Which policy mixes are best for decarbonising passenger cars? Simulating interactions among taxes, subsidies and regulations for the United Kingdom, the United States, Japan, China, and India.

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Abstract

Reducing transport emissions, in particular CO_2 emissions from passenger vehicles, is a key element in mitigating the risk of climate change. Conventional welfare economics recommends the use of comprehensive pricing of carbon emissions, which may not necessarily be the most effective approach in transport systems. This paper uses an evolutionary technology diffusion model to simulate the impact of climate policies on passenger car emissions in the US, UK, Japan, China and India up to 2050, seeking to understand policy interaction. We analyse six commonly seen policy instruments and explore systematically the impact of combining each of these policies by developing 63 scenarios for the US, UK, China, Japan, and India. We assess both the policies' effectiveness in achieving emissions reductions and their cost-effectiveness in doing so. We show how the diffusion dynamics of the system can lead to interaction of policy levers, generating synergies in some cases (combined effectiveness more than the sum of its parts), and mutual impediment effects in others (combined effectiveness less than the sum of its parts). The paper identifies particular combinations of regulatory, procurement and fiscal policies that are particularly effective at generating rapid change without needing the use of very high fuel taxes or carbon pricing. Notably, combining electric vehicle mandates with taxes and regulations on combustion vehicles is highly effective, as it simultaneously improves the availability of low-carbon options while penalising high carbon options. Simple principles for policymaking can be inferred.

1. Introduction

The transport sector is the third greatest contributing sector to global carbon emissions [1] and was responsible for over 24% of energy-related carbon dioxide (CO_2) emissions in 2016. In particular, the passenger light-duty vehicle (PLDV) fleet is projected to expand from 900 million in 2012 to 1.7 billion in 2035 [2]. The rapid diffusion of electric vehicles (EVs) and improvements in the cost-effectiveness of non-electric car fleets is important in limiting energy demand growth by curbing oil use and limiting greenhouse (GHG) emissions [3,4].

Understanding a suitable stringency and the structure of public policies is necessary to influence the adoption of new car technologies. Human-technology systems (or socio-technical regimes) possess inertia and display resistance to change, which makes them durable for multiple social, economic and technical reasons [5]. The transition to low emissions vehicle

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fleets may require diverse policy instruments that allow existing technologies in niches to diffuse into the market. The design, level, and structure of the instruments determine the effectiveness of the policies in achieving long-term emissions targets. In policy practice, diverse types of policies are almost always introduced simultaneously, aiming to control different types of externalities (e.g. fuel use, road use, emissions). These incentives likely interact in ways not always fully understood, providing price and regulatory signals for purchase decisions and use behaviours, thereby compounding their effect on the transition to low-emission vehicles.

The impacts of the policies are typically heterogeneous across countries and time, and can be non-linear, partly due to the inherent high heterogeneity of markets [6]. Some consumer markets are less likely to adopt low-emission technology until a certain critical mass is reached. Particular combinations of policies could be more effective in overcoming technological lock-ins and decarbonising private transport than others. This must be understood when designing new frameworks aiming at rapid decarbonisation.

Many studies consider one policy in isolation (e.g. [7,8]). Of the studies exploring policy packages, most have looked at the integrated impact of policy mixes in achieving deep CO_2 emissions reductions [9–11]. Although a few studies have examined the interaction of policies [12–14], these studies predominantly have investigated the impact of policy interactions in the US and Canada.

However, no studies have comparatively explored interaction effects between policies across multiple countries. Similarly, none have examined whether the same insights hold between developed nations (e.g. the US, the UK, Japan) and large, emerging economies (e.g. China, India) with high-demand growth. Thus, insights offered by recent research have remained tied to national contexts, and are difficult to translate.

In the transport literature, significant consideration has been given to the synergies and trade-offs between policies [15]. There are trade-off (or reinforcement) effects between two policies if the presence of two policies offers a smaller (or larger) CO_2 mitigation benefit than the sum of the effectiveness of either policy alone. This study aims to quantify the trade-offs and synergies that exist between policies for mitigating CO_2 emissions from passenger cars in the five major economies: the US, the UK, China, India and Japan. These countries have been chosen for this study because their vehicle markets possess very different characteristics, which are the results of different histories of policies and regulations, and they also constitute a major component of the global car fleet [6]. This comparative study enables us to examine how the structures of different car markets influence the levels of policy stringencies necessary to induce transitions in current passenger car systems. In this paper, the higher the policy stringency, the higher the cost of the policy for the consumers (taxes) and the government (EV subsidy). In the same manner, the more stringent the EV mandate, the more ambitious the EV target sales. We discuss possible options available to policymakers to minimize trade-off effects and maximize synergies in policy design. In pursuit of these objectives, this paper addresses the following questions:

1) Can an evolutionary model of vehicle fleets predict and explain trade-off or reinforcement effects between any existing types of policy instruments on the diffusion of PLDVs in each of

the five countries? How significant are the trade-off and reinforcement effects on overall incentives?

2) How do the trade-off and reinforcement effects between policy instruments affect the costs and efficiencies of the policy combinations, and can this be used to guide policy design?

To answer these questions, we performed scenario analysis using the FTT:Transport model, an evolutionary technology diffusion model for road transport technology, as a submodule of the Integrated Assessment Model (IAM) named E3ME-FTT-GENIE (see [9]). The Future Technology Transformations (FTT) family of models consists of FTT:Power [16], FTT:Transport [9], FTT:Heat [17] and FTT:Steel [18]. The purpose of the design of the FTT models is to simulate the evolution of fleets through technology diffusion dynamics that follow standard theory on the diffusion of innovations [19]. The model makes use of coupled S-shaped curve (non-equilibrium) dynamics, driven by agent decisions, following preferences, decision rules and perceived incentives, calibrated to reproduce observed technology trajectories. The FTT models use a modified evolutionary version of discrete choice theory in which social influence is integrated [20]. Its strong path-dependence and high policy resolution allow explicit assessment of policy interactions, with a modelling horizon of 2050. The paper is structured in comparative form, and aims to unearth general principles for low-carbon policymaking that are context-independent in path-dependent transport systems.

The algorithm used is based on a simulation of dynamical systems, as opposed to the systems optimization frequently used in technology models. The FTT models enable modelling of technological diversity, heterogeneous consumer decision-making and the complex evolving interactions between policies. The FTT:Transport model offers a highly detailed set of policy packages, and allows the modelling of different transition pathways that then lead to different future technology scenarios [9].

The remaining paper is structured in the following manner: Section 2 provides a literature review of previous research on the analysis of policies. Section 3 discusses existing policies for encouraging low emission vehicles in the five major economies. Section 4 describes the model and methodology used to perform the scenario analysis. Section 5 details the variables and data sources used in this study. Section 6 provides the assumptions for the scenario analysis. Section 7 presents the results of this scenario analysis and discusses their policy implications. Section 8 offers insights for policymakers, and finally, section 9 provides a conclusion.

2. Literature review

The scenarios most often assessed by the IPCC have primarily focused on harmonised carbon pricing/taxing as a policy strategy [21]. Focusing on transport, other studies have analysed the mid- to long-term impacts of various individual policy instruments on the CO_2 emissions from the PLDV sector using quantitative models [8,13,23–29]. Most studies have only examined the impacts of various taxes on long term CO_2 emissions. For instance, Kloess et al. [24] investigated the effect of various tax incentives and technological progress on the Austrian passenger car fleet. Using the UK Transport model, Brand et al. [30] assessed the long-term scenario of several low-carbon fiscal policies, such as vehicle purchase taxes, road taxes and scrappage programs, as well as their effects on CO_2 emissions from the PLDVs.

The zero-emission vehicle (ZEV) mandates have existed only in the US and some regions of Canada. Sykes and Axsen [13] examined the impact of the ZEV mandate on the long term sales in North America using CIMS-ZEV. Karplus et al. [8] studied the cost and effectiveness of fuel economy standards, alone and in conjunction with economy-wide policies constraining GHG emissions. Small [31] assessed the cost and effectiveness of fuel tax, vehicle efficiency standards, and financial subsidies on CO_2 emissions reduction from passenger light-duty vehicles in the US with the National Energy Modelling System (NEMS). Morrow et al. [23] analysed 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 to reduce GHG emissions and oil consumption in the US transportation sector. Outside North America, studies have only analysed the impacts of various financial incentives on developed countries.

Thus, as discussed above, many studies on policy instrument analysis have focused on studying the impact of one instrument on a particular country [25,32,33]. However, individual policy instruments have limited effectiveness or must be unrealistically stringent, whereas the combination of instruments can be more effective. In fact, a more integrated policy mix of strong policies is required for deep GHG emissions [34]. 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 [10,23,29], while ignoring the interactions among the policy instruments on the emissions of PLDVs. Despite the prevalence of policy mixes in many nations and regions [35], very little transportation research has studied policy interactions, particularly for policy mixes for light-duty vehicles [15]. While it is important to examine the overall impact of a group of policies, the interactions among the policy instruments are central to any policy mix because of their collective influence on the effectiveness and cost-effectiveness of instruments in the mix, and thus the design of the policy strategy [19,36,37].

When systems are path-dependent, and various policies are combined, they can be either mutually reinforcing or work against one another, depending on how they are designed and implemented [38]. For example, policies focusing on improving vehicle choice availability (technology push) can reinforce the impact of policies influencing pricing (technology pull) [39]. In other words, there can be synergies or interference effects between instruments, and it is thus important to understand the effects of policy interactions. The design of an effective policy package requires an understanding of policy interactions [34]. Several studies have discussed the possible impacts of policy synergies and policy mixes on the effectiveness and the impacts of policies regarding emissions reductions in the energy sector [13,34,36,37]. However, few studies go beyond qualitative statements. An exception is a study by Viguié and Hallegatte [42], which provides a multicriteria analysis on the trade-off and synergies of various urban climate policies, such as zoning and public transport subsidies. Elsewhere, Fischer and Fox [43] carried out scenario analysis on carbon taxes and rebates for mitigating carbon leakage. More specific to light-duty vehicles, Axsen and Wolinetz [44] simulated the impact of incentives and mandate-based strategy on plug-in EV sales in Canada. Jenn et al. [12] examined the individual and combined effect of light-duty vehicle GHG emission standards and the Zero Emissions Vehicle policy in the US.

Thus, we identify two main gaps in existing studies for the analysis of policy instruments on long-term CO_2 emissions. First, existing studies, as we have illustrated, have focused on studying policies for only one country or region. Although this approach is useful in understanding the impact of policies on a certain country, it does not allow for the inference of impact for other countries, or explain why or under what conditions the policies would be effective and be cost-efficient. Second, many existing studies have been ex-post policy evaluation studies. None of these studies examine the interactions between multiple policies within the PLDV sector using a dynamic model. A comparative study of policy interactions across several countries with different characteristics is required to provide insights into policy actions in passenger road transport.

3. Current policy contexts and needs

The levels and designs of incentives vary greatly across our case study countries. This section summarises the main policy objectives and policies that have been implemented in the UK, the US, Japan, China, and India to encourage the diffusion of low-emission vehicles.

3.1 UK

The UK has adopted a target of net-zero emissions for 2050, which includes transport [45]. The EU first established a law requiring new cars registered in the EU to emit no more than an average of 130 grams of CO_2 per kilometre (gCO_2/km) by 2015. By 2021, the average fleet target for new cars is 95 grams of CO_2 per kilometre. From 2021 onwards, assuming some minimum degree of regulatory alignment with the EU for transport, the average emissions of all newly registered cars of a manufacturer must be below that target [46].

Vehicle Excise Duty (VED), also commonly known as vehicle road tax, is an annual tax levied on vehicles using public roads. Typically, it is levied on the basis of vehicle characteristics, such as engine size, weight, or power. More recently, the CO_2-graded VED was recalibrated with higher band resolution and slightly higher duties [30]. In addition to the exemption from the VED, in the UK, the electric car (plug-in car) grant is intended to incentivise electric car purchases by offering 4,500 GBP toward the purchase of an electric car (plug-in car) on a zero-emission range of at least 70 miles [45].

3.2 US

The transport sector has surpassed the power sector as the single largest US emitter of GHGs for the first time since 2016. Following the US withdrawal from the Paris Agreement, 24 states formed the US Climate Alliance and will uphold the original US commitment, reducing emissions 26% to 28% below 2005 levels by 2025 [47]. This could change again if the US re-joins the Paris Agreement.

Since 2011, the federal government has offered an income tax credit to owners of fuel-efficient vehicles, ranging from $2,500 to $7,500 per vehicle, based on each vehicle's traction, battery capacity and gross vehicle weight rating [48].

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. Under the Obama Administration's standards, the auto industry was required to double the fuel economy of vehicles to an average of approximately 54 miles per gallon by 2050. However, more recently, under the Trump administration, the EPA has been considering freezing the fuel-efficiency targets at 2020 levels [49].

Many states and local governments offer a wide variety of incentives beyond what the federal government requires. These incentives take many forms, including rebates, income tax credits, sales tax exemptions, and fee exemptions. Among all the non-fiscal policies that have an obvious bias towards NEVs, the zero-emission vehicle (ZEV) credit mandate in California is the most representative incentive. It sets minimum sale percentages of ZEVs and credits to be given to the manufacturers based on vehicle type and all-electric range [50,51].

3.3 Japan

Japan has pledged a 26% emissions reduction in GHG below 2013 levels by 2030, including the transport sector [52]. In 1998, Japan initiated the Top Runner Approach, which has set mandatory efficiency standards for automobiles based on the most efficient products. By 2015, the Ministry of Economy, Trade and Industry (METI) announced that the new standard to be achieved by passenger cars was 12.7-23.5 km/L. If these numerical targets in the new standards are successfully achieved, fuel efficiency in the target fiscal year (FY) of 2022 will improve by 26.1% from the actual level in FY2012 [53].

There are nine different taxes for owning cars in Japan, including acquisition tax, consumption tax, tonnage tax, automobile tax, gasoline tax, diesel tax, LPG tax, and in-use consumption tax [54]Zero-emissions vehicles are exempt from both the acquisition and the tonnage tax. The owners of cars that are compliant with the 2015 FES enjoy up to an 80% reduction in acquisition tax, and a 75% reduction in automobile tonnage tax [54].

3.4 China

Under the Paris Agreement, China committed itself to reach peak carbon emissions around 2030. More recently, President Xi announced a net-zero emissions target for 2060, thus current policy regimes are likely to change. Meanwhile, the transport sector has become one of China's fastest-growing economic sectors [55]. At the national level, to reduce its dependency on foreign oil and to encourage more fuel-efficient vehicle technologies, the passenger vehicle market has been subject to fuel economy standards since 2004. The Chinese government also provides direct subsidies for the purchase of EVs at both central and local levels. According to the driving mileage of vehicles, the EV purchaser can receive up to RMB 55,000 (USD 8,000) in subsidies from the central government. However, in 2019, China's Ministry of Finance announced its plan to reduce by half subsidies for EVs sold in the country with driving ranges of 400 or more kilometres to RMB 250,000 (USD 3,600) [56]. Beyond this, many local governments provide additional subsidies. For example, in Shenzhen, Guangzhou and Beijing, owners of certain EVs (with ranges above 250km) can receive subsidies of up to RMB 110,000 (USD 17,000). EVs are also exempt from various taxes and regulations, such as purchase tax, license lottery (in Beijing and Guangzhou), and toll charges [57].

The New-Energy Vehicle Credit Program was finalized in September 2017 and was implemented in 2018. Under the NEV credit program, car manufacturers with over 30,000 annual vehicle sales in the country are required to produce 10% NEVs in 2019 and 12% in 2020 [58]. Companies that do not reach their quotas will face fines, but they could buy credits from manufacturers having a surplus.

3.5 India

India's NDC sets a target for reducing emissions by 33% to 35% between 2005 and 2030. The transport sector is a key area for meeting this goal [59]. To promote eco-friendly vehicles, in 2015, the Indian government launched the FAME (Faster Adoption and Manufacturing of Hybrid and Electric vehicles) measure to incentivise HEV and EV purchases. Under FAME India, the Indian government will provide incentives from Rs. 138,000 (USD 2,000) for every electric car sold [60].

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 EVs, India has reduced the excise duty from 8% for conventional cars, to 4% for EVs [61]. In addition, individual states have their own incentives for energy-efficient vehicles.

The Government of India set the first fuel economy standards for the nation in 2014. This standard set a fleet target of 130gCO_2/km, which came into effect in 2017. It proposed that the standard could tighten to 113gCO_2/km by 2022 [62].

4. Methodology

4.1 Model overview – the FTT:Transport model

The Future Technology Transformation (FTT) model is a loose framework method that models technological diffusion dynamically, based on technological competition in markets. The FTT:Transport model assumes the presence of an adaptive, evolving, path-dependent market with heterogeneous agents. We assume revealed preferences, in that the observed cost distribution for recent vehicle sales corresponds to the heterogeneity of consumer preferences and choices (see [6,9] for details).

The FTT framework models technological diffusion by a set of logistic differential equations of the Lotka-Volterra family, which represent gradual technological substitution processes [16]. Under the FTT framework, consumers are more likely to choose a technology that has a higher market share as a result of availability, visibility, social influence and network effects, all of which we represent combined simply as adoptions proportional to current market shares (see Equation 1). It is well established that these bandwagon effects substantially influence the profiles of diffusion of vehicle models [63,64]. As shown in Appendix B.6, if one adds bandwagon effects such as social influence in a discrete choice model, one obtains a Lotka-Volterra (replicator dynamics) evolutionary system that generates S-shaped curves [20]. Following evolving choices and preferences, a flow of market shares exists from arbitrary technology category j towards category i, denoted as follows:

$$\Delta S_{j\rightarrow i} \propto \frac{S_j\, S_i}{\tau} F_{ji}\left(\Delta C_{ji}\right)\Delta t. \tag{1}$$

A reverse flow also exists from technology i to technology j, as shown here:

$$\Delta S_{i\rightarrow j} \propto \frac{S_i\, S_j}{\tau} F_{ij}\left(\Delta C_{ij}\right)\Delta t. \tag{2}$$

$\Delta S_{j\to i}$ denotes the flow of shares from car technology j to i, τ is the turnover rate for cars and Δt is an arbitrary time span. $F_{ij}(\Delta C_{ij})$ represents the fraction of agents that prefer technology i over j based on the difference in mean generalized cost of technology i and j. The shape of $F_{ij}(\Delta C_{ij})$ is derived from the cost-distribution curves that correspond to the heterogeneity of consumer choices (see Appendix B.5.2). The FTT:Transport model assumes the presence of a diverse market with heterogeneous agents. This is accomplished by using a probabilistic treatment of consumer decision-making and by using a distribution of cost values. We obtained the price data of every single model type sold in each country and matched the price data (e.g. car price, fuel cost) to the sales of that car model (see Appendix B.5.1, Fig. B3), unlike traditional models that take 'representative car model(s)'. We assume that the cost distribution corresponds to the heterogeneity of consumer choices as a result of revealed preferences obtained in this rich dataset (see Appendix B.5.2).

The rate of diffusion for one car technology is influenced by the width of the cost distribution for each segment of car technology and the market share of the technology (Equation 1). Hence, a policy (e.g. EV subsidy) does not lead to an instant diffusion of the target vehicles (e.g. EVs). Consumers do not respond to the incentives simultaneously (see Appendix B.5.2). Based on technological path dependence, the higher the current market share, the faster the rate of diffusion will be for those target vehicles. Hence, the effectiveness of a policy may be different across different markets, depending on market shares, and the heterogeneity of the market.

Capital costs (car prices) are influenced by learning curves, typically stronger for new technologies, reinforcing diffusion [9]. Hence, the 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:

$$I_i(t) = I_{0,i}\left(\frac{W_i(t)}{W_{0,i}}\right)^{-b_i} \tag{3}$$

Purchase decisions are affected by four components: consumer preference, government policies, market environment and each car model's availability. Each of these components leads to a dynamic change of market share using the Future Technology Transformation (FTT) framework. Notably, a substantial source of path-dependence in the model originates from the fact that the availability of vehicles endogenously evolves in the model: the more a car model is available, the more it is purchased. The more it is purchased, the more it is noticed and demanded, and the more it is made available. The diffusion of innovations always follows this basic mechanism [19,20].

CO_2 emissions from passenger vehicles are defined as follows:

$$E_{k,t} = G_{k,t} * CO_{2k,t} \tag{4}$$

In which $G_{k,t}$ is the demand for transport service for technology k, determined by market shares of technology k (discussed above) and the total demand for passenger car transport (see Appendix B.1). $E_{k,t}$ is the amount of fleet emissions in Gt/yr, and $CO_{2k,t}$ is the emissions factor.

4.2 Policy simulations in the FTT:Transport model

Financial incentives such as EV subsidies, road tax and fuel tax have been adopted by all of the countries in this study (i.e. the UK, the US, Japan, China and India). 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 (e.g. California) and China, and this has the potential to rapidly scale EV manufacturing and adoption [51,65]. For that reason, all of these policy types must be represented in all of the countries in the model. In this paper, policy formulations take six possible forms: vehicle tax, annual registration tax, EV subsidy, fuel tax, EV mandate, and fuel economy standards.

4.2.1 Pecuniary incentives

In the FTT:Transport model, the cost of operating a vehicle is calculated using what we termed the Levelised Cost of Transportation (LCOT) [12]:

$$LCOT_i = \sum_t \frac{\frac{(I_i - EVS_i)}{CF_i} + \sum_t \frac{\frac{RT_i(t)}{CF_i} + \left(F_i(t) + FT_i(t)\right) * \left(FE_i(t) * Dist_t\right) + MR_i(t)}{(1+r)^t}}{\sum_t \frac{1}{(1+r)^t}} \quad (5)$$

In which I_i, F_i *and* 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 the purchase time. FT_i is the fuel tax, in USD/litre. The fuel cost depends on fuel consumption (FE_i) and the distance travelled each year ($Dist_t$). $RT_i(t)$ is the annual registration tax, which is vehicle/class-specific, paid by car owners (t) once per year. CF_i is the capacity factor, km/y. This represents the breakeven cost of transportation per unit of distance, which is comparable across choices when buying a vehicle. All pecuniary policies influence this quantity in the model; however, due to consumer discounting, different types of taxes are not exactly equivalent, according to how they arise through time.

4.2.2 Intangibles

The intangibles include the components that are valued by consumers to satisfy 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 values of the intangibles are empirical parameters that we obtained from making the FTT diffusion trajectory match the trajectory observed in our historical data at the year of the beginning of the simulation (see Appendix B.5.4 for more information). The derivations for the 'intangibles' and the uncertainty analysis are presented in Appendix B.5.4.2.

4.2.3 Fuel economy regulation and EV mandates

Fuel economy regulation is modelled by influencing the flow of share values 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 as follows:

$$\Delta S_{j \to i} \propto S_i S_j F_{ij} \Delta t \quad (6)$$

In a hypothetical case where conventional petrol cars are phased out, we assume that F_{ij} is 0 so that there can no longer be any gain in market shares for conventional petrol cars.

