high RT scenario. We also assumed that EVs are exempt from the annual registration tax in the high RT scenario and the very high RT scenario.

China	Baseline	Current RT	High RT	Very high RT
Econ Petrol	0	80	120	160
Mid Petrol	0	106	159	212
Lux Petrol	0	384	576	768
Econ Diesel	0	80	120	160
Mid Diesel	0	106	159	212
Lux Diesel	0	384	576	768
Econ CNG	0	80	120	160
Mid CNG	0	106	159	212
Lux CNG	0	384	576	768
Econ FFV	0	80	120	160
Mid FFV	0	106	159	212
Lux FFV	0	384	576	768
Econ Hybrid	0	80	120	160
Mid Hybrid	0	106	159	212
Lux Hybrid	0	384	576	768
Econ EV	0	0	0	0
Mid EV	0	0	0	0
Lux EV	0	0	0	0

Table 7.19: Registration tax assumptions for India (in USD). We assumed that there is no policy instruments introduced in the baseline scenario. The current RT scenario represents the current registration tax level in India. We assumed that the registration tax is 50% higher than the current level in the high RT scenario and 100% higher in the very high RT scenario

India	Baseline	Current RT	High RT	Very high RT
Econ Petrol	0	44	67	88
Mid Petrol	0	103	154	206
Lux Petrol	0	150	226	300
Econ Diesel	0	44	67	88
Mid Diesel	0	103	154	206
Lux Diesel	0	150	226	300
Econ CNG	0	44	67	88
Mid CNG	0	103	154	206
Lux CNG	0	150	226	300
Econ FFV	0	44	67	88
Mid FFV	0	103	154	206
Lux FFV	0	150	226	300
Econ Hybrid	0	44	67	88
Mid Hybrid	0	103	154	206
Lux Hybrid	0	150	226	300
Econ EV	0	36	0	0
Mid EV	0	82	0	0
Lux EV	0	120	0	0

Table 7.20: EV subsidy assumptions for the UK, US, Japan, China and India (in USD). The current EV subsidy scenario assumes that the levels of EV subsidies are consistent with the current levels. High EV subsidies assume that the EV subsidy level is 50% higher than the current level. Very high EV subsidy scenarios assume that the EV subsidy is 100% higher than the current subsidy levels.

		Baseline	Current EV subsidy	High EV subsidy	Very high EV subsidy
UK	Econ EV	0	-4000	-6000	-8000
	Mid EV	0	-5000	-7500	-10000
	Lux EV	0	-7000	-10500	-14000
US	Econ EV	0	-5000	-7500	-10000
	Mid EV	0	-9000	-13500	-18000
	Lux EV	0	-10000	-15000	-20000
Japan	Econ EV	0	-5000	-7500	-10000
	Mid EV	0	-9000	-13500	-18000
	Lux EV	0	-10000	-15000	-20000
China	Econ EV	0	-3500	-5250	-7000
	Mid EV	0	-8000	-12000	-16000
	Lux EV	0	-15000	-22500	-30000
India	Econ EV	0	-1334	-2001	-2668
	Mid EV	0	-3081	-4622	-6162
	Lux EV	0	-4514	-6771	-9028

Table 7.21: Fuel tax assumptions (in USD). The baseline scenario assumes that there is no policy incentive in place. The current FT scenario assumes that the levels of petrol tax are consistent with the current levels in individual countries. The high FT scenario assumes that the fuel tax is 50% higher than the current levels. Very high FT assumes that fuel tax is 100% higher than the current levels.

Fuel tax	Baseline	Curent FT	High FT	Very high FT
UK	0.00	0.60	0.90	1.20
US	0.00	0.05	0.08	0.10
Japan	0.00	0.50	0.75	1.00
China	0.00	0.06	0.09	0.12
India	0.00	0.5	0.75	1.00

Table 7.22: EV mandate program assumptions

EV mandate	Baseline scenario	EV mandate low	EV mandate mid	EV mandate high
All countries	0	5\% new sales are EV	10\% new sales are EV	15\% new sales are EV

Table 7.23: Number of new EV sales under the EV mandate program assumptions (thousands)

Number of PLDVs (thousands)	UK	US	Japan	China	Inida
EV mandate low (5\%)	115	550	280	950	150
EV mandate mid (10\%)	230	1100	560	1900	300
EV mandate high (15\%)	340	1650	845	2850	450

Table 7.24: Phase-out standards assumptions for the UK, US, Japan, China and India. The 'current phase-out scenario' assumes that the fuel economy standard is introduced in 2030, followed the historical phase-out standard or phase-out standards proposed by the UK, US, Japan, China and India. The 'stringent phase-out scenario' assumes that the same phase-out standard is introduced in 2025.

Current phase-out scenario		
Reductions in CO_2 emissions (%)	Implementation year	Reductions in CO_2 emissions (%) (year of reference 2016)
UK	2030	40%
US	2030	20%
Japan	2030	20%
China	2030	35%
India	2030	20%
Stringent phase-out scenario		
UK	2025	40%
US	2025	20%
Japan	2025	20%
China	2025	35%
India	2025	20%

Chapter 8

Income effect on scenario analysis

Global economic growth is estimated at 3.1% in 2015 and is projected to be 3.4% in 2016 and 3.6% in 2017 (IMF, 2016). The trend is projected to continue with a slowdown in global growth after 2020 (PWC, 2015). In particular, countries such as China and India are likely to sustain long-term growth despite a slowdown of the Chinese economy. With rapid economic growth in the fast developing countries, we are likely to see fast growth in the middle class with rapidly rising incomes.

Consumers' choices and behaviour are not sufficiently taken into account in most global IAMs, even though there is extensive evidence that income and social influence are the key drivers in the diffusion of vehicles (McCollum et al., 2016). Consumer preferences, with increasing income, drive choices towards increasingly carbon-intensive engines (Gallachóir et al., 2009; Zachariadis, 2013). Using historical data on the new vehicle fleet in Ireland, Gallachóir et al. (2009) finds the purchasing trends towards larger size PLDVs over time have considerably offset the improvements in the technical efficiency of individual car models. With automobile sales data from Germany in the years 1998-2008, Zachariadis (2013) finds that German consumers might not choose to buy the same gasoline car they would have bought a few years earlier; instead, they preferred a more powerful diesel car than what they might have bought otherwise. Studies on the relationships between income and car prices generally focus on specific areas or countries. It is challenging to obtain surveys on consumer income and car prices that span several countries.

Climate change mitigation scenarios are increasingly designed to be more 'realistic' by incorporating the dynamics of consumer behaviour. While income is a major determinant for car ownership and car choices, previous global IAMs have not fully taken that into account. On the one hand, rising income determines the demand for PLDVs and the demand for travel, and on the other, rising incomes can lead consumers to choose vehicles of higher fuel intensity, thus counteracting the effect of climate policies. The former is normally addressed in most models, while the latter is rarely considered in models. The income effect on vehicle choice may become an important consideration when informing policy-making using models because as income rises, consumers may choose to purchase more expensive and luxury higher emissions PLDVs and thus counteract the fuel efficiencies improvement of new PLDVs. The lack of consideration of incomes on car purchases and emissions in models suggests there are limits to how well current models can inform climate policy-making in consumer markets, such as vehicle purchases.

In this chapter, we study the relationship between household income and the household's willingness to pay for PLDVs in several countries. We are interested in the following questions:

1. Does an individual′s income explain the price of his/her car purchase? (Section 8.3)
2. How can technological diffusion, energy consumption and emissions be made to respond to income changes in the FTT-Transport model? (Section 8.4)
3. How will the changes in income impact the effectiveness of the individual policy instruments for reducing emissions from PLDVs? (Section 8.5)

To achieve the research goal for this chapter, we first collected data regarding household incomes and household expenditure on car purchases from national surveys for six countries: the US, the UK, China, Korea, Russia and Spain [1]. To find the effects of incomes changes on household expenditure on car purchases (i.e. household car prices), we regress income changes on household car prices. The prices paid by households were taken as the consumers' willingness to pay for PLDVs. We find that income is a significant factor that positively affects car purchase prices paid by consumers in all six countries. To extend our results of income changes on household car prices to countries other than those studied here, we extrapolate the income effect on the price consumers paid to other countries, including the UK, US, Japan, China and India. To do this, we regress the income price effect of the US, UK, China, Korea, Russia and Spain on a cultural index called Hofstede′s indices. Hofstede′s indices describe how a country′s cultural acceptance of unequal distributions of power strengthens/weakens the relationship between higher income

[1] These six countries are chosen due to data availability.

and higher willingness to pay. We find the effect of income changes on car prices in the UK, US, Japan, China and India using Hofstede′s indices as proxies for which survey data are not readily available.

Then, the next challenge is to represent the extent to which the income effect on household car prices (i.e. the effect of income changes on households' willingness to pay for PLDVs) in the FTT-Transport model. We find the changes in average willingness to pay for PLDVs over time based on income change using the income effect on household car prices found previously. By finding a link between the average willingness to pay for PLDVs and the change in willingness to pay for individual PLDV classes in the FTT-Transport model, the changes in willingness to pay for individual PLDV classes can be identified. These are then added to the LCOT matrices (the cost matrices of the FTT-Transport model) to reflect change in the perceived costs when income changes. Last, using the FTT-Transport model, we find the impact of income changes on the consequent changes in technological shares and emissions, assuming policy scenarios discussed in Chapter 7. Overall, we find that although rising income has a noticeable effect on emissions, the effect is not large but may cancel out existing policies.

This chapter presents the results of a small EPSRC-funded pilot project (through a research grant programme called ReCoVER) carried out in collaboration with Charlie Wilson and Hazel Pettifor from the University of East Anglia and led by myself and Dr Mercure. The work division is indicated in Appendix B.

8.1 Data

To compare the relationship between income and the prices consumers are willing to pay in a number of countries, we have acquired data from national surveys. Table 8.1 presents data sources for various national surveys, including survey year, number of data points and variables available. Due to data availability, survey data were collected only for the US, the UK, China, Korea, Russia and Spain [1].

[1] UK Understanding Society is the largest panel survey in the world, containing rich information regarding people's preference towards PLDVs and driving habits. However, the survey has car engine size data without car price data. The car price data is derived from our dataset in which engine sizes and car prices are matched using the MarkLine data.

Table 8.1: Household survey data sources.

	Data source	Year	Sample size (purchasers for new vehicles)
UK	UK Understanding Society	2011/2012	962
Spain	The Survey of Household Finances	2011	364
US	Panel Study of Income Dynamics (PSID)	2010/2011	259
Russia	Russian Federation (RLMS-HSE)	2013/2014	122
China	China Panel Studies (CFPS)	2010/2012	397
Korea	Korea Labour and Income Panel Study (KLIPS)	2011	272

8.2 Regression methodology

In this section, we find the relationships between income and prices paid by consumers using national survey data and Hofstede's dimensions of national culture (see details below). The consumption of luxury or large engine size PLDVs is partly determined by practicality and partly by self-presentation attitude [1] as consumers express their individuality and social status (e.g. it is more likely for consumers to buy luxury PLDVs as they become richer in a society in which social status is important). Hence, as we find in Mercure and Lam (2015), there is a positive relationship between car price and engine size.

The purpose of the regression exercise is to test how variations of income affect purchase prices paid by consumers, both within country and across states, with cross-sectional data. As we have shown in Table 8.3, we tested how variations in different socio-economic factors, in particular household income, affect the car prices paid by the consumers, thereby predicting the differences for the UK, the US, Korea, Spain, Russia and China. We then regressed the prices of car purchases (dependent variable) against income (independent variable) while controlling for cultural differences and income inequality (control variables).

We first performed within country multivariate Ordinary Least Square (OLS) regression to capture the effect of consumer incomes on car purchasing prices for the UK, the US, Korea, Spain, Russia and China, considering various socio-economics factors such as individual characteristics, household characteristics, driving behaviour, stated vehicle preferences and revealed vehicle preferences (see Table 8.3 for details) that affect purchase prices. We have taken and tested all the variables in the consumers' survey related to the car preferences and car prices paid

[1] Self-presentation is behaviour that attempts to convey some information or image about oneself to other people (Baumeister and Hutton, 1987).

by consumers. Variables under the stated vehicle preferences section (e.g. comfort, environmentally friendly) are available in the UK Understanding Society survey, but not the others. The results for the OLS estimated equation are reported in Table 8.3.

To capture the effect of income on car prices paid by consumers to countries outside of the six countries where we have collected survey data, we run a pooled OLS regression, controlling the difference between countries by the interaction effect between the incomes and a dummy variable for each country. Here, we evaluate the extent to which there are significant differences between income and car prices between countries. To measure the extent to which income effect and country effect influence car prices, the following model is specified:

$$lnP_{k,i} = \beta_0 lnx'_{k,i} + \beta_1 \alpha_k * lnY_{i,t} + \epsilon_{k,i} \tag{8.1}$$

with k=UK, US, Korea, Russia, Spain, China and i = Household.
$LnP_{k,i}$ is the log of the car prices paid by household i in country k, the coefficient β_1 captures the interaction effect of country effect (represented by a country dummy α_k) and household income ($lnY_{i,t}$) and $\epsilon_{i,k}$ is the error term. $x'_{k,i}$ is the vector of explanatory variables listed in Table 8.3.

A common approach for measuring national cultural variation on consumer choice is Hofstede's five dimensions (Hofstede, 2011). To capture the effect of cultural differences on the income effect on car prices, we performed a meta-regression model and regressed income effect on prices paid by consumers against Hofstede's scores of national culture. Hofstede's dimensions of national culture is a framework for cross-cultural communication. (Hofstede, 2011) proposes five dimensions along which cultural values can be analysed: power distance, individualism, uncertainty avoidance, masculinity vs femininity and long-term orientation (see definition of Hofstede's indices in Table 8.2). They measure the effects of a society's culture on the values of its members and how these values relate to social behaviour (Hofstede, 2011). Note that because Hofstede's dimensions reflect general societal attitudes, we assume they do not change dramatically over time.

8.3 Regression results

The results indicate that income is a significant factor that positively affects car purchase prices paid by consumers in all countries studied. This implies that higher income households tend to purchase more expensive PLDVs than mid/low-income

Table 8.2: Hofstede's dimensions of national culture. Source: Hofstede Centre.

Culture dimension	Definition
Power distance index	The extent to which less powerful members of organisations and institutions accept and expected that power is distributed unequally.
Individualism	The degree of interdependence a society maintains among its member.
Masculinity vs Femininity	The extent to which the society will be driven by competition achievement and success, heroism, assertiveness and material rewards for success.
Uncertainty Avoidance Index	The extent to which the members of a culture feel threatened by ambiguous situations.
Long-term vs Short-term orientation	The degree to which a society has to maintain some links with its past while dealing with challenges of present and future.
Indulgence vs Restraint	The extent to which people try to control their desires and impulse.

households. This is consistent with our prior expectations that higher incomes induce people to buy more expensive PLDVs and that income is a significant factor explaining the prices of PLDVs purchased by consumers. Depending on the country, income explains around 31% of variance in price in the UK and 15% in the US, while 24% of the variance in car prices in Russia can be explained by income movement. Similarly, in China and Korea, income explains 16% and 15% of the price movement, respectively.

Household characteristics such as household size and number of children under 15 years of age negatively affect the price consumers pay for PLDVs in most of the countries studied; that is, the larger the size of the household, the less they will spend on purchasing a car. Together, these factors explain up to 34% of the variance in the car purchase prices in the UK. The number of bedrooms in the purchasers' home explains up to 25% and 13% of the variance in the car purchase prices in the US and Spain, respectively. In terms of driving behaviour, the number of PLDVs owned by the household is the most significant factor in affecting vehicle choices, explaining up to 18% of price variance in the UK and Korea.

Table 8.3: OLS multivariate regression measuring the effects of consumer income on car prices, evaluating the effects of other household and vehicle attributes, with the purchase price as the dependent variable. Each group of variables are identified in the literature as factors that will influence the willingness to pay for PLDVs by consumers.

Country	**UK**	**US**	**Korea**	**Russia**	**Spain**	**China**
Income (US$2011)	**0.09****	**0.157***	**0.396****	**0.476****	**0.197****	**0.335****
Individual characteristics						
gender (female=1)	-0.144**	-0.054	-0.100	0.144	-0.082	0.037
age	0.082*	-0.006	0.002	0.053	-0.046	0.118*
Household characteristics						
household size	-0.162*	n/a	-0.023	n/a	0.06	-0.048
number kids under 15	0.183**	-0.100	-0.034	n/a	-0.019	-0.060
number bedrooms/rooms/floor space	0.103**	0.243**	n/a	n/a	0.131*	n/a
urban/rural location (1=urban)	-0.068*	n/a	n/a	-0.010	n/a	-0.096
own home (1=yes)	-0.029	-0.0161	0.075	0.034	0.091	n/a
Driving behaviour/Vehicle Use						
number PLDVs owned by household	0.179**	0.007	-0.132*	n/a	0.002	n/a
Use car daily	-0.013	n/a	n/a	n/a	n/a	n/a
Annual mileage (last year, miles)	0.034	n/a	n/a	n/a	n/a	n/a
Use for business	n/a	-0.1571*	n/a	n/a	n/a	n/a
Stated vehicle preferences						
Costs (purchase/running/resale value tax/insurance)	-0.099**	n/a	n/a	n/a	n/a	n/a
comfort	0.023	n/a	n/a	n/a	n/a	n/a
small engine	-0.261**	n/a	n/a	n/a	n/a	n/a
large engine	0.154**	n/a	n/a	n/a	n/a	n/a
environmentally friendly/low emissions	-0.015	n/a	n/a	n/a	n/a	n/a
electric vehicle	0.015	n/a	n/a	n/a	n/a	n/a
style/design/image of brand/model	0.051	n/a	n/a	n/a	n/a	n/a
interior space/functionality/boot size	0.056	n/a	n/a	n/a	n/a	n/a
reliability	0.021	n/a	n/a	n/a	n/a	n/a
safety	-0.016	n/a	n/a	n/a	n/a	n/a
speed/performance	0.044	n/a	n/a	n/a	n/a	n/a
other features (cd player, music system etc)	0.054	n/a	n/a	n/a	n/a	n/a
Vehicle revealed preferences						
make/model year	n/a	-0.023	n/a	n/a	n/a	n/a
N	962	259	272	122	364	397
Total R2 (explained variance)	**0.312**	**0.1493**	**0.1472**	**0.2483**	**0.0895**	**0.1552**
Adjusted R2 (number explanatory vars and n)		0.1185				

*Statistically significant at $p<0.001$
**Statistically significant at $p<0.05$

Table 8.4: Meta-analysis testing the PD scores on the income effect on prices. PD scores explain the differences between countries.

