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Global CO_2 impacts of light-duty electric vehicles

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ABSTRACT

Electric vehicles (EV) offer a solution for decarbonization of transport. We evaluate global scenarios of EV deployment and their impacts on total global CO_2 emissions. For this assessment, we enhance the MIT Economic Projection and Policy Analysis (EPPA) model to represent the fleet dynamics of light-duty vehicles (LDV), including internal combustion engine (ICE) vehicles and EVs. For EV fleet, both plug-in hybrid vehicles (PHEV) and battery electric vehicles (BEV) are considered. We consider several illustrative scenarios and find that global LDV stock is projected to grow from 1.1 billion vehicles in 2015 to 1.65–1.75 billion in 2050, while global EV stock is growing from about a million in 2015 to about 585–825 million in 2050. At this level of market penetration, EVs would constitute one-third to one-half of the overall LDV fleet by 2050 in different scenarios, with the stricter carbon constraints implied in the *Paris to 2 °C* scenario leading to the largest EV share. Our modeling suggests that EV uptake will vary across regions. China, the U.S., and Europe remain the largest markets in our study timeframe, but the EV presence is projected to grow in all regions. While the global LDV fleet grows by about 50% by 2050, the corresponding CO_2 emissions from LDV are reduced by about 50% in 2050 relative to 2015. Global carbon intensity of LDVs are reduced by about 70% from 2015 to 2050.

1. Introduction

Understanding the future trends in households' private light-duty (i.e., cars and light trucks) vehicles (LDV) ownership is crucial for projecting fuel use and emissions. LDVs provide a substantial source of fuel demand and the resulting greenhouse gas (GHG) emissions. For example, LDVs in USA currently account for almost half of petroleum demand (Heywood et al., 2015). In 2015, GHG emissions from LDVs in USA were about 1,000 million tonnes of CO_2-equivalent ($MtCO_2e$), which accounted for about 16% of the total GHG emissions in USA (EPA, 2017a). Improving fuel efficiency of internal combustion engine-based cars (ICE) and switching from gasoline and diesel ICEs to electric vehicles (EV) and other alternative fuel vehicles are critical options for GHG emission reduction.

Computable general equilibrium (CGE) models are insightful tools for projecting the future energy use and GHG emissions. CGE models provide an economy-wide coverage with interlinkages between sectors and regions, but usually these models provide projections at an aggregated level of sectoral representation of economy, with private transportation combined with other sectors (see, for example, IPCC, 2014; EPA, 2017b for CGE modeling discussion). Traditional datasets for CGE models, like Global Trade Analysis Project (GTAP) dataset (Aguiar et al., 2016), do not provide any disaggregated data for private transportation. As a result, modeling groups that are interested in transportation modeling rely on additional data routines that provide the necessary details for LDV projections (Paltsev et al., 2005).

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The Economic Projection and Policy Analysis (EPPA) model (developed at Massachusetts Institute of Technology, MIT) is a CGE model that represents the global economy. In each region of the model, a representative agent seeks an optimal consumption bundle subject to a budget constraint and a set of endogenously-determined prices of goods and services. The model also simulates production in each region at a sectoral level and explicitly represents interactions among sectors (through inter-industry inputs) and regions (via bilateral trade flows). Sectoral output is produced from primary factors including multiple categories of depletable and renewable natural capital, produced capital, and labor. Intermediate inputs to sectoral production are represented through a complete input–output structure. The EPPA model can provide an examination of the economy-wide effects of different policies, and incorporates numerous current and advanced technologies to provide details about the resulting technology mix for different policy approaches.

In general, economy-wide models, like EPPA, seek to represent economic transactions in monetary terms. In this paper we expand the usual representation in the following ways: (1) we create a consistent approach for modeling both economic flows (i.e., in monetary terms) and physicals flows (i.e., number of vehicles, fuel use, associated emissions) for several types of LDVs: current fleet of ICE vehicles, current fleet of battery electric vehicles (BEV), current fleet of plug-in hybrid electric vehicles (PHEV), future fleet of ICE vehicles, future fleet of BEV, and future fleet of PHEV; (2) we provide an assessment for battery improvements, fuel efficiency, and other components that affect costs and performance of LDVs (such as motor cost, operating costs, ownership costs, etc.); (3) in contrast to the previous approaches that relied on data at an aggregate level for expenditures on car purchases and fuel use to calibrate the total household transportation expenditures (e.g., Karplus et al., 2013), we provide a novel approach for calculating the required expenditures based on the vehicle cost data, fuel expenditures (gasoline and electricity), home charges for BEV and PHEV, services such as insurance and maintenance. We also provide a description of historic data that can be used by other modeling groups to calibrate their models.

In terms of the EPPA model improvement, in contrast to the earlier studies using EPPA for energy use projections and GHG emissions we have used actual cost items data representing different powertrains. This allowed us to develop another important novelty described in this paper: Using these data we created a total cost of ownership (TCO) model of several powertrains to parametrize the new structure of household transport sector that also can be used by other modeling groups to improve their analysis of different decarbonization strategies.

This new approach has several fundamental advances: First, in comparison to the previous structures, we capture the BEV and PHEV adoption dynamics in early periods as the current penetration of EVs are not solely driven by the relative cost of these vehicles with respect to their comparable ICEs. For this purpose, we introduce two types of vehicles and two types of BEV vehicles (described in detail in Section 2.2). Second, we specify a segment for vehicles that represent those trips that will not be served by PHEVs and BEVs. Third, we specify advanced ICE vehicles that in the future will be more economically competitive and overtake the trips that are currently served by other vehicles.

In addition to methodological advances described above, we perform a scenario analysis for 18 different regions of the world. We provide the results for penetration of different types of LDVs and the resulting CO_2 emissions up to 2050 for the scenario based on the current market trends and fuel efficiency policies, for the scenario where the Paris Agreement commitment are not strengthened after 2030, and for the scenario where decarbonization actions are enhanced to be consistent with limiting global average surface temperature to 2 °C relative to preindustrial levels. To our knowledge, this is the first study that provides these results at this level of disaggregation.

There are several approaches to represent different categories of LDVs in energy-economic models. Girod et al. (2013) and van Vuuren et al. (2017) provide model comparisons focusing on transport sector outcomes. Most of the models that explicitly address evolution of LDV fleet by type (i.e., ICE, EV, etc.) and the corresponding fuel mix are either models of transportation sector only or partial equilibrium models that include or are softly connected to detailed fleet models. In comparison to a CGE setting, these approaches do not explicitly represent full inter-industry and inter-region linkages and impacts on the overall economy, which are important for evaluation of climate policies. However, it is more challenging to represent fleet type details in a CGE setting due to a more complex structure of this type of models. An overview by Girod et al. (2013) includes only partial equilibrium or transportation sector models, such as GCAM, POLES, TIMER, IEA-MoMo, and GET models. Edelenbosch et al. (2017) provide an overview of the models described in van Vuuren et al. (2017) and it includes AIM, DNE21 +, GCAM, GEM-E3, IMACLIM-R, IMAGE, POLES, MESSAGE, REMIND, TIAM-UCL, and WITCH.

As described above, most of the above-mentioned models represent transportation details either in a limited fashion (e.g., with a single transportation sector that combines all modes of transportation) or, in contrast, they represent very detailed transportation options, but in a transport sector-only models. An advantage of the approach described in this paper is that it combines the strengths of two approaches, where both key dynamic of inter-industry and inter-regional interactions are captured and LDV sector also has a detailed representation of current and future fleets of ICEs, PHEVs, and BEVs.