For EV mandates, it is assumed that the policies exogenously change the shares of vehicle types at a specific point in time.[5] We assume that market shares flow from conventional cars j to EVs i by assigning exogenous shares to $\Delta SE_{j\rightarrow i}$. For example, assuming that x% of the new car sales have to be EVs; then

$$\Delta SE_{j\rightarrow i} = x\% * \frac{NewSales}{Fleet} \tag{7}$$

This approach models mandates with targets that require specific percentages of EV sales. Our approach is not exactly the same as some of the real-world EV mandates, for which the government sets an EV production quota (e.g. the China New Energy Vehicle [NEV] mandate and the California ZEV mandate program) or assigns a NEV credit. However, this approach resembles the impact of EV mandates for which the government intends to foster the diffusion of EVs by increasing the shares of EVs sold. Here we interpret the EV mandate much like if it were a public purchasing program forcing an exogenous diffusion of the technology.

4.3. Two policy interactions

4.3.1. Definition of policy effectiveness

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

$$Effectiveness = \sum_i \int_{2016}^{2050} \left(E_{t,i,s} - E_{t,i,0}\right)dt \tag{8}$$

where $E_{t,i,s}$ is the emissions sum over all technologies i between the years 2016 and 2050 under scenario s, when policies are imposed. $E_{t,i,0}$ is the emissions sum over all technologies between the years 2016 and 2050, without any policies in the counterfactual baseline scenario. The effectiveness index captures the potential effects of a policy across technologies and the cumulative emissions reduction achieved by a particular policy.

4.3.2 Policy interactions

In the FTT model, each layer of policy plays a specific role in the decarbonisation of the transport sector. When the policies are simultaneously simulated in the model, they influence the each other's effectiveness. For example, taxing high-emission vehicles with a vehicle tax will encourage consumers to purchase low-emission vehicles. In a consumer market with limited EV models available, a consumer will be more likely to choose a lower-emission petrol car, due to the path-dependent nature of the model (Equation 1). However, in the presence of the EV mandate, manufacturers are encouraged to produce more EVs and to offer more options to consumers. The higher EV shares in the FTT model lead to a higher rate of diffusion for EV,

[5] This could also be, for example, a public procurement policy in which large numbers of vehicles are purchased to force an increase in availability and infrastructure.

considering the S-shaped technological diffusion curve (Equation 1). Hence, policy interactions emerge endogenously in the FTT:Transport model. With different current market shares and cost distributions (see Appendix B.5.1, Fig. B3) for different countries, consumers respond to policies differently across different markets.

To study the interactions between policies, we simultaneously implement the policies in the model. We define the interactions between policies in terms of the total effectiveness minus the effectiveness of individual policies to measure whether certain combinations achieve more or less than their individual components:

$$Int(x1,x2) = Eff(x1,x2) - Eff(x1) - Eff(x2) \qquad (9)$$

where $Int(x1,x2)$ is the interaction between two policies, $Eff(x1,x2)$ is the total effectiveness of two policies, $Eff(x1)$ and $Eff(x2)$ are the effectiveness of policies $x1$ and $x2$*, respectively,* when two policies are both present and used simultaneously. We cannot isolate the impacts of either policy in a scenario where they are both present and interacting simultaneously. $Int(x1,x2)$ is positive if there is a reinforcement effect between two policies and $Int(x1,x2)$ is negative if there is a trade-off effect between two policies. In this paper, the sizes of the reinforcement effect and the trade-off effect are determined by the magnitude of $Int(x1,x2)$. Hence, the larger the reinforcement effect is, the larger the 'additional effectiveness' will be in reducing CO_2 emissions for combining two policies in a package (see Equation 8 for the definition of policy effectiveness). If policies do not interact, $Int(x1,x2) = 0$ and $Eff(x1,x2) = Eff(x1) + Eff(x2)$. Note that this calculation requires three FTT simulations, and since they are path-dependent, this implies the comparison of three independent storylines, which could differ across several dimensions.

4.3.3 Policy cost-effectiveness

We consider the cost of a policy in three dimensions: the cost to consumers (*ConsumerCost*), the cost to the Exchequer (e.g. EV subsidies) (*ExchequerCost*), and the cost to manufacturers (*MCost*) (e.g. for fuel economy standards and EV mandates). For clarity, we assume that the costs are positive for individual parties/groups. For example, we assume that the 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 policies. Hence, we have:

$$TotCost = ConsumerCost + ExchequerCost + MCost \qquad (10)$$

The cost-effectiveness of a policy is equal to the change in the cumulative emissions as a result of the policy ($Effectiveness$) divided by the total cost of the policy ($TotCost$). Notably, we do not include any discounting in the cost calculation. Hence, we have the following:

$$Cost\ effectiveness = \frac{Effectiveness}{TotCost} \qquad (11)$$

The methodology for calculating the cost for each policy is documented in Appendix D.

5. Data collection

For the present study, an extensive original database detailing the technological profile of cars and populations was built. The 2016 data for new registration per vehicle model type were obtained from MarkLines [66] and matched to recent prices and car specifications, extracted from the official websites of the manufacturers. Data gathering for FTT:Transport is described in detail in [9].

The data sources and key parameters for the FTT:Transport model are presented in Appendix A.1 (Table A1) and Appendix A.2 (Table A3-A7), respectively.

6. Policy scenarios and assumptions

In this study, policies are first tested individually, and then we combine the policies to assess the interactions between policies. The scenarios are modelled to demonstrate the impact of individual policies and combinations of policies on CO_2 emissions until 2050. The analysis consists of 63 scenarios, including all possible policy combinations of six commonly seen policies for five countries. Table 1 provides an overview of these scenarios.

Table 1
An overview of the scenarios.

1 policy scenario	2 policies scenario	3 policies scenario	4 policies scenario	5 policies scenario	6 policies scenario
1. RT	1. RT+FE	1. FE+FT+EVS	1. KS+FT+VT+EVS	1. KS+FT+VT+EVS+FE	1. KS+FT+VT +EVS+FE+RT
2. FT	2. RT+FT	2. FE+FT+RT	2. KS+FE+VT+EVS	2. KS+VT+EVS+FE+RT	
3. EVS	3. EVS+RT	3. EVM+FT+RT	3. KS+FT+FE+VT	3. KS+FT+VT+EVS+RT	
4. VT	4. FT+FE	4. EVM+RT+FT	4. KS+RT+VT+EVS	4. KS+FT+EVS+FE+RT	
5. FE	5. EVS+FT	5. FE+EVM+FT	5. KS+RT+FE+VT	5. KS+FT+VT+FE+RT	
6. EVM	6. EVS+FE	6. EVS+FE+EVM	6. KS+RT+FT+VT	6. FT+VT+EVS+FE+RT	
	7. VT+RT	7. EVS+FE+RT	7. KS+FT+FE+EVS		
	8. VT+FT	8. EVS+RT+EVM	8. KS+FE+EVS+RT		
	9. VT+FE	9. EVS+RT+FT	9. KS+RT+FT+EVS		
	10. VT+EVS	10.VT+RT+FT	10. KS+RT+FT+FE		
	11. FT+EVM	11.EVS+FT+VT	11. RT+FE+VT+EVS		
	12. RT+EVS	12.RT+VT+FE	12. FT+FE+VT+EVS		
	13. FE+EVM	13.FT+VT+FE	13. FT+VT+EVS+RT		
	14. EVS+EVM	14.VT+EVM+RT	14. RT+FT+VT+FE		
	15. VT+EVM	15.FT+VT+EVM	15. RT+FT+FE+EVS		
		16.EVS+VT+EVM			
		17.FE+EVM+VT			
		18.EV+VT+RT			
		19.FE+FT+EVM			
		20.EVM+FT+EVS			

Note: RT = "Registration Tax"; FT= "Fuel Tax"; EVS = "EV Subsidy"; VT= "Vehicle Tax"; FE= "Fuel Economy Standard"; EVM = "EV Mandate"

Policy assumptions for the scenarios are presented in Table 2. Under individual policy scenarios, policy measures that have already been implemented will continue to be used in the future with the same dynamics, but with increased stringency. In this paper, policy stringency is defined as a higher price of CO_2 mitigation. For taxes, a higher price per unit of CO_2 implies higher stringency. A higher subsidy is interpreted as more stringent than a lower subsidy. Larger improvements in fuel efficiency for new cars imply more stringent fuel economy regulations. In addition, an EV mandate is more stringent when the government sets a higher EV sales target.

Assuming that policies will become more stringent in the future, financial incentives will be 50% higher than those of the current policies in individual countries.[6] We assume that passenger car owners/operators would pay a registration fee/vehicle tax based on engine size or their emissions, consistent with existing policies around the world. Zero emission vehicles such as EVs will be exempt from paying car acquisition taxes (VT) until 2050. The amount of EV subsidies depends on battery size and EV ranges. We assume that EV subsidies would be phased out by 2040.

Following the proposals by the EU and US, in the 'fuel economy regulation scenario', we assume that current inefficient petrol cars and diesel cars would be phased out in 2025, replaced by more advanced models featuring additional innovations designed to reduce energy use and emissions. Beyond this, we assume that the fuel economy for the advanced petrol and diesel

[6] The figure 50% was chosen for the sake of a uniform analaysis across policy instruments only for identifying synergies and interference effects and not for any normative purpose.

cars is 30% higher than that of the current petrol cars in the UK, and 20% higher than that in the US. Since the long-term fuel economy standards (up to 2030) for Japan, China and India have not yet been recorded/published, we used adopted fuel economy standards in our analysis. Hence, in the ‘fuel economy regulation scenario’, we assume that current petrol and diesel cars in China, India, and Japan would be phased out by 2030. Instead, they would be replaced by advanced petrol and diesel cars that will be 35% more efficient than the current petrol cars in China, and 20% more efficient than those in Japan and India, as shown in Table 2.

Since the EV mandate is absent in the UK, India and Japan, we assume that these would be introduced and that their stringencies would be the same for other countries such as China, for scenario analysis purposes. Under the EV mandate scenario, we assume that 10% of new car sales are EV, consistent with the level China proposed beginning in the year 2019. For the purpose of scenario analysis, we assume that the level of EV mandates would remain constant until 2050. We acknowledge that EV mandates could become more stringent over time. Thus, a more stringent scenario is tested and demonstrated in Appendix G. Notably, in the FTT:Transport model, the initial diffusion of EVs will lead to further EV diffusion. This implies that EV mandates can be removed after a certain sales threshold is reached.

Table 2

Policy assumptions in the scenario analysis from 2020 to 2050.

UK	2020	2025	2030	2035	2040	2045	2050
Registration tax	\$120-\$1200	\$120-\$1200	\$120-\$1200	\$120-\$1200	\$120-\$1200	\$120-\$1200	\$120-\$1200
Fuel tax	\$0.9	\$0.9	\$0.9	\$0.9	\$0.9	\$0.9	\$0.9
EV subsidy	\$3000-\$5250	\$3000-\$5250	\$3000-\$5250	\$3000-\$5250	\$3000-\$5250	--	--
Vehicle Tax[1]	\$30-\$450	\$30-\$450	\$30-\$450	\$30-\$450	\$30-\$450	\$30-\$450	\$30-\$450
Fuel economy regulation	--	30%	30%	30%	30%	30%	30%
EV mandate	10%	10%	10%	10%	10%	10%	10%

US	2020	2025	2030	2035	2040	2045	2050
Registration tax	\$290-\$600	\$290-\$600	\$290-\$600	\$290-\$600	\$290-\$600	\$290-\$600	\$290-\$600
Fuel tax	\$0.075	\$0.075	\$0.075	\$0.075	\$0.075	\$0.075	\$0.075
EV subsidy	\$7000-\$14250	\$7000-\$14250	\$7000-\$14250	\$7000-\$14250	\$7000-\$14250	--	--
Vehicle tax[1]	\$1880-\$3100	\$1880-\$3100	\$1880-\$3100	\$1880-\$3100	\$1880-\$3100	\$1880-\$3100	\$1880-\$3100
Fuel economy regulation	--	20%	20%	20%	20%	20%	20%
EV mandate	10%	10%	10%	10%	10%	10%	10%

Japan	2020	2025	2030	2035	2040	2045	2050
Registration tax	\$320-\$480	\$320-\$480	\$320-\$480	\$320-\$480	\$320-\$480	\$320-\$480	\$320-\$480
Fuel tax	\$0.75	\$0.75	\$0.75	\$0.75	\$0.75	\$0.75	\$0.75
EV subsidy	\$7500-\$14000	\$7500-\$14000	\$7500-\$14000	\$7500-\$14000	\$7500-\$14000	--	--
Vehicle Tax[1]	\$580-\$1260	\$580-\$1260	\$580-\$1260	\$580-\$1260	\$580-\$1260	\$580-\$1260	\$580-\$1260
Fuel economy regulation	--	--	20%	20%	20%	20%	20%
EV mandate	10%	10%	10%	10%	10%	10%	10%

China	2020	2025	2030	2035	2040	2045	2050
Registration tax	\$80-\$380	\$80-\$380	\$80-\$380	\$80-\$380	\$80-\$380	\$80-\$380	\$80-\$380
Fuel tax	\$0.9	\$0.9	\$0.9	\$0.9	\$0.9	\$0.9	\$0.9
EV subsidy	\$8000-\$14000	\$8000-\$14000	\$8000-\$14000	\$8000-\$14000	\$8000-\$14000	--	--
Vehicle Tax[1]	\$1000-\$4600	\$1000-\$4600	\$1000-\$4600	\$1000-\$4600	\$1000-\$4600	\$1000-\$4600	\$1000-\$4600
Fuel economy regulation	--	--	35%	35%	35%	35%	35%
EV mandate	10%	10%	10%	10%	10%	10%	10%

India	2020	2025	2030	2035	2040	2045	2050

Registration tax	$440-$1500	$440-$1500	$440-$1500	$440-$1500	$440-$1500	$440-$1500	$440-$1500
Fuel Tax	$0.75	$0.75	$0.75	$0.75	$0.75	$0.75	$0.75
EV subsidy	$1000-$3000	$1000-$3000	$1000-$3000	$1000-$3000	$1000-$3000	--	--
Vehicle Tax[1]	$130-$450	$130-$450	$130-$450	$130-$450	$130-$450	$130-$450	$130-$450
Fuel economy regulation	--	--	20%	20%	20%	20%	20%
EV mandate	10%	10%	10%	10%	10%	10%	10%

[1]Zero emissions vehicles such as EVs are exempt from paying vehicle tax until 2050.

7. Results

7.1 Baseline scenario

Fig. 1 presents the results from our model for the policy scenarios when there are no policies in place. The baseline scenarios are used as benchmarks for other scenarios with incentives. As shown in Fig. 1, in the absence of new policies, India, the US, and the UK are projected to be dominated by petrol cars. Hybrid cars in Japan generate around 0.4 Tpkm/year (Tera person-kilometres per year), and electric cars will generate around 1.3 Tpkm/year in China by 2050.

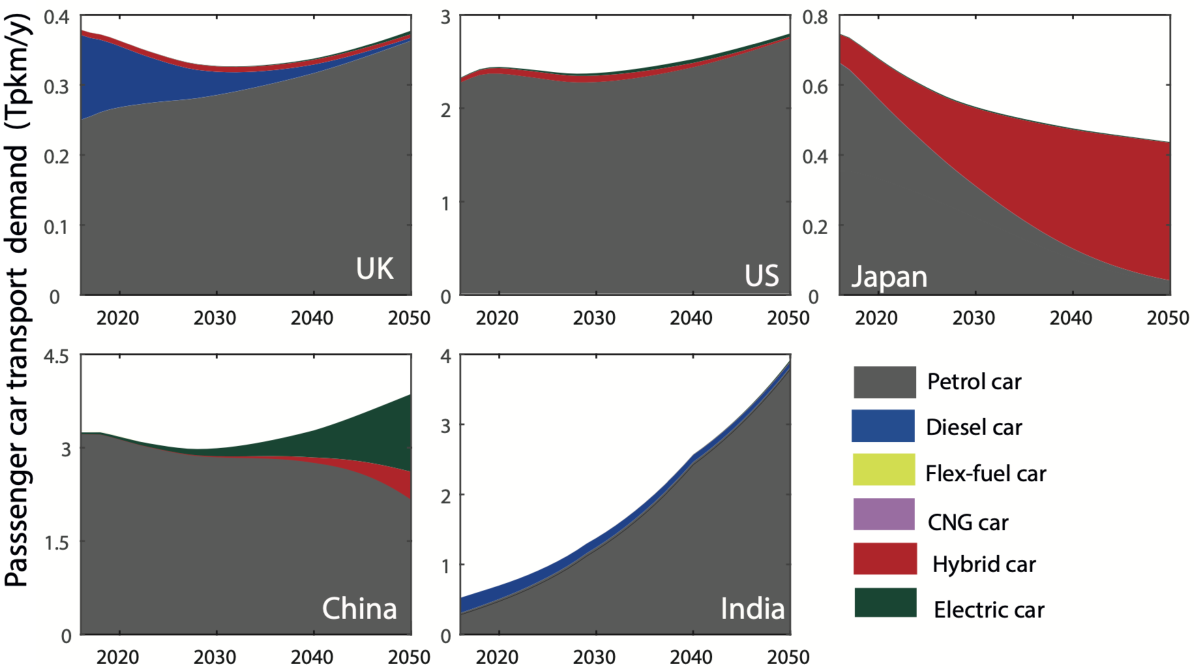

Fig. 1. Baseline scenario results. Passenger car transport demand in Tpkm/year for the UK, US, Japan, China, and India.

7.2 Scenarios with individual policies

This section analyses the effectiveness of individual policies when these incentives are introduced independently (without interactions) for different countries. Tables 3 and 4 show the effectiveness and cost-effectiveness of individual policies.

Among financial incentives, the annual registration tax is the most effective in all the countries. This is because the total cost of the annual registration tax is among the highest of all policies. For example, in the US, the annual registration tax is USD 600 per year under the high registration tax scenario. For buyers that hold on to their cars for 10 years, this amounts to USD 6,000 over the lifetime of a car.

Comparatively, the effectiveness of financial incentives is the lowest in India. This is because the shares for EVs and hybrid cars are still minimal in India. When the shares for new energy technologies are small, the rate of diffusion is low because many people do not have access to EVs or an EV infrastructure and perhaps do not trust EVs (e.g. range anxiety). In such a situation, financial incentives affect only a very small subset of all vehicle owners.

Among the five countries studied, the EV subsidy is the most effective in China, leading to 420 $MtCO_2$ cumulative emissions reductions. In contrast, the diffusion of EVs as a result of EV subsidies has a minimal effect on the total emissions in the PLDV sector in India and Japan. In India, this is because the shares for EVs are very small (less than 0.1%) despite the presence of EV subsidies, which is the lowest among all of the countries. Similarly, while the shares for EVs are higher in Japan than India, the shares for EVs (in the car fleet) in Japan were still below 0.3% in 2018, and 1% in 2019 in China. The lower the market shares are for the technologies, the larger the lock-in effect is in the FTT model, and the lower the rate of technological diffusion is.

Table 3
Cumulative emissions reduction from PLDVs ($MtCO_2$ emissions) as a result of vehicle tax (VT), annual registration tax (RT), fuel tax (FT), EV subsidy (EVS), fuel economy standards (FE), EV mandate (EVM).

Emissions reduction ($MtCO_2$)					
Policy	UK	US	Japan	China	India
VT	2.7	118.2	5.0	157.1	2.6
RT	77.5	2185.4	34.0	764.7	169.0
FT	18.8	35.8	17.2	249.0	13.6
EVS	88.1	115.9	1.8	423.0	5.1
FE	194.7	2743.1	69.1	1313.2	1350.3
EVM	160.6	1666.1	52.3	1844.7	1247.2

Table 4
The cost-effectiveness of individual policies (2016 USD/tCO_2).
Note: the values are the average costs per tCO_2 avoided.

Cost of policy (\$/ton CO_2)					
Policy	UK	US	Japan	China	India
VT	512.1	5207.9	8664.7	1678.9	8038.3
RT	1833.3	479.2	5025.9	151.2	3459.9
FT	2247.9	439.0	1574.8	865.9	2098.5
EVS	88.5	100.8	955.1	365.1	136.1
FE	29.7	16.7	12.7	14.7	10.6
EVM	3.4	2.8	11.7	1.2	3.4

Therefore, when the shares for the new energy technologies are small, we find that EV mandates are more effective than financial incentives. As shown in Table 3, cumulative emissions are reduced by more than 1000 $MtCO_2$ in India. Since there are more first-time car buyers in India, we assume that there are proportionally more new cars in India than elsewhere, and that the India's effective turnover rate (or buying rate) would therefore be higher than in developed countries. In fact, we find that the EV mandate is the most cost-effective policy in reducing emissions and encouraging the diffusion of EVs in all countries. This finding contradicts the economic theory that taxes (or technology-neutral policies) are more cost-effective than technology-specific strategies [67], such as the EV mandate. We argue that in the presence of market and infrastructure failure within the transport sector, without technologically specific policies, consumer choices could not be incentivised collectively by an externality price.

Our results differ from the findings of Fox et al. [68] that tax scenario is more cost-effective than technology-specific standards such as EV mandates. These differences stem from the strong path-dependence structure in the FTT:Transport model. In the present study, we assume that the EV mandate has a plateau, instead of becoming more stringent over time (as assumed by Fox et al. [68]). In the FTT:Transport model, once the EV reaches a certain market share, the technology will take off without more stringent EV mandates.

Under the 'fuel economy scenario assumptions', advanced petrol and advanced diesel cars penetrate the market, replacing conventional petrol cars and diesel cars. 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 luxury petrol cars (i.e. engine size 2000cc and above, such as SUVs) in the baseline scenario in the US. Thus, we find that as a result of the 'fuel economy scenario assumptions', cumulative emissions fall by more than 2000 $MtCO_2$ in the US.

7.3 Effectiveness and cost-effectiveness of two policy combinations – scenarios with interactions

In this section, we study how the effectiveness of policies changes when two policies are combined. Overall, we find that the sum of the effectiveness of two policies is generally not equal to the sum of the effectiveness of policies applied individually, but it could be either smaller (trade-off effect) or larger (reinforcement effect) than two policies implemented on their own, depending on the structure and levels of policies (Fig. 2). The cost of each policy combination (Table 6) and the average cost for each policy combination (average efficiencies) are shown in Fig. 3. Thus, we conclude two main observations from the scenario analysis.

First, we generally find a trade-off effect between the various types of financial incentives under this analysis (as shown in the red bars of Fig. 2), whereas the degree of the trade-off effect depends on the stringency of individual policies in each country. This is because financial incentives are charged based on the 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 'additional effectiveness' of adding more financial incentives will be lower because the costs (of pairing incentives) for consumers of more efficient cars will be less than those for consumers with 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, vehicle tax, fuel tax and EV subsidy.

Fig. 3 shows that, in general, the costs of two financial policies in combination are higher than the average cost of two policies. This finding, to some degree, confirms the principle of welfare economics that only one tax should be used at a time to maximise cost-effectiveness. Overall, when the combination of policies is not sufficiently effective, these policies could result in very high costs per ton CO_2 emission reduction. For instance, in the case of Japan, the average cost and combination cost of vehicle tax and EV subsidy are both over 6000 USD/ton CO_2 emission reduction (Table 5).