	Coefficient	Standard error
Intercept	0.0640	0.2865
PD	0.3640	0.1575
Gini	-0.1526	0.8324

Table 8.5: Interaction effect of country and income on car prices. OLS regression model examining effect of δ income on δ price and predicting differences of the UK, the US, Korea, Russia, Spain and China.

Interaction effect (log income US$2011 x country)	
UK	0.08
US	0.18
Korea	0.25
Russia	0.31
Spain	0.28
China	0.28
n	2606
Adjusted R2	0.41

Note: both country effects and interaction effects between income and price are significant for all countries at $p \leq 0.05$

The model shows there are significant differences in the relationship between income and price for different countries. We performed a meta-regression model and regressed income effect on prices paid by consumers against Hofstede's scores of national culture. We have tested all of Hofstede's indices and found that only the power distance (PD) score has a significant explanatory power on the income effect on the prices consumers paid. The PD score expresses the degree to which the less powerful members of a society accept and expect that power is distributed unequally. Hence, status is deemed more important in the countries with a high PD score. The stronger the effect of social status (i.e. the stronger the effect of set hierarchy in a society), the more important the income effect is on the average price of purchased PLDVs (as shown in Figure 8.1). The estimates from the regression of the income effect on car prices and the PD scores (with uncertainty) are shown in Table 8.4. The PD scores are high in Asian countries such as China and Japan, but relatively low in countries such as northern European countries. Consumers purchase vehicles to reflect their social status in the countries with high PD scores (see Table 8.6 for comparisons).

Using the regression results of PD scores on the income car price, we extrapolate the income effect on the price of PLDVs on each country based on their PD and GINI scores (see Table 8.6). The results express the mean income effect on price, estimated from the meta-regression of PD and GINI on the log-income effect on the log-vehicle-price.

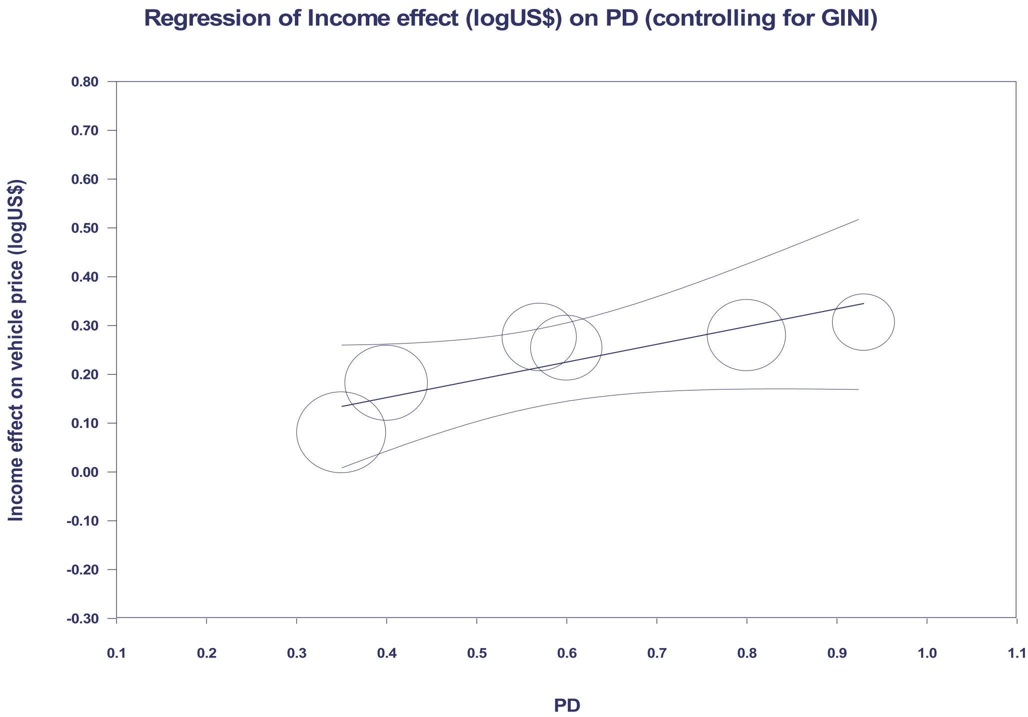

Figure 8.1: The positive relationship between the income effect on car prices and the PD score, based on the regression results in Table 8.4

Table 8.6: The mean income effect on the average car prices extrapolated to 50 countries with PD scores and the GINI coefficient (see text for details).

		Power distance	GINI coefficient	Mean income effect on price
1	Belgium	0.65	0.29	0.26
2	Denmark	0.18	0.29	0.09
3	Germany	0.35	0.31	0.14
4	Greece	0.6	0.35	0.23
5	Spain	0.57	0.36	0.22
6	France	0.68	0.34	0.26
7	Ireland	0.28	0.32	0.12
8	Italy	0.5	0.34	0.19
9	Luxembourg	0.4	0.31	0.16
10	Netherlands	0.38	0.29	0.16
11	Austria	0.11	0.30	0.06
12	Portugal	0.63	0.36	0.24
13	Finland	0.33	0.28	0.14
14	Sweden	0.31	0.27	0.14
15	UK	0.35	0.35	0.14
16	Czech Republic	0.57	0.27	0.23
17	Estonia	0.4	0.32	0.16
18	Cyprus	NA	0.32	NA
19	Latvia	0.44	0.36	0.17
20	Lithuania	0.42	0.34	0.17
21	Hungary	0.46	0.29	0.19
22	Malta	0.56	NA	NA
23	Poland	0.68	0.33	0.26
24	Slovenia	0.71	0.25	0.28
25	Slovakia	1	0.27	0.39
26	Bulgaria	0.7	0.36	0.26
27	Romania	0.9	0.28	0.35
28	Norway	0.31	0.26	0.14
29	Switzerland	0.34	0.33	0.14
30	Iceland	0.3	0.26	0.13
31	Croatia	0.73	0.25	0.29
32	Turkey	0.66	0.39	0.25
33	Macedonia	NA	NA	NA
34	US	0.4	0.41	0.15
35	Japan	0.54	0.32	0.21
36	Canada	0.39	0.34	0.15
37	Australia	0.36	0.35	0.14
38	New Zealand	0.22	NA	
39	Russian Federation	0.93	0.41	0.34
40	Rest of Annex	NA	NA	NA
41	China	0.8	0.42	0.29
42	India	0.77	0.34	0.29
43	Mexico	0.81	0.48	0.29
44	Brazil	0.69	0.54	0.23
45	Argentina	0.49	0.45	0.17
46	Colombia	0.67	0.56	0.22
47	Rest of Latin America	NA	NA	NA
48	Korea	0.6	0.31	0.23
49	Taiwan	0.58	NA	NA
50	Indonesia	0.78	0.36	0.29

8.4 Linking the income car price effect to the FTT

If there exists a positive relationship between income changes and prices, then consumers′ willingness to pay for more expensive PLDVs increases with income (i.e. they are willing to purchase more expensive PLDVs when they become richer) and vice versa. In this section, we demonstrate how we represent changes of willingness to pay for vehicles of different types in the FTT-Transport model as income changes.

To understand what effect the changes of engine sizes (i.e. shares for Econ, Mid and Lux) has as a result of the changes in average income, we need to know how changes in average income lead to changes in the relative attractiveness of each vehicle class (i.e. increases in income make Lux vehicles more attractive and Econ vehicles less attractive). If this information is available, then the income effect on the relative attractiveness of an individual vehicle class can be derived by adding the perceived cost changes (as a result of the income effect) to the original car prices. Since this information is unavailable, the solution is to search for a hypothetical car price for individual car classes that lead to changes in the average price consistent with a given change in income through the model's process of diffusion.

We define parameter A as the relationship between the average car prices across all PLDV categories and car prices for individual technologies (i.e. how changes in the perceived costs of individual PLDV classes lead to changes in the average prices). The A parameter enables us to find the extent to which change in willingness to pay for each technology leads to change in the average car price, as follows:

$$A_i = (log\langle LCOT\rangle - log\langle LCOT\rangle^{base})/(logLCOT(m_i) - logLCOT(m_i)^{base}), \quad (8.2)$$

where $LCOT$ is the levelised cost for transportation. m_i is the PLDV classes (i.e. Econ, Mid and Lux) where there is a change in the willingness to pay for PLDVs as a result of income changes, $LCOT(m_i)$ is the perceived $LCOT$ with the income effect on PLDV classes m_i at time 0, $LCOT(m_i)^{base}$ is the original LCOT without the income effect of vehicle class m$_i$ [1]. Note that incomes are calculated using a log scale in order to be consistent with the $LCOT$ calculations. ⟨⟩ represents an average of all PLDV classes (e.g. ⟨LCOT⟩ is the average perceived $LCOT$ with the income effect). Hence, Equation 8.5 shows the extent to which changes in the

[1] i=1 for a Econ car, i=2 for a Mid car, i=3 for a Lux car

average $LCOT$ for each PLDV class leads a change in the average $LCOT$ as the result of the income effect (assuming that the income effect increases the average car prices purchased by consumers).

The A value is defined as the model's response to individual price changes, i.e. the extent to which the model gives average price changes in response to changes in individual prices, for each PLDV class. We found these A parameters by imposing hypothetical price changes and observing the model's response [1]. We then use these A parameters to disaggregate average price changes [2] to individual price changes.

We assume that the A parameter is neither dependent on time nor income rate. However, A can be time dependent, particularly when the composition of vehicle technologies changes significantly, e.g. after 30 years. Hence, the early years estimation is more accurately calculated than the later years. In principle, it is possible to find an A parameter for each price change. However, this is very time-consuming for simulation purposes, especially when there are 59 countries over a 30-year time period.

The changes in average prices paid by consumers in response to changes in income are derived from Equation 8.1. We take GDP per cap as a proxy for income, and our GDP projection is retrieved from IIASA's SSP1 database (see Chapter 5 Table 5.5 for assumptions on GDP per cap).

Let $DelPr(i,t)$ be the change in the perceived $LCOT$ for an individual technology (i) with the income effect. Then we have

$$DelPr(i,t_0) = \frac{log(\langle LCOT\rangle / \langle LCOT^{base}\rangle)}{A_i} \tag{8.3}$$

and therefore

$$DelPr(i,t_0) = \beta * \frac{log(i(t)/i(2012))}{A_i}, \tag{8.4}$$

where $i(t)$ is the income in the year t and $\langle LCOT\rangle$ is the average $LCOT$ for technology with the income effect. $DelPr(i,t_0)$ is the change in the willingness to pay for PLDVs in log scale over time, calculated with the log change in the average car price and the A_i parameter. The effect of income on average car prices is represented by β.

[1] A sensitivity analysis was carried out to explore the change in the hypothetical prices changes on the A values and on the result of the simulations using the FTT-Transport (see Appendix A).

[2] Averages are applied across technologies weighted by their shares.

Hence, the new perceived $LCOT$ for each technology m_i is

$$log(LCOT(m_i)) = log(LCOT(m_i)^{base}) + DelPr(i, t_0), \tag{8.5}$$

$DelPr(i, t_0)$ is added to the log prices of Econ, Mid or Lux PLDVs of all technologies, depending on the engine size distribution of a particular country. Note that $DelPr$ is the relative changes in costs as a result of the income effect. Typically, we find that is positive for Econ PLDVs and negative for Lux PLDVs because Econ PLDVs become less attractive (and hence more costly) and Lux PLDVs become more attractive (and hence less costly).

Note that this change of definition in the cost of PLDVs as perceived by buyers requires us to redefine the γ parameters for all vehicle types (see definitions of γ parameters in Chapter 3), which means the set of values for γ are not the same in the presence of the income effect, as compared with those used in Chapter 7 without the income effect. This is because γ values change when one more explanatory parameter (i.e. income) is added to the Equation 7.1. This will compensate for the differences between the historical technological shares and the new projected shares at the beginning of the projections, when $DelPr$ is added to the simulation at every time step. Hence, if the effect of income on vehicle choice is specified explicitly, then the definition of γ changes, and therefore it needs to be recalculated in comparison with the model without the income effect.

8.5 Simulations

This section explores the extent to which income effect influences the results of the scenario analysis in Chapter 7 compared to when there is no income effect, according to the representation of the income effect explored in this chapter.

8.5.1 Baseline scenario

In the baseline scenario, we assume there is no policy in place, as we assume in Chapter 7. The purpose of this scenario is to capture the income effect on technological change, energy use and emissions from PLDVs, and to compare the scenario without the income effect and with the income effect. Figure 8.2 shows the services generated by PLDVs in the presence of the income effect in the baseline scenario. Table 8.7 and Table 8.8 present the emissions from PLDVs with the income effect and changes in emissions as a result of the income effect, under the same policy scenarios assumed in Chapter 7.

Based on our model projections, in the case of UK, we find that as income rises, the shares for Mid and Lux petrol PLDVs increase at the expense of Econ petrol PLDVs. In the case of the US, compared with the scenarios without the income effect, the income effect of which does not lead to a significant change in the market composition for PLDV technologies in the baseline scenario. Although car owners in the US may purchase more expensive PLDVs as they become richer (because of the income effect), this is not captured in the model. This is because based on our engine size classification (to be consistent with Eurostat), all PLDVs with engine sizes larger than 2000cc are defined as luxury PLDVs, while in fact most existing PLDVs in the US are already larger than 2000cc. In the case of Japan, Lux hybrid PLDVs gain around 5% market share as a result of the income effect compared with scenarios without the income effect.

Based on our models, consumers purchase large engine vehicles as income increases, the extent depends on the size of the income effect (i.e. income change, income effect size) on total emissions from PLDVs. Consumers have options to upgrade their PLDVs to any luxury models that are available in the market. For most countries, before the diffusion of low emissions PLDVs, this implies that consumers will have to choose from more expensive petrol PLDVs and diesel PLDVs. Hence, we find that in the case of the UK and India, the income effect leads to an increase in the fleet shares for Lux petrol or diesel vehicles.

Based on the replicator dynamics equation in the FTT-Transport model (see Section 3.3, Chapter 3), the probability of consumers choosing a Lux hybrid PLDVs or Lux EVs increases if these vehicles are preferred (i.e. when there are at least a few models of hybrids and EVs available for consumers to choose from). In the case of Japan, as income increases, consumers can either choose to upgrade to Lux petrol car models or Lux hybrid car models.

As we have shown previously, our model projects that there will be around 30% EV fleet shares in China by 2050 in the baseline scenario. This implies that consumers will likely choose between upgrading their PLDVs to more expensive petrol PLDVs, hybrid PLDVs or EVs. As Figure 8.2 shows, based our model projections, some consumers choose to buy Lux petrol PLDVs, while others choose to buy Mid or Lux EVs. Moreover, we find that the overall shares for EVs increase at the expense of conventional petrol PLDVs according to the model. The reason is that as more people choose Mid and Lux EVs, the shares for Mid and Lux EVs increase, and the rate of technological diffusion for EVs increases (because more EV models become available) as a result of path dependency and the replicator dynamics equation (see Section 3.3, Chapter 3) in the FTT-Transport model. In addition, without the income effect, based on our model, it is more expensive (in terms of LCOT) to replace small petrol PLDVs with Mid EVs or Lux EVs than scenarios with the income effect. As income increases, the perceived cost difference (in terms of LCOT) between Mid EVs or Lux EVs and small petrol PLDVs decreases. In the FTT-Transport model, the relative price difference between Mid/Lux EVs and small/mid petrol PLDVs becomes smaller as a result of the $DelPr(t)$ (see discussions in Section 8.4).

Table 8.8 shows the changes in emissions as result of the income effect, as compared with the emissions levels without the income effect in the baseline scenario. In the presence of the income effect, we find that emissions increased by less than 5.5% in all countries except China, where emissions fall by more than 1% as a result of the income effect in the baseline scenario. As observed in Figure 8.2, when income rises, the shares for Mid PLDVs and the shares for luxury PLDVs (all car technologies) increase in all countries, consistent with our expectations.

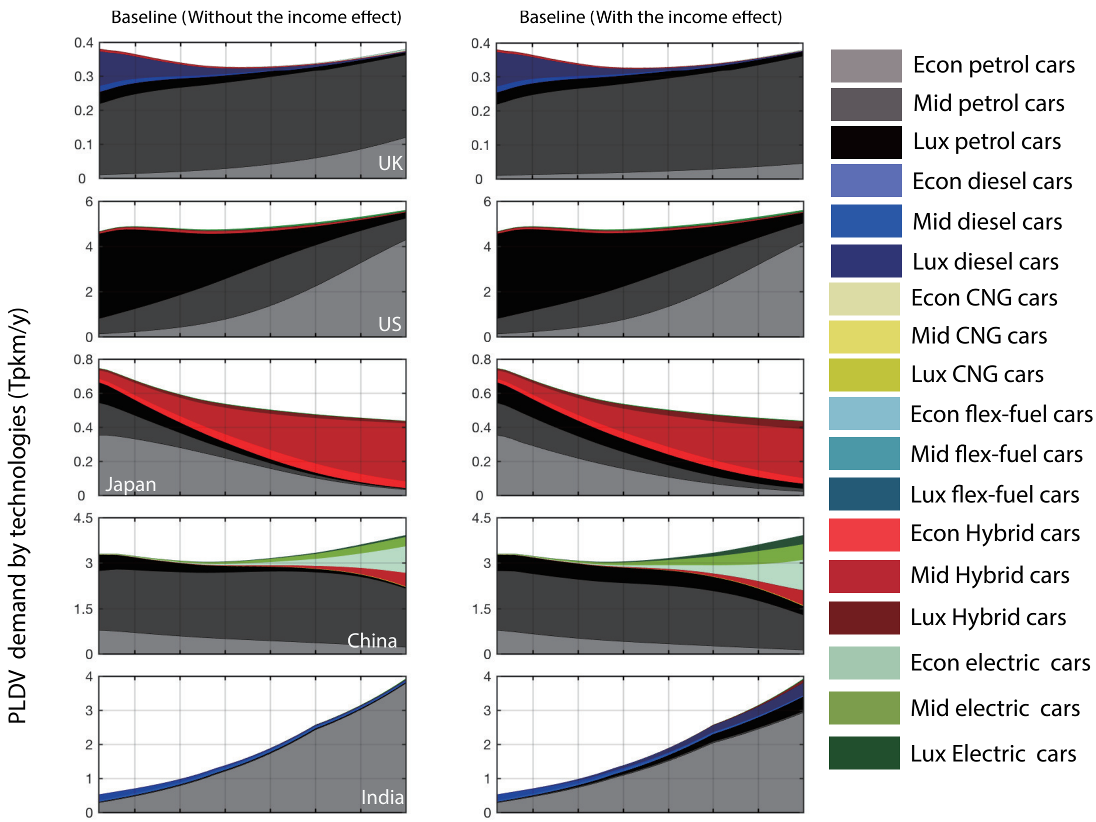

Figure 8.2: PLDV service demand by PLDV energy technologies in Tpkm/year for the five countries, including UK, US, Japan, China and India, with and without the income effect. The first column shows the PLDV technology mix in the baseline scenario and without the income effect. The second column shows the PLDV technology mix in the baseline scenario and with the income effect.