Models such as AIM, GEM-E3, and IMACLIM also have a general equilibrium structure with an explicit representation of inter-industry interactions. However, AIM does not explicitly model transportation technologies and transport demand is derived using a top-down method, where energy demand is input to a production function driven by gross domestic product (GDP) growth (Fujimori et al., 2014). In GEM-E3, transportation dynamics is provided by a separate PRIMES-TREEMOVE module that is softly linked to a CGE part (Karkatsoulis et al., 2017). In IMACLIM the modal shares are calculated endogenously and compete on the basis of cost through a logit distribution (Waisman et al., 2013).

In comparison to the approaches adopted in these models, a novel contribution of this paper is in expanding transportation sector details by explicitly representing in a CGE structure both the current LDV deployment (where BEVs and PHEVs are adopted even when their relative costs are higher than comparable ICEs) and the future LDV mix when more economically competitive BEVs and

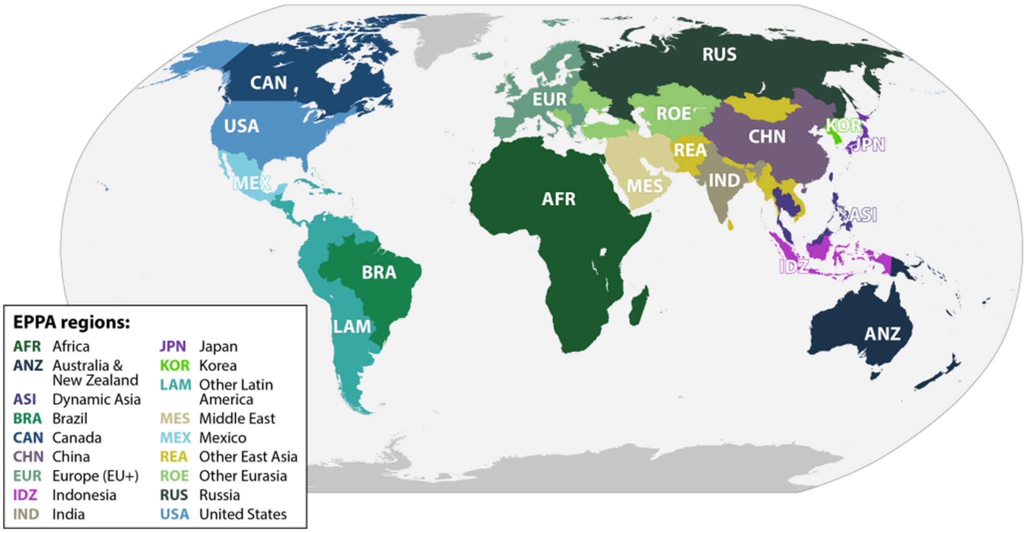

Fig. 1. Regions in the EPPA model.

FCEVs are available. In comparison to approaches that link CGE model with detailed fleet/transportation modules, an explicit representation of transportation sector detail within CGE structure potentially avoids the issues related to consistency among model solutions and convergence between the models.

In comparison to documentation of these CGE models (Fujimori et al., 2014; Karkatsoulis et al., 2017; Waisman et al., 2013), as another contribution provided by our paper, we describe our detailed methodology in parametrizing the enhanced household transport sector (including input data), which allows other modeling groups to learn and/or use our approach and adjust the corresponding parameters as more data become available.

The paper is organized as follows. Section 2 introduces the main updates to transport-related features of the EPPA model. In Section 3 we provide the results from EPPA model for the total stock of light-duty vehicles and electric vehicle for 2020–2050 and the resulting CO_2 emissions in different illustrative scenarios. Section 4 concludes.

2. Private transportation details in the EPPA model

For illustration of our approach for representing the private LDVs in CGE models, we discuss the data at the level of regional aggregation of the MIT Economic Projection and Policy Analysis (EPPA) model, which represents some major individual countries (USA, China, India, Japan, and others) and some aggregated regions (EU, Africa, The Middle East and others). Fig. 1 provides a map of the EPPA regions. Additional information about the EPPA model is available in Appendix A. The procedures described in this paper can be applied for different regional aggregating schemes.

In order to represent LDVs in economy-wide models, the following baseyear (i.e., initial year of the model) information is needed for all regions of the model: data in physical terms on stocks of private light-duty vehicles and quantities of fuel used; and data in monetary terms (e.g., in US dollars) that represent expenditures on vehicles, their required services, and fuel. In addition, to represent competitiveness of the alternative fuel vehicles (e.g., battery-electric vehicles (BEV) or plug-in hybrid electric vehicles (PHEV)), data on costs of these vehicles relative to the costs of internal combustion engine (ICE) vehicles are needed. We discuss these components below.

2.1. Baseyear data requirements

The number of light-duty vehicles in each of EPPA's 18 regions in 2005, 2010, and 2015 is provided in Table 1 (in Appendix B we offer a discussion how we combined the data from different sources). Europe and USA are the regions with the largest numbers of LDV (about 260 million and 240 million LDVs in 2015, correspondingly). China's LDVs are growing fast, from about 20 million in 2005, to about 60 million in 2010 and to about 140 million in 2015. Japan and Russia are the fourth and fifth-ranked regions with about 60 million and 45 million LDVs in 2015, respectively. The total global number of LDVs grew from about 700 million in 2005 to about 1 billion in 2015.

The LDV numbers in Table 1 include EVs and their stocks are growing rapidly in many countries. Table 2 presents the data for EV stocks in 2015–2017 for the EPPA model regions. We develop regional numbers (that combine PHEVs and BEVs) from the reports from the International Energy Agency (IEA, 2017a, 2018). China, USA and EUR have the largest number of EVs. In 2015–2017, the number of EVs in China increased from about 300 thousand to 1.2 million, in USA from about 400 thousand to about 760 thousand and in Europe from about 330 thousand to about 740 thousand. The global number of EVs almost tripled in two years, it grew from 1.2 million in 2015 to 3.1 million in 2017. For the EPPA model, we use information for EVs for 2015 and calibrate the growth to 2020

Table 1
Stock of Private Light-Duty Vehicles (million vehicles) in the regions of the EPPA model.

EPPA Region	2005	2010	2015
AFR	15.19	20.75	26.54
ANZ	13.32	14.74	16.78
ASI	19.17	23.17	30.78
BRA	18.93	26.89	35.47
CAN	18.12	20.27	22.07
CHN	20.5	60.18	141.48
EUR	233.44	246.7	261.9
IDZ	5.08	8.89	13.48
IND	7.63	13.27	22.47
JPN	57.09	58.35	60.99
KOR	11.12	13.63	16.56
LAM	20.37	27.74	35.74
MES	17.06	23.06	33.96
MEX	14.3	21.15	26.94
REA	3.12	4.8	7.22
ROE	19.74	26.72	33.27
RUS	25.57	34.35	44.25
USA	215.52	224.56	242.42
Global	735.27	869.19	1072.31

Table 2
Stock of electric vehicles (BEV + PHEV) in 2015–2017 in EPPA regions (thousand vehicles).

EPPA Region	2015	2016	2017
AFR	3.6	6.1	10
ANZ	4.6	7.5	13.2
ASI	4.2	6.7	11
BRA	0.2	0.3	0.7
CAN	17.7	29.3	46
CHN	312.8	648.8	1227.8
EUR	334.7	517.4	741.5
IDZ	1.7	2.8	4.6
IND	4.4	4.8	6.8
JPN	126.4	151.3	205.4
KOR	6	11.2	25.9
LAM	4.5	7.4	12.5
MES	4.2	6.9	11.7
MEX	0.3	0.7	0.9
REA	0.9	1.5	2.5
ROE	4.1	6.8	11.4
RUS	5.5	9	15.2
USA	404.1	563.7	762.1
Global	1239.5	1982.1	3109.1

based on the current trajectories[1]. We discuss the process of the calibration later in the paper.