Table 5
The interaction effect between two policies. When the interaction effect is positive, there is a reinforcement effect between the two policies. When the interaction effect is negative, there is a trade-off effect between two policies.

The interaction effect of two policies ($MtCO_2$)					
Scenario	UK	US	Japan	China	India
1.RT+FE	-27.1	-501.8	-25.5	-322.3	-320.9
2.RT+FT	-18.7	-34.6	-16.7	-243.2	-24.2
3.EVS+RT	-0.84	-98.7	-1.8	-401.6	-16.3
4. FT+FE	-6.5	-0.93	-10.1	-66.5	-14.8
5. EVS+FT	-0.38	-29.4	-0.49	-99.3	-1.3
6.EVS+FE	-0.21	-1.2	-0.02	-269.5	-1.0
7. VT+RT	-17.1	-129.2	-5.1	-190.5	-3.0
8. VT+FT	-0.02	-0.48	-1.3	-3.3	-0.07
9. VT+FE	-14.7	-4.1	-2.5	-109.6	-0.09
10. VT+EVS	-0.16	-36.3	-0.14	-10.8	-1.2
11. FT+EVM	8.1	20.3	9.0	200.7	19.0
12. RT+ EVM	62.3	2324.1	16.1	536.9	676.8
13. FE+ EVM	46.4	715.2	23.3	790.1	492.2
14. EVS+ EVM	6.9	150.0	3.5	274.8	21.5
15. VT+ EVM	12.9	145.6	0.69	10.8	0.63

Table 6

The cost-effectiveness of two policy combinations (2016 USD/tCO_2).

Cost of two policy combinations ($/ton CO_2)					
Scenario	UK	US	Japan	China	India
1.RT+FE	925.5	274.4	3998.4	87.1	1655.0
2.RT+FT	2151.2	471.6	3034.9	574.3	2709.2
3.EVS+RT	1833.7	483.6	5093.9	418.4	3606.1
4. FT+FE	928.7	81.2	1668.8	339.2	1395.1
5. EVS+FT	2448.4	447.1	1755.1	1057.4	2406.9
6.EVS+FE	38.5	28.2	212.4	115.1	55.2
7. VT+RT	2288.8	734.4	5709.5	491.5	3726.6
8. VT+FT	1730.6	1575.6	2176.5	1288.9	2418.9
9. VT+FE	66.0	204.8	1082.0	200.5	115.1
10. VT+EVS	489.4	2646.8	6641.8	774.0	3683.7
11. FT+ EVM	569.2	73.5	805.2	196.2	229.6
12. RT+ EVM	203.6	178.1	1301.4	32.4	95.1
13. FE+ EVM	17.9	7.6	60.4	5.6	7.4
14. EVS+EVM	37.9	40.9	315.4	185.3	7.0
15. VT+EVM	44.7	269.0	706.5	128.4	16.0

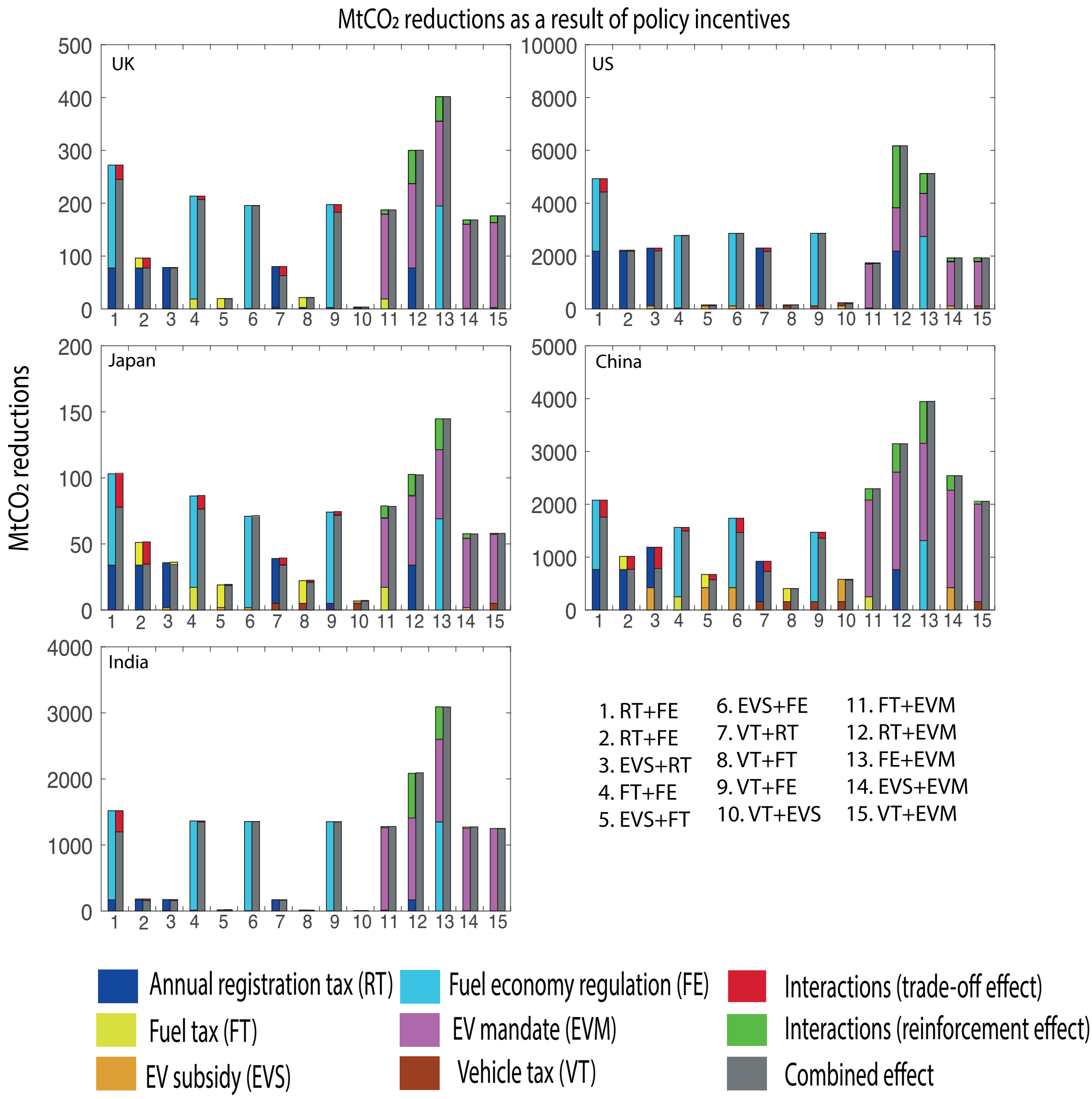

Fig. 2. Policy effectiveness (in absolute values) and interactions between policies. Policy effectiveness is defined as cumulative emissions reductions (between 2016 and 2050) achieved by a given policy or set of policies. The bar diagram shows the effectiveness of policies in absolute terms (i.e. CO_2 emissions reductions achieved by the policies). The grey bars show the total effectiveness of two policies of the corresponding scenarios. The green bar shows the reinforcement effect between the policies in the corresponding scenarios. The red bars show the trade-off effect between two policies in the corresponding scenarios.

Second, there is a reinforcement effect between EV mandates and other policies, as shown in the green bars in Fig. 2. Hence, the costs of combining EV mandates and their pairing policies (except for the EV subsidy) are lower than the average costs of two policies, the extent of which depends on the reinforcement effects between the two policies (Fig. 3). Thus, one could see the EV mandate as an ‘enabling’ policy, enhancing the effects of other policies. The size of the reinforcement effect depends on specific countries and the magnitude of the policies. In particular, the interaction effects are among

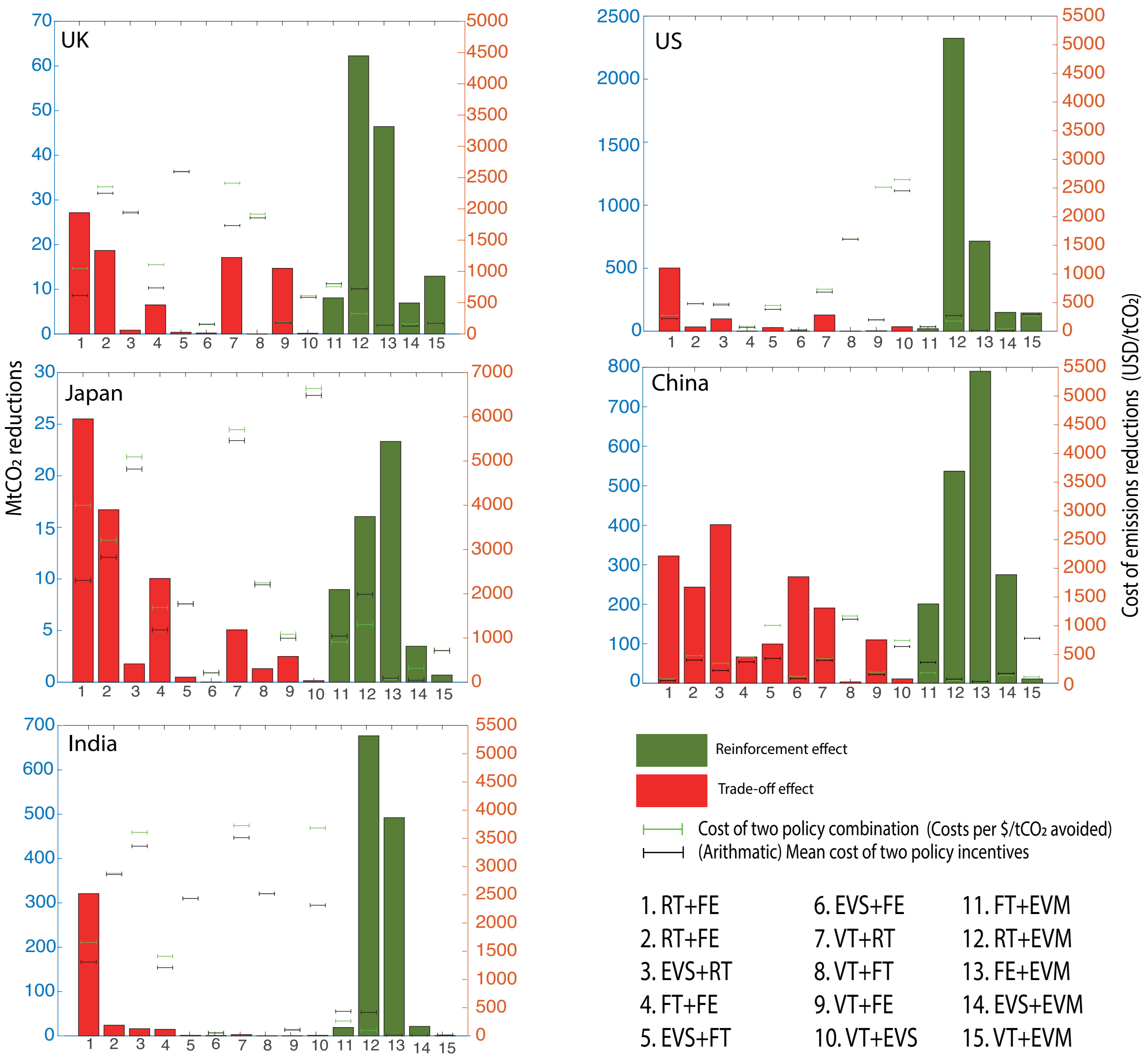

Fig. 3. Left axis: the red bars show the trade-off effects between two policies in the corresponding scenarios. The green bars show the reinforcement effect between the policies in the corresponding scenarios. Right axis: the green error bars show average efficiencies of corresponding scenarios. The black error bars show the efficiencies of two policy combinations.

the largest between annual registration taxes and EV mandates, as well as between fuel economy regulations and EV mandates. The EV mandates increase the availability and visibility of EVs. A higher availability of EVs enables the other policies to have stronger effects by giving a broader range of choice to consumers. Notably, it is implicitly assumed for clarity that the higher availability of EVs would be accompanied by wider deployment of the charging infrastructure. Regulations or policies that increase the EV fleet shares by imposing long-term fleet emissions targets for vehicle manufacturers are also essential.

In reality, there are likely to be more than two combined policies (since most policy frameworks already include more than two policies). The following section extends our conclusions for two policy interactions to the scenarios with three to six policies.

7.4 Effectiveness and cost-effectiveness of more than two policy combinations – scenarios with multiple interactions

In this section, we study the interactions between multiple policy instruments applied simultaneously by adding policies to the existing two-policy mixes and examining the changes in interactions between policies. The objective of this exercise is to understand how the trade-off and synergetic effects between policy strategies evolve, and the implications of the interactions between multiple policies on policymaking. Here we will focus on three-policy mixes (Tables 7–8 and Fig. 4), as more complex mixes could logically be inferred from these results. We show results for four to six policy mixes in Tables E1–E6 in Appendix E.

As shown in Fig. 4, in most cases, the effectiveness of three policies combinations (the grey bars) are higher than two policy combinations. When three policies are combined, consistent with two policy combinations, trade-offs originate from combining multiple financial policies, while synergies arise from combining policies with the 'enabling' EV mandates, multiplying their impact.

The overall trade-off effects of three policy combinations are larger than those trade-off effects of two policy combinations, due to the accumulation of trade-off effects between pairs of policies. However, we observe that the overall trade-off effects of three policy combinations are smaller than the sum of the trade-off effects of individual pairs. The explanation for this finding is that the additional financial incentive (e.g. EV subsidy) increases the shares for low emissions vehicles (e.g. EVs) slightly, and this encourages more people to purchase EVs with the same policy combinations improves the effectiveness of the policy package. Hence, the cost of three policy combinations is smaller than the average cost of individual pairs, as shown in Table 7. It is more cost-effective to combine three financial incentives than pairing financial incentives. This result is contrary to what is predicted by welfare economics, that there are more penalties the more instruments are used. In the FTT:Transport model, due to the interactions between policies, the introduction of another layer of policy could improve the overall effectiveness of the 'policy package', and thereby improve the cost-effectiveness of the original policy combination.

Similarly, in the cases of four- and five-policy combinations, in the absence of an EV mandate, we observe that while the overall trade-off effects increase with the number of policies, the overall trade-off effects are smaller than the sum of the trade-off effects of individual pairs. For example, the trade-off effects between fuel tax, EV subsidies, vehicle tax, and fuel economy standards are smaller than the trade-off effect when the registration tax is added to the policy package for all of the countries (Tables E1 and E3 of Appendix E). This is because in the FTT model, due to path dependency (see Equation 1), when the shares for EV are very low (as assumed in most countries), and the original policy package (four policy package) does not lead to significant change in the diffusion pathway, addition policies such as annual registration tax offers limited benefits for significantly reducing emissions.

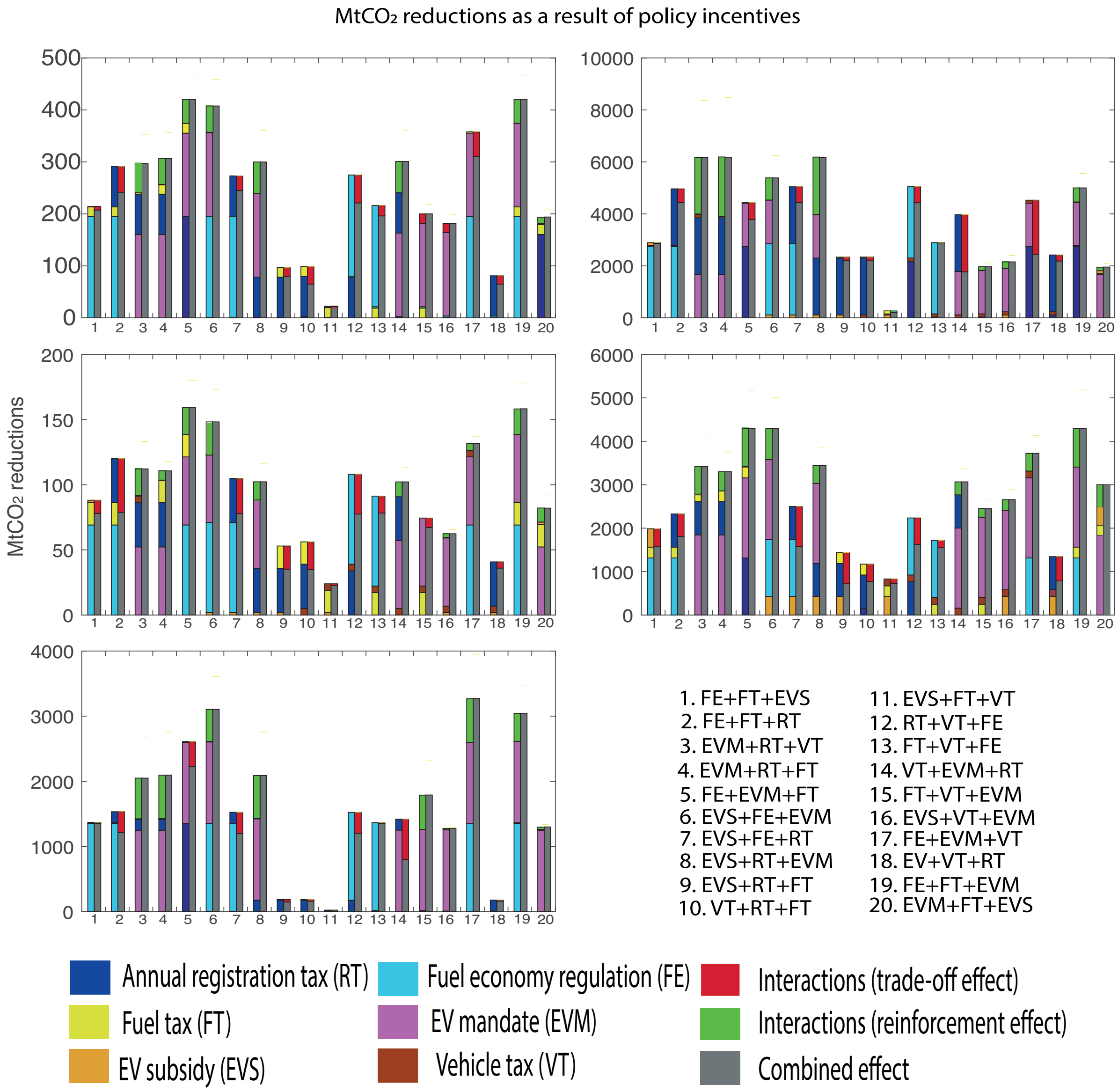

Fig. 4. Policy effectiveness (in absolute values) and interactions between policies. Policy effectiveness is defined as cumulative emissions reductions (between 2016 and 2050) achieved by a given policy or set of policies. The bar diagram shows the effectiveness of policies in absolute terms (i.e. CO_2 emissions reductions achieved by the policies). The grey bars show the total effectiveness of three policies of the corresponding scenarios. The green bar shows the reinforcement effect between the policies in the corresponding scenarios. The red bars show the trade-off effect between the policies in the corresponding scenarios.

Table 7
The interaction effect between three policies. When the interaction effect is positive, there is a reinforcement effect between the two policies. When the interaction effect is negative, there is a trade-off effect between two policies.

The interaction effect of three policies ($MtCO_2$)					
Scenario	UK	US	Japan	China	India
1.FE+FT+EVS	-6.9	-30.1	-10.1	-400.1	-16.1
2.FE+FT+RT	-49.3	-523.4	-41.4	-514.4	-319.4
3.EVM+RT+VT	56.2	2196.3	20.9	656.3	629.7
4.EVM+RT+FT	49.7	2292.6	7.2	440.2	664.9
5.FE+KS+FT	46.5	665.2	20.8	887.3	382.7
6.EVS+FE+EVM	51.4	860.3	25.1	715.2	502.1
7.EVS+FE+RT	-28.0	-603.2	-27.1	-921.6	-326.4
8.EVS+RT+EVM	61.0	2207.8	14.2	407.3	667.6
9.EVS+RT+FT	-17.1	-122.6	-17.9	-717.3	-41.0
10.VT+RT+FT	-33.8	-141.9	-21.2	-401.3	-25.4
11.EVS+FT+VT	-0.52	-60.1	-1.4	-105.9	-2.1
12.RT+VT+FE	-53.7	-618.5	-30.6	-606.0	-321.0
13. FT+VT+FE	-20.0	-4.7	-13.0	-170.3	-12.0
14.VT+KS+RT	60.2	2196.3	10.9	299.3	619.7
15.FT+VT+EVM	18.0	146.5	7.2	197.5	525.9
16.EVS+VT+EVM	17.5	253.9	3.3	231.3	19.5
17.FE+EVM+VT	47.7	2077.1	5.3	407.9	432.7
18.EV+VT+RT	-16.2	-229.4	-4.8	-560.4	-17.4
19.FE+RT+EVM	46.5	555.2	19.8	587.3	685.4
20.EVM+FT+EVS	13.8	137.4	10.8	305.5	33.1

In the presence of EV mandates, when three policies are combined, we find that there are always reinforcement effects between policies. Hence, the costs of three- policy combinations in the presence of an EV mandate are smaller than combinations of financial policies in the absence of an EV mandate. Moreover, the cost-effectiveness is the highest when the EV mandate is combined with fuel economy regulation and an EV subsidy for the US, the UK, Japan, and India. However, the sizes of the overall reinforcement effects are smaller than the sum of interaction effects between policies. For example, when an EV mandate is combined with annual registration tax and vehicle tax, we find that the overall reinforcement effects are smaller than the sum of the reinforcement effects and trade-off effects (i.e. the sum of interactions between EV mandate and fuel tax, interactions between EV mandate and vehicle tax, and the interactions between annual registration tax and vehicle tax). This is because the reinforcement effects between the EV mandates and the financial incentives fall as more financial incentives are added, due to limited effectiveness of a fixed EV mandate and the inertia of technological diffusion. Therefore, to maintain the same levels of reinforcement effects, it would be necessary to increase the stringencies of the EV mandate while adding financial policies (see Appendix G).

In particular, the sizes of the overall reinforcement effects depend on the trade-off effects between policies relative to the reinforcement effects between policies.

Table 8
The cost-effectiveness of three policy combinations (2016 USD/tCO_2).