8.5.2 Policy scenarios with the income effect

This section summarises the results we obtained as a result of the income effect, under the same policy scenarios presented in Chapter 7. Table 8.7 shows the emissions from passenger PLDVs under the registration tax scenario (RT scenario), the EV subsidy scenario (EV sub scenario), the fuel tax scenario (FT scenario), the EV mandate and the fuel economy regulation (FE regulation).

Overall, in the UK, the US, Japan and India, we find that EV subsidy and EV mandate are weaker in counteracting the income effect as compared with the annual registration tax, fuel tax and fuel economy regulation. We notice that the effect of EV subsidies on emissions varies between countries, depending on the shares of EVs as a result of the subsidies. For countries with very small EV shares after the introduction of EV subsidy, such as the UK, the US, Japan and India, we find a weak effect of the EV subsidy compared with the income effect, which means consumers' preference for PLDVs does not change significantly before or after the introduction of the EV subsidy in the presence of the income effect (i.e. the presence of the EV subsidy makes a small difference to the results in the baseline scenario). Hence, as incomes rise, the subsidy will have to become larger or more expensive to maintain the same effectiveness.

Similarly, because the fuel tax by itself has a very small effect on the diffusion of car technologies, we find that fuel tax has a small effect on emissions and the income effect. Hence, in the presence of the income effect and the fuel tax, we find that total CO_2 emissions are higher in the presence of the income effect compared with the CO_2 emission levels without the income effect (except for China).

For China, we find that, assuming the same level of EV subsidy (high EV sub scenario), CO_2 emissions from PLDVs are lower with the income effect compared to the scenarios without the income effect. Similarly, although the effect of fuel tax is small compared with the income effect, we find that emissions fall further in the presence of the income effect under the fuel tax scenarios in China. As we have discussed in the baseline scenario (Section 8.5.1), according to our model, as income increases, Chinese consumers are more likely to upgrade their PLDVs to Mid/Lux petrol cars or Mid/Lux EVs when the shares for EVs are high. If the real price difference (after adding $DelPr$) between Mid/Lux EVs and small/mid petrol PLDVs becomes smaller as a result of rising income, then it is more likely that consumers choose Mid/Lux EVs when their incomes rise. In particular, the price difference between Econ petrol PLDVs and Mid/Lux EVs falls further when EV subsidy is added. Hence, based on our model, emissions are lower in the presence of the income effect under the EV subsidy scenarios and fuel tax scenarios.

As the EV mandates become stronger, we find that income effect on the total emissions becomes smaller for all countries, but the effect is not significant. For example, we find that while emissions are 3.37% higher as a result of the income effect under a low EV mandate program in India, the emissions from PLDVs as a result of the income effect are less than 3% higher under a high EV mandate programme. Similarly, in the case of Japan, with a very low EV mandate programme, we find that emissions are around 5.3% higher in the presence of the income effect as a result of the diffusion for luxury hybrid PLDVs, and this is 5.2% under a high EV mandate scenario. Although the income effect can be partly absorbed by the EV take off, this is not sufficient to cut emissions below the scenarios without the income effect in all countries except for China. In the case of China, the effect of the EV mandate programme further reinforces the income effect and leads to nearly a 2% emissions reduction below the scenario without the income effect under the high EV mandate scenario.

After the introduction of EV mandates, by model construction, the fleet shares for EVs are higher than the baseline scenario (see model construction for EV mandates in Chapter 7 Section 7.2.2). As we have shown in the baseline scenario (Section 8.5.1), the shares for EVs reach 30% by 2050 in the baseline scenario without the income effect for China. After the introduction of the EV mandates, the shares for EVs increase further to 40% without the income effect. This implies there will be more EV models available in China than elsewhere, and consumers are likely to be less sceptical about EVs (as a result of social influence and the replicator dynamics equation in the FTT-Transport model, see Chapter 3 Section 3.3). Hence, after the introduction of EV mandates, the shares for EVs increase further as a result of the income effect.

Since the effectiveness of the EV mandates is not strong enough to lead to a significant diffusion for EVs (see results in Chapter 7) for all countries except China, this still means that less than 20% of fleet shares are EV by 2050 (see discussions in Chapter 7). When fleet shares for EVs are low, there are likely to be fewer EV models available in the market (than in the countries where fleet shares for EVs are relatively higher) due to the replicator dynamics equation in the FTT-Transport model. We find that EV mandate is not strong enough to reinforce the income effect and lead to an emissions reduction.

In the presence of the registration tax, we notice that the overall income effect is very small on the total emissions, leading to a less than 1% increase in emissions for the UK, the US and Japan. The income effect partly counteracts the presence of the registration tax, and the income effect decreases with increasing tax levels. The effect of the registration tax on the car technological diffusion dominates, and the income effect on car composition is smaller than the effect of the registration tax. Similarly, we find that fuel tax is more effective in mitigating the income effect than the EV subsidy and EV mandate in the UK, US, Japan and India. For example, we find that emissions increase by 1.7% with the income effect in the baseline scenario. Under the high FT scenario, we find that emissions increase by 0.84% for the UK.

We find that the fuel economy regulation is among the most effective measures in counteracting the income effect, especially in countries where there are many petrol and diesel PLDVs. For the US, as a result of the income effect, the emissions from PLDVs increase by only 0.3% in the presence of the stringent regulation, compared to 1.12% without regulation. Similarly, in the case of India, as a result of the income effect, we find that emissions increase by only 0.2% in the presence of the regulation, compared to 3.4% without regulation. This is because while the income effect leads to an increase in the shares for Mid and Lux petrol and diesel PLDVs, the phase-out regulations improve the fuel economy of the Mid and Lux petrol and diesel PLDVs.

Although the presence of the phase-out regulation reduces the emissions caused by the income effect, the overall emissions as a result of the income effect and in the presence of regulations are still higher than the scenarios without the income effect and with 'stringent regulation scenario (see Table 8.8). This is because while regulations force consumers to adopt a more efficient technology (e.g. a more efficient petrol PLDVs), this is not sufficient to overcompensate for the emissions generated by the luxury models of the technologies as a result of the income effect.

The effectiveness of the policy incentives in mitigating the income effect depends on the income projections, although we have only considered one income scenario (SSP1), to be consistent with our approach in Chapter 7. In reality, it is possible to see higher income rises than projected. When there is a higher income scenario, we are likely to find that more Lux PLDVs are bought in all countries. If the choice for low emissions vehicles (such as EVs) remains limited, we are likely to find that emissions increase further because of the income effect. If there are many EV models available, consumers are more likely to find an EV model that matches their preferences. When income rises further, some consumers may choose Lux EV models over Lux petrol models, especially when the real price difference between

Econ petrol PLDVs and Lux EVs becomes smaller.

Table 8.7: Cumulative CO_2 emissions ($MtCO_2$) under the baseline scenario, the annual RT scenarios, EV subsidy scenarios, fuel tax scenarios and fuel economy regulation scenarios, with the income effect.

With the income effect	UK	US	Japan	China	India
Registration tax					
Baseline	1472	29874	1961	16126	8819
Current RT	1389	27559	1838	15004	8490
High RT	1389	27559	1838	14959	8490
Very high RT	1362	28264	1838	14919	8488
EV subsidy					
Baseline	1472	29874	1961	16126	8819
Current EV sub	1462	29712	1956	15301	8812
High high EV sub	1448	29647	1954	15074	8808
Very high EV sub	1442	29540	1952	14987	8806
Fuel tax					
Baseline	1472	29874	1961	16126	8819
Current FT	1431	29676	1888	15882	8614
High FT	1417	28589	1860	15728	8477
Very high FT	1406	29518	1831	15573	8343
EV mandate					
Baseline	1472	29874	1961	16126	8819
Current EV mandate	1458	29775	1956	15824	8689
EV mandate low	1440	29713	1952	15612	8674
EV mandate high	1424	29609	1948	15398	8452
Fuel economy regulations					
Baseline	1472	29874	1961	16126	8819
Current regulation scenario	1329	28287	1846	13770	8204
Stringent regulation scenario	1292	27461	1819	13157	7896

Table 8.8: Change in cumulative CO_2 emissions ($MtCO_2$) under the baseline scenario, the annual RT scenarios, EV subsidy scenarios, fuel tax scenarios and fuel economy regulation scenarios, with the income effect.

Without the income effect	UK	US	Japan	China	India
Registration tax					
Baseline	1.71%	1.12%	5.29%	-1.35%	3.37%
Current RT	0.34%	0.46%	0.55%	-1.86%	1.52%
High RT	0.34%	0.46%	0.54%	-1.89%	1.52%
Very high RT	0.30%	0.46%	0.54%	-2.15%	1.49%
EV subsidy					
Baseline	1.71%	1.12%	5.29%	-1.35%	3.37%
Current EV sub	1.71%	1.09%	5.17%	-1.95%	3.36%
High high EV sub	1.63%	1.08%	5.12%	-2.32%	3.35%
Very high EV sub	1.57%	1.08%	5.11%	-2.57%	3.34%
Fuel tax					
Baseline	1.71%	1.12%	5.29%	-1.35%	3.37%
Current FT	1.06%	0.88%	4.33%	-1.39%	3.33%
High FT	0.82%	0.84%	3.79%	-1.41%	2.49%
Very high FT	0.84%	0.67%	3.31%	-1.48%	1.76%
EV mandate					
Baseline	1.71%	1.12%	5.29%	-1.35%	3.37%
Current EV mandate	1.62%	1.12%	5.27%	-1.38%	3.34%
EV mandate low	1.22%	1.12%	5.25%	-1.75%	3.04%
EV mandate high	0.92%	1.11%	5.23%	-1.81%	2.88%
Fuel economy regulations					
Baseline	1.71%	1.12%	5.29%	-1.35%	3.37%
Current regulation	0.96%	0.67%	4.84%	-2.74%	0.43%
Stringent regulation	0.42%	0.30%	4.10%	-2.92%	0.18%

8.6 Discussion

This section examines the income effect on PLDV technological diffusion and emissions using the FTT-Transport model. We conclude three main findings from this chapter. Firstly, although rising income has a noticeable effect on emissions, the effect is not large. The income effect at most cancels that of existing policies. The size of the income effect mainly depends on the economic development and fleet size structure/distribution of a country.

Secondly, the income effect can lead to increases or decreases of emissions depending on the availability of luxury low-carbon models in the future. With fast diffusion of EVs, the income effect can reinforce the effect of policies that support the diffusion of EVs. Hence, it is possible for the income effect to reinforce policy incentives. This is because as the shares for EVs and hybrid PLDVs increase, the number of models available in the market increases, and this encourages consumers to purchase the luxury low-carbon models. The policy implication for this is that it will be useful to adopt policy incentives early on encourage the fast diffusion for EVs.

Thirdly, as income rises, we find that it is more likely for consumers to purchase luxury and higher emissions vehicles, and thus counteract the fuel efficiency improvement caused by technological diffusion and fuel economy improvements. Policies can be made more stringent to cancel the effect of rising incomes and reach the same outcomes as without the income effect.

Chapter 9

Conclusion

9.1 Background and motivation

Technology plays a fundamental role in transforming the energy system in the private light-duty vehicle (PLDV) sector. Technological substitution in the PLDV sector enables the replacement of existing technologies with more efficient, lower emissions technologies. Determined by technological development, consumers' choices and social institutions, the rate of technological transitions in the PLDV sector is the key to significant emissions reduction in the transportation sector. Although some technologies have become widely available, there is a strong path dependence in the transition of passenger technological systems due to the stability of current automotive systems and the dominance of internal combustion engine technology.

Policy interventions are important in the process of technological transitions because many of the new car technologies are still relatively expensive or are perceived to perform poorly compared with incumbent technologies. Policy incentives are essential in influencing consumers' choices through cost reduction (both quantifiable and non-quantifiable costs) and improving the social institutions for niche technologies.

Despite the importance of low emissions technologies in reaching the long-term emissions reduction targets, there is a gap in understanding the carbon emissions reduction effects of various policy instruments. In particular, the interactions between policy instruments and their effects on the diffusion of low emissions vehicles have not been studied in detail.

We developed a model of technological change for the PLDVs termed the Future Technology Transformation (FTT)-Transport model. This model describes the competition between various car technologies with the Lotka-Volterra competition (LVC) equations. This approach emphasises the importance of path dependence in the process of technological transitions as a useful tool for understanding the dynamic structure of transitions pathways.

Using the FTT-Transport model, in this thesis, we run a number of scenario analyses to determine the effectiveness and efficiency of five policy instruments (annual vehicle registration tax, EV subsidies, fuel tax, the EV mandate programme and the fuel economy standards) at different levels on the emissions of private PLDVs in the UK, the US, Japan, China and India. By studying the interactions among any two policy instruments, we analyse both trade-off and reinforcement effects between policies in different countries. The analysis provides useful insights for policymakers regarding how policies should be designed and combined to maximise the effectiveness and efficiency of the policy instruments in reducing emissions reductions from passenger cars.

In this chapter, we summarise the main findings of the thesis and the policy implications of this research. We also discuss the limitations of this thesis and highlight areas for further study.

9.2 Key research questions

In this thesis, we built a simulation model of technological change for PLDVs (FTT-Transport model) for five major countries: the UK, the US, Japan, China and India. The FTT-Transport model was built using the FTT framework. It utilises a dynamic set of coupled logistic equations, similar to replicator dynamics and LVC equations, that are used here to represent market competition and technological transition in the diffusion of low emissions PLDVs. The demand for PLDV transport services is estimated with regressions for each country and coupled with the FTT-Transport model to calculate the emissions from the PLDVs.

Using the FTT-Transport model, we conduct a number of scenario analyses with five key policies in the UK, US, Japan, China and India, including annual registration tax, fuel tax, EV subsidy, fuel economy regulations and the EV mandate programme for each country, to address four key research questions:

1) How will each of these policy measures at different levels impact the diffusion of various private PLDV technologies and emissions from the PLDVs in the UK, US, Japan, China and India?

2) What is the cost for each policy incentive at different levels of stringencies, and how does the efficiency for each policy instrument vary as it becomes more stringent?

3) Are there trade-off or reinforcement effects between any two policy instruments on the diffusion of private PLDVs in each of the five countries?

4) How will the changes in income impact the effectiveness of the individual policy instruments for reducing emissions from private PLDVs?

9.3 Key research findings

9.3.1 Scenario analysis without the income effect

Impact of policy incentives in the five countries

This section discusses the results and impact of individual policy incentives on PLDV technological diffusion at different levels and summarises the impact of these policies in different countries. Given that policy relevance is defined at the country level, in this section, we will discuss the meaning of the findings in the context of each country.

In the UK, many tax signals and incentives (e.g. annual registration tax) are now directly linked to vehicle emissions and fuel type. However, comparatively, the shares for EVs and hybrid cars remain low in the UK (less than 10% fleet shares in 2016). Overall, based on the FTT-Transport model, we find that the current tax levels are ineffective in reducing emissions significantly should these policies be introduced individually. We find that when used on their own, the annual registration tax is comparatively more effective than other policy incentives (e.g. fuel tax or EV subsidies) for the UK and leads to the further diffusion of hybrid cars (more than 40% hybrid cars diffusion), assuming that the annual registration taxes for petrol and diesel cars are twice the current levels. This difference is due to the structure of the annual registration tax in the UK, where owners of hybrid cars pay approximately 50% of the annual registration tax in the UK.

In the US, the fleet is dominated by large petrol engine PLDVs. The current fuel tax in the US is among the lowest in the world. Hence, based on the FTT-Transport model, among the financial incentives, we find that the current fuel tax is the least effective policy incentive in the US, due to the low (current) fuel tax levels there. We find that fuel economy regulation is one of the most effective policy incentives in the US, with cumulative emissions falling by nearly 6% in the US, assuming the current fuel economy regulation. This reduction is because there are a large number of large engine PLDVs and emissions are reduced significantly when there is a shift from conventional luxury vehicles to more fuel efficient vehicles in the US.

Japan has one of the highest hybrid shares among all countries, and its fuel tax is also the highest among the five countries in this study. We therefore find that the fuel tax is a comparatively more effective financial incentive in Japan, leading to 2.8% cumulative emissions reductions, under the baseline fuel tax scenario. This difference is due to the baseline fuel tax level in Japan being higher than in other countries in this study. On the other hand, we find that fuel economy standards that phase out conventional petrol and diesel cars are the least effective policy incentives because in the baseline scenario, Japan is the only country with very low petrol car fleet shares by 2050, due to large shares of hybrid cars projected.

China leads the EV market and has the highest EV fleet shares among the five countries. We find that fuel economy regulation has comparatively more effective policy incentives in reducing CO_2 emissions in China. We determine that the phase-out regulations not only encourage the diffusion of advanced petrol cars but also promote shifts from conventional petrol cars to EVs because the price difference between the advanced petrol cars and EVs is smaller and the initial EV shares are higher in China. If the EV subsidy levels are twice the current levels, EV subsidies increase the shares for EVs from approximately 35% in the baseline scenario to more than 60% in 2050, leading to nearly 6% cumulative emissions reductions in 2050. The effectiveness of EV mandates is higher in China than other countries because China has the highest EV fleet shares (among the five countries), and car sales as a proportion of the total car fleet are much larger in developing countries, where the car ownership rates are smaller and many consumers are first-time car buyers (i.e. decision-making is more frequent).

Compared with other countries, there are very few EVs and hybrid cars in India. Among the five countries, the current policies (i.e. taxes and EV subsidies) that encourage low emissions PLDVs are the weakest in India. When policies are introduced alone, we find that EV mandates are among the most effective policy incentives in India. We determine that the financial incentives (e.g. EV subsidy, annual registration tax and fuel tax) are ineffective in encouraging the diffusions of low emissions vehicles in India, leading to a less than 1% emissions reduction under the current policy scenarios there. As a result of the replicator dynamics equation, when the fleet shares for a technology are low, there are fewer models in the market, and consumers are more reluctant to choose a technology that is not common (see Chapter 3 Section 3.3.2 for explanations). When the fleet shares for EVs are very low (less than 0.1%), financial incentives such as EV subsidies are ineffective in encouraging the fast diffusion of EVs because the rates of technological diffusions increase as the fleet shares for the technology increase, based on the replicator dynamics equation in the FTT-Transport model (see Chapter 3 Section 3.3).