To evaluate refined oil consumption by LDVs, we use the GTAP data (Aguiar et al., 2016) for the total use of oil by households. We apply the region-specific shares (see Table 3) for the use in personal transportation from Karplus (2011) to adjust for oil in final consumption that is not used for transportation (e.g., for heating). Consistent with our approach for classification of private LDVs (see Appendix B), we modified the GTAP data for USA and EUR. Based on the data from IEA MoMo (IEA, 2017b) and EIA (2017b), we update USA transportation refined oil consumption to about 15.1 exajoules (EJ) in 2011. Similarly, we update the EUR refined oil consumption in transportation according to the reported volume in IEA MoMo (IEA, 2017b). For other regions, IEA MoMo and GTAP data provide consistent values. Refined oil consumption in household transportation for the EPPA regions is reported in Table 3.

Economy-wide models also need information on LDV expenditures in monetary terms. Previous approach (Paltsev et al., 2004; Karplus et al., 2013) relied on data at an aggregate level for expenditures on car purchases and fuel use to calibrate the total household transportation expenditures based on the GTAP data. In the novel approach used in this paper, we calculate the required expenditures based on the vehicle cost data, fuel expenditures (gasoline and electricity), home charges for BEV and PHEV, services such as insurance and maintenance based on real total cost of ownership of owning such vehicles. Table 4 summarizes our estimates. For fuel (gasoline and electricity), maintenance, insurance, license/registration/taxes and depreciation, we use data from AAA (2018)

[1] For 2020 we calibrate the PHEV and BEV stock based on their growth rates between 2015 and 2017. After 2020, the EPPA model determines the fleet mix based on the competiveness of different vehicle types.

Table 3
LDV Refined Oil Use (EJ) in 2004, 2007 and 2011 and a Share of Oil Used in Household Transport in Total Refined Oil Consumption by Households.

EPPA Region	2004	2007	2011	Share
AFR	1.36	1.45	1.73	0.88
ANZ	0.54	0.53	0.54	0.99
ASI	0.87	0.87	0.9	0.85
BRA	0.76	0.8	1.01	0.9
CAN	0.91	0.96	0.97	0.92
CHN	1.99	2.42	3.14	0.85
EUR	7.52	6.85	6.62	0.86
IDZ	0.36	0.34	0.39	0.45
IND	0.6	0.68	0.81	0.45
JPN	1.63	1.52	1.41	0.83
KOR	0.37	0.37	0.37	0.8
LAM	1.14	1.21	1.31	0.85
MES	0.79	0.88	0.91	0.32
MEX	0.91	0.99	1	0.86
REA	0.18	0.19	0.25	0.44
ROE	0.31	0.33	0.34	0.39
RUS	0.93	1.06	1.16	0.99
USA	16.13	16.45	15.13	0.99

Table 4
Components of Cost of Ownership for Different Types of Vehicles.[1]

	Medium ICE Sedan	Hybrid Vehicle	Plug in Hybrid Vehicle	Battery Electric Vehicle	Hydrogen Fuel Cell
Annual Operating Costs					
Fuel	$1,250	$855	$685	**$514**	$3,231
Maintenance, repair and tires	$1,320	$1,140	$1,140	$1,140	$1,140
Annual Ownership Costs					
Full-coverage insurance	**$1,232**	**$1,200**	$1,208	**$1,215**	$1,697
License, registration, taxes	**$690**	**$617**	$790	**$790**	$790
Depreciation (15,000 miles annually)	**$3,580**	**$3,068**	$4,270	**$5,471**	$4,870
Finance Charge	**$770**	**$621**	$652	**$683**	$683
Annual Costs					
Fuel	$1,250	$855	$685	$514	$3,231
Services	$3,242	$2,957	$3,138	$3,145	$3,627
Total Ownership Costs					
Vehicle	$30,319	$33,694	$43,570	$55,697	$65,552
Fuel	$13,750	$9,405	$7,531	$5,657	$35,538
Services	$35,662	$32,527	$34,513	$34,595	$39,897
Total Ownership	$79,731	$75,626	$85,613	$95,950	$140,987

[1] The detailed bottom-up cost analysis of BEV and PHEVs in this study was used to determining the relative cost of these vehicles compared with representative ICEs (see Ghandi and Paltsev (2019) for details). Table 4 also shows the underlying additional cost item data to estimate the total cost of ownership of different powertrains. The underlined numbers in bold are from AAA (2018).

for owning and operating a medium sedan, a hybrid and a battery electric vehicle. These values are underlined in Table 4. Other numbers are our own calculations based on AAA (2018) data. In particular, for PHEVs, we assume an average cost between BEV and hybrid for items such as fuel, insurance, depreciation and finance charges.

For license, registration and taxes, we have added a flat $100 to a medium sedan's equivalent cost to reflect several US states including California's flat additional charges on PHEVs and BEVs (NCSL, 2017). We consider finance charges (for 5 years) as a part of total cost of owning a car. Vehicle costs are based on Ghandi and Paltsev (2019), where a relative cost of BEV is 1.8 higher than a cost of a medium ICE sedan. The relative cost of a PHEV vehicle is 1.4 higher than for an ICE vehicle. Based on DOE (2017a), we used 11 years as a lifetime of the vehicle. We have estimated that the total cost of owning and operating is the lowest for a hybrid vehicle at about $75,600, followed by ICE vehicle at about $79,700, followed by a PHEV at about $85,600 and a BEV at about $96,000.

We also calculated the total cost of ownership for hydrogen fuel cell electric vehicle (FCEV). Our estimate on the cost of vehicle is based on Toyota Mirai 2017 MSRP of $58,000. The fuel cost of FCEV is based on 65 kg/mile of fuel consumption (Extremetech, 2019) and 14$/kg cost of hydrogen (CAFCP, 2019). For a full coverage insurance cost of a Fuel Cell vehicle, we average over several insurance companies quotes for Mirai 2017 (Zebra, 2018). Based on these data, we have estimated the total cost of owning of a hydrogen fuel cell vehicle at about $141,000.

In our modeling, we use information on relative costs of different vehicles and shares of costs on vehicle, fuel, and services. We base them on the U.S data because of lack of the relevant comprehensive data for other regions of the world. While the use of relative data in combination with historic regional data accounts partially for a regional variability, care should be given to the results of our regional modeling. Our approach can be used when region-specific data become available to provide a finer resolution to region-specific analysis.

2.2. Household transportation structure in the EPPA model

The EPPA model is a multi-region, multi-sector computable general equilibrium (CGE) of the global economy (model documentation for the basic version is available in Chen et al (2017)). Critical data that determine the structure of the model are contained in social accounting matrixes (SAM), which represent a snapshot of the economy of each region in the model for the base year at the aggregate sectoral level. SAMs are developed from systems of national income and product accounts and input–output tables that quantify the inter-industry flows of goods and services. For the initial data for historic periods the EPPA model relies on an aggregation of the Global Trade and Policy (GTAP) dataset and additional data (see Appendix A for sectoral and regional representation of the model and information about additional datasets).

EPPA is built on microeconomic theory principles through a representation of consumers' utility maximization and producers' cost minimization by explicitly representing market clearance condition (i.e., balance between supply and demand), normal profit condition (i.e., balance between value of inputs and value of outputs in production), and income balance condition (i.e., value of income must be equal to the value of factor endowments and tax revenue). In the model, prices are determined endogenously. The model simulates the world economy through time to produce scenarios of economic activities (production, consumption and trade at regional and sectoral level), GHG, aerosols, other air pollutants emitted by human activities. These emission scenarios are input into a coupled model of atmospheric chemistry and climate to produce scenarios of atmospheric chemistry and changes in atmospheric composition and hence the need for EPPA to run long simulation horizon.