Cost of three policy combinations (\$/tCO_2) Scenario	UK	US	Japan	China	India
1.FE+FT+EVS	633.6	64.9	1020.1	349.3	345.0
2.FE+FT+RT	861.4	243.4	1697.2	253.6	726.7
3.EVM+RT+VT	443.1	202.1	1644.8	86.2	1097.6
4.EVM +RT+FT	717.1	154.2	2113.9	107.7	810.6
5.FE+ EVM +FT	312.3	34.3	897.1	150.0	121.6
6.EVS+FE+ EVM	35.6	21.4	207.6	99.1	24.9
7.EVS+FE+RT	525.0	215.5	2336.6	183.9	807.1
8.EVS+RT+ EVM	448.4	157.6	1518.6	212.2	589.8
9.EVS+RT+FT	1483.0	340.2	1659.3	441.9	1092.0
10.VT+RT+FT	1562.6	741.0	1972.9	549.0	2215.7
11.EVS+FT+VT	932.8	1325.7	2334.1	738.4	1732.2
12.RT+VT+FE	547.7	375.7	2919.7	226.6	525.0
13. FT+VT+FE	594.3	226.9	1200.2	490.0	641.9
14.VT+ EVM +RT	443.1	202.1	1644.8	106.2	897.6
15.FT+VT+ EVM	736.9	300.0	1703.5	537.5	600.6
16.EVS+VT+ EVM	76.4	1559.4	1878.4	240.6	1012.4
17.FE+ EVM +VT	37.4	101.8	379.6	61.8	70.7
18.EV+VT+RT	1203.7	706.0	5102.3	469.0	3428.3
19.FE+RT+ EVM	348.1	36.2	1014.0	176.4	739.6
20. EVM +FT+EVS	677.6	118.6	819.2	342.6	681.3

Thus, when four policies are combined, the overall reinforcement effects fall further as more policies are added, although there are still reinforcement effects between the EV mandate and other policies. Hence, the overall costs of policies are higher when financial incentives are added to the policy combinations with an EV mandate.

When five policies are combined, the trade-off effects between policies start to dominate. Hence, we find that there are trade-off effects between an EV mandate, the fuel tax, the vehicle tax, the fuel economy regulation, and the annual registration tax, although the trade-off effects are much smaller than the sum of the trade-off effects between any financial incentives (Table E3 of Appendix E). For this reason, according to our analysis, in a policy mix, the presence of an EV mandate is a necessary but insufficient condition for the reinforcement effects between policies.

7.5 Scenario analysis

The scenario analysis in Fig. 5 illustrates the technological mixes as a result of financial incentives and fuel economy standards, and compares them with the technological mixes when EV mandates are introduced. When the EV mandates are added, as a result of the reinforcement effects, the shares for EVs increase significantly for all countries. Hence, cumulative emissions fall significantly, especially in developing countries (e.g., China and India). This suggests that the EV mandate is an essential component of any policy mix, as it multiplies the effects of all the other policies multiple times.

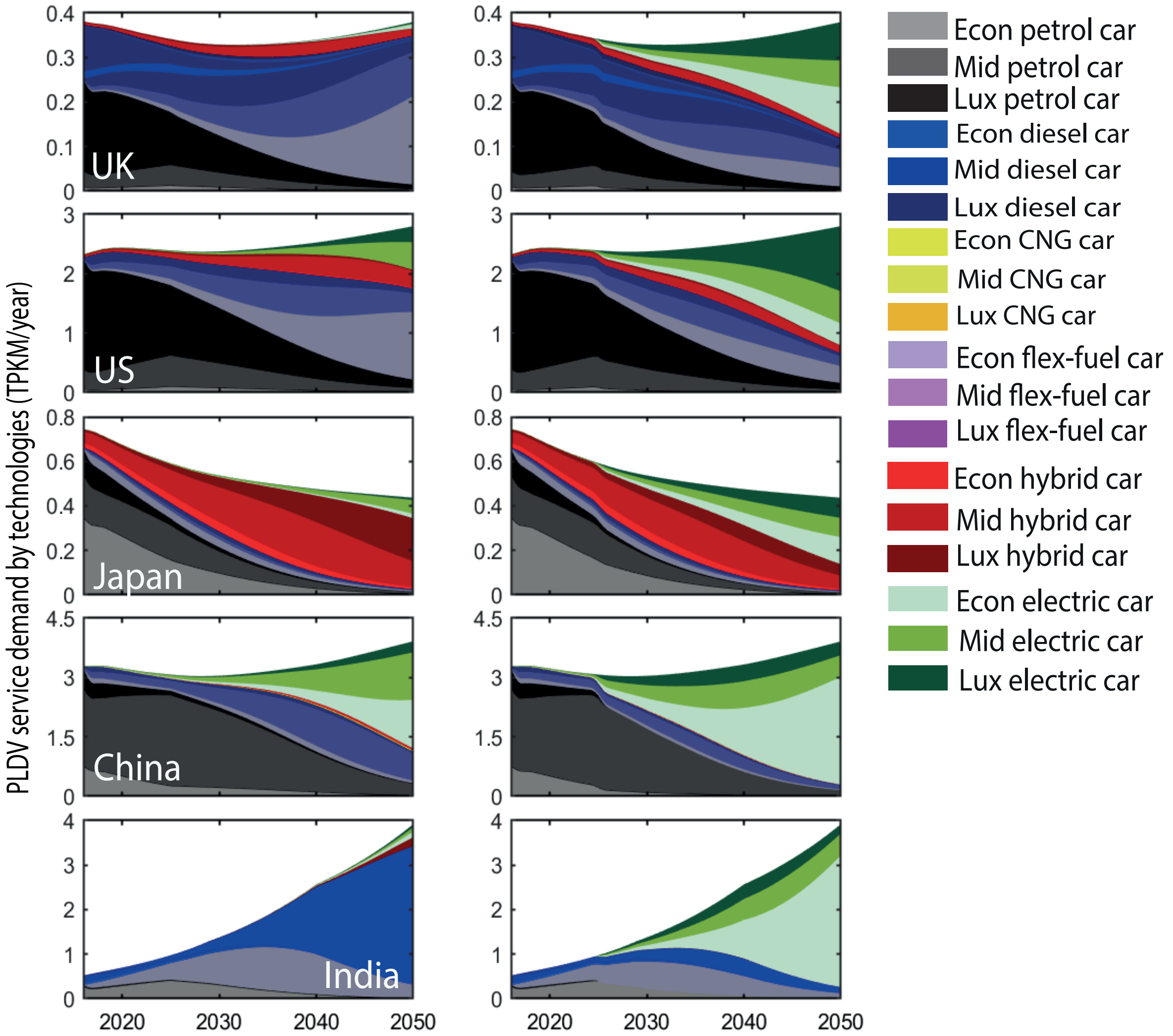

Fig. 5. PLDV service demand by 18 energy technologies in Tpkm/year for five countries. The first *column* shows the PLDV technological mix when vehicle tax, annual registration tax, fuel tax, EV subsidy, and fuel economy standards are combined. The second column shows the PLDV technological mix when the EV mandate is added to the financial policies and fuel economy standards.

The overall policy effectiveness of the EV mandate is the smallest in Japan because of the rapid hybrid car diffusion in the baseline scenario takes over the market. Intuitively, we observe smaller emissions reduction effects in switching from hybrid cars to EVs, than in switching from conventional petrol or diesel cars to EVs. While financial incentives encourage people to purchase low-emission vehicles, these incentives might not be sufficient for the purchase of EVs. The diversity of EVs and the availability of infrastructure deployed as a result of EV mandates have an impact on consumer preferences, especially when EV buyers are entitled to tax breaks and subsidies. If we assume that EV markets grow with their charging infrastructure, incentives that encourage the availability of EV models or EV charging stations (as we assume happens with EV mandates) are necessary to support EV adoption and thus reduce emissions from passenger cars.

8. Analysis and policy implications

This research sought to promote a better understanding of the interactions between existing policies for policymakers in five major economies. We simulate scenarios for various incentive measures already implemented, and examine the interactions between policies by analyzing both trade-off and reinforcement effects between any pair of policy instruments and multiple policies. We created 63 scenarios, consisting of all possible policy combinations of the six commonly seen policies for five countries.

Overall, we find that there are trade-off effects between all types of financial incentives because such incentives are charged based on the fuel economy (e.g. fuel tax) or engine size (e.g. annual registration tax). This implies that the outcomes of each policy combination are not merely additive. If consumers are incentivised to buy more energy-efficient vehicles due to one of the financial incentives, then the effectiveness of the paired incentives will be lower because the total cost (of taxation) imposed on consumers buying more efficient cars is smaller than the taxation imposed on consumers buying less efficient cars. Hence, the existence of one incentive weakens the overall financial incentives of another policy.

Policymakers should consider the trade-off effects, which weaken the overall effectiveness of the policy combinations. More stringent financial incentives have to be introduced to compensate for the trade-off effects of financial incentives. Our analyses on the interactions of multiple policies reveal that the overall trade-off effects of multiple policy combinations are smaller than the sum of the trade-off effects of individual pairs and that the effectiveness improves as more financial instruments are added to the existing policy mix. However, this may prove more costly as cost-effectiveness falls when more financial incentives are added. The results suggest there might be a trade-off between policy effectiveness and cost-effectiveness of adding financial incentives.

On the other hand, there are reinforcement effects between the EV mandate and all of the other policies. Since the EV adoption rate increases with higher starting EV shares, the EV mandate magnifies the impact of the other policies. When there are more EVs available, there are more choices for consumers, which improves the effectiveness of taxes on emissions in comparison with situations presenting fewer choices.

We determine that while the EV mandate is not always the most effective policy to significantly cut emissions when introduced on its own, there are substantial reinforcement effects between an EV mandate and financial incentives (e.g. fuel tax, EV subsidy, annual registration tax). Therefore, it is more cost-effective to introduce financial incentives with the EV mandate. We find that in the analyses of multiple policy combinations, the presence of an EV mandate in policy mixes substantially reduces the cost of emission reductions. However, with an EV mandate, we find that overall reinforcement effects fall as more financial policies are added to the policy mixes. This suggests that a stronger EV mandate is required when more financial incentives are introduced to mitigate the trade-off effects (see Appendix G). As the number of EVs on the road increases, it will be possible to achieve further emissions reduction as a result of the existing financial incentives.

The non-linearity in a policy mix permits building policy combinations that lead to more effective outcomes than a set of policies developed independently. The appropriate number and selection of policies are dependent upon the prevailing economic conditions and the current structure of the automobile market in individual countries. Table 9 presents key findings regarding the effects of policies are introduced in isolation and in combination with other policies. Generally, we find that policy combinations achieve the highest reinforcement effect when an EV mandate is combined with fuel economy regulation. Certain car market conditions, such as the number of EVs on-road and stringencies of existing policies, are major influences on the choice of policies. Hence, in the UK and the US, we find that the reinforcement effect is the highest when an EV mandate is combined with fuel economy regulation, EV subsidies and registration taxes. In China, on the other hand, where the annual registration tax is relatively lower than in the US and the UK, the reinforcement effect is the highest when an EV mandate is combined with fuel economy regulations and fuel tax. In countries such as Japan, where current car fleets are already more fuel-efficient than other countries in this study, we find that the most effective combination emerges when fuel economy regulation is combined with EV mandates and an EV subsidy.

The existence of synergistic effects contradicts basic principles of standard welfare environmental economics, which assumes that policies do not interact positively. The standard theory, which has considerable influence on present-day structuring of policies, states that the use of one instrument per externality should be used, and that more instruments would lead to inefficiencies. In our context here, this would mean observing only trade-offs. We do observe this, but only in a very limited number of cases. Due to path-dependence in transport systems, we find that the combination of policies of different natures and structures work most efficiently. For example, while a single fiscal instrument such as a tax on fuel would have to be unrealistically high to achieve emissions targets. However, in combination with other types of instruments – such as fuel economy regulations and EV mandates – such a tax could be substantially lower and produce the same outcome at a much lower cost to both public budgets and consumers

Table 9.
Summary of key results. Column 1 presents the most effective policy when the policy is introduced in isolation. Column 2 presents the combination with the largest reinforcement effect for each country.

	Most effective policy in isolation	The policy combination with the largest reinforcement effect
UK	FE	EVM+FE+EVS+RT
US	FE	EVM+FE+EVS+RT
Japan	FE	EVM+FE+EVS
China	EVM	EVM+FE+FT
India	FE	EVM+FE+RT

9. Conclusion

General principles for road passenger transport policymaking, true for all markets, that can be inferred from this work are that one has to (1) create or enhance the availability of zero-carbon vehicles, inorder to enhance the effectiveness of other policies, and (2) tax and/or regulate out the purchase and/or use of high carbon vehicles to disincentivise their presence on roads. If either of those things is not done, the effectiveness and cost-effectiveness of policies, irrespective of what they are, are much lower than they could otherwise be. (3) Layering policies (adding policies to existing policies) without careful evaluation could be ineffective and cost inefficient due to policy interactions.

Following that, policymakers must choose whether they prioritise effectiveness or cost-effectiveness (cost over rapidity of emissions reductions). When synergies arise, lower stringency policies can be used to achieve goals; when interference arises, higher stringency has to be used to achieve goals. This can guide the choice of policymakers for the composition of policy packages, in which financial incentives generally tend to interfere with one another, whereas financial and non-financial policies tend to synergise. Across countries, fuel economy regulation that phases out less fuel-efficient cars is the most effective policy when introduced in countries with many large, conventional cars (e.g. the US). We find that policy synergies seem to be lower in Japan, where there are a number of hybrid cars in the baseline scenario. In the FTT:Transport model, the incumbent technologies have a distinct advantage and cause technological lock-in. Achieving a significant long-term CO_2 emissions objective becomes more difficult with the same policy and stringency in the presence of technological lock-in. Hence, an EV mandate is a useful policy to kick-start the diffusion of EVs in countries where the shares for EVs are low.

Notably, in this study, we assume that policies are introduced simultaneously when the shares for EVs are low. Further studies should look into the timing of the policies on the overall interactions between policies. Beyond these general rules, the model must be used with tailored scenarios to explore specific policy questions. We conclude that policy interactions are a very important topic to study, and that more systematic research should be conducted on this subject.

Limitations exist in the current methodology and projections. We assume that consumer demand induces the diffusion of technology in the private passenger car transport sector and that automakers are treated exogenously.

In this research, we find that an EV mandate is the most cost-effective policy. This is partly because we assume that the cost of an EV mandate to consumers is the difference between the prices of EVs and conventional cars (see Appendix D.5). Over time, consumers could potentially 'gain' from EV purchases if the prices of EVs were to fall below the prices of conventional cars due to technological learning. In reality, policies such as EV mandates set annual EV credit targets instead of sales targets, as assumed in this paper. We have not taken into consideration the cost of EV mandates on the manufacturers or the government. For instance, to facilitate the implementation of EV mandates or EV subsidies, governments and manufacturers often need to invest in the construction of EV-charging infrastructure, and this has not been considered here. Hence, we acknowledge that the cost consideration for EV mandate may be simplified.

As with other energy models, there are parametric uncertainties regarding the FTT:Transport model. Sensitivity analyses were carried out to evaluate the effects of the parametric uncertainties on the sizes of policy interactions (see Appendix F).

Appendix A: Data

A.1. Data sources for key variables in FTT:Transport

For the present study, an original database detailing the technological profile of cars and populations was built, as required by the methodology. The data sources for the main variables are summarised in Table A1.

Table A1
Data sources for the main variables.

Variable	Data source
PLDV sales (differentiated by engine size and technology)	MarkLines database[66]
PLDV price	Car manufacturers' websites / Car dealers' websites
Fuel cost (gasoline and diesel)	[69]
Electricity price	[70]
O&M cost	[71]
Fuel economy	Car manufacturers' websites
Discount rate	[72] [73]
Learning rate	[74] [75]
Mechanical survival rate	[76] [77]

Table A2
Data sources for the transport regression model

Variables	**US**	**UK**	**Japan**	**China**	**India**
Period	1970-2015	1970-2015	1970-2011	1990-2015	1990-2015
GDP per capita	[78]	[78]	[78]	[78]	[78]
Oil price	[79]	[79]	[79]	[79]	[79]
Road length	[80]	[81]	[82]	[83]	[84]
Urbanization	[85]	[85]	[85]	[85]	[85]
Urban density	[86]	[86]	[86]	[86]	[86]
Average fuel economy standard	[87]	[88]	[88]	[88]	[88]
PLDV kilometer per vehicle	[89]	[90]	[82]	[83]	[84]

A.2. Initial parameters

Tables A3–A7 show the values of the parameters assumed in the model for the UK, the US, Japan, China and India, respectively.

The learning rate and the discount rate are subject to a degree of uncertainty. To account for the uncertainties regarding learning rates, a sensitivity analysis is presented in Appendix F, where we examine the extent to which the difference in learning rate creates uncertainties for the model.

Table A3
The initial parameters assumed for the UK.

Type	Engine size	Prices of cars (USD/ vehicle)	Standard deviation of price (USD/vehicle)	Fuel cost (USD /km)	Energy use (MJ/vk m)	Private discount rate	Learning rate	Intangible
Petrol	Econ	16927	6504	0.09	1.70	0.15	1%	0.45
	Mid	31795	10901	0.10	1.77	0.15	1%	0.20
	Lux	40594	28669	N/A	2.15	0.15	1%	0.40
Adv Petrol	Econ	20312	6504	N/A	1.36	0.15	5%	0.45
	Mid	38153	10901	N/A	1.42	0.15	5%	0.20
	Lux	48712	28669	N/A	1.72	0.15	5%	0.40
Diesel	Econ	22931	22931	N/A	1.32	0.15	1%	0.82
	Mid	32758	32758	N/A	1.76	0.15	1%	0.94
	Lux	38483	38483	0.08	2.05	0.15	1%	0.90
Adv Diesel	Econ	27517	22931	0.04	1.05	0.15	5%	0.82
	Mid	39310	32758	0.05	1.40	0.15	5%	0.94
	Lux	46180	38483	0.06	1.64	0.15	5%	0.90
CNG	Econ	N/A	N/A	N/A	N/A	0.15	1%	0.00
	Mid	N/A	N/A	N/A	N/A	0.15	1%	0.00
	Lux	N/A	N/A	N/A	N/A	0.15	1%	0.00
Flex Fuel	Econ	N/A	N/A	N/A	N/A	0.15	5%	0.00
	Mid	N/A	N/A	N/A	N/A	0.15	5%	0.00
	Lux	N/A	N/A	N/A	N/A	0.15	5%	0.00
Hybrid	Econ	25224	1217	0.05	1.29	0.15	10%	1.20
	Mid	36034	4895	0.06	1.35	0.15	10%	0.30
	Lux	47767	11810	0.08	2.02	0.15	10%	0.10
Electric	Econ	22931	970	0.02	0.54	0.15	15%	0.00
	Mid	32758	1200	0.03	0.76	0.15	15%	0.00
	Lux	51656	1350	0.04	0.94	0.15	15%	-0.60

Note: 'Econ' denotes cars with engine sizes smaller or equal to 1400cc. 'Mid' denotes cars with engine sizes larger than 1400cc and smaller than 2000cc. 'Lux' denotes cars with engine sizes larger than 2000cc. N/A indicates that data is not available or that the car technology is not widely used in the country.

Table A4
The initial parameters assumed for the US.

Type	Engine size	Prices of cars (USD/ vehicle)	Standard deviation of price (USD/vehicle)	Fuel cost (USD /km)	Energy use (MJ/vk m)	Private discount rate	Learning rate	Intangible
Petrol	Econ	17939	2283	0.07	2.74	0.15	1%	-0.72
	Mid	20749	4391	0.07	2.87	0.15	1%	-0.06
	Lux	29744	15588	0.09	3.42	0.15	1%	0.42
Adv Petrol	Econ	21527	2283	0.06	2.19	0.15	5%	-0.72
	Mid	24899	4391	0.06	2.30	0.15	5%	-0.06
	Lux	35693	15588	0.07	2.74	0.15	5%	0.42
Diesel	Econ	N/A	N/A	0.06	N/A	0.15	1%	0.00
	Mid	24899	1202	0.07	2.92	0.15	1%	0.00
	Lux	35693	3043	0.08	3.47	0.15	1%	0.00
Adv Diesel	Econ	N/A	N/A	0.05	N/A	0.15	5%	0.00

Type	Engine size	Prices of cars (USD/ vehicle)	Standard deviation of price (USD/vehicle)	Fuel cost (USD /km)	Energy use (MJ/vkm)	Private discount rate	Learning rate	Intangible
	Mid	35855	1202	0.05	2.34	0.15	5%	0.00
	Lux	51398	3043	0.06	2.78	0.15	5%	0.00
CNG	Econ	17939	2283	0.03	1.37	0.15	1%	0.00
	Mid	20749	4391	0.04	1.61	0.15	1%	0.00
	Lux	29744	15588	0.05	1.81	0.15	1%	0.00
Flex Fuel	Econ	19733	2103	0.05	1.94	0.15	5%	0.00
	Mid	22834	4560	0.05	2.04	0.15	5%	0.00
	Lux	32718	13901	0.06	2.43	0.15	5%	0.00
Hybrid	Econ	23958	984	0.03	1.29	0.15	10%	0.00
	Mid	28795	3881	0.03	1.49	0.15	10%	-0.12
	Lux	34007	14744	0.04	2.20	0.15	10%	-0.06
Electric	Econ	29744	1230	0.00	0.54	0.15	15%	-0.12
	Mid	30707	3940	0.01	0.76	0.15	15%	-0.40
	Lux	90229	24942	0.01	0.94	0.15	15%	-1.90

Note: ‘Econ’ denotes cars with engine sizes smaller or equal to 1400cc. ‘Mid’ denotes cars with engine sizes larger than 1400cc and smaller than 2000cc. ‘Lux’ denotes cars with engine sizes larger than 2000cc. N/A indicates that data is not available or that the car technology is not widely used in the country.

Table A5

The initial parameters assumed for Japan

Type	Engine size	Prices of cars (USD /vehicle)	Standard deviation of price (USD/vehicle)	Fuel cost (USD /km)	Energy use (MJ/vkm)	Private discount rate	Learning rate	Intangible
Petrol	Econ	12936	2872	0.06	1.90	0.15	1%	0.76
	Mid	21321	3746	0.07	2.01	0.15	1%	0.52
	Lux	27991	15787	0.08	2.28	0.15	1%	0.40
Adv Petrol	Econ	15523	2872	0.06	1.52	0.15	5%	0.76
	Mid	25584	3746	0.06	1.61	0.15	5%	0.52
	Lux	33589	15787	0.08	1.82	0.15	5%	0.40
Diesel	Econ	N/A	N/A	0.06	2.12	0.15	1%	0.00
	Mid	N/A	N/A	0.07	2.40	0.15	1%	0.00
	Lux	33590	3432	0.09	2.95	0.15	1%	0.00
Adv Diesel	Econ	N/A	N/A	0.05	1.70	0.15	5%	0.00
	Mid	N/A	N/A	0.06	1.92	0.15	5%	0.00
	Lux	40306	3432	0.07	2.36	0.15	5%	0.00
CNG	Econ	N/A	N/A	0.05	N/A	0.15	1%	0.00
	Mid	N/A	N/A	0.06	N/A	0.15	1%	0.00
	Lux	N/A	N/A	0.07	N/A	0.15	1%	0.00
Flex Fuel	Econ	N/A	N/A	N/A	N/A	0.15	5%	0.00
	Mid	N/A	N/A	N/A	N/A	0.15	5%	0.00
	Lux	N/A	N/A	N/A	N/A	0.15	5%	0.00
Hybrid	Econ	19513	2914	0.04	1.35	0.15	10%	0.00
	Mid	22735	4845	0.04	1.44	0.15	10%	-0.32

Type	Engine size	Prices of cars (USD /vehicle)	Standard deviation of price (USD/vehicle)	Fuel cost (USD /km)	Energy use (MJ/vkm)	Private discount rate	Learning rate	Intangible
	Lux	45301	13194	0.06	1.71	0.15	10%	-0.72
Electric	Econ	19513	590	0.02	0.54	0.15	15%	0.00
	Mid	31288	1523	0.03	0.76	0.15	15%	-0.30
	Lux	45301	2320	0.03	0.94	0.15	15%	-0.60

Note: 'Econ' denotes cars with engine sizes smaller or equal to 1400cc. 'Mid' denotes cars with engine sizes larger than 1400cc and smaller than 2000cc. 'Lux' denotes cars with engine sizes larger than 2000cc.
N/A indicates that data is not available or that the car technology is not widely used in the country.