To summarise, the effectiveness of policy incentives varies between countries, depending on the levels of the incentives, structure of the incentives and current market shares for certain PLDV technologies (e.g. the shares for hybrid cars or EVs). Financial incentives are more effective in countries where the levels of incentives are high and the shares for niche technologies (e.g. EVs or hybrid cars) are relatively high. Fuel economy regulation is more effective in countries where, on average, engine sizes for conventional cars are large. When the shares for niche technologies are low, based on the replicator dynamics equation in the FTT-Transport model (see Chapter 3 Section 3.3), the rates of diffusion for the niche technologies will remain low unless some parties (e.g. government, consumers or manufacturers) kick-start the market by buying/selling certain numbers of EVs.

In reality, there is always more than one policy in place, and using combinations of policies is likely to have implications on our results. Hence, we will discuss the interactions between policy incentives in each country and their implications.

Policy interactions

We examine the interactions between policy incentives by analysing both trade-off and reinforcement effects between any pair of policy instruments. We created ten scenarios, consisting of all possible pairs of policy combinations of the five policy incentives.

Overall, we find that there is a trade-off effect with one another with all the financial incentives because such incentives are charged based on fuel economy (e.g. fuel tax) or engine size (e.g. annual registration tax). If consumers are incentivised to buy more energy-efficient vehicles due to one of the incentives, then the effectiveness of the pairing incentives will be lower because the total cost (of taxation) for consumers of more efficient cars is smaller than the total cost for consumers of less efficient cars. Hence, the existence of one incentive weakens the overall financial incentives of another policy.

On the other hand, there is a reinforcement effect between the EV mandate programme and all the other policy incentives. This happens because, based on the replicator dynamics equation (see definitions in Chapter 3 Section 3.3), the EV adoption rate increases with the initial EV shares. When there are more EVs around, there is more choice for consumers, which improves the effectiveness of taxes on emissions in comparison with situations in which there is less choice.

The size of the reinforcement effect depends on countries. For example, in the case of the US and China, the reinforcement effect is the largest when the annual registration tax is combined with the EV mandate. There is also a strong reinforcement effect between the EV mandate and fuel economy regulations in China and the US. For the UK and India, the largest reinforcement effect can also be found between EV mandate and fuel economy regulation. For Japan, there is a relatively large reinforcement effect between the EV mandate and fuel tax.

The cost of policy incentives

While it is important to have an effective policy framework that reduces emissions significantly, a policy needs to be cost efficient to be feasible. Among all policy incentives, the annual registration tax is one of the most expensive. The cumulative annual registration tax costs US car owners around 185 billion USD per year and 30 billion USD per year for Japanese car owners under the 'high RT scenario'. For all countries, we find that efficiencies fall when the annual registration tax and EV subsidy become stricter (i.e. cost per ton CO_2 reductions increases as the tax levels increase). For other policies, such as fuel tax and EV mandates, we find that the efficiencies of policies could either increase or decrease as policies become more stringent. For all countries, we determined that the efficiencies of the EV subsidy and EV mandate are higher than the annual registration tax. This result is particularly the case in countries where the fleet shares for EVs are already relatively higher than for other countries. When policies are introduced alone, compared with other policy incentives, we find that fuel economy regulations are among the most efficient because, based on our calculations (see methodology in Chapter 7 for details), the fuel economy regulations cost less than 10 USD/tCO_2 emission reductions for all countries.

In most cases, combinations of two policies lead to higher efficiencies than when the less efficient policy is introduced independently. In particular, among all the two-policy combinations, we find that the efficiencies are the highest when the EV mandate is combined with fuel economy regulations, costing less than 30 USD/tCO_2

for the US and China. In reality, there are always more than two policies in place. The efficiencies for the policy combinations depend on the interactions (i.e. trade-off or reinforcement effects) between policy incentives and their costs. We are likely to find efficient policy combinations when two policies are reinforced and the costs for the policy incentives are relatively low.

These findings imply that there is a large range of abatement costs for CO_2 emissions reductions from PLDV, depending on the policy instruments, levels of policy instruments and numbers of EVs in individual countries. This large range is because in reality, a large number of policy initiatives is taken to reduce emissions from PLDVs and encourage the diffusion of low emissions vehicles. Each policy and combination of policies will bear different costs and effectiveness as a result of the structure and goal of the policies.

It is difficult to compare the costs of abatement found in this study with other modelling groups. The difference is that in this study, we calculate the costs of abatements based on instruments and countries, while other studies calculate the emissions achieved by certain carbon prices (although a carbon tax has rarely existed in the PLDV sector at a regional or global level).

For example, in the MESSAGE model, at 50 USD/tCO_2, it is possible to reduce the cumulative emissions by 2.5 $GtCO_2$ (2010-2050) globally. In our study, the relationship between carbon price incentives and cumulative emissions depends on the instruments we take and how the instruments/combinations of instruments are implemented. For example, it is possible to achieve 2.5 $GtCO_2$ emissions reductions in the US with a cost equivalent 3200 USD/tCO_2 using the annual registration tax (at twice the current levels) and fuel tax (at twice the current levels). It is also possible, however, to achieve 2.5 Gt CO_2 emissions reductions with a cost equivalent to 26 USD/tCO_2 based on fuel economy regulations.

The difference in the costs of abatement arises from the difference in the rates of technology adoptions as a result of various policy incentives. For example, we find that fuel economy regulations are more efficient in reducing emissions than the annual registration tax in many countries. This is because while people may respond to the annual registration tax differently (e.g. some car buyers may be less sensitive to the annual registration levels than others), the phase-out regulation essentially prevents all consumers from buying higher emissions models.

Overall, policy incentives have different effectiveness and efficiency as a result of the market fleet distributions and their stringency and structure (see section 9.3.1). While existing studies/models tend to focus on pricing externalities and policy optimisation, this study takes real instruments and tests the effectiveness and efficiency of these instruments on the dynamic change of PLDV technologies and CO_2 emissions reductions.

Note that our finding does not imply that policy-makers should simply choose one policy over another for cost benefit; the efficiency of policy incentives may fall as policy incentives become more stringent. We may find that it is not cost-efficient to increase certain taxes (e.g. annual registration tax) for some countries without altering the tax structure or combining incentives with other policy incentives. In addition, policies exist for other purposes (besides CO_2 emissions reductions), such as financing road infrastructure. This research suggests that policy-makers should assess the cost of the policies and efficiencies of policy incentives based on the structure of the PLDV market and the effectiveness of policy incentives for the individual countries.

9.3.2 Scenario analysis with income effect

In this thesis, we perform a series of regression analyses and find a positive relationship between income changes and the prices consumers are willing to pay for cars. Because higher prices tend to be associated with more powerful vehicles with higher emissions (Mercure and Lam, 2015), this association implies that as income rises, an income effect on vehicle prices would cancel or partially cancel the effects of policies for decarbonisation. In this study, we perform a series of scenario analyses that assume the presence of the income effect. We find that although rising income has a noticeable effect on emissions, the effect is small (i.e. less than 5% emissions increase as a result of the income effect). The income effect affects consumers' choices differently in each of the countries, depending on the rate of income increases, the distribution of car engine sizes in the market and the market shares for low emissions vehicles.

In the case of China, we find that overall emissions from PLDVs fall as income rises. Although the shares for Lux petrol cars increase in the presence of the income effect, we find there is an increase in the shares for Mid EVs and Lux EVs in China. As income increases, the total market shares for EVs increase by 10%, from around 30% to 40%. According to our model, this happens in China because the EV fleet shares are relatively higher in China compared to other countries. According to the model of technological diffusion and the replicator dynamics equation in the FTT-Transport model, when EV fleet shares become larger and more models of

EVs are available, consumers are more likely to upgrade their Econ/Mid petrol cars to Mid/Lux EVs than countries where there are very few EV models in the market. We find that the income effect leads to further emissions reductions, compared with the scenario without the income effect, under the same policy incentives. Hence, with fast diffusion of EVs, the income effect can reinforce the effect of policies that support the diffusion of EVs. This result implies that it is possible for other countries to achieve further emissions reductions as a result of income increase as the shares for EVs increase.

For the UK and the US, we determine that including the income effect in the model does not increase emissions significantly for two reasons. Firstly, in the US and the UK, the rate of income rise has been slow compared with developing countries, and thus the income effect for the UK and the US is weaker. In this case, the preference shifts between technology categories will not be significant after including the income effect. Secondly, in the case of the US, because people already own luxury cars according to the classification in the FFT-Transport model, an increase in incomes will not lead to further upgrades of engine sizes [1].

Then, assuming the presence of the income effect, we test the same scenario assumptions as in the scenarios without the income effect and tested three different levels of the annual registration tax, fuel tax, EV subsidy, EV mandate programme and phase-out regulation. We examine how the income effect cancels out the effectiveness of policy incentives. Overall, as income rises, we find it is more likely for consumers to purchase luxury (and thus higher emissions) vehicles and counteract the fuel efficiency improvement caused by technological diffusion and fuel economy improvements. Policies can be made more stringent to cancel out the effect of rising incomes and reach the same outcomes as without the income effect.

9.4 Policy implications

9.4.1 Individual incentives

For the UK, we find that the annual registration tax needs to be twice the current levels (high RT scenario) to allow a 40% diffusion of hybrid cars and reduce the cumulative emissions by around 7%. The reason is that there is a financial incentive to purchase hybrid cars, given that owners of hybrid cars pay approximately 50% of

[1]Note that this is a model artefact, but we continue to use this because the US is the only country to have such large engines on average.

annual registration tax in the UK. In addition, we determine that the current EV subsidy level in the UK leads to less than 5% EV fleet by 2050 and only results in less than 1% cumulative emissions reduction (taking into account the indirect emissions from EVs). It may be more effective to strengthen the EV subsidy in the UK and introduce fuel economy regulations that gradually phase out both conventional and hybrid cars.

We also find that in the US, some tax incentives such as the current EV subsidy and current fuel tax are too low to cut emissions significantly (they reduce cumulative emissions by less than 2%). Among all the policy incentives, we observe that the fuel economy regulation is the most effective policy incentive because it encourages the uptake of more efficient models, given that consumers prefer larger engines and higher emissions cars in the US. The policy implication is that it is useful to improve the fuel economy regulations further in the future for the US.

In the case of Japan, to reduce emissions further, it is beneficial to improve the fuel economy regulations further and to phase out hybrid cars gradually to encourage the further diffusion of zero emissions vehicles (e.g. fuel cell cars or EV) in Japan. As income rises, we find that the fuel economy regulations are the most effective policy incentives in mitigating the income effect that leads to the increase in the shares for luxury hybrid cars in Japan.

We note that current policy incentives such as EV mandates and EV subsidies are more effective in China than in other countries for two reasons. Firstly, there are already more EVs in China due to some existing policies (e.g. EV license plate allowances). When there are more EV models available in the market, we expect people will be more likely to choose EVs given the same policy incentives, as a result of the replicators dynamics equations in the FTT-Transport model (see Chapter 3 Section 3.3). Secondly, there are many first-time car buyers, and therefore the current turnover rates (or average lifetimes) across the country are lower in China than in the UK or the US (see assumptions in Chapter 4). However, as income rises and more people start to own a car, the average turnover rates in China may increase. Hence, it may be useful to introduce a scrappage policy to incentivise people to upgrade their old cars for new car models.

For India, we find that current policy incentives, such as the EV subsidy and annual registration tax, are too weak to significantly cut emissions from PLDVs in India. This is because the EV fleet shares in India are currently very low (less than 10,000 PLDVs). We find that the most effective policy incentive in India is the EV mandate, although this policy does not exist in India.

In reality, in no country would policy-makers use only one policy instrument. Hence, it is important to understand the interactions between policy instruments and their policy implications, an issue that is discussed in the next section.

9.4.2 Policy interactions

Overall, we determine that while the EV mandate is not always the most effective policy incentive to cut emissions significantly when it is introduced individually, there is a reinforcement effect between EV mandate and financial incentives (e.g. fuel tax, EV subsidy, annual registration tax). Therefore, it is more efficient to introduce financial incentives with the EV mandate (i.e. there is a reinforcement effect). To increase the effectiveness of financial incentives, it is useful to introduce regulatory measures that increase the number of EVs on the road (and hence EV models available and infrastructure), due to the reinforcement effect between the financial incentives and the EV mandate. As the number of EVs on road increases, it is possible to achieve further emissions reduction as income rises.

On the other hand, the government should consider the trade-off effect, which weakens the overall effectiveness of the policy combinations. Our analysis suggests that more stringent financial incentives have to be introduced to compensate for the trade-off effect between policy incentives.

9.5 Limitations

This section discusses the main limitations of this research and how these limitations are mitigated or tested.

In this research, we have identified the available technologies, although new technologies will emerge in the future. However, it is impossible for this model to predict technologies that have not penetrated the market. In addition, the data for the costs of new energy technologies (such as fuel cell cars) are not readily available, and we can only model what already exists in the market.

Hence, we have not considered fuel cell cars in the model, largely because in 2016 (the starting year), there were very few such cars in any of the global regions. As technologies continue to improve, there will be next-generation cars in the next 30 years. However, as a result of strong path dependence and turnover rates, car technologies usually take a relatively long period of time to penetrate the market and replace the old generation technologies. Therefore, it is less likely that niche technologies that are radically different from existing car technologies will penetrate the market quickly and gain significant market shares by 2050.

Similar to other energy models, there are parametric uncertainties regarding the FTT-Transport model. In Appendix A , with sensitivity analysis, we test the uncertainties about the learning rate, discount rate and oil prices. The model is more sensitive to variations in learning and turnover rate parameters in the countries with different alternative technologies than countries where there are dominant technologies. However, typically, changes in model outcomes induced by individual parametric variations are smaller than five times the original variations in the parameters.

For new cars, the fuel consumption factor is obtained from the car manufacturers. However, it is possible that we underestimate the true fuel use or emissions. Firstly, the fuel use factors we have taken from the car manufacturers may not accurately reflect the fuel consumption in reality. Secondly, it is challenging to estimate the emissions from older car models. Thirdly, the on-road fuel use and emissions from PLDVs depend on a number of other factors, such as driving speed and road type.

In finding how the income effect impacts the total CO_2 emissions from PLDVs, we translate how average income changes translate into changes of willingness to pay for different sizes of PLDVs. However, there have been significant challenges in determining how income changes affect the willingness to pay for particular engine sizes and PLDV technologies. We use the A parameter to convert the average price changes to price changes for individual engine sizes of particular technologies. We find the A parameters by imposing hypothetical price changes for individual technologies and observing the model response. Although this methodology is the best we could find to convert the average price (that consumers are willing to pay) to prices of individual technologies, A values may change over time, particularly when the PLDV technological composition changes significantly over time as a result of policy incentives.

Last, future research can improve the FTT-Transport model with respect to the following areas. It is useful to include more policy instruments (e.g. parking fees, congestion charges) to reflect the spectrum of policy incentives in the real world. By expanding our study to more countries, we may be able to learn lessons from the success and failure of policies in different contexts. Future studies could improve the model by regularly updating this model and its parameters. For example, the model could include new PLDV technologies when they emerge and update their costs and fleet shares.

9.6 Further study - other transportation technologies

This thesis analyses the impact of policy incentives on the future emissions of private PLDVs, while decarbonisation options exist on many different levels, including modal shifts from travel modes with high carbon intensity such as aviation or private vehicles to transportation with lower carbon intensity buses, trains or ships. Even though this PhD thesis does not examine the impact of modal shifts on the PLDV vehicle kilometres travelled per year, this is an important subject of future research.

Within the passenger transport sector, the aviation sector has experienced rapid growth as the world economy expands, moving more than three billions. Some studies suggest that CO_2 emissions in the civil aviation section are likely to experience a three-fold increase between 2000 and 2050 (Horton and Britain, 2006; Berghof et al., 2005).

As technologically autonomous vehicles evolve, future research should take into account the extent to which autonomous vehicles could impact passenger transport demand, congestion and travel behaviour. The shift from privately owned passenger vehicles to a shared-use system with some degree of automation may decrease energy use and emissions through travel route optimisation, although there are still large uncertainties because autonomous vehicles could induce travel demand and attract new user groups (Wadud et al., 2016). Car sharing allows more passengers to be carried by each vehicle and thus improves the utilisation factors compared to private vehicles. This advantage encourages investment in high capital cost and more fuel efficient technologies that offer lower operating costs per mile (Wadud et al., 2016).

Although freight transport is outside the scope of this thesis, the significance of freight energy demand and CO_2 emissions within the transport sector has been growing steadily (Eom et al., 2012). In contrast to passenger transport, freight transport is shaped by the logistics of production and consumptions, linked to the growth of the economy and trading between regions (Onstein et al., 2018). Within the freight transport area, truck and the road transport have the largest shares in many developed countries. In the EU, road transport accounted for over three-quarters (76.4 %) of total inland freight transport (EC, 2019). In the US, 60% of goods were transported by truck in 2015, compared with 18% by pipelines and 9% by rail. The specific energy efficiency of heavy-duty trucks has improved slightly, but road transport still consumes significantly more energy per tonne-kilometre (tkm) than rail or ship freight transport (Eom et al., 2012). In contrast to road passenger transport, heavy-duty trucks are more difficult to electrify, particularly long-haul trucks.

Globalization and the movement of goods across countries involve roads, railways, inland waterways, and ocean and coastal routes. As a complement to other modes of transportation, maritime transportation plays an important role in international shipping connecting roads, railways, and inland waterways through ocean and coastal route (Eyring et al., 2010). Maritime transportation is often seen as a complement or a substitute to other modes of freight transport. Globally, maritime transport emits around 1,000 million tonnes of CO_2 annually and is responsible for about 2.5% global GHG. Although this is not the largest sector in terms of transport emissions, the emissions are predicted to increase between 50% and 250% by 2050 (Tavasszy and De Jong, 2013).

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Appendix A

Sensitivity analysis

Like other dynamical models, there are a number of parametric uncertainties for the FTT-Transport model. If we take into consideration the possible consequences of these assumptions, we have to analyse the effect of potential changes of starting values on the final results by a sensitivity analysis. The sensitivity analysis provides insight into the effects of uncertainties on our projections.

We carried out a sensitivity analysis of responses of the model to the most important parameters of the FTT: Transport under the baseline scenario assumptions, the high RT scenario assumptions, the high EV subsidy scenario assumptions, the high fuel tax scenario assumptions, the high EV mandate assumptions and the scenario with fuel economy regulations (see assumptions in Chapter 7). The scenarios with the most stringent policy incentives were chosen to carry out the sensitivity analysis, for exploratory purpose. Although we could, in principle, carry out a sensitivity analysis for all scenarios, but this would not improve the amount of insight in comparison with the tables given here.