EPPA, as a CGE model, represents the circular flow of goods and services in the economy; supply of factor inputs (labor and capital services) to the producing sectors, and provides a consistent analysis of the supply of goods and services from producing sectors to final consumers (households) by balancing in each period. In the model, government collects taxes and distributes the full value of the proceeds to households. Prices of goods must reflect the cost of all inputs, wages and return on capital. EPPA keeps track of the physical flows of carbon-based fuels and resources in the economy through time, their different calorific values, and also their GHG emissions in order to identify the specific sectors that are most affected as a result of policies.

A fundamental feature of EPPA's modeling is its representation of the ability of individuals to make trade offs among the inputs to both production and consumption. For producers, this reflects the underlying technology and the extent to which labor, capital, and energy can be substituted for each other. The technical ability or willingness to make such trade offs is summarized in elasticities of substitution. Elasticities of substitution are important determination of the estimates of the cost of policies to control GHG emissions.

In EPPA, technological change is an important source of growth in the economy like capital accumulation. EPPA models technology change in three ways: 1) exogenous augmentation of the supplies of labor and natural resources; 2) exogenous reduction of energy use per unit output through time; 3) and energy technologies (also known as backstop technologies) that currently unused, but which come into play as supplies of current energy resources deplete causing price rise or as policies penalize the GHG emission conventional energy sources. The time of entry for backstop technologies in a simulation depends on their cost relative those of current fuels, as they endogenously change in simulation of EPPA. As mentioned, one novel contribution of this paper is to base the introduction of BEVs and PHEVs in the market on a detailed total cost of ownership analysis of ICEs, BEVs and PHEVs.

Formulating a mathematical problem using general equilibrium involves modeling the economy as an optimization problem and solution to problem is sought via solving a large non-linear programming in which an objective function is maximized/minimized subject to set of constraints. In EPPA we use a mixed complimentarity approach (Rutherford, 1995) to solve the model.

For our analysis in this paper, we performed the following steps to enhance the EPPA model. In step 1, we specified the dimensions of the representation of private transportation in terms of technologies, input requirements, consumers, taxes, government support, countries and active markets. Then, in step 2, we specify a particular structure of functional forms. In this study, we introduced a completely new production function for the household transport sector accounting for detailed analysis around BEVs and PHEVs relative cost and their penetration potentials. The needed detailed data assessment is a part of the third step of the process to construct micro-consistent datasets. Step 4 involves calibration of the enhanced model. To carry this part and as another important contribution of this paper, all underlying data in term of fleet, vehicles mile traveled and fuel consumption were updated according with actual data at the global level. In this modeling setup, a final step involves running the model with all its new features to replicate the data for historic periods.

As mentioned, in a CGE framework, production and consumption decisions are described by relationships between inputs and outputs, their relative prices, and tax/subsidies consideration. Fig. 2 provides a schematic of the modified household transportation sector in the EPPA model. In comparison to the previous structure (Chen et al., 2017), in this paper we capture the BEV/PHEV adoption dynamic in early periods as the current penetration of EVs is not solely driven by the relative cost of these vehicles with respect to their comparable ICEs.

For the purposes of representing current and potential future fleet dynamics, we introduced two types of ICE vehicles (ICE1 and ICE2 in Fig. 2) and two types of BEV vehicles (BEV1 and BEV2 in Fig. 2). ICE1 vehicles represent those trips that will not be served by PHEVs and BEVs. We base ICE1 on the assumption that there will be no comparable EVs for a subset of ICE applications, including those that are currently served by large SUVs and trucks. We assign a share of those applications as 20% based on Nicholas et al. (2017), who suggest that the maximum annual miles driven on BEVs are around 12,000 miles. Considering 15,000 as annual miles for the average annual driving distance in USA (AAA, 2018), we assume that in the next several decades BEVs could at best only serve

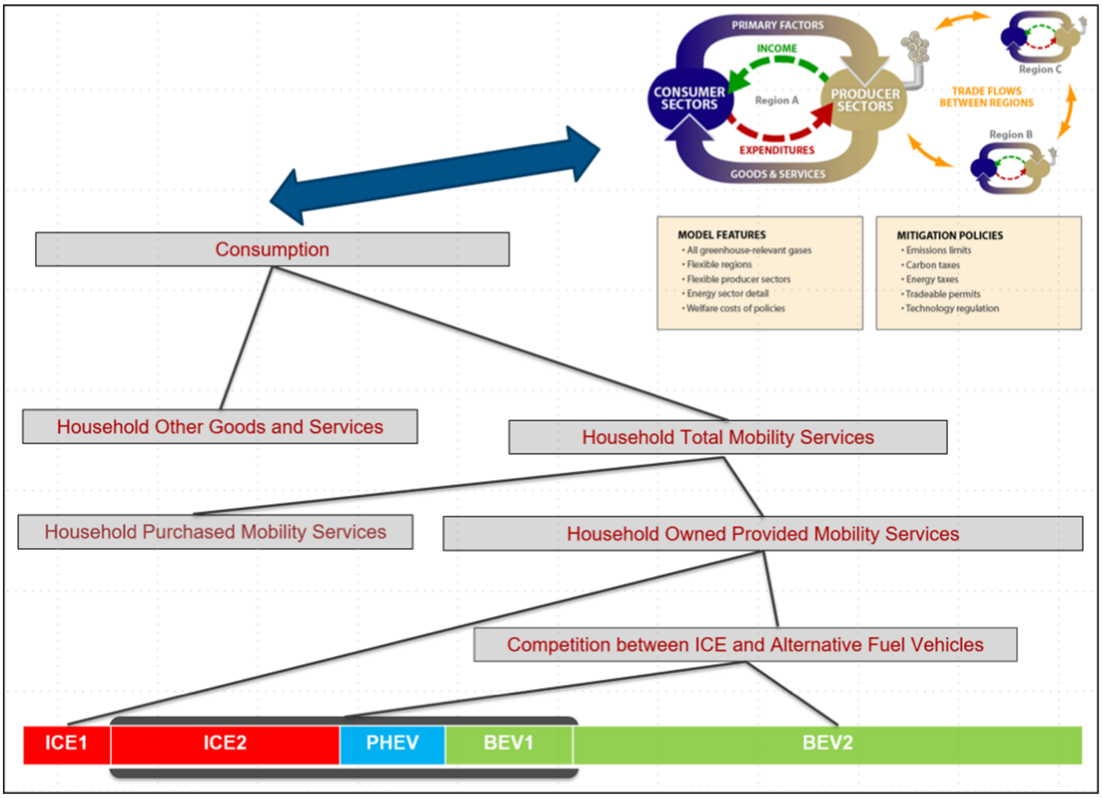

Fig. 2. Schematics of the Private Transportation in the EPPA model.

80% of the driving needs of households. Therefore, we initially assign 20% to ICE1 that are not substitutable with EVs and 80% to ICE2 that are substitutable with EVs (BEVs and PHEVs). A distinction between BEV1 and BEV2 vehicles allows us to represent the current deployment of BEVs and the option for the future more economically competitive BEVs that can completely overtake the trips that are currently served by ICE2 vehicles.

The darker shaded area in Fig. 2 represent the current fleet of ICE2, PHEV and BEV1. Over time, these vehicles can be substitutable based on their relative costs. This representation allows us to capture the current fleet dynamics, where the relative costs of PHEV and BEV vehicles are higher than comparable ICEs, and as a result, penetration of EVs is rather limited. With advances in battery technologies, BEV2 vehicles can take over this market segment. This distinction between ICEs and BEVs in our modeling framework suggests that these two vehicle technologies are perfect substitutes to each other in certain portions of the market. (As a part of our sensitivity analysis, we later provide the scenarios where the share of non-substitutable ICE1 is reduced to 5% from 20%).