Table A6

The initial parameters assumed for China.

Type	Engine size	Prices of cars (USD /vehicle)	Standard deviation of price (USD/vehicle)	Fuel cost (USD /km)	Energy use (MJ/vkm)	Private discount rate	Learning rate	Intangible
Petrol	Econ	8901	2872	0.06	2.09	0.15	1%	0.78
	Mid	16780	3746	0.08	2.36	0.15	1%	0.00
	Lux	41177	15787	0.10	2.91	0.15	1%	-0.72
Adv Petrol	Econ	10681	2872	0.05	1.67	0.15	5%	0.78
	Mid	20135	3746	0.07	1.89	0.15	5%	0.00
	Lux	49412	15787	0.08	2.32	0.15	5%	-0.72
Diesel	Econ	13450	N/A	0.06	2.12	0.15	1%	0.00
	Mid	21303	N/A	0.07	2.40	0.15	1%	0.00
	Lux	47300	3432	0.08	2.95	0.15	1%	1.00
Adv Diesel	Econ	16140	N/A	0.05	1.70	0.15	5%	0.00
	Mid	25564	N/A	0.05	1.92	0.15	5%	0.00
	Lux	56760	3432	0.07	2.36	0.15	5%	1.00
CNG	Econ	8901	2872	0.04	1.97	0.15	1%	-0.31
	Mid	16780	3746	0.05	2.13	0.15	1%	0.00
	Lux	41177	15787	0.06	2.54	0.15	1%	0.00
Flex Fuel	Econ	N/A	N/A	N/A	N/A	0.15	5%	0.00
	Mid	N/A	N/A	N/A	N/A	0.15	5%	0.00
	Lux	N/A	N/A	N/A	N/A	0.15	5%	0.00
Hybrid	Econ	20042	6843	0.03	1.28	0.15	10%	-0.72
	Mid	24019	4427	0.04	1.50	0.15	10%	-1.00
	Lux	39960	4400	0.05	1.85	0.15	10%	-0.84
Electric	Econ	9575	3128	0.01	0.54	0.15	15%	-0.60
	Mid	27073	4371	0.02	0.76	0.15	15%	-0.90
	Lux	42424	11429	0.03	0.94	0.15	15%	-1.30

Note: 'Econ' denotes cars with engine sizes smaller or equal to 1400cc. 'Mid' denotes cars with engine sizes larger than 1400cc and smaller than 2000cc. 'Lux' denotes cars with engine sizes larger than 2000cc.
N/A indicates that data is not available or that the car technology is not widely used in the country.

Table A7

The initial parameters assumed for India.

Type	Engine size	Prices of cars (USD/vehicle)	Standard deviation of price (USD/vehicle)	Fuel cost (USD/km)	Energy use (MJ/vkm)	Private discount rate	Learning rate	Intangible
Petrol	Econ	8897	2733	0.05	1.56	0.15	1%	0.38
	Mid	20545	8147	0.08	2.28	0.15	1%	0.06
	Lux	30097	6942	0.12	3.42	0.15	1%	-0.48
Adv Petrol	Econ	10676	2733	0.04	1.24	0.15	5%	0.38
	Mid	24654	8147	0.06	1.82	0.15	5%	0.06
	Lux	36616	6942	0.10	2.74	0.15	5%	-0.48
Diesel	Econ	12132	2698	0.04	1.54	0.15	1%	0.40
	Mid	17919	8192	0.06	2.27	0.15	1%	0.80
	Lux	27844	9372	0.07	2.76	0.15	1%	-0.20
Adv Diesel	Econ	14558	2698	0.03	1.82	0.15	5%	0.40
	Mid	21503	8192	0.05	2.21	0.15	5%	0.80
	Lux	33413	9372	0.06	1.50	0.15	5%	-0.20
CNG	Econ	9249	1239	0.04	1.97	0.15	1%	0.12
	Mid	13166	1570	0.05	2.13	0.15	1%	-0.08
	Lux	N/A	N/A	N/A	N/A	0.15	1%	0.00
Flex Fuel	Econ	N/A	N/A	N/A	N/A	0.15	5%	0.00
	Mid	N/A	N/A	N/A	N/A	0.15	5%	0.00
	Lux	N/A	N/A	N/A	N/A	0.15	5%	0.00
Hybrid	Econ	N/A	N/A	N/A	N/A	0.15	10%	0.00
	Mid	38192	4427	0.04	1.43	0.15	10%	-0.80
	Lux	54189	4400	0.05	1.96	0.15	10%	-1.10
Electric	Econ	9575	3128	0.00	0.54	0.15	15%	0.00
	Mid	27073	4371	0.01	0.76	0.15	15%	-0.08
	Lux	42424	1493	0.02	0.94	0.15	15%	-0.20

Note: 'Econ' denotes cars with engine sizes smaller or equal to 1400cc. 'Mid' denotes cars with engine sizes larger than 1400cc and smaller than 2000cc. 'Lux' denotes cars with engine sizes larger than 2000cc.
N/A indicates that data is not available or that the car technology is not widely used in the country.

Appendix B: FTT:Transport model methodology

B.1 Passenger car transport demand

Transport demand is driven by income, population, urban density, family structure and other demographic factors. Studies have also found induced and rebound effects on the demand for passenger car transport. More specifically, they find that the demand for transport increases with economic and infrastructure development. For example, the enhancement of road capacity in the US and Britain positively impacts transport 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.

The demand estimation in this section consists of two parts. The first part is the construction of an econometric model that 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.

B.2 Empirical model specification

The empirical model specifies kilometres per PLDV in the country i as a function of GDP per capita (*Y*), fuel cost in terms of oil price (*FP*), and a group of variables, including urbanization (*U*), road lengths (*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.

$$\ln KM_{it} = \beta_0 + \beta_1 lnKM_{it-1} + \beta_2 lnY_{it} + \beta_3 lnFP_{it}$$

$$+\beta_4 lnM_{it} + \beta_5 lnU_{it} + \beta_6 lnUD_{it} + \beta_7 lnFE_{it} \tag{B.1}$$

The interpretation for each variable is indicated in Table B1. The following section summarises the rationale for each variable in Equation B.1.

Income

Income is known to drive transport demand, and it is recognised as the main driver of transport demand growth per capita income 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 [91].

Fuel price

Since fuel prices affect fuel costs' share of 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 [92,93]. Price elasticities are almost always negative: an increase in price leads to lower demand, and vice versa.

Table B1
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

Urbanization

Urbanization rate is defined as the share of the urban population to the total population [85]. 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 [94]. With a higher urbanisation level and as a result of agglomeration economies, 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 to all aspects of urban life, the average distance travelled by cars declines [91,95].

Urban density

Travel distances are often shorter in cities that 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. found that there is a negative relationship between passenger car fuel consumption and urban density [64].

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 the US, Nolan and Lem [95] concluded that the expansion in road capacity has a positive impact on traffic demand. In the case of China, Chai et al. [96] found that when road accessibility (measured in mileage) is increased by 1%, road traffic demand increases by 1.26%.

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 [97].

B.2 Empirical model specification

The results for the pooled OLS estimates are presented in Table B2. A country dummy variable is added to account for the unobserved effect. With the Breusch-Pagan test, we analyze whether it is valid to pool the data. The null hypothesis H0 for the Breusch-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 B2 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 road transport 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 a positive effect on road transport 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 that distance per car increases as more roads are built (induced demand). Fuel efficiency improvements will result in a transport 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 FE model and test this with the Hausman test. Table B2 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 transport 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.

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 B2 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 the FE model. In order to validate the assumptions of the Arellano-Bond GMM estimator, we carry out the Sargan 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 B2
Regression results for the Pooled OLS model, the 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

B.3 Car population projection

Car ownership models are used to forecast transport demand, energy consumption, and emission levels. 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 [98]. 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 [98–100].

The Gompertz curve is an S-shaped growth curve that relates per capita vehicle ownership to GDP per capita. While vehicle scrappage is not explicitly included, it has been tested empirically to represent growth trend of vehicle stock [98]. We examine trends in the growth of vehicle stocks for a large sample of countries and employ the Gompertz function to estimate the relationship between the number of vehicles and per capita income.

Following the previous studies, we estimate car stock with a Gompertz model:

$$V_{i,t} = V_i^* e^{\alpha e^{\beta EF_{i,t}}} \quad \text{(B.2)}$$

Which is equivalent to the following:

$$\ln\left(\ln\left(\frac{V_{i,t}}{V_{i,t}^*}\right)\right) = \ln(\alpha) + \beta EF_{i,t} \tag{B.3}$$

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^* 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 β parameter determines the shape of the S-shape curve. We find the α and β by regressing $\ln(\ln(\frac{V_{i,t}}{V_{i,t}^*}))$ against $EF_{i,t}$.

Fig. B.1 shows the historical fleet sizes for the five countries (solid black lines). Vehicle stock projections were done on the basis of Equation B.2 with the parameters shown in Table B4. The dashed lines in Figure B2 show the car fleet size projections between 2016 and 2050 under three GDP assumptions, namely, the SSP1, SSP3, and SSP5 assumptions (see Table B4 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 [101]. 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 higher GDP growth projections under SSP5 compared to SSP3 for China and India.

Table B4

World GDP per capita projections by income group, based on the Shared Socioeconomic Pathways (SSP) [101].

	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%

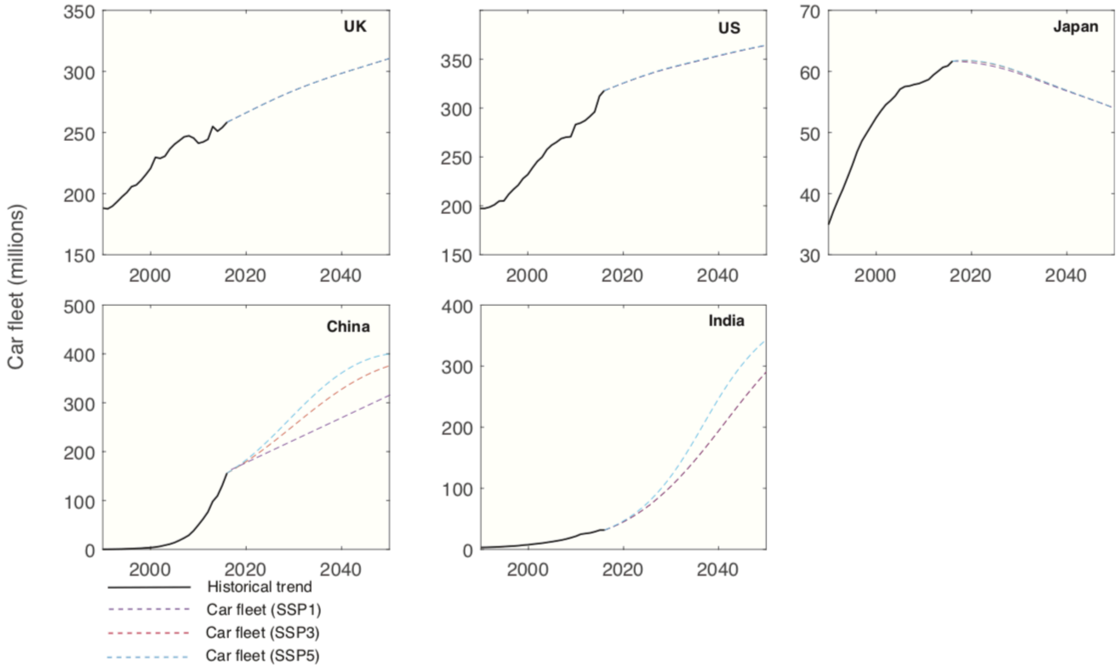

Fig. B1. Historical and projected car fleets (in millions) under the SSP1, SSP3, and SSP5 assumptions

B.4 Projections for the demand for PLDV services

The transport distance for a PLDV per year is estimated with Equation B.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 10 oil price scenarios in addition to the baseline scenario. The baseline scenario oil price is taken from the projection made in the IEA New Policy Scenario [102]. 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 scenarios [102].

The projections for car distance per year under different oil price scenarios are shown in Fig. B.1. For the US, the UK, China, and India, the car distance projected tends to decrease between 2020 and 2030 but starts to increase between 2040 and 2050. It is assumed that oil prices will increase more steeply between 2020 and 2030 compared to the period 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 ofincrease 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 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 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.

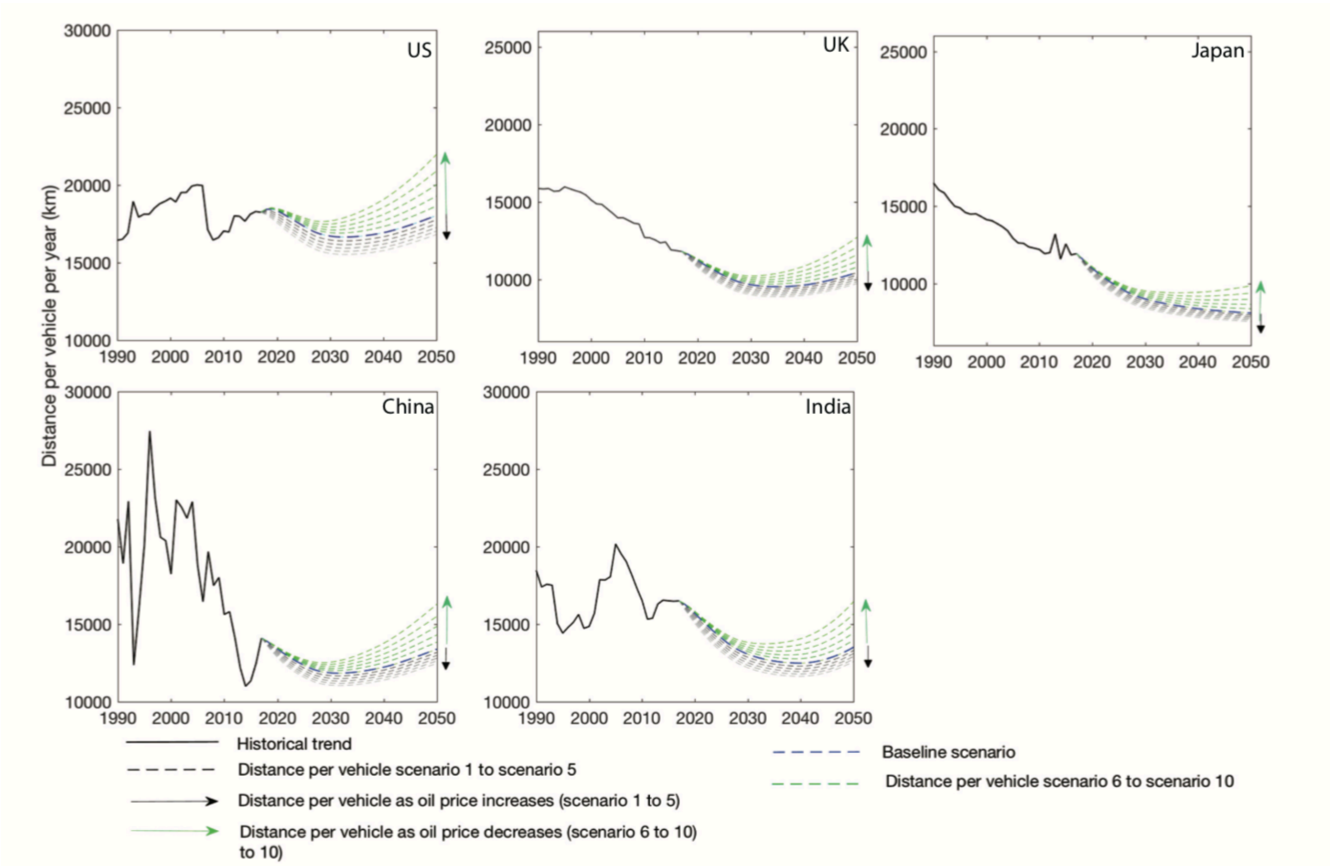

Fig. B2. Average distance travelled by car per year under GDP per capita assumption SSP1. The solid black lines are the historical trend for the distance travelled by cars. The dashed green lines represent the distance travelled per car as oil prices decrease (i.e., the lower the oil prices, the lighter 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).

B.5 The decision-making core model

We detail here the decision-making module of the FTT:Transport model. Part of this section is replicated from the Supplementary Information of Mercure et al. [9].

B.5.1 Heterogeneity in the vehicle market

Consumers in vehicle markets are highly heterogeneous, and this heterogeneity varies by country. Sales for new passenger cars were obtained from MarkLines and matched to price and fuel consumption information from car manufacturers. Note that MarkLines data are comprehensive, not samples. Fig. B3 (also see [6]) shows an example of price heterogeneity in five countries, the US, UK, China, Japan, and India in 2012. For this paper, we have updated the cost distribution to 2016. We observe that the heterogeneity of vehicle markets varies widely between nations.

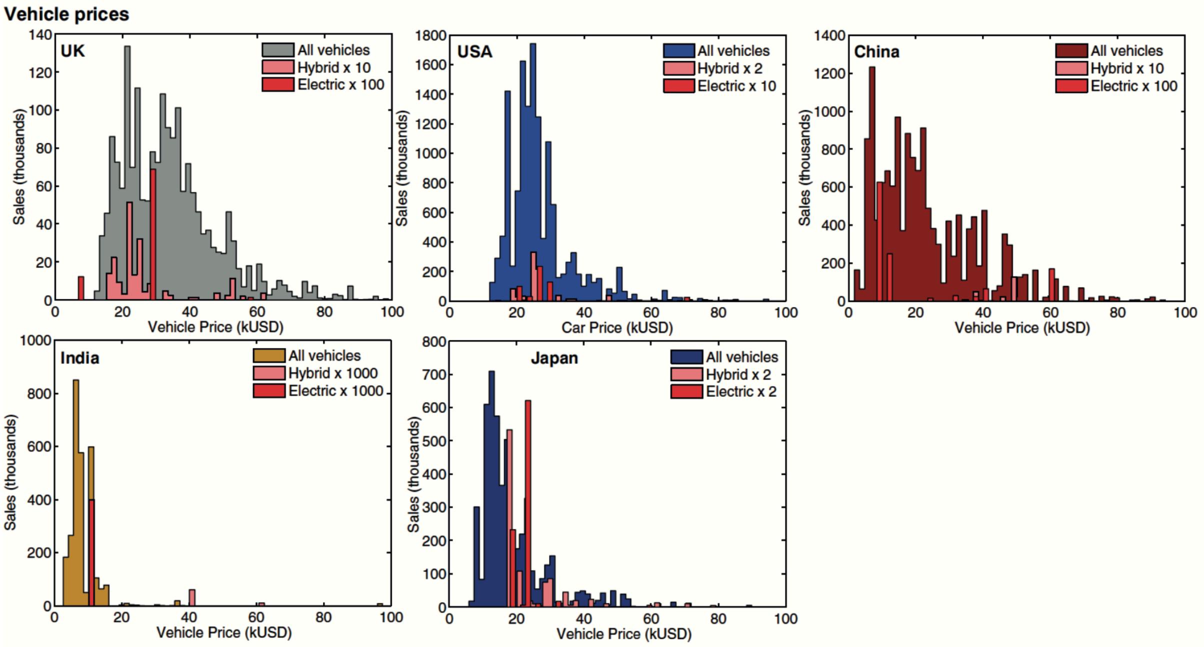

Fig. B3. Price distributions for vehicles in 2012 for the five major economies, reproduced from [6].

B.5.2 Perceived costs and decision-making

In consumer behaviour theory, consumers are most likely to make purchases according to their own experiences with the technology or to the consumption experiences of their peers gained through social interaction [103] and visual influence (demonstrated by [63] in the US). It is also likely that the choices of consumers are influenced by their peers through the ‘bandwagon effect’ [33]. 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 [6].

We postulate here that distributions of perceived costs correspond to distributions of observed costs, with a possible constant offset between them. People, we assume, when considering purchasing a vehicle, most likely choose something they have seen being purchased, perhaps by someone they know, such that they were able to gather information (i.e., they most likely do not choose something they know nothing of, and they gather reliable information predominantly through observations of their peers). Their observations of the fleet are a subset of what is on roads, and every agent observes something slightly different. This may be due to their belonging to a particular social group and social class, and they are most likely to choose amongst what their peers have previously chosen, which itself is a subset of what the whole market has to offer (e.g. poor rural households perhaps purchase different types of vehicles to rich suburban families, which itself is different than single, middle-class persons). Thus, we assume restricted technology/information access. In other words, agents do not choose what they do not know, and they do not know all of the markets.

The FTT model uses a modified version of discrete choice theory in the form of an evolutionary theory. It uses observed distributions of costs to represent agent heterogeneity (a form of revealed preferences) (see [6]). Consumer decisions are modelled with chains of binary logits. In discrete choice theory [104,105], 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 Fig. B4. We assume that consumers are choosing between technology i and technology j with cost distributions $f_i\,(C\,,\;C_i\,)$and $f_j\,(C\,,C_j)$,respectively, assuming that $F_j(C)$ is the cumulative distribution of $f_j\,(C\,,C_i)$. 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. Hence, the fraction of agents making the choice preferring i over j is as follows:

$$F_{ij}(\Delta C_{ij}) = \int_{-\infty}^{\infty} F_j(C) f_i\,(C - \Delta C_{ij}) dC, \qquad \Delta C_{ij} = C_i - C_j \qquad \text{(B.4)}$$

In the standard discrete choice model, f_i is a double exponential Gumbel distribution. Using the standard error propagation method (see SI of [9] for mathematical details), we have:

$$F_{ij}(\Delta C_{ij}) = \frac{1}{1+\exp(\Delta C_{ij}/\delta_{ij})}\,, \qquad \delta_{ij} = \sqrt{\delta_i^2 + \delta_j^2} \qquad \text{(B.5)}$$

The width of the cost distributions δ_i and $\delta_j$determine the probability of consumers choosing one technology over another. This is how the rates of technological diffusion relate to consumer heterogeneity.