A.1 Choice of parameters for the sensitivity analysis

It is important to analyse model responses to variations in key parameters, so that the model is not highly sensitive to very specific values for any particular parameter. We chose the parameters that would generate the most changes in emissions and technological shares. This includes parameters that change the prices/attractiveness for PLDV (e.g. learning rates, EV prices, discount rates, fuel costs), technical parameters (turnover rates, A values) and non-pecuniary costs (e.g. γ values). The sensitivity analysis is carried out for each country because the aim of the sensitivity analysis is to examine how changes in parameters would affect the projection results in the previous chapters of this thesis.

The parameters varied here are as follows:

1. Learning rates for the EVs. We did not vary the learning rate for conventional petrol and diesel cars because the learning for the mature technologies is insignificant [1];

2. Consumer discount rates; (equal for all vehicle types);

3. The price of electric vehicles;

4. γ values for all vehicle types;

5. The rate of vehicle purchase (turnover rate); turnover rates here mean the rate of acquisition of new vehicle.

6. Oil prices; this affects both the attractiveness of the technologies and the demand for transportation in the passenger car sector.

7. $A_{i,k}$ values (see Chapter 8 for definition); this affects how the change in the average willingness to pay for cars is related to a per unit of change in willingness to pay for cars of individual engine technologies, as a result of the income effect.

We varied 20 parameters by quantities we consider representative of uncertainty, according to existing literature and historical data. For example, the range of learning rates were considered based on Nykvist and Nilsson (2015); Weiss et al. (2012). We have assumed a low EV learning rate scenario (assumed 5% learning rate) and a high EV learning rate (assumed 15% learning rate) scenario (previously, we assumed the learning rate for EV is 10%). We have tested the uncertainties regarding the EV prices (10% uncertainty). Following EC (2012), we have tested a low discount rate scenario (5% consumer discount rate) and a high consumer discount rate scenario (25% discount rate) against the baseline scenario where we have taken a 15% discount rate (previously, we assumed the discount rate is 15%).

The γ values are derived from the historical trends of technological diffusion (see definitions for γ values in Chapter 3). However, the fitting of γ values are only

[1] Conventional vehicles do not have learning cost reductions because their cumulative production numbers are large.

accurate to a certain extent, which we estimate at between 5% to 20%, depending on the availability of historical data (e.g. EVs have less historical data than petrol cars). In the sensitivity analysis, we vary the γ values by 10% for every car technology to explore the effect of uncertainties in γ values on the final projections. In principle, γ values are constants derived from historical data; we do not expect large uncertainties with the γ values. Note that it is nonsensical or violates the model if we vary the γ values too much (i.e. above 10%). For example, if we vary the γ values by 30%, then we will find that the diffusion trajectory is no longer consistent with the historical trends, and this violates the assumptions that γ values are derived (see Chapter 3 Section 3.4.2 for more information).

The turnover rates represent the rate of acquisition of new vehicles, i.e. the rate of decision-making. In developed countries, the more often people change a new car, the higher the turnover rate and the younger the average fleet age. The rates of acquisition vary between car owners, related to their incomes, car loans, reliability and quality. Here, we tested the scenarios when the turnover rates are 20% and 50% higher than the baseline scenario.

The fluctuations of oil prices have a significant effect on the efficiency of cars purchased by consumers and the distance travelled by cars over time. As we have discussed in Chapter 3, in the FTT-Transport model, oil prices affect total emissions through the demand equations and through consumer choice over car technologies. We have assumed four oil price scenarios: a very low oil price scenario (50% lower than the 2016 oil price level), a low oil price scenario (20% lower than the current oil price projections), a high oil price scenario (20% higher than the current oil price scenario) and a very high oil price scenario (50% higher than the current oil price scenario). Note that it is possible for the oil prices to fall or increase more than 50% of the current oil price projections. The aim of this analysis is to study the effect of a fluctuation in oil prices on the model projections. The oil price scenarios take into account the oil price uncertainties under the IEA Current Policy Scenario and 450 Scenario (see IEA (2016)).

As discussed in Chapter 8, we defined the $A_{i,k}$ value for each technology category class as the change in average cost per unit of change in individual willingness to pay for cars. We assumed there is a linear relationship between prices for individual car technologies and the average price. To examine whether this will have an effect on the scenario analysis, we took a different $A_{i,k}$ value and implement the new $A_{i,k}$ value within the model. To explore the extent to which this assumption impacts on the total emissions, we varied A value by different amounts (10%, 30% and 50%)

to see how this affects the shift in technological shares and CO_2 emissions.

A.2 Results of the sensitivity analysis

Results of the sensitivity analysis is presented in Table A.1-A.3 (the 'baseline scenario'), A.4-A.6 (the 'high RT scenario'), A.7-A.9 (the 'high EV sub scenario'), A.10-A.12 (the 'high FT scenario'), A.13-A.15 (the 'stringent phase-out scenario') and A.16-A.18 (the 'high EV mandate'). Numbers shown refer to percent changes in a scenario in which a parameter variation is imposed against the corresponding scenario without the variation. Changes in shares are in the year 2050, while changes in emissions are cumulated to 2050. Instead of going through each table, we focus on the parameters and policy scenarios that have the largest impact on the projections (i.e. the parameters that generate the largest uncertainties). It is important to analyse model responses to variations in key parameters to ensure the model is not 'highly sensitive' to very specific values for any particular parameter. As a benchmark, we adopt the definition that a change of X% of CO_2 emissions that results from a parameter variation of Y% is 'small' if X is five times smaller Y and 'large' if X is of the order of Y. This is a reasonable definition because if X% change is larger than Y% parameter variation, then we may see a large propagating uncertainty. However, if we have X% much smaller than Y%, then the output uncertainty is much smaller than the input uncertainty for each parameter. We conclude this analysis with the following broad findings.

Learning rates, EV prices and discount rates tend to have a small impact on the results (i.e. less than 1% changes in emissions as a result of 5%, 10% and 10% variation in learning rates, EV prices and discount rates respective) for most countries. The effects of the learning rates [1] on the scenario analysis is the largest in the countries with the highest market shares of EV, such as China, where a 2% decrease in CO_2 emissions is the result of a 5% variation (higher) in the learning rates parameter in the baseline scenario. The effect of learning rate on emissions increases under the high RT scenario. For example, emissions increase by 4% as a result of 5% variation (lower) in learning rates.

The effect is negligible in the baseline scenario in the countries where there are very few EVs on road (i.e. India), where we find that there is no change in emissions as a result of 5% variation in the learning rates parameter in the baseline scenario.

[1]Note that learning is a process that is assumed global in the FTT-Transport model.

Similarly, we find that the effect of EV price uncertainties are the largest in China, leading to 1% increase in CO_2 emissions as a result of 10% variation in the EV prices in the baseline scenario. On the other hand, in the case of India, we find that there is no change in emissions as a result of 10% variation in the EV prices in the baseline scenario. The effects of learning rates uncertainties increase as policies that encourage EV diffusion are more stringent.

Similarly, for all countries, we find that there is less than 4% change in CO_2 emissions as a result of 20% variation in the γ value in the baseline scenario. As we have expected, changes in γ for one technology mostly affects its own pace of diffusion. Hence, we find that changes in γ values have almost no impact on the emissions projections when the shares for EVs are under 1%. Overall, the relatively low impact of varying the γ parameters is explained by the fact that the model is not sensitive to small changes in pecuniary cost for individual technologies. Since the model has some degree of momentum and inertia in its diffusion trajectories, changes in the costs data creates a change in the trajectory, but not an instantaneous change to the shares.

We find that there is less than 10% change in CO_2 emissions as a result of 50% variation in the oil price in the baseline scenario. The effect of oil prices on car emissions is more significant in China. This is because of two reasons. First, since the average turnover rate in China (average lifetimes of cars) is smaller than the developed countries (see Chapter 4), under the FTT-Transport model, this means that consumers are allow to choose more frequently and thus react to changes in oil price. Second, the higher availability of low emissions vehicles (e.g. EVs) means consumers are more likely to shift to low emissions technologies when there is a change in oil price.

In the baseline scenario, we find that cumulative emissions increase by 11% and 12% increase for Japan and China respectively as a result of 50% variation in the turnover rate parameter in the baseline scenario. In the case of Japan, shares for hybrid cars are 16% lower as a result of 50% variation in the turnover rate parameter. The impact of turnover rate is smaller in the countries where the shares for EV and hybrid cars are smaller in the baseline scenario. For example, for India, we find that there is 1% increase in emissions as a result of 50% variation in the turnover rate parameter. As policies become more stringent, we find that the turnover rates uncertainties have a larger impact on emissions. Among the policy scenarios, we find that the emissions uncertainty is the largest under the high EV mandate scenario, with emissions in China increasing by 19% as a result of a 50%

variation in the turnover rate parameter. This is because the rates of technological transitions for EVs slow down when turnover rates are 50% higher (i.e. consumers make decisions to purchase cars less often).

Assuming the presence of the income effect, for all countries, we find that emissions increase by less than 3% as a result of 50% variations in A parameter in the baseline scenario. This is largely because the income effect has a relatively small impact on emissions and changes of fleet shares. Hence, in the baseline scenario, we find the uncertainty is the smallest in the US where the income effect is generally small, with only around a 1% increase in emissions as a result of 50% variation in A parameter and largest in Japan, leading to a nearly 3% increase in emissions as a result of a 50% of variation in A parameter.

We conclude that the model is more prone to change as a result of variations in EV technological learning rates and turnover rates in China and Japan, under the baseline scenario and the policy scenarios. The model is more sensitive to variations in learning and turnover rate parameters in the countries with different alternative technologies than countries where there are dominant and conventional technologies. The model is less sensitive as a result of variations in the consumer discount rates, γ values, oil prices and A values. Except for China and Japan, where there is at least 30% of EVs and hybrid cars projected, we find that the model is less sensitive to variations in the learning rates and the turnover rates. As technologies for EVs evolve, the improvement in the knowledge of EV battery learning rates will reduce the uncertainties of our results. Note that in the FTT-Transport model, we do not allow varying of the availability of technologies for the following reasons. Altering the existing technologies involves introducing new technologies with small market shares. Hypothetical new technologies with very small shares will take longer than our projection period (until 2050) to diffuse to any significant degree, even if they are low cost and enjoy substantial support from governments, due to the diffusion dynamics in the FTT-Transport model.

Table A.1: Sensitivity analysis on key technological parameters under the baseline scenario (UK and US).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.50	-0.87	-0.03	0.00	0.00	0.90
	Learning rate -5%	0.84	0.49	0.01	0.00	0.00	-0.50
	EV prices +10%	0.08	0.48	0.00	0.00	0.00	-0.48
	EV prices -10%	-0.08	-0.54	0.00	0.00	0.00	0.55
	Turnover rate +20%	2.56	4.12	0.53	0.00	-3.11	-1.55
	Turnover rate + 50%	5.82	7.09	0.68	0.00	-5.32	-2.45
	Discount rate +10%	0.33	0.19	0.00	0.00	-0.09	-0.11
	Discount rate -10%	-0.06	-0.38	0.00	0.00	0.18	0.20
UK	All γ +20%	-0.49	-3.17	0.00	0.00	0.00	3.17
	All γ -20%	0.27	1.33	0.06	0.00	-0.01	-1.38
	EV γ +10%	-0.45	-0.78	0.71	0.00	1.18	-1.10
	EV γ -10%	0.22	0.21	-0.11	0.00	0.23	-0.33
	Hybrid γ +10%	0.19	0.14	0.10	0.00	-0.56	0.32
	Hybrid γ-10%	-0.84	-0.52	-0.11	0.00	1.04	-0.40
	Petrol γ +10%	-0.61	-0.13	0.08	0.00	0.14	-0.10
	Petrol γ -10%	0.52	0.67	0.24	0.00	-0.38	-0.52
	Diesel γ +10%	0.36	-0.03	0.03	0.00	0.08	-0.08
	Diesel γ -10%	-0.31	0.03	-0.03	0.00	-0.07	0.07
	Oil price +20%	-2.58	-0.25	-0.01	0.00	0.45	-0.20
	Oil price +50%	-3.93	-0.67	-0.03	0.00	0.14	0.56
	Oil price -20%	1.03	0.24	0.01	0.00	-0.15	-0.10
	Oil price -50%	3.44	1.04	0.03	0.00	-0.83	-0.24
	A values +10%	1.04	0.10	0.08	0.00	-0.18	0.00
	A values +30%	1.27	0.18	0.10	0.00	-0.28	0.00
	A values +50%	1.89	0.20	0.14	0.00	-0.34	0.00
	Learning rate +5%	-0.54	-0.64	0.00	0.00	0.00	0.64
	Learning rate -5%	0.88	0.79	0.00	0.00	0.00	-0.79
	EV prices +10%	0.16	0.00	0.00	0.00	0.00	0.00
	EV prices -10%	-0.23	-0.70	0.00	0.00	0.00	0.70
	Turnover rate +20%	1.32	1.50	0.00	0.00	-0.01	-1.49
	Turnover rate + 50%	2.93	3.29	0.00	0.00	-0.55	-2.74
	Discount rate +10%	0.14	0.16	0.00	0.00	-0.01	-0.15
	Discount rate -10%	-0.26	-0.40	0.00	0.00	0.13	0.27
US	All γ +20%	-0.69	-1.72	0.00	0.00	0.06	1.66
	All γ -20%	0.73	0.80	0.00	0.00	-0.06	-0.74
	EV γ +10%	-0.24	-1.07	0.00	0.00	0.00	1.08
	EV γ -10%	0.03	0.03	0.00	0.00	-0.03	0.00
	Hybrid γ +10%	-0.04	-0.03	0.00	0.00	0.03	0.00
	Hybrid γ-10%	0.03	0.03	0.00	0.00	-0.03	0.00
	Petrol γ +10%	-0.11	0.14	0.00	0.00	0.00	-0.14
	Petrol γ -10%	0.12	-0.22	0.00	0.00	0.00	0.22
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-3.64	-0.12	0.00	0.00	0.05	0.07
	Oil price +50%	-6.08	-0.37	0.00	0.00	0.08	0.29
	Oil price -20%	3.12	0.13	0.00	0.00	-0.10	-0.03
	Oil price -50%	7.62	0.22	0.00	0.00	-0.01	-0.22
	A values +10%	0.76	0.00	0.00	0.00	0.00	0.00
	A values +30%	0.88	0.00	0.00	0.00	0.00	0.00
	A values +50%	1.31	0.00	0.00	0.00	0.00	0.00

Table A.2: Sensitivity analysis on key technological parameters under the baseline scenario (Japan and China).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
Japan	Learning rate +5%	-0.10	-0.15	0.00	0.00	0.00	0.15
	Learning rate -5%	0.12	0.11	0.00	0.00	0.00	-0.11
	EV prices +10%	0.05	0.04	0.00	0.00	0.17	-0.22
	EV prices -10%	-0.06	-0.04	0.00	0.00	-0.52	0.57
	Turnover rate +20%	5.13	8.47	0.02	0.00	-8.62	0.14
	Turnover rate + 50%	10.87	16.28	0.02	0.00	-16.42	0.12
	Discount rate +10%	0.20	0.22	0.00	0.00	-0.14	-0.08
	Discount rate -10%	-0.14	-0.17	0.00	0.00	0.15	0.02
	All γ +20%	-1.54	-2.40	0.01	0.00	2.40	-0.01
	All γ -20%	4.41	8.34	-0.01	0.00	-8.35	0.02
	EV γ +10%	-0.01	-0.01	0.00	0.00	-0.06	0.07
	EV γ -10%	0.34	0.61	0.00	0.00	-0.71	0.10
	Hybrid γ +10%	-0.29	-0.53	0.00	0.00	0.61	-0.08
	Hybrid γ-10%	0.34	0.61	0.00	0.00	-0.71	0.10
	Petrol γ +10%	-0.80	-1.18	0.01	0.00	1.16	0.02
	Petrol γ -10%	1.18	1.88	0.00	0.00	-1.85	-0.03
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-2.28	-0.02	0.00	0.00	-0.09	0.11
	Oil price +50%	-4.72	-0.05	0.00	0.00	-0.20	0.26
	Oil price -20%	2.76	0.02	0.00	0.00	0.11	-0.13
	Oil price -50%	6.53	0.05	0.00	0.00	0.30	-0.34
	A values +10%	1.86	0.42	0.00	0.00	-0.42	0.00
	A values +30%	2.04	0.55	0.00	0.00	-0.55	0.00
	A values +50%	2.95	1.02	0.00	0.00	-1.02	0.00
China	Learning rate +5%	-2.31	-2.49	-0.20	-0.10	0.00	2.79
	Learning rate -5%	3.41	3.14	0.11	0.00	0.00	-3.25
	EV prices +10%	0.99	4.28	0.00	0.03	0.37	-4.69
	EV prices +10%	-1.10	-4.79	0.00	-0.04	-0.54	5.37
	Turnover rate +20%	6.56	10.79	0.00	-0.08	-2.29	-8.41
	Turnover rate + 50%	11.94	19.70	0.00	-0.01	-2.98	-16.70
	Discount rate +10%	0.62	2.08	0.00	0.01	-0.04	-2.05
	Discount rate -10%	-0.96	-1.73	0.00	-0.02	0.05	1.70
	All γ +20%	-1.18	-4.08	0.00	-0.03	0.45	3.67
	All γ -20%	1.07	4.15	0.00	0.02	-1.01	-3.16
	EV γ +10%	-1.09	-4.80	0.00	-0.04	-0.25	5.08
	EV γ -10%	0.58	0.33	0.00	0.01	-1.32	0.98
	Hybrid γ +10%	-0.03	-0.21	0.00	0.00	0.81	-0.59
	Hybrid γ-10%	0.05	0.33	0.00	0.01	-1.32	0.98
	Petrol γ +10%	0.51	0.76	0.00	0.00	-0.84	0.07
	Petrol γ -10%	-0.46	0.52	0.00	-0.01	-0.02	-0.49
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-5.13	-0.20	0.00	-0.01	-0.02	0.22
	Oil price +50%	-7.00	-0.35	0.00	-0.01	-0.04	0.53
	Oil price -20%	6.42	0.24	0.00	0.01	0.02	-0.24
	Oil price -50%	8.83	0.46	0.00	0.02	0.06	-0.64
	A values +10%	0.40	-0.64	0.00	0.00	0.21	0.43
	A values +30%	0.74	-1.56	0.00	0.00	0.40	1.16
	A values +50%	1.03	-2.40	0.00	0.00	0.96	1.44