Fig. 2 also provides information on how household own provided mobility services are related to purchased mobility services (i.e., public transportation, taxi, etc.) and the remaining consumption of other goods and services. It also includes a typical circular CGE diagram where consumers provide factors of production to producing sectors (sectors of the EPPA model are provided in Appendix A) and consume goods and services provided by producing sectors. The circular diagram also provides a simplified illustration of the model interconnections among different world regions (see Fig. 1) and different economic sectors.

Our approach allows for a technology rich representation within the CGE model structure. In comparison to approaches that link a CGE model with detailed fleet/transportation modules, it potentially avoids the issues related to consistency among model solutions and convergence between the models. In terms of mitigation policies, our enhanced approach still allows to incorporate country-wide and sector-specific emission constraints, carbon taxes, energy/fuel taxes, tradeable emission permits, technology regulations such fuel standards, emission standards, and renewable fuel standards. Additional information about the structure of the EPPA model can be found in Paltsev et al. (2004, 2005), Karplus et al. (2015), Chen et al (2016, 2017).

2.3. Technology specific factor for new technology penetration

In our enhanced version of the EPPA model, we consider BEV2 vehicles as a so-called “backstop” technology, which means that under certain conditions this technology may fully overtake its substitute. The rate of technology diffusion is determined by the technology specific factor (Morris et al., 2019), which enables the simulation of multiple dynamics, including rents associated with new technology and adjustment costs related to expanding new technology. Karplus et al. (2010) suggested to use the rate of EV adoption based on data for conventional hybrid (non-plugin Toyota Prius) vehicle penetration over the period 1998 to 2008. Based on

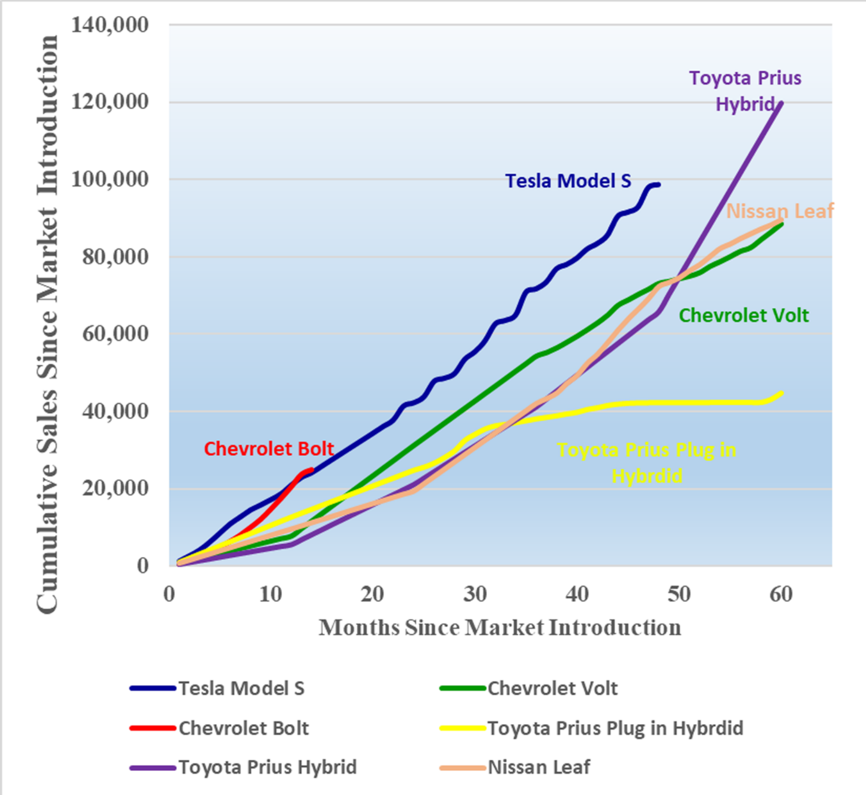

Fig. 3. Cumulative Sales since Introduction to a Market for Selected BEV, PHEV and HEV. Data Source: Carsalesbase (2018)

data from Carsalesbase (2018), Fig. 3 shows the cumulative sales of different EVs from the time of their introduction to the market. A non-plugin hybrid Toyota Prius was introduced to the US market in 2000. Chevy Volt (PHEV) and Nissan Leaf (BEV) entered the US market in December 2010. Toyota PHEV Prius entered the market in April 2012, and Tesla started the sales of its Model S in June 2012.

As can be seen from Fig. 3, medium range BEVs (Nissan Leaf) extended range PHEVs (Chevy Volt), low range PHEVs (Toyota PHEV Prius) and non-plugin hybrid Toyota Prius have followed a similar path in terms of cumulative sales in their first few years after their introduction to the market. In Fig. 3, the line for Toyota PHEV Prius combines two generations of the vehicle. In anticipation of the second generation, the cumulative sales of first generation Prius Plug-in Hybrid slowed down significantly.[2] Fig. 3 also shows that cumulative sales of the long range BEVs (Chevy Bolt and Tesla Model S) have had somewhat higher growth rates, but followed a similar general path as other EVs. These results provide a justification for similar rates of initial adoption of EVs, which is controlled by a technology-specific factor in the EPPA model (Karplus et al., 2010). Once a substantial experience with new technology is gained, the limitation on the speed of adoption is gradually removed as described in Morris et al. (2019).

2.4. Vehicle fuel efficiency in EPPA

Regional fuel efficiency of LDV fleet varies, with Europe, Japan and USA having the most fuel efficient fleets of 24–26 miles per gallon (MPG) in 2015 (Yang and Bandivadekar, 2017). In terms of the future trajectory for fuel efficiency of LDVs, we assume that the fuel efficiency standards are increased in all regions by 1–2% per year. In USA and Europe they increase by 1.4%, in China by 1.3%, in India by 1.1%. In most developing countries, the assumed increase is faster (close to 2%) to bring them closer to the fleet efficiency of developed countries. For USA, our assumption is driven by a recent assessment by the US Energy Information Administration (EIA, 2018) following the EPA/NHTSA proposed rulemaking for Corporate Average Fuel Economy and GHG regulations in 2018. For other regions, we updated fuel efficiency targets by region based on latest assessments by the ICCT (Yang and Bandivadekar, 2017) and MIT (Karplus et al., 2015). Table 5 summarizes fuel efficiency targets for the EPPA model regions.

[2] First generation Prius Plug-in Hybrid sales slowed down significantly during late 2015 and 2016. However, with the introduction of new Prime Prius (second generation Prius PHEV), sales have gone up in 2017 (Carsalesbase, 2018).

Table 5
Fuel efficiency (MPG) targets for EPPA regions.