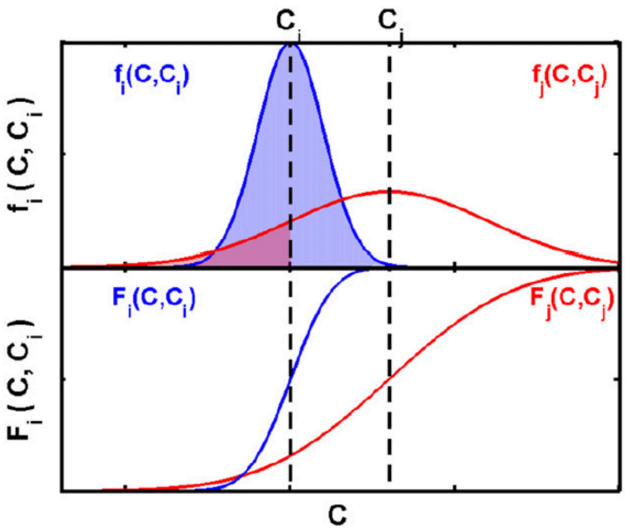

Fig. B4. Top: cost distributions for two technologies i and j. The red shaded area indicates the number of units of technology j cheaper than the median cost of technology i. Bottom: cumulative probability distribution functions of technology i and j. Replicated from [16]

In the FTT:Transport model, the price distributions (e.g. Fig. B3) are segmented according to passenger car technology, and engine size used to parameterise $f_i\ (C,\ C_i)$. The average and median prices, emissions, and engine sizes with their standard deviation are presented in Tables A3-A7 of Appendix A.

B.5.3. The levelised cost of transportation (LCOT)

For the decision-making component of this model, we separate the investor in transport technology from the consumer of transport services. We think of them as separate entities for clarity, even though in some cases they might be the same person. Whether the roles are fulfilled by the same actors or not, they are quite distinct, where the investor purchases a vehicle to sell a transport service to the consumer. This is done to clarify the distinction between technology investment and associated market competition, and the consumption of the service that technologies produce. It also allows for the possibility that a person who purchases a car can still travel by train or plane and not use the car he purchased. The mode choice is distinct from the technology choice, even when performed by the same person.

The cost of the vehicle, as perceived by the investor purchasing a vehicle or unit of transport technology, must be taken to include all components relevant to the decision making. Many of the components are easy to quantify from available data. Others are not straightforward, and we show here how this is done. When a vehicle is purchased, an initial investment is made, or a loan is obtained, for the capital cost, and henceforth fuel and maintenance costs are:

$$LCOT_i = \sum_t \frac{\frac{(I_i - EVS_i)}{CF_i} + \sum_t \frac{\frac{RT_i(t)}{CF_i} + \left(F_i(t) + FT_i(t)\right) * \left(FE_i(t) * Dist_t\right) + MR_i(t)}{(1+r)^t}}{\sum_t \frac{1}{(1+r)^t}} \tag{B.6}$$

Here I_i, F_i, *and* 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 the purchase time. 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, which is vehicle and class-specific, paid by car owners once per year. CF_i is the capacity factor, in km/y.

Several terms in Equation B.6 are distributed, while others are single-valued. Investment cost distributions can be assigned to distribution of preferences, but variations can also arise in all other parameters. The discount rate could also be distributed, but we have not included this at this stage. It is to be kept in mind however that in a root mean square calculation, any dominating parameter rapidly makes smaller contributions negligible. Here, the vehicle price distribution dominates; it has the largest standard deviation. Nevertheless, we keep energy use and maintenance parameters distributed.

B.5.4. The generalised cost as a comparison measure

B.5.4.1 The intangibles

As inferred from the price distribution of sales, transport costs are not the only factors that consumers consider when purchasing a vehicle. Many additional aspects (e.g. comfort and luxury) are valued by the consumer, of which we have little information beyond the price distribution of what is purchased. We keep in mind that technologies have different pecuniary costs, particularly across engine size classes; despite this, higher costs appear compensated by higher benefits, such that higher cost luxury vehicles maintain market shares.

Were we to simulate technology diffusion based on bare LCOT distribution comparisons, the lowest LCOT technologies would diffuse more successfully, which is not consistent with our historical data. Clearly, components would be missing in the LCOT—for instance, comfort, acceleration, and style—which we may call the "intangibles". We define "intangibles" for this model as the difference between the generalized cost, which leads to observed diffusion, and the LCOT, as calculated from pecuniary vehicle properties for which we have data. The value of the intangibles, γ_i, is an empirical parameter obtained from making the FTT diffusion trajectory match the trajectory observed in our historical data, at the year of the start of the simulation.

Adding γ_i to Equation B.6 produces the following:

$$C_i = \ln\left(\frac{LCOT_i^2}{\sqrt{LCOT_i^2 + \Delta LCOT_i^2}}\right) + \gamma_i \tag{B.7}$$

When $\gamma_i = 0$, we obtain a rate of diffusion that does not normally match historical diffusion. One, and only one, set of γ_i leads to the diffusion of technology in the simulation to have the same rate as the historical rate at the starting point of the simulation. The interpretation of the γ_i parameters is that they ensure that FTT projects in the future a diffusion trajectory (the rate of change of shares) that is the same as what is observed in historical data, and represents all costs not explicitly specified as perceived by agents.

B.5.4.2 Determining the non-pecuniary γ_i values in practice

The unique set of γ_i cannot be obtained by simple optimization, as too many spurious local solutions arise. We, therefore, designed a dedicated graphical user interface software that enables one to robustly determine these parameters by hand (see Fig. B5). This is done for each technology in every region, making it a time-consuming procedure, but visual inspection ensures that the parameters are not spurious. We find that γ_i values follow what is expected: luxury models have large negative values (large benefits). Since generalized cost differences already exist in the baseline, diffusion trends exist in the baseline, a fact that is observed in the data, and the determination of the γ_i parameters is of primary importance. 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 $\gamma_i$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 minimized. In the case that other capital costs remain unchanged, γ_i is independent of scenario assumptions and is a constant value, i.e., it only has to be found once. A sensitivity analysis has been carried out to assess how the uncertainties in γ_i affect the simulations of the FTT:Transport model.

Finally, it is to be noted that changing one γ_i value in a set for one region requires to re-determine all the others, as it changes the relative values of all technologies. Furthermore, if the definition of the LCOT is changed for any reason (e.g., adding a pecuniary parameter, or changing the discount rate), the empirical γ_i must all be re-determined since their meaning also changes. In this sense, the $\gamma_i$contain everything of relevance that is not explicitly represented in the LCOT; the more parameters are included in the LCOT, the less are implicitly represented in the γ_i. It takes a few hours to determine all γ_i values.

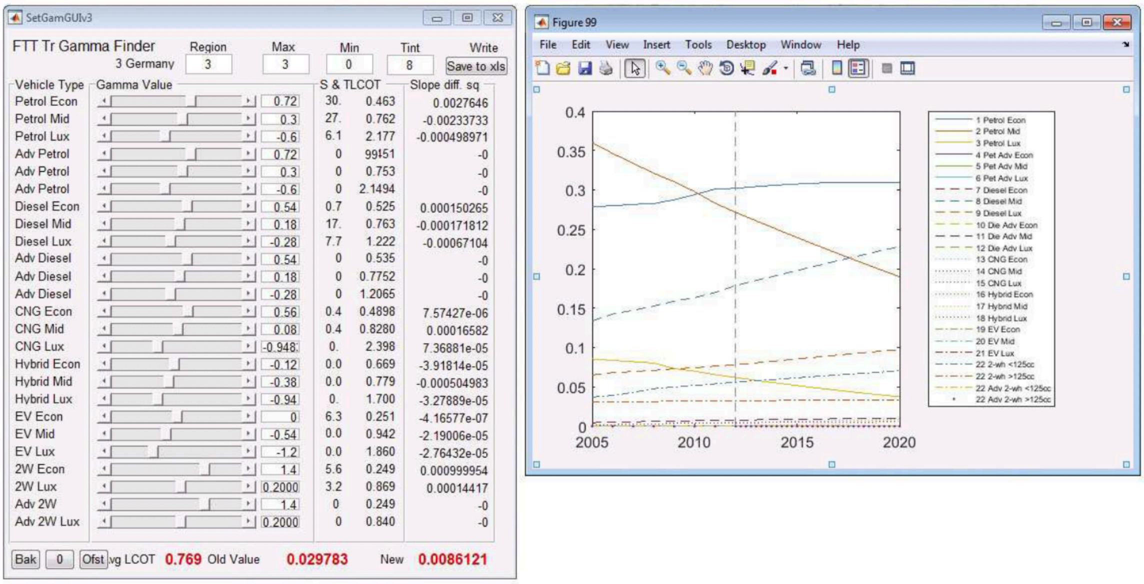

Fig. B5. Graphical user interface used to determine γ_i parameters. Sliders or value inputs are used in order to change the diffusion trajectory of the model (to the right of the dashed line) until it is consistent with historical data (to the left of the dashed line).

B.5 Population dynamics

New vehicle purchases cover both replacements and increases in the total population. We assume that sales are limited by the demand, not by the supply. During a time span Δt, out of a total $\xi_{tot}(t)$ of new registrations in a particular region, a certain fraction of sales is allocated to different technology categories according to consumer preferences F_{ij} as derived above, and replacement rates, denoted by $1/\tau_i$. These parameters can be understood as determining the rate of influx and out-flux of sales shares in and out of technology categories i and j in a set of n possibilities. Using the variable N_i for the vehicle population in category i, increases in N_i due to purchases being allocated into i, related to the replacement of vehicles scrapped in category j (i.e. substitutions of i for j at the time of scrappage), corresponds to the following:

$$\Delta N_{j\to i} = \begin{bmatrix} \text{Fraction of} \\ \text{prod. capacity} \\ \text{belonging to } i \end{bmatrix}_i \begin{bmatrix} \text{Consumer} \\ \text{preferences} \end{bmatrix}_{ij} \begin{bmatrix} \text{Fraction of} \\ \text{destructions} \\ \text{belonging to } j \end{bmatrix}_j \begin{bmatrix} \text{Number of} \\ \text{destructions} \end{bmatrix}_{tot} \qquad \text{(B.8)}$$

where destructions of vehicles in j are allocated to categories according preferences, which direct flows of units between categories. Meanwhile, the number of vehicles purchased that are not replacements are:

$$\Delta N_i^{\uparrow} = \frac{1}{n}\sum_j^n \begin{bmatrix}\text{Fraction of}\\ \text{prod. capacity}\\ \text{belonging to } i\end{bmatrix}_i \begin{bmatrix}\text{Consumer}\\ \text{preferences}\end{bmatrix}_{ij} \begin{bmatrix}\text{Population}\\ \text{increase}\end{bmatrix}_{tot} \qquad \text{(B.9)}$$

The numbers of vehicles and vehicle destructions follow directly from the sum of the sales time series, multiplied with the survival function over all ages (numbers), or its derivative (deaths), which correspond to convolutions. The equations

$$N_j(t) = \int_0^\infty \xi_j(t-a) l_j(a) da \qquad \text{(B.10}$$

and

$$d_j(t) = \int_0^\infty \xi_j(t-a) \frac{dl_j(a)}{dt} da \simeq \frac{N_i}{\tau_i} \qquad \text{(B.11}$$

follow, where d_j denotes deaths, a vehicle age, and $l_j(a)$ the measured survival function for technology j. In a scheme where computational power minimisation is sought, deaths can be conveniently and safely approximated with the total population divided by the life expectancy, ${N_j}/{\tau_j}$.

Thus, equations B.7 and B.8 are rewritten this way:

$$\Delta N_{j\to i} = \frac{N_i/t_i}{\sum_k N_k/t_k} F_{ij} \frac{N_j/t_j}{\sum_k N_k/t_k} \Delta N_{tot} = S_i \frac{\bar{t}\bar{\tau}}{t_i \tau_j} F_{ij} S_j \frac{N_{tot}}{\bar{\tau}} \Delta t \qquad \text{(B.12)}$$

Here, $\bar{t}$ and $\bar{\tau}$ are the average industry growth rate and life expectancy, while the S_i are technology category shares of the total fleet. For convenience, we define the matrix of time constants as $A_{ij} = \bar{t}\bar{\tau}/t_i\tau_j$. For all flow $\Delta N_{j\to i}$ of substitutions between i and j, a reverse flow $\Delta N_{i\to j}$ exists, and a net trend results:

$$\Delta N_{ij} = N_i \left(A_{ij}F_{ij} - A_{ji}F_{ji}\right) N_j \frac{N_{tot}^{\downarrow}}{\bar{\tau}} \qquad \text{(B.13)}$$

The growth of the fleet can also be expressed in a similar way:

$$\Delta N_i^{\uparrow} = \frac{1}{n}\sum_j^n \frac{N_i/t_i}{\sum_k N_k/t_k} F_{ij} \Delta N_{tot}^{\uparrow} \qquad \text{(B.14)}$$

where $\Delta N_{tot}^{\uparrow}$ is the time dependent population growth rate, in principle determined by the change in demand and capacity factor. We can combine both equations B.11 and B.13 in a convenient way, by considering expressing it in terms of shares of the total population by technology $S_i = N_i/N_{tot}$, instead of absolute numbers, which must involve a chain derivative:

$$\frac{dN_i}{dt} = N_{tot}\frac{dS_i}{dt} + S_i\frac{dN_{tot}}{dt} \tag{B.15}$$

The second term cancels with the equation for the population growth, leaving:

$$\Delta S_{ij} = S_i\big(A_{ij}F_{ij} - A_{ji}F_{ji}\big)S_j\frac{\Delta t}{\bar{\tau}} \tag{B.16}$$

This equation expresses exchanges of market shares between technology categories i and j according to preferences and rates of replacement. Cumulating all gains or losses to technology i at the expense or profit of all other categories, we sum over j and obtain the replicator dynamics equation:

$$\Delta S_i = \sum_j S_i\big(A_{ij}F_{ij} - A_{ji}F_{ji}\big)S_j \tag{B.17}$$

There, the net flow of shares is regulated by the product of the matrices $A_{ij}F_{ij}$ minus its transpose. While the matrix A_{ij} is interpreted to represent industrial dynamics and reliability, the matrix F_{ij} is interpreted to represent consumer choices according to our decision-making model. Thus, they are completely independent.

B.6 Social influence and technological diffusion

In this section, we show briefly that including social influence or other bandwagon effects in a discrete choice model leads to the replicator dynamics equation. Note that this is shown in [20] and the SI of [9], reproduced here for reference.

Discrete choice models define a linear random utility model, in which the utility U_i^* (associated with purchasing a particular type of vehicle i) is expressed as a function of a number of variables *V,* such as income, gender, and distance travelled and so on, and regression parameters β and ε.

$$U^* = \beta_i^1 V_i^1 + \beta_i^1 V_i^1 + \beta_i^2 V_i^2 + \beta_i^3 V_i^3 + \beta_i^4 V_i^4 \ldots + \varepsilon_i \tag{B.18}$$

We look for the probability that option i is chosen over other options,

$$P(U > max[U_1, U_1, U_1 \ldots U_1]) = P(U > U_1)P(U > U_2)\ldots P(U > U_n) \tag{B.19}$$

This leads to the multinomial logit model (MNL) (see [20] for the mathematical deviation):

(B.20)

$$P_i = \frac{e^{\frac{U_i}{\sigma}}}{\sum_j e^{\frac{U_j}{\sigma}}}$$

Taking the probabilistic choice P_i as determining the shares of the market, this determines how the market evolves, in equilibrium, for changes in variables.

If we assume the existence of social influence, the relative frequency of picking product i-using agents is the share of the market occupied by product i. This dynamic also arises with most other types of bankdwagon effects, for example where the frequency of product availability in markets where scale of production is constrained by and grows with returns on sales and market size. Re-evaluating equation B.19 by instead multiplying on each side the probabilities calculated individually for all N agents, with $N_1, N_2 \ldots, N_n$ as the numbers of agents, we have:

$$P\big(U > \max\big[U_{1,} U_{2,} \ldots U_{n,}\big]\big)^N = P(U > U_1)^{N_1} P(U > U_2)^{N_2} \ldots P(U > U_n)^{N_n} \qquad \text{(B.21)}$$

Taking market share $S_i = N_i/N$, then we have:

$$P\big(U > \max\big[U_{1,} U_{2,} \ldots U_{n,}\big]\big) = P(U > U_1)^{S_1} P(U > U_2)^{S_2} \ldots P(U > U_n)^{S_n} \qquad \text{(B.22)}$$

The solution is then:

$$P_i = \frac{S_i e^{\frac{U_i}{\sigma}}}{\sum_k S_k e^{\frac{U_k}{\sigma}}} \qquad \text{(B.23)}$$

Preferences Pi are instantaneous, but purchases happen at a rate τ_i^{-1}, following consumer needs. We then take preferences as the rate of change of shares.

$$\frac{dS_i}{dt} = \frac{1}{\tau_i^{-1}} \frac{S_i e^{\frac{U_i}{\sigma}}}{\sum_k S_k e^{\frac{U_k}{\sigma}}} \qquad \text{(B.24)}$$

This is a form of replicator dynamics that can be converted to the version used in this paper (see [20]).

Appendix C: Costs of PLDV technologies over time

As described in Equation 3 of Section 4.1, in the FTT:Transport, we assume that the capital costs of cars fall by a certain percentage (determined by a learning rate) every time the total quantity manufactured doubles. Tables C1–C5 show the capital costs of cars from 2020 to 2050 using the FTT:Transport model in the baseline scenario.

Table C1
Capital costs of cars for the UK from 2020 to 2050 using the FTT:Transport model in the baseline scenario.

UK	Engine size	2020	2025	2030	2035	2040	2045	2050

Petrol	Econ	16927	16927	16927	16926	16926	16926	16926
	Mid	31794	31794	31794	31793	31793	31792	31792
	Lux	40593	40593	40592	40592	40591	40591	40590
Adv Petrol	Econ	27516	27514	27512	27511	27509	27507	27505
	Mid	39308	39305	39303	39300	39298	39295	39293
	Lux	61985	61981	61976	61972	61968	61965	61961
Diesel	Econ	22931	22931	22931	22930	22930	22930	22929
	Mid	32758	32758	32757	32757	32757	32756	32756
	Lux	38483	38482	38482	38481	38481	38480	38480
Adv Diesel	Econ	27516	27515	27513	27512	27510	27508	27507
	Mid	39308	39306	39304	39302	39299	39297	39295
	Lux	46178	46175	46173	46170	46167	46164	46161
CNG	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Lux	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Flex Fuel	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Lux	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Hybrid	Econ	25223	25220	25213	25204	25196	25185	25172
	Mid	36032	36027	36018	36006	35993	35978	35959
	Lux	47765	47758	47746	47729	47713	47693	47668
Electric	Econ	22917	22873	22798	22704	22598	22468	22309
	Mid	32738	32675	32568	32434	32282	32096	31869
	Lux	51625	51524	51357	51144	50906	50612	50254

Table C2

Capital costs of cars for the US from 2020 to 2050 using the FTT:Transport model in the baseline scenario.

US	Engine size	2020	2025	2030	2035	2040	2045	2050
Petrol	Econ	17939	17938	17938	17938	17938	17938	17937
	Mid	20749	20749	20748	20748	20748	20748	20747
	Lux	29744	29743	29743	29743	29742	29742	29741
Adv Petrol	Econ	17938	17937	17936	17934	17933	17932	17931
	Mid	20748	20747	20745	20744	20743	20741	20740
	Lux	29742	29740	29739	29737	29735	29733	29731
Diesel	Econ	21526	21526	21526	21526	21525	21525	21525
	Mid	24899	24899	24898	24898	24898	24897	24897
	Lux	35692	35692	35692	35691	35691	35690	35690
Adv Diesel	Econ	17938	17937	17936	17935	17934	17933	17932
	Mid	20748	20747	20746	20745	20744	20742	20741
	Lux	29743	29741	29739	29738	29736	29734	29732
CNG	Econ	17939	17939	17939	17939	17938	17938	17938
	Mid	20749	20749	20749	20749	20749	20749	20749
	Lux	29744	29744	29744	29743	29743	29743	29743
Flex Fuel	Econ	19733	19733	19733	19733	19733	19732	19732
	Mid	22834	22834	22834	22834	22834	22834	22833
	Lux	32718	32718	32718	32718	32717	32717	32717
Hybrid	Econ	23956	23953	23946	23938	23929	23919	23907
	Mid	28794	28790	28782	28772	28761	28749	28734

	Lux	34005	34001	33991	33979	33967	33953	33935
Electric	Econ	29726	29660	29556	29425	29279	29103	28893
	Mid	30688	30620	30513	30378	30227	30046	29828
	Lux	90174	89975	89659	89263	88820	88286	87648

Table C3

Capital costs of cars for Japan from 2020 to 2050 using the FTT:Transport model in the baseline scenario.

Japan	Engine size	2020	2025	2030	2035	2040	2045	2050
Petrol	Econ	12936	12936	12936	12936	12935	12935	12935
	Mid	21320	21320	21320	21320	21319	21319	21319
	Lux	27991	27991	27990	27990	27989	27989	27989
Adv Petrol	Econ	15523	15522	15521	15520	15519	15518	15517
	Mid	25583	25582	25580	25578	25577	25575	25573
	Lux	33588	33585	33583	33581	33579	33577	33575
Diesel	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Lux	33590	33589	33589	33589	33588	33588	33587
Adv Diesel	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Lux	40304	40302	40300	40298	40295	40293	40290
CNG	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Lux	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Flex Fuel	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Lux	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Hybrid	Econ	19512	19510	19504	19497	19490	19482	19472
	Mid	22733	22730	22724	22716	22708	22698	22686
	Lux	45301	45294	45282	45266	45250	45230	45207
Electric	Econ	19501	19458	19390	19304	19209	19093	18955
	Mid	31269	31200	31090	30953	30800	30615	30394
	Lux	45273	45173	45015	44816	44594	44327	44006

Table C4

Capital costs of cars for China from 2020 to 2050 using the FTT:Transport model in the baseline scenario.

China	Engine size	2020	2025	2030	2035	2040	2045	2050
Petrol	Econ	8901	8901	8901	8900	8900	8900	8900
	Mid	16779	16779	16779	16779	16779	16778	16778
	Lux	41176	41176	41175	41175	41174	41174	41173
Adv Petrol	Econ	10680	10680	10679	10678	10678	10677	10676
	Mid	20134	20133	20132	20131	20129	20128	20127
	Lux	49410	49406	49403	49400	49397	49394	49391
Diesel	Econ	10681	10681	10681	10681	10680	10680	10680
	Mid	20135	20135	20135	20135	20134	20134	20134
	Lux	49412	49411	49411	49410	49410	49409	49408
Adv Diesel	Econ	12817	12816	12815	12815	12814	12813	12812
	Mid	24162	24160	24159	24158	24156	24155	24153

	Lux	59292	59289	59286	59282	59279	59275	59272
CNG	Econ	8901	8901	8901	8901	8901	8901	8901
	Mid	16779	16779	16779	16779	16779	16779	16779
	Lux	41177	41177	41176	41176	41176	41176	41176
Flex Fuel	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Lux	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Hybrid	Econ	19999	19996	19991	19984	19976	19968	19957
	Mid	24017	24014	24007	23999	23990	23980	23967
	Lux	39958	39952	39941	39927	39913	39896	39875
Electric	Econ	9570	9548	9515	9473	9426	9369	9302
	Mid	27056	26997	26902	26783	26650	26490	26299
	Lux	42398	42304	42156	41970	41762	41511	41211

Table C5

Capital costs of cars for India from 2020 to 2050 using the FTT:Transport model in the baseline scenario.