Table A.3: Sensitivity analysis on key technological parameters under the baseline scenario (India).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	0.00	0.00	0.00	0.00	0.00	0.00
	Learning rate -5%	0.00	0.00	0.00	0.00	0.00	0.00
	EV prices +10%	0.04	0.21	0.00	0.03	-0.21	-0.21
	EV prices -10%	-0.03	-0.19	0.00	-0.04	0.19	0.19
	Turnover rate +20%	0.44	-1.96	2.96	-0.36	-0.48	-0.16
	Turnover rate + 50%	0.99	-2.43	3.50	-0.18	-0.48	-0.41
	Discount rate +10%	0.22	0.79	-0.59	0.01	-0.10	-0.10
	Discount rate -10%	-0.48	-0.85	-0.54	-0.02	1.24	0.17
India	All γ +20%	-1.49	-2.34	2.12	-0.08	0.15	0.15
	All γ -20%	0.42	0.81	-0.51	0.04	-0.16	-0.19
	EV γ +10%	0.01	0.04	0.00	0.03	-0.04	-0.04
	EV γ -10%	0.01	-0.01	0.00	0.01	0.00	0.00
	Hybrid γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Hybrid γ-10%	0.00	0.00	0.00	0.00	0.00	0.00
	Petrol γ +10%	0.47	0.65	0.76	0.00	-0.75	-0.67
	Petrol γ -10%	-0.27	-0.81	1.05	-0.01	-0.11	-0.11
	Diesel γ +10%	0.12	0.72	-0.51	0.00	0.00	-0.21
	Diesel γ -10%	-0.97	0.20	-0.58	0.00	0.00	0.38
	Oil price +20%	-2.82	-0.24	0.00	0.00	0.11	0.13
	Oil price +50%	-6.48	-0.61	0.00	-0.01	0.28	0.29
	Oil price -20%	1.79	0.26	0.00	0.00	-0.11	-0.14
	Oil price -50%	5.97	0.56	0.00	0.01	-0.29	-0.37
	A values +10%	0.78	-0.94	0.88	0.00	0.06	0.00
	A values +30%	1.44	-2.08	1.70	0.00	0.38	0.00
	A values +50%	2.51	-3.02	2.55	0.00	0.47	0.00

Table A.4: Sensitivity analysis on key technological parameters under the 'high RT' scenario (UK and US).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.48	-1.13	-0.04	0.00	0.00	1.17
	Learning rate -5%	0.90	0.62	0.01	0.00	0.00	-0.63
	EV prices +10%	0.01	0.02	0.00	0.00	0.06	-0.08
	EV prices -10%	-0.01	-0.02	0.00	0.00	-0.05	0.06
	Turnover rate +20%	2.67	4.26	0.61	0.00	-3.25	-1.62
	Turnover rate + 50%	6.09	8.12	0.71	0.00	-6.27	-2.56
	Discount rate +10%	0.27	0.09	0.00	0.00	-0.08	-0.01
	Discount rate -10%	-0.41	-0.16	0.00	0.00	0.15	0.02
UK	All γ +20%	-0.59	0.00	0.00	0.00	0.00	0.00
	All γ -20%	0.66	0.00	0.00	0.00	0.00	0.00
	EV γ +10%	-0.58	-0.34	0.00	0.00	0.03	2.29
	EV γ -10%	0.24	0.25	-0.12	0.00	0.25	-0.36
	Hybrid γ +10%	0.17	0.12	0.09	0.00	-0.49	0.28
	Hybrid γ-10%	-0.74	-0.29	-0.10	0.00	0.74	-0.35
	Petrol γ +10%	-0.68	-0.14	0.12	0.00	0.13	-0.11
	Petrol γ -10%	0.56	0.73	0.26	0.00	-0.42	-0.56
	Diesel γ +10%	0.33	-0.11	0.10	0.00	0.09	-0.09
	Diesel γ -10%	-0.07	0.08	-0.03	0.00	-0.04	-0.01
	Oil price +20%	-2.31	-0.22	-0.03	0.00	0.43	-0.18
	Oil price +50%	-3.53	-0.60	-0.03	0.00	0.13	0.50
	Oil price -20%	1.92	0.22	0.01	0.00	-0.13	-0.09
	Oil price -50%	3.09	0.94	0.03	0.00	-0.74	-0.22
	A values +10%	1.32	0.15	0.10	0.00	-0.25	0.00
	A values +30%	1.61	0.23	0.11	0.00	-0.34	0.00
	A values +50%	2.42	0.22	0.18	0.00	-0.40	0.00
	Learning rate +5%	-0.71	-0.65	0.00	0.00	0.00	0.65
	Learning rate -5%	0.95	0.88	0.00	0.00	0.00	-0.88
	EV prices +10%	0.08	0.37	0.00	0.00	0.02	-0.39
	EV prices -10%	-0.07	-0.34	0.00	0.00	-0.02	0.35
	Turnover rate +20%	2.20	1.61	0.00	0.00	-0.01	-1.59
	Turnover rate + 50%	4.89	3.54	0.00	0.00	-0.58	-2.96
	Discount rate +10%	0.10	0.13	0.00	0.00	-0.03	-0.10
	Discount rate -10%	-0.31	-0.21	0.00	0.00	0.05	0.16
	All γ +20%	-0.71	-1.86	0.00	0.00	0.07	1.79
US	All γ -20%	0.40	0.76	0.00	0.00	-0.07	-0.70
	EV γ +10%	-0.30	-1.22	0.00	0.00	0.00	1.23
	EV γ -10%	0.04	0.04	0.00	0.00	-0.04	0.00
	Hybrid γ +10%	-0.05	-0.06	0.00	0.00	0.06	0.00
	Hybrid γ-10%	0.04	0.04	0.00	0.00	-0.04	0.00
	Petrol γ +10%	-0.13	-0.12	0.00	0.00	0.00	0.12
	Petrol γ -10%	0.14	0.26	0.00	0.00	0.00	-0.26
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-2.36	-0.21	-0.01	0.00	0.40	-0.18
	Oil price +50%	-3.59	-0.61	-0.03	0.00	0.12	0.51
	Oil price -20%	0.84	0.24	0.01	0.00	-0.16	-0.09
	Oil price -50%	3.21	0.95	0.03	0.00	-0.82	-0.16
	A values +10%	0.64	0.06	0.00	0.00	-0.06	0.00
	A values +30%	0.74	0.08	0.00	0.00	-0.08	0.00
	A values +50%	1.10	0.11	0.00	0.00	-0.11	0.00

Table A.5: Sensitivity analysis on key technological parameters under the 'high RT' scenario (Japan and China).

Country	Variations in Key Parameters	Emissions (%) CO_2	Changes in shares in 2050(%) Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.19	-0.11	0.00	0.00	0.00	0.11
	Learning rate -5%	0.20	0.13	0.00	0.00	0.00	-0.13
	EV prices +10%	0.02	0.00	0.00	0.00	0.54	-0.54
	EV prices -10%	-0.02	0.00	0.00	0.00	-0.48	0.48
	Turnover rate +20%	6.04	9.96	0.02	0.00	-10.14	0.17
	Turnover rate + 50%	12.78	19.15	0.02	0.00	-19.31	0.14
	Discount rate +10%	0.47	0.00	0.00	0.00	0.06	-0.06
	Discount rate -10%	-0.10	0.00	0.00	0.00	-0.09	0.09
	All γ +20%	-1.31	0.00	0.00	0.00	0.00	0.00
Japan	All γ -20%	5.21	0.00	0.00	0.00	0.00	0.04
	EV γ +10%	-0.03	-0.03	0.00	0.00	-0.11	0.13
	EV γ -10%	0.70	1.27	0.00	0.00	-1.48	0.21
	Hybrid γ +10%	-0.61	-1.10	0.00	0.00	1.26	-0.16
	Hybrid γ-10%	0.70	0.74	0.00	0.00	-0.87	0.13
	Petrol γ +10%	-1.64	-1.45	0.01	0.00	1.41	0.03
	Petrol γ -10%	2.46	3.42	0.19	0.00	-3.55	-0.05
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-2.00	-0.02	0.00	0.00	-0.08	0.10
	Oil price +50%	-4.15	-0.04	0.00	0.00	-0.18	0.23
	Oil price -20%	2.43	0.02	0.00	0.00	0.09	-0.11
	Oil price -50%	6.14	0.04	0.00	0.00	0.26	-0.30
	A values +10%	0.54	0.14	0.00	0.00	-0.14	0.00
	A values +30%	0.59	0.19	0.00	0.00	-0.19	0.00
	A values +50%	0.85	0.38	0.00	0.00	-0.38	0.00
	Learning rate +5%	-2.06	-3.21	-0.26	-0.13	0.00	3.60
	Learning rate -5%	4.43	3.52	0.14	0.00	0.00	-3.66
	EV prices +10%	0.19	0.46	0.00	0.02	0.07	-0.55
	EV prices -10%	-0.17	-0.41	0.00	-0.01	-0.06	0.49
	Turnover rate +20%	7.14	11.75	0.00	-0.09	-2.49	-9.16
	Turnover rate + 50%	14.23	20.45	0.00	-0.01	-3.25	-17.19
	Discount rate +10%	0.15	0.28	0.00	0.01	0.02	-0.30
	Discount rate -10%	-0.19	-0.42	0.00	-0.01	-0.02	0.45
China	All γ +20%	-1.77	-4.65	0.00	-0.03	0.46	4.23
	All γ -20%	1.23	4.48	0.00	0.02	-1.24	-3.26
	EV γ +10%	-1.42	-4.20	0.00	-0.05	-0.32	4.57
	EV γ -10%	0.65	1.55	0.00	0.01	-0.02	-1.54
	Hybrid γ +10%	-0.05	-0.24	0.00	-0.01	1.03	-0.78
	Hybrid γ-10%	0.07	0.44	0.00	0.01	-1.73	1.28
	Petrol γ +10%	0.67	1.25	0.00	0.01	0.01	-1.27
	Petrol γ -10%	-0.55	-0.65	0.00	-0.01	0.00	0.66
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-4.74	-0.18	0.00	0.00	-0.02	0.20
	Oil price +50%	-6.47	-0.32	0.00	-0.01	-0.04	0.37
	Oil price -20%	5.93	0.22	0.00	0.01	0.00	-0.22
	Oil price -50%	8.15	0.56	0.00	0.01	0.02	-0.59
	A values +10%	1.02	-1.75	0.00	0.00	0.67	1.08
	A values +30%	1.88	-3.94	0.00	0.00	1.00	2.95
	A values +50%	2.62	-6.13	0.00	0.00	2.47	3.66

Table A.6: Sensitivity analysis on key technological parameters under the 'high RT' scenario (India).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.12	-0.30	0.00	0.00	0.00	0.30
	Learning rate -5%	0.14	0.24	0.00	0.00	0.00	-0.24
	EV prices +10%	0.03	0.24	0.00	0.02	-0.27	-0.27
	EV prices -10%	-0.03	-0.22	0.00	-0.01	0.25	0.25
	Turnover rate +20%	0.46	-2.05	3.09	-0.38	-0.50	-0.17
	Turnover rate + 50%	1.03	-2.54	3.65	-0.19	-0.50	-0.42
	Discount rate +10%	0.49	0.55	0.00	0.01	-0.20	-0.37
	Discount rate -10%	-0.66	-0.81	0.00	-0.01	0.40	0.41
India	All γ +20%	-1.34	-4.21	2.10	-0.08	0.16	0.16
	All γ -20%	0.52	2.89	-0.96	0.02	-0.68	-1.26
	EV γ +10%	-0.01	-0.01	0.00	0.00	0.00	0.01
	EV γ -10%	0.01	0.01	-0.05	0.06	0.00	-0.02
	Hybrid γ +10%	-0.01	-0.01	0.00	0.00	0.01	0.00
	Hybrid γ-10%	0.01	0.01	0.00	0.00	-0.01	0.00
	Petrol γ +10%	0.56	0.77	-0.08	0.01	0.09	-0.79
	Petrol γ -10%	-0.32	-0.95	0.20	-0.01	0.32	0.45
	Diesel γ +10%	0.14	1.89	-1.43	0.00	0.00	-0.46
	Diesel γ -10%	-0.76	-0.78	0.48	0.00	0.00	0.30
	Oil price +20%	-5.01	-0.20	0.00	0.00	-0.02	0.22
	Oil price +50%	-6.84	-0.33	0.00	-0.01	-0.04	0.39
	Oil price -20%	6.27	0.21	0.00	0.01	0.02	-0.24
	Oil price -50%	8.62	0.45	0.00	0.01	0.05	-0.52
	A values +10%	0.84	-1.11	0.93	0.00	0.18	0.00
	A values +30%	1.56	-2.24	1.82	0.00	0.42	0.00
	A values +50%	2.97	-3.30	2.79	0.00	0.51	0.00

Table A.7: Sensitivity analysis on key technological parameters under the 'high EV subsidy' scenario (UK and US).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
UK	Learning rate +5%	-0.44	-0.33	-0.01	0.00	0.00	0.34
	Learning rate -5%	0.82	0.48	0.01	0.00	0.00	-0.49
	EV prices +10%	0.05	0.43	0.00	0.00	0.00	-0.43
	EV prices -10%	-0.04	-0.82	0.00	0.00	0.00	0.82
	Turnover rate +20%	3.22	5.19	0.67	0.00	-3.91	-1.95
	Turnover rate + 50%	7.34	8.93	0.85	0.00	-6.70	-3.08
	Discount rate +10%	0.19	0.18	0.00	0.00	-0.09	-0.10
	Discount rate -10%	-0.24	-0.34	0.00	0.00	0.18	0.16
	All γ +20%	-0.49	-3.17	0.00	0.00	0.00	3.17
	All γ -20%	0.27	1.13	0.06	0.00	-0.01	-1.18
	EV γ +10%	-0.59	-2.18	0.00	0.00	0.00	2.18
	EV γ -10%	0.36	1.54	0.07	0.00	-0.02	-1.59
	Hybrid γ +10%	-0.66	-0.94	0.85	0.00	1.45	-1.36
	Hybrid γ-10%	0.26	0.23	-0.13	0.00	0.28	-0.38
	Petrol γ +10%	0.31	0.07	0.15	0.00	-0.54	0.32
	Petrol γ -10%	-1.01	-0.62	-0.14	0.00	1.24	-0.48
	Diesel γ +10%	-0.73	-0.15	0.12	0.00	0.17	-0.14
	Diesel γ -10%	0.69	0.80	0.28	0.00	-0.46	-0.62
	Oil price +20%	-2.49	-0.22	-0.01	0.00	0.43	-0.19
	Oil price +50%	-3.79	-0.65	-0.03	0.00	0.14	0.54
	Oil price -20%	0.99	0.22	0.01	0.00	-0.15	-0.09
	Oil price -50%	3.32	1.01	0.02	0.00	-0.80	-0.23
	A values +10%	0.88	0.12	0.07	0.00	-0.19	0.00
	A values +30%	1.06	0.17	0.07	0.00	-0.24	0.00
	A values +50%	1.62	0.21	0.12	0.00	-0.33	0.00
US	Learning rate +5%	-0.63	-0.94	0.00	0.00	0.00	0.94
	Learning rate -5%	1.02	1.04	0.00	0.00	0.00	-1.04
	EV prices +10%	0.43	1.25	0.00	0.00	0.00	-1.25
	EV prices -10%	-0.49	-3.01	0.00	0.00	0.00	3.01
	Turnover rate +20%	1.43	1.46	0.00	0.00	-0.01	-1.44
	Turnover rate + 50%	3.18	3.19	0.00	0.00	-0.53	-2.65
	Discount rate +10%	0.15	0.28	0.00	0.00	-0.06	-0.22
	Discount rate -10%	-0.28	-0.55	0.00	0.00	0.12	0.43
	All γ +20%	-0.64	-1.72	0.00	0.00	0.02	1.70
	All γ -20%	0.80	0.32	0.00	0.00	-0.06	-0.26
	EV γ +10%	-0.27	-1.22	0.00	0.00	0.00	1.22
	EV γ -10%	0.04	0.04	0.00	0.00	-0.04	0.00
	Hybrid γ +10%	-0.05	-0.04	0.00	0.00	0.04	0.00
	Hybrid γ-10%	0.04	0.04	0.00	0.00	-0.04	0.00
	Petrol γ +10%	-0.14	-0.16	0.00	0.00	0.00	0.16
	Petrol γ -10%	0.15	0.28	0.00	0.00	0.00	-0.28
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-3.36	-0.13	0.00	0.00	0.06	0.07
	Oil price +50%	-5.62	-0.35	0.00	0.00	0.07	0.28
	Oil price -20%	2.88	0.12	0.00	0.00	-0.09	-0.02
	Oil price -50%	6.63	0.24	0.00	0.00	-0.01	-0.23
	A values +10%	1.06	0.07	0.00	0.00	-0.07	0.00
	A values +30%	1.22	0.12	0.00	0.00	-0.12	0.00
	A values +50%	1.83	0.17	0.00	0.00	-0.17	0.00