EPPA Region	2015	2020	2025	2030	2035	2040	2045	2050
AFR	20	21	22	23	25	26	28	30
ANZ	20	21	22	24	25	27	30	32
ASI	16	16	17	18	19	21	23	24
BRA	21	22	23	25	27	28	30	31
CAN	20	22	24	25	27	29	31	32
CHN	21	23	25	26	28	30	32	34
EUR	26	28	30	32	34	37	39	42
IDZ	17	18	19	20	22	23	25	27
IND	24	25	27	28	30	32	34	35
JPN	23	25	26	27	29	31	33	35
KOR	17	18	20	21	22	24	26	27
LAM	16	17	18	19	20	21	23	25
MES	14	15	16	18	20	23	25	28
MEX	13	14	16	18	20	22	25	28
REA	16	17	19	20	22	23	26	28
ROE	21	23	24	26	28	30	33	36
RUS	20	21	22	24	25	27	30	31
USA	25	26	29	31	33	35	37	40

2.5. Battery cost

In Fig. 4, we provide an overview of estimates for battery pack costs from different studies for 2014 and 2015. Most of the estimates reflect the historic values representing cost of the battery pack in $/kWh, except for the estimates from NAS (2013), which provides a projection for 2015. For our analysis, we focus on two averages over the listed estimates. The first average (yellow line in Fig. 4) takes into consideration only the estimates for 2015, and it yields 347 $/kWh. The red line on Fig. 4 represents the average estimates for 2014, and it is equal to 503 $/kWh. For this analysis we take into consideration the decrease in the cost of the battery and used 350 $/kWh as the 2015 battery pack cost of a representative BEV.

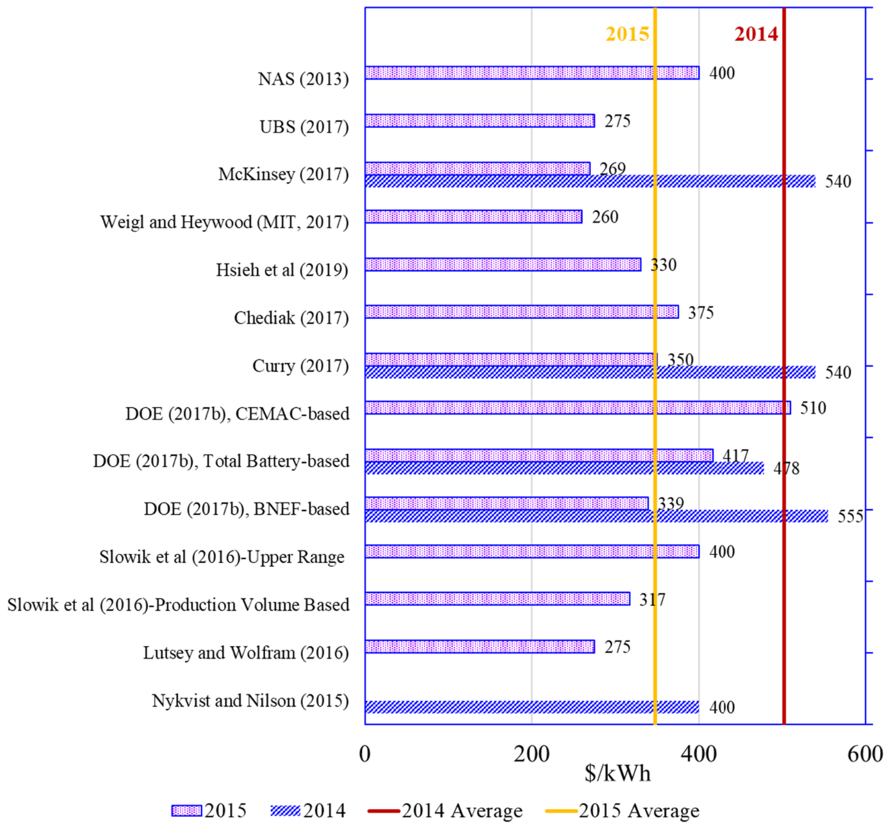

Fig. 4. Summary of BEV Battery Pack Cost Estimates for 2014–2015.

Table 6
2020–2030 BEV Battery Cost Projection Summary.

Source	2020	2025	2030	Critical Assumptions
Bloomberg New Energy Finance (Zamorano, 2017)	160	109	73	19% learning rate based on Lit-ion average battery pack prices for every doubling of cumulative production capacity 2010–2016
ICCT, (Slowik, Pavlenko, & Lutsey, 2016)		183		Average estimate based on the study's range of estimate 150–225 for 2023 for the hypothetical BEV deployment of 4.4 million BEVs in 2023
Our Estimation for 2030 based on ICCT, (Slowik, Pavlenko, & Lutsey, 2016)			114	Similar cost reduction rate for the years after 2023 at 25% (high volume production), 42% (medium volume production) and 44% (low volume production) as in ICCT, (Slowik, Pavlenko, & Lutsey, 2016). 20 million annual BEV sales in 2030 are assumed for this calculation
UBS Evidence Lab, (2017)		130		NMC811 total battery pack cost
Hsieh et al Green, (2019)	200	150	130	Cost f raw materials, learning rate for materials synthesis process
ICCT, Wolfram and Lutsey, (2016)	225	160		
National Academy of Sciences (2013)			250	
US DOE 2022 Target		125		DOE target for 2022 announced in 2016
Our adopted estimate	193	146	130	

Table 6 summarizes battery pack cost projections for 2020–2030 from several studies and also lists assumptions for these projections. For 2030, some studies assume a reduction of battery pack cost below 100$/kWh. While technological progress and different chemistry may reduce the cost to this level, Hsieh et al. (2019) analyzed the cost of raw materials for the advanced battery, NMC811, and concluded that the costs in 2030 are projected to be around 130$/kWh. The PHEV battery pack cost are higher by 60$/kWh. Based on Hsieh et al (2019), after 2030 we keep the battery costs constant due to growing contribution of active materials costs and slower learning rate of the material synthesis process. Additional issues related to battery costs are discussed in Appendix C.

2.6. Motor cost

For motor related cost estimates, we rely on NAS (2013), which provides the estimates for 2010, 2030 and 2050 (we extrapolated the estimates for 2015, 2020 and 2025 using a polynomial of order 2). NAS (2013) reports the fixed cost of the electric motor in PHEV and BEV at $668 and the variable cost as 12$/kWh in 2010. By 2030, the fixed cost of the electric motor in PHEV is projected to be reduced to $393 and the variable cost is reduced to 6$/kWh. The corresponding numbers for 2030 for BEVs are $425 and 7$/kWh. Based on the assumed motor sizes, in Table 7 we present the results of calculations for total cost of electric motors in PHEV and BEV of different types.

For the low range PHEV we assume 78 kW motor based on 2017 BMW 330e, 2017 Mercedes C350, 2017 Ford C-Max Energi and 2017 Ford Fusion Energi electric motor size. For the extended range PHEV we consider the fact that both 2017 Chevy Volt and 2017 Prius Prime configurations have two electric motors with an average power of 85 kW (motor 1) and 76 kW (motor 2). For the medium range BEV we assume 104 kW motor based on 2017 Nissan Leaf, 2017 Ford Focus EV and 2017 BMW i3 electric motor size. For the long range BEV we use 197 kW motor size based on 2017 Chevy Bolt and 2017 Tesla Model S 75D. The resulting electric motor costs are reduced from the range of about $1,500–3,000 in 2010 to $900–1,900 in 2030.

2.7. Total BEV/PHEV vehicle cost

We also include the costs of additional components for BEV and PHEVs such as EV transmission ($330), home charger ($1,000) and other EV system costs ($870, that include control unit, regenerative braking system, and onboard charger) and credits for the ICE related components that are not required in BEVs ($3,730). We base these costs on NAS (2013) estimates and IEA Global EV Outlook (IEA, 2017c) for a home charger.

Table 8 summarizes the total incremental cost estimates relative to the ICE vehicle until 2030. A medium range BEV in 2010 is estimated to have a total incremental cost of about $15,000 relative ICE, which is reduced to about $4,000 by 2030. Other types of EVs experience similar cost reductions (from $32,000 to $9,000 for the long range BEV, from $7,000 to $4,000 for the low range PHEV, and from $11,000 to $6,000 for the extended range PHEV). We assume that after 2030, the relative costs of vehicles will stay

Table 7
Electric motor cost estimates ($).