India	Engine size	2020	2025	2030	2035	2040	2045	2050
Petrol	Econ	8897	8897	8896	8896	8896	8896	8896
	Mid	20545	20545	20544	20544	20544	20544	20543
	Lux	30097	30096	30096	30096	30095	30095	30094
Adv Petrol	Econ	10676	10675	10674	10674	10673	10672	10671
	Mid	24653	24651	24650	24648	24647	24645	24643
	Lux	36115	36112	36110	36107	36105	36103	36101
Diesel	Econ	12132	12132	12132	12132	12132	12132	12131
	Mid	17920	17920	17919	17919	17919	17919	17919
	Lux	22742	22742	22742	22742	22741	22741	22741
Adv Diesel	Econ	14558	14557	14557	14556	14555	14554	14553
	Mid	21503	21502	21501	21499	21498	21497	21496
	Lux	27290	27288	27287	27285	27284	27282	27280
CNG	Econ	8897	8897	8897	8897	8897	8897	8897
	Mid	20545	20545	20545	20545	20545	20545	20544
	Lux	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Flex Fuel	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Lux	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Hybrid	Econ	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mid	68188	68179	68160	68136	68112	68083	68047
	Lux	54186	54178	54163	54144	54125	54102	54073
Electric	Econ	9570	9548	9515	9473	9426	9369	9302
	Mid	27056	26997	26902	26783	26650	26490	26299
	Lux	42398	42304	42156	41970	41762	41511	41211

Appendix D: Calculating the costs of policies

D.1 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.

$$TotalRT = \sum_i \int_{2018}^{2050} (RT_{i,t} * S_{i,t} * Fleet_t)dt. \qquad \text{(D.1)}$$

Where $TotalRT$ is the total annual registration tax paid by the consumers between 2018 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.

D.2 Vehicle tax

We assume that the vehicle tax is the tax levied on a vehicle at the time of vehicle acquisition. The total cost of vehicle tax for consumers in a country each year is equal to the number of new car sales multiplied by the corresponding vehicle tax. In this research, we assume that the rate of vehicle tax is dependent on PLDV technologies and engine sizes.

$$TotalVT = \sum_i \int_{2018}^{2050} (VT_{i,t} * S_{i,t} * NewSales_t)dt \qquad \text{(D.2)}$$

Here, $TotalVT$ is the total vehicle tax paid by consumers between 2018 and 2050. $VT_{i,t}$ is the vehicle 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 $NewSales_t$ is the total car fleet at time t.

D.3 Fuel tax

We assume that fuel tax is paid by 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. Following Table B2, we assume that distance travelled falls when fuel tax increases the cost of fuel for consumers. 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.

$$TotalFT = \sum_i \int_{2018}^{2050} (FT_{i,t} * FE_{i,t} * Dist_t(FP_{i,t}) * S_{i,t} * Fleet_t)dt \qquad \text{(D.3)}$$

Here, $TotalFT$ is the total fuel tax paid by consumers between 2018 and 2050. $FT_{i,t}$ is the fuel tax (in USD per litre) paid by owners of technology i in year *t*. $FE_{i,t}$ 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 at time t and $Dist_t$ is the average distance travelled by an average fleet, depending on the levels of fuel tax. The fuel price elasticity of travel demand is determined in Table B2.

D.4 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.

$$TotalSub = \int_{2018}^{2050} Sub_{i,t} * EV_{i,t}\, dt \qquad \text{(D.4)}$$

where $TotalSub$ is the total EV subsidies paid by the government between 2018 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.

D.5 EV mandate

We assume that the costs for the EV mandates are paid by car manufacturers or the consumers. We assume that the total costs of the EV mandates equal the difference in the prices of EVs and of 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 of conventional cars multiplied by the 10% of new car sales.

$$TotalKS = \int_{2018}^{2050} (EVCost_t - AvgCost_t) * NewEV_t\, dt \qquad \text{(D.5)}$$

$TotalKS$ is the cost of the EV mandate programme to the manufacturer or to the consumers between 2018 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.

We assume that the cost of EV mandate to the consumers is the difference between the prices of EVs and of conventional cars. This implies that consumers could potentially 'gain' from EV purchases if the prices of EVs were to fall below the prices of conventional cars. We have not taken into consideration the cost of the EV mandate on manufacturers and the government. For instance, to facilitate the implementation of the EV mandate or EV subsidies, governments and manufacturers often need to invest in the construction of EV charging infrastructure, and this has not been considered.

D.6 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 assume that the costs of fuel economy standards ($FEcost$), which are 3% of the gross car sales, are partly absorbed by car manufacturers, with fuel savings enjoyed by the consumers.

Consistent with our cost assumptions, we assume that the costs of advanced cars are, on average, 20% more expensive than conventional petrol cars[7].

$$FEcost = MC - Fuelsaving + \int_{2018}^{2050} (NewCar_t * AvConvPr_t)*20\% \, dt \qquad (D.6)$$

where

$$MC = 3\% * \int_{2018}^{2050} NewCar_t * AvPrice_{i,t} *20\% \, dt \qquad (D.7)$$

and

$$FuelSavings = \int_{2018}^{2050} (FE_{adv} - FE_{conv}) * FP_t * Dist_t dt \qquad (D.8)$$

Here, MC is the cost of fuel economy standards ($FEcost$) borne by car manufacturers, which is equal to 3% of the gross sales. $NewCar_t$ is the number of new cars (advanced petrol cars/advanced diesel cars) sold in time t, $AvPrice_{i,t}$ is the average car price at time t, $AvConvPr_t$ is the average price for conventional cars, and FE_{adv} and FE_{conv} are the fuel economy (in litre/km) for 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.

Appendix E: Effectiveness and cost-effectiveness for four to six policy combinations

Table E1
The interaction effect between four policies. When the interaction effect is positive, there is a reinforcement effect between the four policies. When the interaction effect is negative, there is a trade-off effect between four policies.

The interaction effect of four policies ($MtCO_2$) Scenario	UK	US	Japan	China	India
1.KS+FT+VT+EVS	14.7	231.9	5.4	214.4	26.5
2.KS+FE+VT+EVS	42.2	725.2	17.5	550.7	369.1
3.KS+FT+FE+VT	37.3	471.9	16.4	719.6	410.5
4.KS+RT+VT+EVS	59.4	2088.3	9.4	201.5	566.2
5.KS+RT+FE+VT	26.1	824.1	3.5	491.9	371.1
6.KS+RT+FT+VT	45.7	1669.2	1.3	212.3	489.0
7.KS+FT+FE+EVS	39.6	684.1	18.1	533.5	269.1
8.KS+FE+EVS+RT	83.6	2382.2	13.2	355.1	514.0
9.KS+RT+FT+EVS	24.5	1012.5	20.3	524.7	405.6
10. KS+RT+FT+FE	36.7	918.7	1.4	547.9	273.7
11. RT+FE+VT+EVS	-4.6	-721.4	-32.2	-1079.9	-329.3
12. FT+FE+VT+EVS	-194.0	-2796.5	-67.0	-1716.8	-1350.8
13. FT+VT+EVS+RT	-27.4	-270.2	-18.8	-674.2	-37.8
14. RT+FT+VT+FE	-66.0	-643.6	-47.3	-795.8	-333.6

[7] We find that the price difference between several powertrain specifications within one car model ranged from 10% to 30% of the car price (from the official car manufacturer's website).

15. RT+FT+FE+EVS	-47.5	-543.1	-45.5	-1223.7	-366.5

Table E2

The cost-effectiveness of four policy combinations (2016 USD/tCO_2).

Cost of four policy combinations (\$/tCO_2)					
Scenario	UK	US	Japan	China	India
1.KS+FT+VT+EVS	882.2	1122.7	2339.0	458.0	1089.0
2.KS+FE+VT+EVS	78.3	1116.3	1915.2	252.8	1216.1
3.KS+FT+FE+VT	839.4	138.2	1253.3	271.1	626.4
4.KS+RT+VT+EVS	466.0	621.2	1858.3	263.3	1192.3
5.KS+RT+FE+VT	363.9	221.5	1587.5	123.3	408.1
6.KS+RT+FT+VT	732.3	216.3	1790.4	238.2	1860.2
7.KS+FT+FE+EVS	535.7	58.4	1007.5	239.6	255.1
8.KS+FE+EVS+RT	348.6	157.0	1275.0	122.4	1020.2
9.KS+RT+FT+EVS	727.3	171.8	1451.5	335.7	824.2
10.KS+RT+FT+FE	754.3	161.0	1620.9	211.1	638.7
11.RT+FE+VT+EVS	548.3	678.8	2945.7	357.5	1625.3
12.FT+FE+VT+EVS	1106.0	1545.3	2721.1	900.5	2175.2
13.FT+VT+EVS+RT	1527.1	1212.8	1867.3	609.2	1850.2
14.RT+FT+VT+FE	886.0	395.0	3494.1	513.7	1750.0
15.RT+FT+FE+EVS	861.3	286.9	3513.9	499.8	1089.6

Table E3

The interaction effect between five policies. When the interaction effect is positive, there is a reinforcement effect between the five policies. When the interaction effect is negative, there is a trade-off effect between five policies.

The interaction effect of five policies (MtCO_2)					
Scenario	UK	US	Japan	China	India
1.KS+FT+VT+EVS+FE	49.6	687.2	17.9	566.7	269.7
2.KS+VT+EVS+FE+RT	27.0	714.8	4.0	275.1	167.6
3.KS+FT+VT+EVS+RT	27.6	810.6	1.2	42.1	269.0
4.KS+FT+EVS+FE+RT	38.3	800.5	-1.5	307.5	400.8
5.KS+FT+VT+FE+RT	57.1	2064.1	-6.8	478.9	328.5
6.FT+VT+EVS+FE+RT	-6.7	-744.6	-48.2	-1189.6	-327.9

Table E4

The cost-effectiveness of policy combinations (2016 USD/tCO_2)

Cost of five policy combinations (\$/tCO_2)					
Scenario	UK	US	Japan	China	India
1.KS+FT+VT+EVS+FE	865.2	1021.4	2253.5	352.5	1191.8
2.KS+VT+EVS+FE+RT	364.1	523.6	1602.0	194.3	1218.2
3.KS+FT+VT+EVS+RT	908.1	1140.8	2970.0	452.9	1825.4
4.KS+FT+EVS+FE+RT	306.7	89.7	1273.6	330.4	143.2

5.KS+FT+VT+FE+RT	746.2	384.0	2101.1	394.7	1607.9
6. FT+VT+FE+RT+EVS	982.2	406.9	4569.4	722.2	865.5

Table E5

The interaction effect between six policies. When the interaction effect is positive, there is a reinforcement effect between the six policies. When the interaction effect is negative, there is a trade-off effect between six policies.

The interaction effect of six policies ($MtCO_2$)					
Scenario	UK	US	Japan	China	India
1.EVM+FT+VT+EVS+FE+RT	20.2	671.2	-35.1	-387.6	167.3

Table E6

The cost-effectiveness of six policy combinations (2016 USD/tCO_2)

Cost of six policy combinations (\$/tCO_2)					
Scenario	UK	US	Japan	China	India
1.KS+FT+VT+EVS+FE+RT	915.7	295.7	3169.2	732.1	462.6

Appendix F: Sensitivity analysis

F.1 Sensitivity analysis – the baseline scenario

In this section, we carry out a sensitivity analysis over most relevant technological parameters of FTT:Transport, including the discount rate, the learning rate, the γ factor (or the "intangible"), and fuel prices. These parameters were chosen because they would generate the most changes in emissions and technological shares.

The parameters varied here are as follows:

1. Learning rates for EVs (not varied for conventional petrol and diesel cars because the learning for mature technologies is insignificant).
2. Consumer discount rates.
3. The price of electric vehicles.
4. γ_i values for all vehicle types.
5. Fuel prices.

The variation used is between 5% and 20%, depending on the parameters (see Table F1). The uncertainty range was chosen based on existing literature for the discount rate, learning rate or variations that we consider as reasonable, such as the γ_i values). Learning rate variations were considered based on [75,106]. We assume a low EV learning rate scenario (5%) and a high EV learning rate (15%) scenario. Following [73], we test a low discount rate scenario (5%) and a high consumer discount rate scenario (25%).

The intangibles (γ values) are derived from the historical trends of technological diffusion. However, the fitting of γ are only accurate to a certain extent, which we estimate between 5% and 20%, depending on the availability of historical data. For instance, EVs have less historical data than petrol cars. In the sensitivity analysis, we vary the γ values by 10% for every car technology in order 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. Varying the γ values too much (i.e., above 10%) would violate the model. For example, if we vary the γ values by 30%, then we will find that the diffusion trajectory is no longer consistent (see Appendix B.5.4.1 for more details).

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. 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 be higher or lower 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.

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 X% is 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% variation in learning rates and 10% variation in EV prices and discount rates for most countries. The effects of the learning rates on the scenario analysis are 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 is negligible in the baseline scenario in the countries where there are very few EVs on-road (i.e., India) and 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.

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 create a change in the trajectory but not an instantaneous change in the shares.

Table F1
Sensitivity analysis of key technological parameters in the baseline scenario

	Sensitivity parameters	Emissions	Change in shares in 2050 (%)				
UK		% change in CO2	Petrol	Diesel	NV	HEV	EV
	EV Learning rate +5%	-0.50	-0.87	-0.03	0.00	0.00	0.90
	EV Learning rate -5%	0.84	0.49	0.01	0.00	0.00	-0.50
	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
	EV price +10%	-0.45	0.48	0.00	0.00	0.00	-0.48
	EV price -10%	0.22	-0.54	0.00	0.00	0.00	0.55
	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	0.04	0.00	-0.83	-0.24
	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.o8	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
US							
	EV Learning rate +5%	-0.54	-0.64	0.00	0.00	0.00	0.64
	EV Learning rate -5%	0.88	0.79	0.00	0.00	0.00	-0.79
	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
	EV price +10%	0.16	0.00	0.00	0.00	0.00	1.08
	EV price -10%	-0.23	-0.70	0.00	0.00	-0.03	-0.50
	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
	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	-0.02	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 -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 -10%	0.00	0.00	0.00	0.00	0.00	0.00
Japan							
	EV Learning rate +5%	-0.10	-0.15	0.00	0.00	0.00	0.15
	EV Learning rate -5%	0.12	0.11	0.00	0.00	0.00	-0.11
	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
	EV price +10%	0.05	-0.01	0.00	0.00	0.17	0.07
	EV price -10%	-0.06	0.61	0.00	0.00	-0.52	-0.10
	Oil price +20%	-2.28	-0.02	-0.02	0.00	-0.09	0.11
	Oil price +50%	-4.72	-0.05	-0.05	0.00	-0.20	0.26
	Oil price -20%	2.76	0.02	0.02	0.00	0.11	-0.13
	Oil price -50%	6.53	0.05	0.05	0.00	0.30	-0.34
	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	-0.80
	Hybrid γ -10%	0.34	0.61	0.00	0.00	-0.69	0.10
	Petrol γ +10%	-0.29	-1.18	0.00	0.00	1.16	0.02
	Petrol -10%	0.34	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 -10%	0.00	0.00	0.00	0.00	0.00	0.00
China							
	EV Learning rate +5%	-2.31	-2.49	-0.20	-0.10	0.00	2.79
	EV Learning rate -5%	3.41	3.14	0.11	0.00	0.00	-3.25
	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
	EV price +10%	0.99	4.28	0.00	0.03	-0.25	5.08
	EV price -10%	-1.10	-4.79	0.00	-0.04	-1.32	0.98
	Oil price +20%	-5.13	-0.20	0.00	-0.01	-0.02	0.22
	Oil price +50%	-7.02	-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
	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	-1.30	0.98
	Petrol γ +10%	0.51	-0.25	0.00	0.00	-0.84	0.07
	Petrol -10%	-0.46	0.31	0.00	-0.01	-0.12	-0.49
	Diesel γ +10%	0.00	0.00	0.00	0.00	0.00	0.00

	Diesel -10%	0.00	0.00	0.00	0.00	0.00	0.00
India							
	EV Learning rate +5%	0.00	0.00	0.00	0.00	0.00	0.00
	EV Learning rate -5%	0.00	0.00	0.00	0.00	0.00	0.00
	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
	EV price +10%	0.04	0.21	0.00	0.03	-0.21	-0.04
	EV price -10%	-0.03	-0.19	0.00	-0.o3	0.19	0.00
	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	0.00	-0.29	-0.37
	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 -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	0.38
	Diesel -10%	-0.97	0.20	-0.58	0.00	0.00	0.13

F.2 Sensitivity analysis – scenarios with interactions

In this section, we examine the impact of parametric uncertainties on the interactions between policies. The parameters are varied by quantities that we considered in the baseline scenario (see Appendix F.1). We conduct the sensitivity analysis for all 63 scenarios (all possible interactions), each with eight parametric variations. Tables F2-F5 present the percentage change in the size of interactions as a result of variations in key parameters that generate the most changes in emissions and technological shares.

Changing EV learning rates have a small impact on the interactions, in particular for countries with a small number of EV (e.g. the UK and India). On the other hand, variations in oil prices have a bigger impact on the interactions between policies. Overall, we find that the percentage change in the sizes of interactions as a result of variations in parameters does not increase with the number of policy interactions. Changes in the size of the interaction effects, as a result of the variation in parameter, are within 30% for all scenarios. This implies that there is no 'directional change'[8] in the interactions as a result of the parametric uncertainties. Hence, we argue that the parametric uncertainties will not change the main conclusions of this paper.

[8] Directional change refers to a change in direction for the interaction effects (e.g. from trade-off effects to reinforcement effects), when the percentage change in the interactions between policies is larger than 100%.

Table F2.

Sensitivity analysis of the parameters on policy interactions (two policy interactions scenario). Each number refers to a percentage change in the s

	Parameters	RT FE (%)	RT FT (%)	EVS RT (%)	FT FE (%)	EVS FT (%)	EVS FE (%)	VT RT (%)	VT FT (%)	VT FE (%)	VT EVS (%)	FT EVM (%
US												
	EV LR +5%	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.35	0.01	0.01
	EV LR -5%	0.00	0.00	-0.01	0.00	0.00	0.80	0.00	0.02	0.67	0.00	0.00
	DR +10%	-4.09	8.45	-2.26	5.39	5.58	-5.33	-1.47	6.24	-6.20	-2.77	3.75
	DR -10%	4.61	7.56	2.07	6.14	6.38	4.98	3.32	7.88	6.72	3.19	-5.14
	OP +20%	2.60	5.67	-7.24	6.62	-7.98	3.17	7.50	3.76	-6.33	6.90	2.33
	OP +50%	6.21	6.68	-10.22	7.10	-11.31	5.04	4.22	5.77	-5.29	3.14	1.55
	OP -20%	-2.73	-5.12	-9.93	-5.10	-9.15	-2.02	-2.49	-7.40	-6.49	-6.32	-4.45
	OP -50%	-6.78	-6.27	-15.23	-6.22	-12.04	-5.52	-8.34	-10.34	-9.67	-5.33	-6.29
UK												
	EV LR +5%	0.01	0.01	0.12	0.14	0.01	-0.14	0.89	0.23	-0.45	0.55	0.12
	EV LR -5%	0.00	0.00	-0.14	-0.04	0.00	0.31	-0.63	-0.45	0.34	-0.29	-0.33
	DR +10%	1.22	4.76	-5.15	-2.45	-2.05	2.46	-3.34	-3.04	3.42	-3.88	5.23
	DR -10%	-2.54	5.30	2.35	4.69	3.14	-3.87	2.59	2.98	2.10	4.39	-4.53
	OP +20%	-2.77	4.78	-9.31	-2.28	-10.20	-3.04	-8.55	-8.95	-1.97	-6.21	-6.28
	OP +50%	-6.98	6.91	-15.24	-6.19	-12.78	-7.82	-14.52	-11.32	-2.09	-10.39	6.07
	OP -20%	2.72	-4.10	-10.10	3.52	-9.66	3.34	-10.34	4.23	2.67	-7.23	-6.54
	OP -50%	2.51	-6.28	-13.37	3.90	-14.02	7.43	-12.63	5.59	3.23	-6.88	5.17
Japan												
	EV LR +5%	8.02	1.68	2.40	3.90	1.22	2.03	4.42	2.10	2.77	5.21	3.08
	EV LR -5%	-4.01	0.74	-3.66	2.74	-1.01	4.01	-3.29	-3.19	-3.24	-6.43	-5.73
	DR +10%	1.43	1.90	-3.35	-2.28	-3.90	2.66	-2.08	-5.60	4.59	-5.59	4.18
	DR -10%	-2.56	1.56	2.64	3.55	3.14	-4.57	3.14	2.74	-5.87	4.76	-6.26
	OP +20%	-4.33	1.59	4.94	-5.20	-5.22	-3.43	-5.70	-6.18	-4.76	-4.39	-3.57
	OP +50%	-10.23	1.70	8.12	-9.27	-9.11	-12.04	-8.23	-8.46	-5.33	-7.64	4.35
	OP -20%	5.29	-2.22	4.02	6.15	-6.37	7.28	-10.45	5.94	-8.13	-9.86	-6.42
	OP -50%	10.53	-2.80	10.81	9.89	-10.04	14.98	-12.07	4.02	-5.21	-6.07	7.05
China												
	EV LR +5%	10.15	5.03	5.41	12.12	3.10	6.65	-8.33	4.75	5.13	-9.34	4.07
	EV LR -5%	9.19	-4.01	3.02	-10.14	-5.12	6.34	9.28	-5.13	5.79	7.45	-5.91
	DR +5%	4.35	7.83	4.62	-3.41	-5.89	7.23	3.75	-6.09	4.12	5.08	9.19
	DR -5%	-3.96	6.49	-4.21	4.04	6.21	-5.50	-6.41	4.17	-4.55	-4.57	-11.21
	OP +20%	-5.52	7.02	-7.73	-5.19	-7.93	-6.33	-6.19	-6.80	-5.18	-8.02	8.66
	OP +50%	-12.78	7.57	-15.39	-9.72	-16.74	-11.31	-6.30	-9.62	-12.07	-4.89	-12.49
	OP -20%	5.56	-7.07	10.37	6.91	-9.36	7.31	-11.21	-11.63	6.44	9.25	12.79
	OP -50%	12.93	-7.43	12.39	10.03	-13.01	14.73	-12.29	-10.43	12.48	10.29	-14.29
India												
	EV LR +5%	0.00	0.01	0.00	0.01	0.00	0.05	0.00	0.01	0.00	0.03	0.04
	EV LR -5%	0.00	0.00	0.00	0.00	0.00	-0.06	0.00	0.00	0.00	-0.12	-0.02
	DR +5%	1.78	1.79	1.03	2.13	1.39	1.20	1.35	2.03	1.48	2.84	3.66
	DR -5%	-1.08	2.59	-0.89	-2.37	-1.44	-2.35	3.48	-1.36	-2.92	1.76	-4.22
	OP +20%	-1.29	2.06	4.49	-2.12	5.77	-2.41	4.39	3.25	-2.33	-2.84	-5.48
	OP +50%	-3.07	2.14	5.08	-3.72	6.34	-3.80	7.04	4.98	-4.10	-1.46	6.39
	OP -20%	1.52	-1.98	-3.19	2.81	-4.39	2.49	-8.21	-5.09	3.86	-2.82	-5.59
	OP -50%	3.37	-1.93	-5.40	4.53	-6.94	2.47	-6.76	-5.49	3.49	-2.24	4.05

Note: EV LR stands for EV learning rate; DR stands for Discount Rate; OP stands for Oil Price

RT = “Registration Tax”; FT= “Fuel Tax”; EVS = “EV Subsidy”; VT= “Vehicle Tax”; FE= “Fuel Economy Standard”; EVM = “EV Mandate”

Table F3.