Table A.8: Sensitivity analysis on key technological parameters under the 'high EV subsidy' scenario (Japan and China).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.05	-0.10	0.00	0.00	0.00	0.10
	Learning rate -5%	0.06	0.09	0.00	0.00	0.00	-0.09
	EV prices +10%	0.05	0.06	0.00	0.00	1.26	-1.33
	EV prices -10%	-0.04	-0.12	0.00	0.00	-3.11	3.24
	Turnover rate +20%	6.50	10.72	0.02	0.00	-10.92	0.18
	Turnover rate + 50%	13.76	20.61	0.02	0.00	-20.78	0.16
	Discount rate +10%	0.02	0.00	0.00	0.00	0.09	-0.09
	Discount rate -10%	-0.06	-0.01	0.00	0.00	-0.12	0.14
	All γ +20%	-1.66	-2.61	0.01	0.00	2.62	-0.01
Japan	All γ -20%	4.62	8.98	-0.01	0.00	-9.01	0.04
	EV γ +10%	-0.15	-0.44	0.00	0.00	-0.12	0.56
	EV γ -10%	0.17	0.61	0.00	0.00	-0.72	0.11
	Hybrid γ +10%	-0.34	-0.57	0.00	0.00	0.66	-0.08
	Hybrid γ-10%	0.37	0.64	0.00	0.00	-0.75	0.11
	Petrol γ +10%	-0.87	-1.29	0.01	0.00	1.26	0.02
	Petrol γ -10%	1.29	2.67	0.00	0.00	-1.40	-1.27
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-2.05	-0.02	0.00	0.00	-0.08	0.10
	Oil price +50%	-4.24	-0.05	0.00	0.00	-0.18	0.23
	Oil price -20%	2.48	0.03	0.00	0.00	0.08	-0.11
	Oil price -50%	5.86	0.06	0.00	0.00	0.24	-0.31
	A values +10%	1.62	0.37	0.00	0.00	-0.37	0.00
	A values +30%	1.74	0.48	0.00	0.00	-0.48	0.00
	A values +50%	2.59	0.99	0.00	0.00	-0.99	0.00
	Learning rate +5%	-2.80	-3.02	-0.24	-0.12	0.00	3.38
	Learning rate -5%	4.13	3.80	0.13	0.00	0.00	-3.94
	EV prices +10%	0.63	3.01	0.00	0.03	0.97	-4.01
	EV prices -10%	-0.51	-5.63	0.00	-0.06	-2.00	7.68
	Turnover rate +20%	8.09	13.31	0.00	-0.10	-2.82	-10.38
	Turnover rate + 50%	16.12	23.17	0.00	-0.02	-3.68	-19.48
	Discount rate +10%	1.20	1.12	0.00	0.01	-0.04	-1.09
	Discount rate -10%	-0.95	-1.77	0.00	-0.02	0.06	1.72
China	All γ +20%	-1.09	-3.34	0.00	-0.03	0.10	3.27
	All γ -20%	1.13	3.49	0.00	0.02	-0.85	-2.65
	EV γ +10%	-2.34	-7.44	0.00	-0.06	0.53	6.96
	EV γ -10%	1.89	3.52	0.00	0.01	-2.05	-1.48
	Hybrid γ +10%	-0.05	-0.72	0.00	-0.01	1.65	-0.92
	Hybrid γ-10%	0.07	0.52	0.00	0.02	-1.73	1.19
	Petrol γ +10%	1.22	1.18	0.00	0.01	-1.30	0.12
	Petrol γ -10%	-0.71	-0.64	0.00	-0.01	-0.03	0.68
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-4.41	-0.18	0.00	0.00	-0.02	0.19
	Oil price +50%	-6.02	-0.31	0.00	-0.01	-0.04	0.37
	Oil price -20%	5.52	0.21	0.00	0.00	0.02	-0.23
	Oil price -50%	7.59	0.41	0.00	0.01	0.05	-0.47
	A values +10%	1.48	-2.91	0.00	0.00	0.98	1.93
	A values +30%	2.74	-5.87	0.00	0.00	1.56	4.30
	A values +50%	3.82	-9.81	0.00	0.00	3.60	6.20

Table A.9: Sensitivity analysis on key technological parameters under the 'high EV subsidy' scenario (India).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	0.00	0.00	0.00	0.00	0.00	0.00
	Learning rate -5%	0.00	0.00	0.00	0.00	0.00	0.00
	EV prices +10%	0.05	-0.28	0.00	-0.03	0.03	0.28
	EV prices -10%	-0.04	0.26	0.00	0.03	-0.03	-0.26
	Turnover rate +20%	0.51	-2.07	3.16	-0.42	-0.48	-0.19
	Turnover rate + 50%	1.16	-2.84	4.08	-0.21	-0.56	-0.47
	Discount rate +10%	0.23	0.66	-0.59	0.01	-0.04	-0.04
	Discount rate -10%	-1.05	-1.66	1.53	-0.02	0.07	0.07
India	All γ +20%	-0.89	-0.67	0.22	0.00	0.11	0.34
	All γ -20%	0.95	0.74	-0.50	0.04	-0.12	-0.17
	EV γ +10%	-0.12	-0.78	0.70	-0.03	0.05	0.05
	EV γ -10%	0.33	0.97	-0.32	0.01	-0.23	-0.42
	Hybrid γ +10%	-0.01	-0.01	0.00	0.00	0.00	0.01
	Hybrid γ-10%	0.02	0.02	-0.08	0.10	0.00	-0.03
	Petrol γ +10%	-0.06	-0.02	0.00	0.00	0.02	0.00
	Petrol γ -10%	0.02	0.02	0.00	0.00	-0.02	0.00
	Diesel γ +10%	0.21	0.28	-0.13	0.01	0.15	-0.31
	Diesel γ -10%	-0.14	-0.87	0.33	-0.02	0.42	0.13
	Oil price +20%	-2.65	-0.22	0.00	0.00	0.10	0.12
	Oil price +50%	-6.34	-0.56	0.00	-0.01	0.28	0.29
	Oil price -20%	1.73	0.24	0.00	0.00	-0.11	-0.14
	Oil price -50%	5.61	0.53	0.00	0.01	-0.27	-0.26
	A values +10%	1.46	-1.93	1.62	0.00	0.31	0.00
	A values +30%	2.40	-3.45	2.80	0.00	0.65	0.00
	A values +50%	3.68	-4.09	3.46	0.00	0.63	0.00

Table A.10: Sensitivity analysis on key technological parameters under the 'high FT' scenario (UK and US).

Country	Variations in Key Parameters	Emissions (%) CO_2	Changes in shares in 2050(%) Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.56	-1.00	-0.03	0.00	0.00	1.04
	Learning rate -5%	0.92	0.51	0.01	0.00	0.00	-0.52
	EV prices +10%	0.06	0.42	0.00	0.00	0.00	-0.43
	EV prices -10%	-0.06	-0.44	0.00	0.00	0.00	0.44
	Turnover rate +20%	2.78	4.45	0.60	0.00	-3.36	-1.68
	Turnover rate + 50%	6.33	7.70	0.74	0.00	-5.77	-2.66
	Discount rate +10%	0.51	0.40	0.02	0.00	-0.18	-0.24
	Discount rate -10%	-0.45	-0.70	-0.03	0.00	0.40	0.34
UK	All γ +20%	-0.49	-3.17	0.00	0.00	0.00	3.17
	All γ -20%	0.29	1.54	0.06	0.00	-0.01	-1.59
	EV γ +10%	-0.53	-3.19	0.00	0.00	0.00	3.19
	EV γ -10%	0.61	1.34	0.06	0.00	-0.01	-1.39
	Hybrid γ +10%	-0.65	-1.25	0.00	0.00	0.48	0.77
	Hybrid γ-10%	0.32	0.23	0.33	0.00	-0.23	-0.33
	Petrol γ +10%	0.15	0.11	0.08	0.00	-0.46	0.26
	Petrol γ -10%	-0.65	-0.30	-0.09	0.00	0.72	-0.33
	Diesel γ +10%	0.43	-0.13	0.11	0.00	0.14	-0.12
	Diesel γ -10%	0.52	0.68	0.23	0.00	-0.38	-0.53
	Oil price +20%	-2.26	-0.20	-0.01	0.00	0.18	0.03
	Oil price +50%	-3.41	-0.54	-0.02	0.00	0.18	0.39
	Oil price -20%	1.89	0.21	0.01	0.00	-0.14	-0.08
	Oil price -50%	3.02	0.84	0.02	0.00	-0.67	-0.20
	A values +10%	1.67	0.21	0.13	0.00	-0.33	0.00
	A values +30%	2.05	0.32	0.12	0.00	-0.43	0.00
	A values +50%	3.27	0.29	0.22	0.00	-0.51	0.00
	Learning rate +5%	-0.46	-0.55	0.00	0.00	0.00	0.55
	Learning rate -5%	0.70	0.63	0.00	0.00	0.00	-0.63
	EV prices +10%	0.19	0.56	0.00	0.00	0.00	-0.56
	EV prices -10%	-0.25	-0.92	0.00	0.00	0.00	0.92
	Turnover rate +20%	2.14	1.57	0.00	0.00	-0.01	-1.55
	Turnover rate + 50%	4.78	3.46	0.00	0.00	-0.57	-2.89
	Discount rate +10%	0.22	0.30	0.00	0.00	-0.07	-0.24
	Discount rate -10%	-0.65	-0.49	0.00	0.00	0.14	0.35
	All γ +20%	-0.73	-1.68	0.00	0.00	0.06	1.62
US	All γ -20%	0.79	0.14	0.00	0.00	-0.09	-0.05
	EV γ +10%	-0.62	-1.56	0.00	0.00	0.06	1.50
	EV γ -10%	0.59	0.73	0.00	0.00	-0.05	-0.69
	Hybrid γ +10%	-0.23	-0.97	0.00	0.00	0.00	0.97
	Hybrid γ-10%	0.03	0.03	0.00	0.00	-0.03	0.00
	Petrol γ +10%	-0.03	-0.03	0.00	0.00	0.03	0.00
	Petrol γ -10%	0.03	0.03	0.00	0.00	-0.03	0.00
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-2.99	-0.10	0.00	0.00	0.06	0.04
	Oil price +50%	-4.85	-0.30	0.00	0.00	0.08	0.22
	Oil price -20%	2.56	0.11	0.00	0.00	-0.08	-0.02
	Oil price -50%	6.25	0.18	0.00	0.00	-0.01	-0.18
	A values +10%	0.79	0.00	0.00	0.00	0.00	0.00
	A values +30%	0.92	0.00	0.00	0.00	0.00	0.00
	A values +50%	1.36	0.00	0.00	0.00	0.00	0.00

Table A.11: Sensitivity analysis on key technological parameters under the 'high FT' scenario (Japan and China).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.12	-0.19	0.00	0.00	0.00	0.19
	Learning rate -5%	0.18	0.00	0.00	0.00	0.07	-0.07
	EV prices +10%	0.04	0.02	0.00	0.00	0.33	-0.35
	EV prices -10%	-0.04	-0.02	0.00	0.00	-0.88	0.90
	Turnover rate +20%	5.84	9.61	0.02	0.00	-9.78	0.16
	Turnover rate + 50%	12.37	18.53	0.02	0.00	-18.68	0.14
	Discount rate +10%	0.30	0.23	0.00	0.00	-0.14	-0.09
	Discount rate -10%	-0.21	-0.31	0.00	0.00	0.24	0.07
	All γ +20%	-1.59	-2.33	0.01	0.00	2.36	-0.04
Japan	All γ -20%	2.32	3.14	-0.01	0.00	-3.25	0.11
	EV γ +10%	-0.03	-0.03	0.00	0.00	-0.13	0.16
	EV γ -10%	0.83	1.49	0.00	0.00	-1.74	0.24
	Hybrid γ +10%	-0.72	-1.29	0.00	0.00	1.49	-0.19
	Hybrid γ-10%	0.83	0.83	0.00	0.00	-0.98	0.15
	Petrol γ +10%	-1.94	-1.57	0.01	0.00	1.51	0.04
	Petrol γ -10%	2.90	3.68	0.16	0.00	-3.77	-0.06
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-1.85	-0.02	0.00	0.00	-0.08	0.09
	Oil price +50%	-3.84	-0.06	0.00	0.00	-0.15	0.21
	Oil price -20%	2.25	0.02	0.00	0.00	0.09	-0.10
	Oil price -50%	5.32	0.05	0.00	0.00	0.23	-0.28
	A values +10%	0.64	0.15	0.00	0.00	-0.16	0.00
	A values +30%	0.70	0.25	0.00	0.00	-0.25	0.00
	A values +50%	1.01	0.48	0.00	0.00	-0.48	0.00
	Learning rate +5%	-2.62	-3.26	-0.23	-0.11	0.00	3.60
	Learning rate -5%	2.96	2.39	0.11	0.00	0.00	-2.49
	EV prices +10%	1.01	4.02	0.00	0.04	0.44	-4.50
	EV prices -10%	-0.96	-3.70	0.00	-0.05	-0.59	4.33
	Turnover rate +20%	6.50	10.72	0.00	-0.08	-2.30	-8.34
	Turnover rate + 50%	12.90	18.61	0.00	-0.01	-3.21	-15.38
	Discount rate +10%	2.54	4.11	0.00	0.03	-0.05	-4.08
	Discount rate -10%	-3.66	-5.43	0.00	-0.04	0.18	5.29
China	All γ +20%	-1.26	-4.85	0.00	-0.03	0.68	4.21
	All γ -20%	1.29	4.56	0.00	0.02	-1.11	-3.47
	EV γ +10%	-1.22	-5.37	0.00	-0.04	-0.28	5.69
	EV γ -10%	1.35	1.20	0.00	0.01	-0.11	-1.10
	Hybrid γ +10%	-0.04	-0.24	0.00	0.00	0.91	-0.67
	Hybrid γ-10%	0.05	0.41	0.00	0.01	-1.52	1.10
	Petrol γ +10%	0.65	0.82	0.00	0.01	-0.94	0.11
	Petrol γ -10%	-0.87	-0.55	0.00	-0.01	0.00	0.56
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-4.24	-0.17	0.00	0.00	-0.02	0.19
	Oil price +50%	-5.78	-0.29	0.00	-0.01	-0.04	0.33
	Oil price -20%	5.30	0.19	0.00	0.00	0.02	-0.22
	Oil price -50%	7.29	0.38	0.00	0.01	0.05	-0.44
	A values +10%	-0.83	-1.19	0.00	0.00	0.30	0.89
	A values +30%	-1.53	-2.91	0.00	0.00	0.83	2.09
	A values +50%	-2.17	-4.86	0.00	0.00	1.98	2.87

Table A.12: Sensitivity analysis on key technological parameters under the 'high FT' scenario (India).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	0.00	0.01	0.00	0.00	0.00	-0.01
	Learning rate -5%	0.00	0.01	0.00	0.00	0.00	-0.01
	EV prices +10%	0.04	0.24	0.00	0.04	-0.26	-0.26
	EV prices -10%	-0.03	-0.20	0.00	-0.05	0.21	0.21
	Turnover rate +20%	0.39	-1.75	2.64	-0.32	-0.43	-0.14
	Turnover rate + 50%	0.88	-2.17	3.12	-0.16	-0.43	-0.36
	Discount rate +10%	1.21	2.97	-2.53	0.03	-0.24	-0.24
	Discount rate -10%	-1.71	-1.73	1.41	-0.04	0.35	0.00
India	All γ +20%	-1.67	-4.36	3.55	-0.09	0.18	0.71
	All γ -20%	0.51	0.86	-0.55	0.04	-0.16	-0.19
	EV γ +10%	-0.02	-0.01	0.00	0.00	0.00	0.01
	EV γ -10%	0.02	0.03	-0.10	0.12	0.00	-0.04
	Hybrid γ +10%	-0.02	-0.02	0.00	0.00	0.02	0.00
	Hybrid γ-10%	0.02	0.02	0.00	0.00	-0.02	0.00
	Petrol γ +10%	-0.14	-0.07	0.00	0.00	0.07	0.00
	Petrol γ -10%	0.04	0.07	0.00	0.00	-0.07	0.00
	Diesel γ +10%	0.19	0.25	-0.12	0.01	0.14	-0.28
	Diesel γ -10%	-0.13	-0.78	0.30	-0.02	0.38	0.12
	Oil price +20%	-2.25	-0.19	0.00	0.00	0.09	0.10
	Oil price +50%	-5.37	-0.49	0.00	-0.01	0.22	0.27
	Oil price -20%	1.43	0.23	0.00	0.00	-0.09	-0.14
	Oil price -50%	5.13	0.51	0.00	0.01	-0.23	-0.29
	A values +10%	0.67	-0.83	0.76	0.00	0.07	0.00
	A values +30%	1.24	-2.04	1.46	0.00	0.58	0.00
	A values +50%	2.16	-2.51	2.19	0.00	0.31	0.00

Table A.13: Sensitivity analysis on key technological parameters under the 'stringent phase-out' scenario (UK and US).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.43	-0.70	-0.02	0.00	0.00	0.72
	Learning rate -5%	0.80	0.67	0.01	0.00	0.00	-0.68
	EV prices +10%	0.05	0.35	0.00	0.00	0.01	-0.36
	EV prices -10%	-0.05	-0.41	0.00	0.00	-0.01	0.42
	Turnover rate +20%	3.25	5.04	0.76	0.00	-3.87	-1.93
	Turnover rate + 50%	7.48	10.20	1.96	0.00	-8.19	-3.97
	Discount rate +10%	0.02	0.03	0.01	0.00	-0.02	-0.01
	Discount rate -10%	-0.03	-0.05	-0.01	0.00	0.03	0.02
UK	All γ +20%	-0.49	-3.17	0.00	0.00	0.00	3.17
	All γ -20%	0.27	1.33	0.06	0.00	-0.01	-1.38
	EV γ +10%	-0.01	-0.07	0.00	0.00	0.00	0.07
	EV γ -10%	0.08	0.13	0.19	0.00	-0.20	-0.12
	Hybrid γ +10%	0.08	0.37	0.01	0.00	-0.38	0.00
	Hybrid γ-10%	-0.08	-0.42	-0.01	0.00	0.43	0.00
	Petrol γ +10%	-0.08	-0.13	0.02	0.00	0.10	0.02
	Petrol γ -10%	0.08	0.13	-0.02	0.00	-0.09	-0.02
	Diesel γ +10%	0.02	0.05	-0.08	0.00	0.03	0.00
	Diesel γ -10%	-0.02	-0.06	0.81	0.00	-0.76	0.01
	Oil price +20%	-1.76	-0.12	-0.01	0.00	0.27	-0.14
	Oil price +50%	-2.77	-0.45	-0.02	0.00	0.12	0.35
	Oil price -20%	0.82	0.14	0.01	0.00	-0.08	-0.07
	Oil price -50%	2.55	0.62	0.02	0.00	-0.26	-0.38
	A values +10%	1.04	0.10	0.08	0.00	-0.18	0.00
	A values +30%	1.27	0.18	0.10	0.00	-0.28	0.00
	A values +50%	1.89	0.20	0.14	0.00	-0.34	0.00
	Learning rate +5%	-0.65	-0.54	0.00	0.00	0.00	0.54
	Learning rate -5%	0.92	0.77	0.00	0.00	0.00	-0.77
	EV prices +10%	0.24	1.45	0.00	0.00	0.89	-2.34
	EV prices -10%	-0.36	-0.66	0.00	0.00	-1.38	2.04
	Turnover rate +20%	2.46	0.97	0.00	0.00	-0.01	-0.96
	Turnover rate + 50%	5.60	2.09	0.00	0.00	-0.34	-1.74
	Discount rate +10%	0.26	1.08	0.00	0.00	-0.71	-0.37
	Discount rate -10%	-0.45	-1.88	0.00	0.00	1.27	0.61
	All γ +20%	-0.86	-1.92	0.00	0.00	0.07	1.85
US	All γ -20%	0.83	0.91	0.00	0.00	-0.07	-0.84
	EV γ +10%	-0.15	-1.19	0.00	0.00	-0.49	1.68
	EV γ -10%	0.13	0.21	0.00	0.00	0.20	-0.40
	Hybrid γ +10%	-0.09	-0.40	0.00	0.00	0.48	-0.08
	Hybrid γ-10%	0.09	0.39	0.00	0.00	-0.46	0.07
	Petrol γ +10%	-0.13	-0.21	0.00	0.00	0.20	0.02
	Petrol γ -10%	0.24	0.14	0.00	0.00	-0.14	0.00
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-1.82	-0.12	-0.01	0.00	0.30	-0.17
	Oil price +50%	-2.71	-0.45	-0.02	0.00	0.08	0.38
	Oil price -20%	0.64	0.19	0.01	0.00	-0.13	-0.07
	Oil price -50%	2.50	0.69	0.02	0.00	-0.58	-0.13
	A values +10%	0.34	0.00	0.00	0.00	0.00	0.00
	A values +30%	0.40	0.00	0.00	0.00	0.00	0.00
	A values +50%	0.59	0.00	0.00	0.00	0.00	0.00