	BEV		PHEV	
	Medium Range	Long Range	Low Range	Extended Range
2010	1,874	2,959	1,573	2,536
2015	1,698	2,680	1,393	2,240
2020	1,504	2,374	1,197	1,919
2025	1,341	2,115	1,035	1,653
2030	1,184	1,867	884	1,407

Table 8
Incremental cost for BEV and PHEV ($).

	BEV		PHEV	
	Medium Range	**Long Range**	**Low Range**	**Extended Range**
2010	15,044	31,804	7,191	11,342
2015	11,601	24,775	6,276	9,686
2020	6,279	13,871	4,927	7,230
2025	4,580	10,440	4,419	6,325
2030	3,901	9,112	4,269	6,079

constant due to a battery cost trajectory (described above) and a gradual removal of government incentives to BEVs and PHEVs.

The data on region-specific numbers of vehicles and fuel use (Tables 1-3) provide a basis for LDV mix representation in the baseyear of the model. In addition to information on the relative costs of different vehicles (from Table 4), shares of expenditures on vehicle, fuel, and services (from Table 4), changes in relative costs over time (Table 8), changes in relative prices (endogenously determined by the model) and evolution of technology specific factors (described Section 2.3) determine the competitiveness of LDV types.

3. Simulation results

As an illustration of our approach, we incorporated the derived data for the number of vehicles, fuel use and the relative costs of vehicles into the EPPA model to make a projection of LDV and EV stocks up to 2050 and the resulting CO_2 emissions. We consider the following scenarios:

(1) the *Reference* scenario, which assumes continued strengthening of fuel efficiency standards for LDVs, as well as expanded use of renewables for power generation (IEA, 2017b). It does not include mitigation pledges made by countries in their submissions for the Paris Agreement (UN, 2015);

(2) a *Paris Forever* scenario, which assumes implementation of commitments under the Paris Agreement by 2030 and continuation of those policies thereafter, but no additional policy action (MIT Joint Program, 2018);

and (3) a *Paris to 2 °C* scenario, which assumes policy action beyond current Paris commitments to ensure that the increase in Earth's average surface temperature (relative to pre-industrial levels) does not exceed 2 °C. We assume that mitigation is achieved through global economy-wide carbon pricing after 2030.

The three scenarios are chosen to represent the range of outcomes regarding the stringency of global GHG mitigation actions. The "no climate policy" *Reference* scenario illustrates the trajectories that would occur in the world without the Paris Agreement. It serves as a benchmark for comparison with policy scenarios. The *ParisForever* scenario evaluates the pledges that countries have made in their Nationally Determined Contributions (NDCs) specified for 2030 and we assume that the countries continue to abide by them after 2030.

While it is desirable to start an aggressive GHG mitigation as soon as possible, we believe that the 2030 NDC pledges represent the current willingness by the countries with respect to globally coordinated actions. Therefore, in the *Paris to 2 °C* scenario, we keep these pledges up to 2030. However, in this scenario we assume that an agreement is reached to implement a globally coordinated climate policy aimed at the deep emission reductions after 2030 consistent with the stabilization of the global average atmospheric temperature at 2 °C above pre-industrial levels with a probability of 66%, with emission profiles specified in Landry et al. (2019).

We combine the reporting for PHEVs and BEVs into a representative EV category and assume a gradual decrease in the cost of batteries (as in Fig. 5) and a gradual decrease in government support to EVs, which is eliminated by 2025. In all scenarios, growth in economic activity and population drives a substantial increase in the global stock of LDVs[3]—from approximately 1.1 billion vehicles in 2015 to an estimated 1.65–1.75 billion vehicles in 2050 (Fig. 5). In the *Reference* scenario, the global stock of LDVs is close to 1.4 billion vehicles in 2030 and about 1.75 billion vehicles in 2050. The implementation of climate-change mitigation policies in the *Paris Forever* and *Paris to 2 °C* scenarios affects fuel prices, vehicle efficiency, income levels of consumers, and their demand for transportation. As a result, the global stock of LDVs in 2030 is about 30 million vehicles smaller in both the Paris scenarios compared to the *Reference* scenario. After 2030, the more aggressive carbon constraints in the *Paris to 2 °C* scenario have a further dampening impact on LDV fleet growth worldwide. Our modeling results for 2050 show 40 million fewer vehicles globally in the *Paris Forever* scenario compared to the *Reference* scenario. The corresponding reduction in the *Paris to 2 °C* scenario is about 125 million vehicles.

In all scenarios, the LDV stock grows in all regions. Fig. 6 shows results for regional LDV stocks in the *Paris Forever* scenario (Appendix A provides more detail about which countries are included in different EPPA regions). Europe (EUR), the U.S. (USA), and China (CHN) are the regions with the largest LDV fleets in 2015.[4] These regions continue to have the largest fleets over the study period (in 2050, their combined share of the global LDV fleet is more than 50%). However, there are differences in the rate of fleet growth between regions. For Europe and the U.S., the model predicts a 22% increase in number of LDVs between 2015 and 2050; in

[3] We use the terms "vehicle fleet" and "vehicle stock" interchangeably.
[4] See Ghandi and Paltsev (2019) for a discussion of historic data.

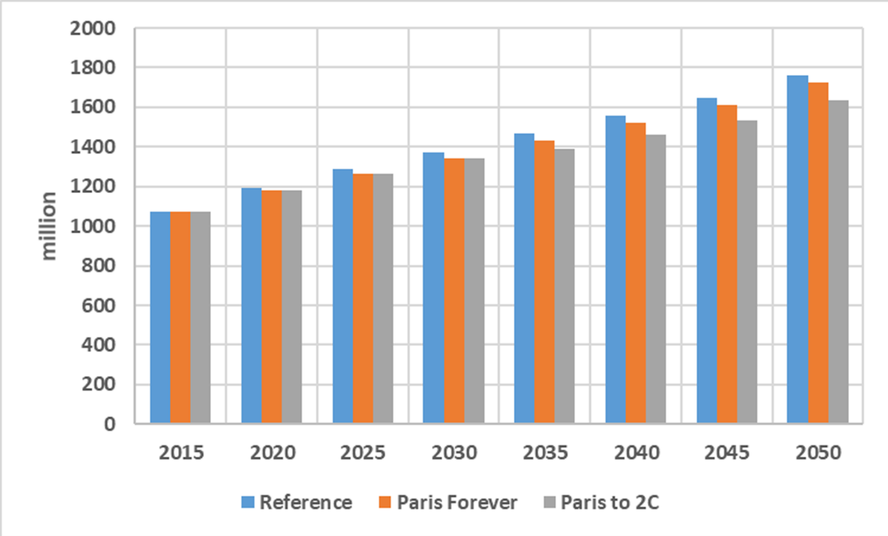

Fig. 5. Global LDV stock.