Sensitivity analysis of the parameters on policy interactions (three policy interactions scenario). Each number refers to a percentage change in the

	Parameters	FT FE EVS (%)	FT FE RT (%)	EVM RT VT (%)	EVM RT FT (%)	FE EVM FT (%)	EVS FE EVM (%)	EVS FE RT (%)	EVS RT EVM (%)	EVS RT FT (%)	VT RT FT (%)	EVS FT VT (%)	RT VT FE (%)	FT VT FE (%)	VT EVM RT (%)	FT VT EV
US																
	EV LR +5%	0.02	0.09	0.08	0.04	4.02	1.32	0.05	0.85	0.12	0.01	0.12	0.04	0.03	0.01	0.0
	EV LR -5%	-0.23	-0.74	-0.01	-0.03	-3.05	4.04	-0.14	3.52	-0.09	-0.01	0.08	-0.06	-0.11	0.03	0.0
	DR +10%	-4.32	6.42	-4.12	-3.53	6.22	5.14	-3.09	4.13	-1.53	-2.14	6.35	-4.22	-4.74	3.06	2.4
	DR -10%	-5.21	-3.52	3.04	4.75	-4.02	-4.66	-4.14	-5.41	1.55	4.26	7.62	6.01	5.32	-3.53	-4.
	OP +20%	0.78	1.52	-5.77	-6.63	-7.72	-10.57	1.54	-9.51	-6.74	1.97	-5.62	3.06	2.74	4.53	3.3
	OP +50%	-4.04	-3.34	-11.26	-9.72	9.62	10.94	-10.59	11.52	-9.47	-10.25	-4.79	-12.34	-11.17	3.78	2.8
	OP -20%	-5.22	6.52	-10.22	-10.06	14.59	14.43	-2.04	13.05	-15.73	5.62	-10.67	4.75	3.54	-6.46	-5.
	OP -50%	6.53	7.60	-11.37	-16.63	12.24	11.15	8.33	12.54	-20.35	10.25	-14.72	7.37	8.82	-4.73	-5.
UK																
	EV LR +5%	0.10	0.09	0.71	0.41	2.64	0.45	0.07	0.21	0.45	0.05	0.21	0.46	0.31	0.10	0.0
	EV LR -5%	-0.22	-0.98	-0.23	-0.34	-1.95	-1.41	-0.34	-0.74	-0.26	-0.06	0.03	-0.84	-0.47	-0.63	-0.
	DR +10%	-1.44	-1.53	-4.36	-5.74	-3.32	-2.04	-1.73	-1.59	-6.73	-1.25	-1.63	-3.17	-2.57	6.55	4.2
	DR -10%	2.04	2.02	3.46	3.67	3.61	1.76	1.77	1.45	2.78	1.74	1.77	3.64	2.05	-8.64	-7.
	OP +20%	-12.95	-6.53	-11.54	-12.53	-12.94	-16.66	-2.47	-14.29	-11.83	-2.29	-8.76	-2.77	-1.35	-6.74	-7.
	OP +50%	9.35	12.63	-12.60	-11.53	12.62	11.07	6.24	12.66	-17.73	8.63	-10.73	3.64	5.27	7.65	6.7
	OP -20%	-9.14	-7.53	-11.35	-10.06	-9.61	-12.42	-2.87	-10.47	-12.73	-9.24	-12.73	-6.41	-4.20	-10.74	-7.
	OP -50%	10.78	11.23	-16.63	-12.93	-9.59	-10.75	8.39	-11.43	-15.77	-12.14	-16.79	9.67	10.52	-15.60	6.3
Japan																
	EV LR +5%	1.04	2.05	1.93	2.15	1.88	1.47	0.17	1.32	3.34	2.19	0.87	0.66	0.32	3.64	2.5
	EV LR -5%	0.78	2.14	-2.56	-1.44	-1.24	1.88	-0.21	1.44	-5.73	-0.98	-0.73	-0.89	-1.63	-4.20	-3.
	DR +10%	2.83	3.05	-4.35	-4.63	2.62	3.45	-1.58	3.09	-4.83	-1.35	-2.87	-1.34	-1.73	6.64	6.3
	DR -10%	-2.59	-4.65	-4.01	3.32	-3.15	-4.22	3.12	-3.52	3.72	-7.26	-2.62	2.04	2.71	-8.74	-7.
	OP +20%	-10.48	-8.56	5.63	6.53	-15.27	-17.57	-5.83	-12.23	6.47	-3.87	-4.82	-6.14	-7.85	-4.56	-5.
	OP +50%	9.95	7.56	7.36	9.48	11.22	10.78	10.04	12.54	9.08	8.42	-11.83	9.97	11.20	6.74	7.6
	OP -20%	12.15	14.63	9.63	6.93	17.60	15.52	4.38	14.23	6.48	-12.73	-7.84	7.74	5.27	-11.7	-10
	OP -50%	-11.75	15.53	11.06	9.07	-11.07	-12.39	-11.44	-10.45	12.28	14.53	-11.93	-11.16	-10.05	-15.74	11.
China																
	EV LR +5%	5.49	4.63	4.67	3.33	19.47	17.77	5.71	14.43	4.84	2.13	1.21	5.17	6.14	4.73	5.5
	EV LR -5%	-4.14	-3.83	5.35	4.06	-17.33	-20.70	-3.69	-18.50	2.98	-3.27	-4.61	-3.87	-4.22	-5.74	-7.
	DR +10%	-5.09	-6.67	3.40	2.49	-4.83	-5.33	-7.23	-6.21	7.84	-7.24	-6.56	-7.54	-6.04	9.69	10.
	DR -10%	6.39	7.53	-4.17	-6.32	7.56	6.12	6.96	7.55	-4.70	8.55	-8.53	6.17	7.20	-10.88	-9.
	OP +20%	8.56	5.47	-8.35	-6.64	5.72	6.74	-2.37	5.41	-7.83	-6.01	-13.62	-5.64	-6.42	10.05	7.6
	OP +50%	-11.75	-9.63	-9.15	-12.33	-13.51	-14.37	19.89	-13.98	-10.78	11.62	-10.66	11.78	12.07	-15.45	-10
	OP -20%	-6.60	8.63	11.62	8.13	-7.78	-8.53	-4.07	-7.41	11.98	17.61	-10.62	-6.49	-5.01	19.47	16.
	OP -50%	-9.50	-14.63	10.50	13.52	-16.53	-13.66	-16.58	-10.76	14.55	-17.52	-16.62	-15.96	-14.52	-17.65	-15
India																
	EV LR +5%	0.03	0.02	0.01	0.05	7.41	6.22	0.04	5.41	0.02	0.00	0.01	0.02	0.03	0.17	0.0
	EV LR -5%	0.04	-0.05	-0.03	0.05	-6.39	8.95	0.00	7.09	0.09	-0.01	0.06	-0.04	-0.08	-0.51	-0.
	DR +10%	5.33	4.47	2.38	1.83	2.54	3.42	6.77	2.24	0.85	2.24	0.98	2.59	3.54	3.64	2.8
	DR -10%	-6.60	-3.63	-1.02	-2.05	-3.83	-2.21	-5.14	1.89	-1.73	-1.52	-1.03	3.24	2.27	-3.47	-3.
	OP +20%	-5.45	-4.86	6.61	5.94	6.58	6.25	-3.41	5.49	7.73	5.45	3.62	5.59	6.23	-7.60	-6.
	OP +50%	-3.07	-6.36	8.73	6.92	-8.90	-8.26	-8.54	-7.56	4.74	-4.62	-5.24	-4.92	-5.14	6.65	4.7
	OP -20%	-5.52	-3.69	-5.49	-3.01	-6.05	-4.92	-2.70	-5.79	-6.73	-7.23	-7.73	-5.52	-6.12	4.74	2.5
	OP -50%	-10.93	-9.37	-6.62	-7.83	-7.39	-6.55	-4.47	-7.58	-5.79	-14.25	-12.36	-8.18	-9.42	6.67	5.6

Note: EV LR stands for EV learning rate; DR stands for Discount Rate; OP stands for Oil Price

RT = “Registration Tax”; FT= “Fuel Tax”; EVS = “EV Subsidy”; VT= “Vehicle Tax”; FE= “Fuel Economy Standard”; EVM = “EV Mandate”

Table F4.

Sensitivity analysis of the parameters on policy interactions (four policy interactions scenario). Each number refers to a percentage change in the

	Parameters	EVM;FT; VT;EVS (%)	EVM;FE; VT;EVS (%)	EVM;FT; FE;VT (%)	EVM;RT; VT;EVS (%)	EVM;RT; FE;VT (%)	EVM;RT; FT;VT (%)	EVM;FT; FE;EVS (%)	EVM;FE; EVS;RT (%)	EVM;RT; FT;EVS (%)	EVM;RT FT;FE (%)	RT;FE; VT;EVS (%)	FT;FE VT;EVS (%)
US													
	EV LR +5%	3.46	2.69	3.16	3.52	3.46	0.06	0.85	1.07	2.75	3.56	0.10	0.06
	EV LR -5%	-2.66	-5.49	-5.27	-2.47	-4.43	-0.07	-0.93	-0.53	-1.93	-1.11	-0.08	-0.14
	DR +10%	7.25	9.56	6.57	5.05	7.55	-2.44	4.24	5.27	4.28	4.96	-2.69	-3.47
	DR -10%	-4.57	-6.02	-5.42	-6.78	-5.71	3.85	-6.50	-6.63	-5.87	-3.77	-3.98	-4.84
	OP +20%	-12.42	-9.05	-11.45	-12.57	-9.45	-7.05	-11.05	-10.27	-14.24	-10.84	2.75	1.58
	OP +50%	10.27	13.86	-10.38	8.24	12.74	-10.26	10.77	-11.04	10.43	9.73	-7.96	-3.94
	OP -20%	5.38	19.04	5.67	3.45	10.87	-11.96	11.01	-9.27	4.23	11.75	-3.88	-6.46
	OP -50%	15.27	12.12	10.09	15.27	11.36	-15.68	13.33	-12.93	14.27	16.83	7.94	4.90
UK													
	EV LR +5%	0.10	1.14	0.45	0.27	1.07	0.90	0.11	1.24	0.69	0.98	0.04	0.21
	EV LR -5%	-0.06	-0.99	-0.14	-0.53	-0.89	-0.67	-0.08	-1.69	-0.17	-1.06	-0.03	-0.14
	DR +10%	-2.64	-1.59	-5.57	-4.56	-2.01	-6.04	-1.96	-3.42	-3.42	-4.75	-1.06	-0.87
	DR -10%	4.04	4.33	4.21	5.47	4.52	4.83	1.05	4.52	4.98	5.74	1.63	2.04
	OP +20%	-10.24	-7.24	-10.05	-9.59	-7.55	-11.05	-10.76	-8.79	-10.52	-10.06	-2.72	-10.48
	OP +50%	7.07	12.75	10.46	10.27	10.65	-14.86	11.75	11.06	-15.27	-10.46	5.62	8.96
	OP -20%	-10.22	-12.77	-12.52	-11.85	-8.37	-7.54	-14.52	-9.58	-8.52	-11.15	-3.36	-10.11
	OP -50%	-12.06	-17.24	-13.25	-14.59	-10.99	-11.73	-15.46	-11.68	-12.92	-13.62	7.68	8.94
Japan													
	EV LR +5%	0.85	1.13	0.53	0.85	1.05	3.08	1.18	2.08	0.08	0.01	0.14	0.87
	EV LR -5%	-0.71	-0.97	-0.86	-1.19	-0.87	-2.07	-0.82	-1.64	-0.17	-0.06	-0.01	0.90
	DR +10%	8.45	1.75	3.48	4.57	1.66	3.40	2.89	2.57	6.27	5.45	-1.47	1.83
	DR -10%	-10.57	-4.17	-5.20	-4.97	-2.29	-3.63	-3.54	-5.54	4.25	6.52	2.37	-3.49
	OP +20%	-11.05	-10.27	-16.25	-12.71	-12.02	-8.37	-11.05	-10.57	-10.75	-12.17	-5.37	-9.97
	OP +50%	14.25	10.37	11.53	13.45	14.90	-11.38	-13.85	-13.84	12.05	11.33	9.56	12.57
	OP -20%	14.05	11.66	12.69	11.48	15.52	10.56	-16.68	12.05	8.22	9.40	9.89	10.97
	OP -50%	-18.25	14.79	-14.38	-12.57	10.07	15.97	-10.35	16.55	-14.27	-15.19	-13.84	-14.97
China													
	EV LR +5%	10.05	12.87	16.05	12.44	18.27	8.07	14.13	12.53	7.55	12.77	4.84	6.45
	EV LR -5%	-9.44	-13.35	-12.07	-17.05	-16.08	-11.67	-19.05	-14.06	-9.42	-15.63	-2.94	-10.67
	DR +10%	-7.57	-3.96	-6.71	-5.32	-3.70	-4.37	-6.38	-2.97	-6.71	-5.33	-4.95	-4.87
	DR -10%	9.24	8.42	5.54	6.37	8.39	8.03	7.22	3.34	9.74	8.22	7.84	7.22
	OP +20%	5.37	6.06	6.20	-7.20	6.72	7.72	5.84	7.06	-6.22	-6.47	-1.95	8.60
	OP +50%	-13.44	-10.06	-10.03	-10.05	-10.73	-11.15	-10.67	-11.55	-8.05	-10.37	14.12	-14.56
	OP -20%	-11.65	-12.94	-8.20	-12.15	8.03	9.51	9.20	10.75	-10.76	-14.53	-10.83	7.93
	OP -50%	-17.24	-11.76	-14.43	-14.54	-10.73	-13.36	-11.84	-12.52	-9.42	-17.66	-14.94	-10.67
India													
	EV LR +5%	2.24	3.68	5.85	5.32	8.72	0.09	2.37	5.80	1.42	3.22	0.02	0.01
	EV LR -5%	-4.03	-5.52	-7.05	4.07	4.55	-0.02	-2.01	6.44	2.09	1.95	-0.04	0.05
	DR +10%	5.25	8.37	3.41	6.75	8.27	2.07	2.57	6.54	5.85	5.38	3.62	6.75
	DR -10%	4.20	-11.75	-5.94	6.23	-10.53	-3.66	-1.68	-11.05	3.77	-6.17	-6.73	-6.49
	OP +20%	4.20	7.33	7.02	7.24	8.32	10.52	5.28	9.54	6.64	5.26	-5.86	6.87
	OP +50%	-5.66	-12.06	-7.19	-5.27	-7.06	-8.52	-6.33	-7.26	-7.38	-9.11	-9.56	-4.63
	OP -20%	-7.23	-8.41	-12.45	-7.67	-10.49	-11.64	-4.27	-12.85	-5.56	-14.67	-2.02	-6.08
	OP -50%	-9.62	-11.39	-10.92	7.63	-9.56	-10.08	-7.52	-18.54	6.28	-19.05	-8.37	-11.98

Note: EV LR stands for EV learning rate; DR stands for Discount Rate; OP stands for Oil Price; RT = "Registration Tax"; FT= "Fuel Tax"; EVS = "EV Subsidy"; VT= "Vehicle Tax"; FE

Table F5.

Sensitivity analysis of the parameters on policy interactions (five and six policy interactions scenario). Each number refers to a percentage change

	Parameters	KS; FT;VT;EVS;FE (%)	KS;VT;EVS:FE:RT (%)	KS;FT;VT;EVS;RT (%)	KS;FT;EVS;FE;RT (%)	KS;FT;VT;FE;RT (%)	FT;VT;FE;RT;EVS (%)	FT;VT (%)
US								
	EV LR +5%	0.97	0.11	0.15	1.14	1.98	0.85	2.69
	EV LR -5%	-0.76	-0.15	-0.22	-0.86	-2.50	-0.74	-5.49
	DR +10%	3.31	3.42	-3.34	3.74	5.14	-5.45	9.56
	DR -10%	-4.01	-4.59	4.25	-5.06	-6.36	7.24	-6.02
	OP +20%	-11.41	3.31	-8.51	-10.63	-11.05	6.62	-9.05
	OP +50%	14.50	-6.54	-11.64	14.76	8.24	-11.06	13.86
	OP -20%	14.86	5.77	-10.91	12.81	12.47	6.56	19.04
	OP -50%	15.32	10.84	-12.53	15.85	15.20	8.73	12.12
UK								
	EV LR +5%	0.42	0.03	0.47	0.44	0.74	1.74	1.14
	EV LR -5%	-0.62	-0.01	-0.59	-0.52	-0.80	-1.36	-0.99
	DR +10%	-3.13	-1.25	-5.38	-2.96	-3.36	-3.34	-1.59
	DR -10%	4.09	2.55	6.44	3.35	5.41	5.75	4.33
	OP +20%	-12.10	-3.64	-9.35	-11.63	-11.05	-2.36	-7.24
	OP +50%	13.46	6.56	-12.65	13.65	-9.98	5.75	12.75
	OP -20%	-11.22	-4.80	-8.63	-12.24	-13.58	-10.56	-12.77
	OP -50%	-13.09	8.24	-13.65	-16.04	-16.85	-15.57	-17.24
Japan								
	EV LR +5%	1.87	0.08	4.39	2.53	0.05	1.34	1.13
	EV LR -5%	-2.09	-0.16	-3.55	-1.08	-0.12	-0.87	-0.97
	DR +10%	-2.42	-1.56	5.24	-3.54	4.28	-1.98	1.75
	DR -10%	-4.83	3.41	-6.69	-5.66	-6.72	2.36	-4.17
	OP +20%	-8.21	-6.64	-7.23	-9.67	-10.55	-7.56	-10.27
	OP +50%	-11.89	7.15	-10.01	-10.07	15.26	10.03	10.37
	OP -20%	-10.39	10.41	9.96	-12.63	8.24	7.56	11.66
	OP -50%	-16.43	-12.54	-12.24	-15.98	-12.24	-10.75	14.79
China								
	EV LR +5%	11.30	5.94	10.48	10.65	14.58	5.66	12.87
	EV LR -5%	-14.38	-3.63	-12.89	-15.99	-10.25	-4.53	-13.35
	DR +10%	-4.87	-5.22	-5.24	-5.13	-6.31	-7.76	-3.96
	DR -10%	4.03	-8.20	7.97	6.65	7.05	5.35	8.42
	OP +20%	6.29	-5.54	10.84	7.34	-8.22	-9.63	6.06
	OP +50%	-8.33	16.24	-12.64	-9.74	-11.54	20.39	-10.06
	OP -20%	9.03	-12.06	11.98	8.55	-12.27	-11.42	-12.94
	OP -50%	-14.87	-16.29	-16.64	-12.06	-19.58	-19.56	-11.76
India								
	EV LR +5%	2.74	0.10	0.25	3.63	2.94	0.44	3.68
	EV LR -5%	-3.83	-0.38	-0.77	-4.56	2.83	-1.06	-5.52
	DR +10%	4.03	2.24	2.95	3.09	4.58	3.24	8.37
	DR -10%	-3.74	-7.52	-3.42	-2.49	-6.75	5.15	-11.75
	OP +20%	7.87	-6.54	8.09	3.30	9.52	10.33	7.33
	OP +50%	-9.49	-10.98	-11.66	-8.57	-11.88	-11.45	-12.06
	OP -20%	-10.94	-5.54	-7.84	-5.66	-8.75	-9.63	-8.41
	OP -50%	-12.14	-8.85	-10.23	-9.09	-15.51	-10.09	-11.39

Note: EV LR stands for EV learning rate; DR stands for Discount Rate; OP stands for Oil Price; RT = "Registration Tax"; FT= "Fuel Tax"; EVS = "EV Subsidy"; VT= "Vehicle Tax"; FE

Appendix G: High EV mandate scenario

In this research, we assume that 10% of new car sales are EV, consistent with the level China proposed in 2019. In reality, to accelerate the rate of EV deployment, many car markets around the world (e.g., California, China, and the EU) have announced aggressive electrification goals, targeting high electric share in a 2020-2050 timeframe [107]. For example, the EU Zero Emission Vehicle (ZEV) mandate targets 15% of EV market shares by 2025 and 35% by 2030. Therefore, in this section, under the 'High EV mandate scenario', we assume that 35% of new car sales are EV by 2030, and by 2040, and 70% of new car sales are EV by 2040 in all five countries: the UK, the US, Japan, China, and India (see assumptions in Table G1).

Table G2 shows the effectiveness of a 'high EV mandate' on reducing cumulative CO_2 emissions in the five countries, in comparison to the less ambitious 'EV mandate scenario' assumed in this paper (see scenario assumptions in Table 1 of Section 6). Note that the 'additional effectiveness' of a more stringent EV mandate is relatively small in China because the shares for electric cars are the highest in China before the imposition of a more ambitious target.

The goal of the analysis is to examine how a higher (or more ambitious) EV mandate affects the levels of trade-off and reinforcement effects. Table G3 shows the interactions between the financial incentives, the EV mandate assumed in Table 1 (Section 6), and the 'high EV mandate' (Table G1). The reinforcement effects between the 'high EV mandate' and other policies are slightly larger than the reinforcement effects between a less ambitious 'EV mandate scenario' and other policies. This implies that reinforcement effects between financial incentives and the EV mandate can be increased by setting a more ambitious EV mandate.

Table G1
High EV mandate assumptions.

Target year	2020	2030	2040
EV sales target	10%	35%	70%

Table G2
The effectiveness of a 'high EV mandate' on reducing cumulative CO_2 emissions in the five countries, in comparison to the less ambitious EV mandate scenario (see assumptions in Table 1 of Section 6).

	EV mandate scenario	High EV mandate scenario
UK	160.6	306.8
US	1666.1	2518.8
Japan	52.3	77.0
China	1844.7	2034.8
India	1247.2	1878.5

Table G3
The interaction effect between five policies. When the interaction effect is positive, there is a reinforcement effect between the five policies. EVM(L) indicates a less ambitious EV mandate (see assumptions in Table 1 of Section 6), and EVM(H) indicates a 'high EV mandate scenario' (see assumption in Table G2).

The interaction effect of five policies (high EV mandate scenario)
($MtCO_2$)

Scenario	UK	US	Japan	China	India
EVM(L)+FT+VT+EVS+RT	27.6	810.6	1.2	42.1	269.0
EVM(H)+FT+VT+EVS+RT	31.1	934.9	1.4	44.0	323.4

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