Table A.14: Sensitivity analysis on key technological parameters under the 'stringent phase-out' scenario (Japan and China).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
Japan	Learning rate +5%	-0.17	-0.24	0.00	0.00	0.00	0.24
	Learning rate -5%	0.13	0.11	0.00	0.00	0.00	-0.11
	EV prices +10%	0.03	0.01	0.00	0.00	0.20	-0.21
	EV prices -10%	-0.02	-0.04	0.00	0.00	0.61	-0.58
	Turnover rate +20%	7.31	10.77	0.02	0.00	-10.93	0.18
	Turnover rate + 50%	13.86	21.25	0.02	0.00	-21.3	0.19
	Discount rate +10%	0.02	0.02	0.00	0.00	0.02	-0.04
	Discount rate -10%	-0.01	-0.02	0.00	0.00	-0.07	0.09
	All γ +20%	-1.42	-4.46	0.00	-0.03	0.49	4.01
	All γ -20%	1.13	4.93	0.00	0.02	-1.41	-3.54
	EV γ +10%	0.00	0.00	0.00	0.00	-0.06	0.07
	EV γ -10%	0.01	0.01	0.00	0.00	-0.03	0.02
	Hybrid γ +10%	-0.05	-0.15	0.00	0.00	0.23	-0.08
	Hybrid γ-10%	0.07	0.17	0.00	0.00	-0.28	0.11
	Petrol γ +10%	-0.17	-0.10	0.00	0.00	0.10	0.00
	Petrol γ -10%	0.24	0.14	0.00	0.00	-0.14	0.00
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-1.52	-0.01	0.00	0.00	-0.05	0.07
	Oil price +50%	-2.98	-0.10	0.00	0.00	-0.13	0.21
	Oil price -20%	1.87	0.02	0.00	0.00	0.06	-0.08
	Oil price -50%	4.70	0.04	0.00	0.00	0.19	-0.23
	A values +10%	0.47	0.11	0.00	0.00	-0.11	0.00
	A values +30%	0.52	0.15	0.00	0.00	-0.15	0.00
	A values +50%	0.75	0.33	0.00	0.00	-0.34	0.00
China	Learning rate +5%	-1.94	-1.80	-0.18	-0.02	0.00	2.00
	Learning rate -5%	2.12	2.46	0.13	0.00	0.00	-2.59
	EV prices +10%	0.70	3.25	0.00	0.10	0.45	-3.80
	EV prices -10%	-0.06	-2.51	0.00	-0.11	-0.65	3.26
	Turnover rate +20%	6.11	9.80	0.00	-0.09	-2.08	-7.63
	Turnover rate + 50%	12.16	17.05	0.00	-0.01	-2.74	-14.30
	Discount rate +10%	0.25	1.18	0.00	0.05	0.02	-1.24
	Discount rate -10%	-0.35	-1.85	0.00	-0.08	-0.02	1.95
	All γ +20%	-1.18	-4.08	0.00	-0.03	0.45	3.67
	All γ -20%	1.07	4.15	0.00	0.02	-1.01	-3.16
	EV γ +10%	-1.27	-2.19	-0.04	-0.37	2.04	0.56
	EV γ -10%	0.13	0.49	0.00	0.00	0.00	-0.50
	Hybrid γ +10%	-0.02	-0.12	0.00	-0.01	0.80	-0.67
	Hybrid γ-10%	0.02	0.13	0.00	0.01	-1.23	1.09
	Petrol γ +10%	0.13	0.60	0.00	0.00	0.00	-0.60
	Petrol γ -10%	-0.11	-0.43	0.00	0.00	0.00	0.43
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-3.91	-0.17	0.00	0.00	-0.01	0.18
	Oil price +50%	-5.66	-0.36	0.00	-0.01	-0.03	0.40
	Oil price -20%	5.11	0.20	0.00	0.00	0.00	-0.20
	Oil price -50%	6.71	0.62	0.00	0.01	0.02	-0.75
	A values +10%	-2.20	-3.59	0.00	0.00	1.46	2.13
	A values +30%	-4.08	-8.55	0.00	0.00	2.16	6.38
	A values +50%	-5.68	-13.30	0.00	0.00	5.36	7.95

Table A.15: Sensitivity analysis on key technological parameters under the 'stringent phase-out' scenario (India).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	0.00	0.00	0.00	0.00	0.00	0.00
	Learning rate -5%	0.00	0.00	0.00	0.00	0.00	0.00
	EV prices +10%	0.04	0.17	0.06	0.10	-0.24	-0.24
	EV prices -10%	-0.04	-0.12	-0.03	-0.11	0.18	0.18
	Turnover rate +20%	0.58	-2.59	3.91	-0.48	-0.61	-0.23
	Turnover rate + 50%	1.27	-3.17	4.58	-0.24	-0.63	-0.54
	Discount rate +10%	2.36	5.40	-4.90	0.05	0.01	-0.55
	Discount rate -10%	-1.82	-9.75	8.61	-0.08	0.00	1.23
India	All γ +20%	-1.22	-4.84	2.12	-0.08	1.95	0.85
	All γ -20%	0.62	0.83	-0.51	0.04	-0.20	-0.16
	EV γ +10%	-0.03	-0.03	0.01	0.05	-0.04	0.01
	EV γ -10%	0.02	0.02	-0.01	0.00	0.01	-0.03
	Hybrid γ +10%	-0.04	0.36	-0.34	-0.01	-0.01	-0.01
	Hybrid γ-10%	0.03	-0.21	0.19	0.01	0.00	0.00
	Petrol γ +10%	0.02	0.02	0.01	0.00	-0.01	-0.02
	Petrol γ -10%	-0.02	-0.02	-0.01	0.00	0.01	0.02
	Diesel γ +10%	0.27	0.36	-0.17	0.01	0.19	-0.40
	Diesel γ -10%	-0.18	-1.12	0.43	-0.02	0.55	0.18
	Oil price +20%	-2.03	-0.17	0.00	0.00	0.08	0.09
	Oil price +50%	-4.61	-0.41	0.00	-0.01	0.18	0.24
	Oil price -20%	1.30	0.20	0.00	0.00	-0.09	-0.11
	Oil price -50%	4.35	0.43	0.00	0.01	-0.15	-0.29
	A values +10%	0.38	-0.51	0.47	0.00	0.04	0.00
	A values +30%	0.71	-1.16	0.73	0.00	0.43	0.00
	A values +50%	1.23	-1.43	1.23	0.00	0.19	0.00

Table A.16: Sensitivity analysis on key technological parameters under the 'EV mandate high' scenario (UK and US).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.78	-1.23	-0.04	0.00	0.00	1.27
	Learning rate -5%	1.41	0.74	0.01	0.00	0.00	-0.76
	EV prices +10%	0.79	3.89	0.00	0.00	0.00	-3.90
	EV prices -10%	-0.89	-4.87	0.00	0.00	0.00	4.87
	Turnover rate +20%	4.06	6.73	0.83	0.00	-5.08	-2.48
	Turnover rate + 50%	9.47	11.58	1.10	0.00	-8.64	-4.04
	Discount rate +10%	0.25	0.23	0.00	0.00	-0.11	-0.12
	Discount rate -10%	-0.30	-0.42	0.00	0.00	0.22	0.20
UK	All γ +20%	-0.49	-3.17	0.00	0.00	0.00	3.17
	All γ -20%	0.27	1.33	0.06	0.00	-0.01	-1.38
	EV γ +10%	-0.10	-0.73	0.00	0.00	-0.01	0.74
	EV γ -10%	0.10	0.66	0.00	0.00	0.01	-0.67
	Hybrid γ +10%	0.06	0.16	0.00	0.00	-0.16	0.00
	Hybrid γ-10%	-0.07	-0.23	-0.24	0.00	0.44	0.03
	Petrol +10%	-1.72	-1.83	0.10	0.00	0.35	1.38
	Petrol -10%	0.39	1.63	-0.09	0.00	-0.20	-1.35
	Diesel +10%	0.02	-0.08	0.00	0.03	0.00	0.05
	Diesel -10%	-0.02	0.77	0.00	-0.71	0.01	-0.06
	Oil price +20%	-2.34	-0.22	-0.01	0.00	0.36	-0.13
	Oil price +50%	-3.57	-0.61	-0.03	0.00	0.13	0.51
	Oil price -20%	0.94	0.21	0.01	0.00	-0.14	-0.08
	Oil price -50%	3.12	0.95	0.02	0.00	-0.75	-0.22
	A values +10%	1.23	0.14	0.09	0.00	-0.24	0.00
	A values +30%	1.47	0.29	0.10	0.00	-0.39	0.00
	A values +50%	2.29	0.30	0.17	0.00	-0.47	0.00
	Learning rate +5%	-0.61	-0.65	0.00	0.00	0.00	0.65
	Learning rate -5%	1.00	0.75	0.00	0.00	0.00	-0.75
	EV prices +10%	0.88	2.71	0.00	0.00	0.02	-2.74
	EV prices -10%	-0.42	-1.50	0.00	0.00	-0.01	1.51
	Turnover rate +20%	3.07	0.92	0.00	0.00	-0.01	-0.91
	Turnover rate + 50%	6.76	1.92	0.00	0.00	-0.02	-1.90
	Discount rate +10%	0.34	0.35	0.00	0.00	-0.07	-0.28
	Discount rate -10%	-0.64	-1.82	0.00	0.00	-4.33	6.14
	All γ +20%	-0.65	-0.89	0.00	0.00	0.04	0.85
US	All γ -20%	0.70	0.75	0.00	0.00	-0.06	-0.69
	EV γ +10%	-0.57	-2.93	0.00	0.00	-0.01	2.94
	EV γ -10%	0.39	1.33	0.00	0.00	0.01	-1.34
	Hybrid γ +10%	-0.04	-0.03	0.00	0.00	0.03	0.00
	Hybrid γ-10%	0.03	0.03	0.00	0.00	-0.04	0.01
	Petrol γ +10%	-0.05	0.45	0.00	0.00	0.00	-0.45
	Petrol γ -10%	0.04	0.54	0.00	0.00	0.00	-0.54
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-2.91	-0.12	0.00	0.00	0.05	0.07
	Oil price +50%	-4.86	-0.30	0.00	0.00	0.07	0.23
	Oil price -20%	2.49	0.10	0.00	0.00	-0.08	-0.02
	Oil price -50%	5.73	0.21	0.00	0.00	-0.01	-0.20
	A values +10%	0.74	0.07	0.00	0.00	-0.07	0.00
	A values +30%	0.86	0.11	0.00	0.00	-0.11	0.00
	A values +50%	1.27	0.14	0.00	0.00	-0.14	0.00

Table A.17: Sensitivity analysis on key technological parameters under the 'EV mandate high' scenario (Japan and China).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	-0.11	-0.20	0.00	0.00	0.00	0.20
	Learning rate -5%	0.32	0.13	0.00	0.00	0.00	-0.13
	EV prices +10%	0.30	0.25	0.00	0.00	2.84	-3.09
	EV prices -10%	-0.11	-0.09	0.00	0.00	-1.70	1.79
	Turnover rate +20%	0.54	0.74	3.64	-0.44	-2.01	0.00
	Turnover rate + 50%	1.12	1.54	7.56	-0.92	-4.16	0.00
	Discount rate +10%	0.02	1.78	0.00	0.00	0.78	-2.56
	Discount rate -10%	-0.52	-6.91	0.00	-0.05	-0.31	7.27
	All γ +20%	-2.24	-2.60	0.01	0.00	2.62	-0.02
Japan	All γ -20%	4.13	9.12	-0.01	0.00	-9.13	0.02
	EV γ +10%	-0.02	-0.03	0.00	0.00	-0.21	0.24
	EV γ -10%	0.02	0.03	0.00	0.00	0.13	-0.16
	Hybrid γ +10%	-0.27	-0.50	0.00	0.00	0.78	-0.28
	Hybrid γ-10%	0.32	6.25	6.84	0.00	-1.04	-12.05
	Petrol γ +10%	-0.79	-1.14	0.00	0.00	1.13	0.00
	Petrol γ -10%	1.18	1.82	0.00	0.00	-1.80	-0.01
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-1.72	-0.01	0.00	0.00	-0.07	0.09
	Oil price +50%	-3.57	-0.05	0.00	0.00	-0.16	0.25
	Oil price -20%	2.09	0.03	0.00	0.00	0.07	-0.10
	Oil price -50%	4.94	0.05	0.00	0.00	0.21	-0.26
	A values +10%	1.77	0.40	0.00	0.00	-0.40	0.00
	A values +30%	1.95	0.59	0.00	0.00	-0.59	0.00
	A values +50%	3.98	0.93	0.00	0.00	-0.93	0.00
	Learning rate +5%	-3.03	-3.51	-0.26	-0.13	0.00	3.90
	Learning rate -5%	3.79	4.13	0.14	0.00	0.00	-4.28
	EV prices +10%	1.30	4.19	0.00	0.04	0.72	-4.95
	EV prices -10%	-1.26	-4.48	0.00	-0.04	-0.82	5.34
	Turnover rate +20%	10.10	7.01	0.00	-0.05	-1.94	-5.01
	Turnover rate + 50%	18.88	12.34	0.00	-0.09	-3.42	-8.82
	Discount rate +10%	1.37	1.87	0.00	-0.01	-0.20	-1.66
	Discount rate -10%	-2.11	-8.63	1.20	-0.05	2.28	5.20
China	All γ +20%	-2.72	-6.57	0.00	-0.05	1.32	5.30
	All γ -20%	2.38	6.48	0.00	0.03	-1.22	-5.29
	EV γ +10%	-1.27	-4.62	0.00	-0.04	-0.37	5.04
	EV γ -10%	1.27	4.67	0.00	0.03	0.32	-5.02
	Hybrid γ +10%	-0.34	-0.15	0.00	0.00	1.08	-0.92
	Hybrid γ-10%	0.22	0.53	0.00	1.64	-1.36	-0.81
	Petrol γ +10%	0.48	0.27	0.00	0.00	0.01	-0.29
	Petrol γ -10%	-0.41	-0.48	0.00	-0.01	-0.02	0.50
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00
	Diesel γ -10%	0.00	0.00	0.00	0.00	0.00	0.00
	Oil price +20%	-3.81	-0.16	0.00	0.00	0.02	0.14
	Oil price +50%	-5.01	-0.27	0.00	-0.01	0.04	0.25
	Oil price -20%	4.77	0.18	0.00	0.00	0.02	-0.20
	Oil price -50%	6.67	0.36	0.00	0.01	0.04	-0.42
	A values +10%	-1.76	-2.53	0.00	0.00	0.85	1.67
	A values +30%	-3.25	-5.10	0.00	0.00	1.36	3.74
	A values +50%	-4.52	-8.52	0.00	0.00	3.13	5.39

Table A.18: Sensitivity analysis on key technological parameters under the 'EV mandate high' scenario (India).

Country	Variations in Key Parameters	Emissions (%)	Changes in shares in 2050(%)				
		CO_2	Petrol	Diesel	CNG	Hybrid	EV
	Learning rate +5%	0.00	0.00	0.00	0.00	0.00	0.00
	Learning rate -5%	0.00	0.00	0.00	0.00	0.00	0.00
	EV prices +10%	0.83	4.14	0.05	0.04	-4.20	-4.20
	EV prices -10%	-0.64	-3.16	-0.04	-0.04	3.21	3.21
	Turnover rate +20%	2.69	2.00	3.03	-1.31	-2.50	-1.20
	Turnover rate + 50%	4.49	3.21	6.11	-2.20	-4.93	-2.19
	Discount rate +10%	0.55	1.23	-1.05	-0.01	-0.26	0.09
	Discount rate -10%	-3.22	-8.63	1.20	-0.05	6.61	0.87
India	All γ +20%	-1.54	-3.15	2.10	-0.08	0.17	0.96
	All γ -20%	0.80	0.85	-0.51	0.04	-0.22	-0.16
	EV γ +10%	-0.06	-0.09	0.01	-0.04	0.04	0.08
	EV γ -10%	0.07	0.06	-0.01	0.03	-0.03	-0.05
	Hybrid γ +10%	-0.02	0.02	-0.01	0.00	0.01	-0.02
	Hybrid γ-10%	0.01	-0.13	0.13	0.00	-0.02	0.02
	Petrol γ +10%	-0.07	-0.08	-0.02	0.00	0.00	0.02
	Petrol γ -10%	0.02	0.02	0.00	0.00	0.00	-0.02
	Diesel γ +10%	0.23	0.28	-0.32	-0.17	0.01	0.20
	Diesel γ -10%	-0.15	-0.19	0.00	0.00	-0.02	0.21
	Oil price +20%	-2.37	-0.25	0.00	0.00	0.14	0.11
	Oil price +50%	-5.45	-0.50	0.00	-0.01	0.24	0.27
	Oil price -20%	1.50	0.22	0.00	0.00	-0.10	-0.12
	Oil price -50%	5.02	0.49	0.00	0.01	-0.17	-0.33
	A values +10%	1.01	-1.21	1.14	0.00	0.08	0.00
	A values +30%	1.86	-2.68	2.19	0.00	0.49	0.00
	A values +50%	3.24	-3.90	3.29	0.00	0.61	0.00

Appendix B

Work division

Given the quantity of work needed for this project, Dr Mercure and I have collaborated on many stages of the model building, and Dr Hazel Pettifor in the UEA has contributed to the study of the social influences on the technology diffusion of alternative fuel cars. Table B.1 provides an overview of the collaborative work with the respective degree of responsibility.

Table B.1: Work divisions between Dr. Mercure, Dr Hazel Pettifor and Miss Aileen Lam

	Dr. Mercure	Miss Lam	Dr Hazel Pettifor
Methodology			
Theoretical framework	50%	50%	-
Computation implementation in MATLAB	50%	50%	-
Connection to the E3ME	100%	0%	-
Data			
Data Collection	10%	90%	-
Data analysis	10%	90%	-
Studies of Policy Framework	0%	100%	-
Scenario analysis	0%	100%	-
Sensitivity analysis	0%	100%	-
Income effect on emissions policy	10%	70%	20%