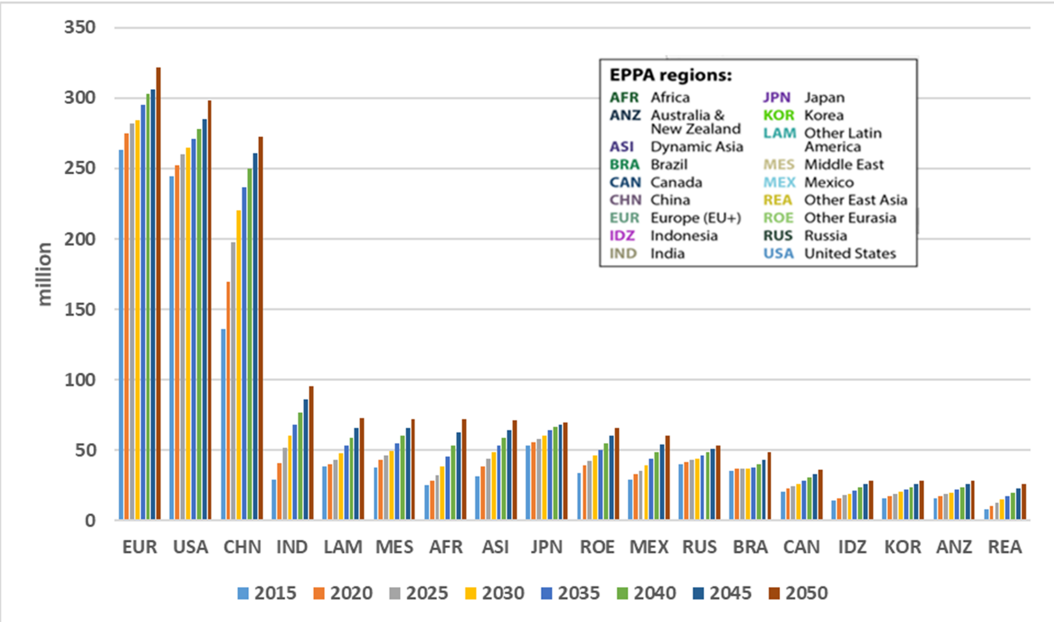

Fig. 6. Regional LDV Stock in the *Paris Forever* Scenario.

China, by contrast, projected fleet growth over this period is about 100%. As a result, the model projects about 320 million vehicles in Europe, about 300 million vehicles in the U.S., and about 275 million vehicles in China in 2050 under the *Paris Forever* scenario.

Some regions experience even faster fleet growth than China, but they start from a smaller base. In India (IND), the LDV fleet is projected to grow 230% by mid-century, from about 30 million vehicles in 2015 to close to 100 million vehicles in 2050. Projected fleet growth in the rest of East Asia (denoted REA in the figure) is 210%, from about 8.5 million vehicles to 26 million vehicles; in Africa (AFR), the fleet grows 190%, from 25 million to 72 million LDVs.

The global stock of EVs is likewise projected to grow significantly and at a much faster rate than the global LDV stock: from about 1 million EVs in 2015 to 585–825 million EVs in 2050 depending on the scenario modeled (Fig. 7). The EV total includes plug-in hybrid vehicles (PHEVs) and battery-electric vehicles (BEVs). In the *Reference* scenario, the EV share of the global LDV fleet is projected to grow to 33% by 2050; in the *Paris Forever* and *Paris to 2 °C* scenarios, with more aggressive climate policies, the EV share grows to 38% and 50%, respectively.

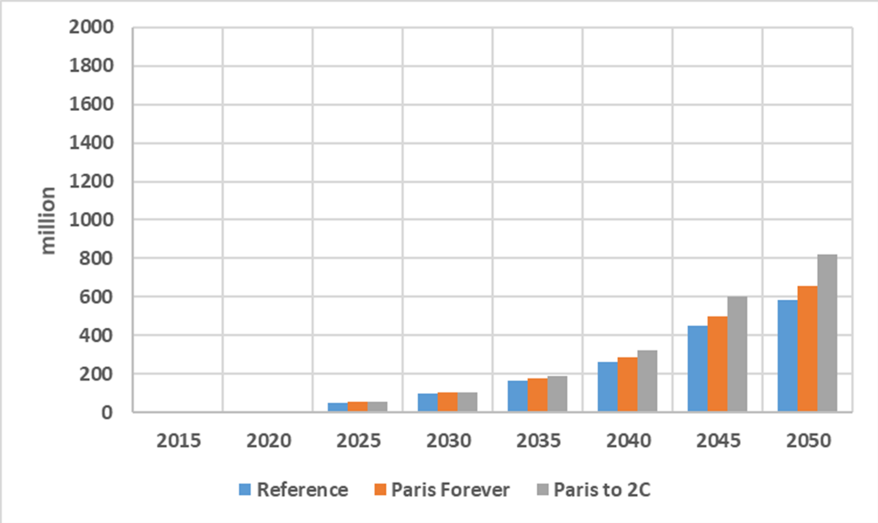

Fig. 7. Global EV Stock.

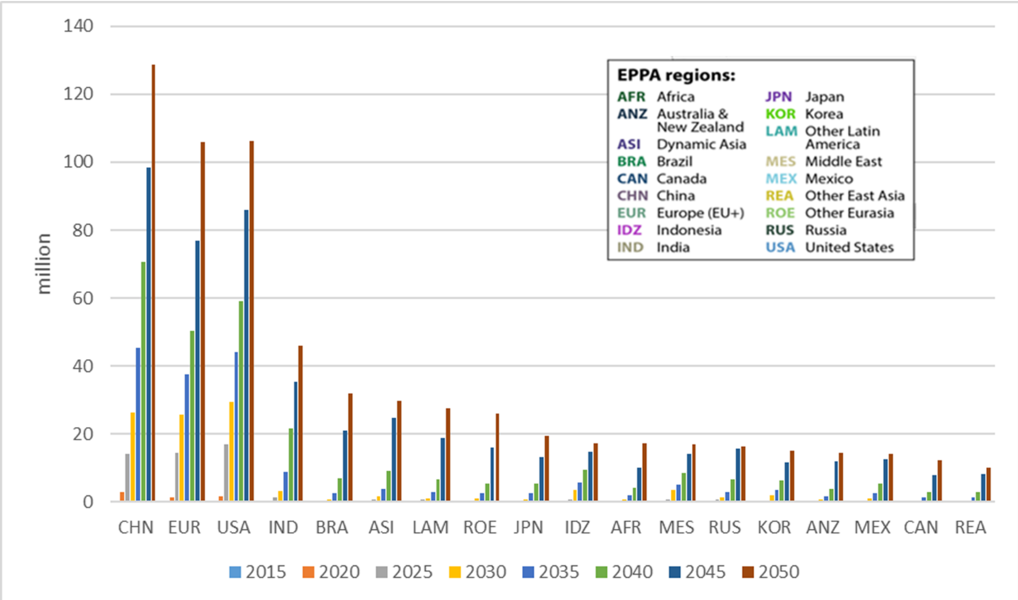

Fig. 8. EV stock by region in the Paris Forever scenario.

Fig. 8 shows our projections for the total EV stock by region in the *Paris Forever* scenario. While the U.S., Europe, and China keep their leadership positions in terms of the size of their EV fleets (with more than 100 million EVs by 2050 in each of these regions), the number of EVs grows in all world regions. By 2050, India (IND), Brazil (BRA), Rest of Eurasia (ROE), Dynamic Asia (ASI), and Japan (JPN) have substantial EV fleets. However, the U.S., Europe, and China together still account for more than half of the global EV stock in 2050.

To compare our results with other major long-term projections, below we briefly discuss the results from IEA (2019), Shell (2018), and Karkatsoulis et al. (2017). IEA (2019) in the Stated Policies Scenario that includes an assessment of the likely effects of announced policies as expressed in official targets and plans (however, the full implementation of some stated goals is not taken for granted) estimate the global share of EVs in 2040 at about 20%. ExxonMobil (2019) in its energy outlook reports the corresponding share at 21%. These numbers correspond to our assessment of 2040 global EV share of 20% in the *Paris Forever* scenario.

Shell (2018) produced the Sky Scenario that is based on what is technically possible and assumes more ambitious emission mitigation actions after 2030. In Shell Sky scenario, the global share of EVs in 2040 is about 60%. Similarly, IEA (2019) has a more aggressive Sustainable Development scenario that assumes a stronger push for electrification in which the number of EVs almost tripled in 2040 in comparison to the IEA Stated Policies Scenarios.

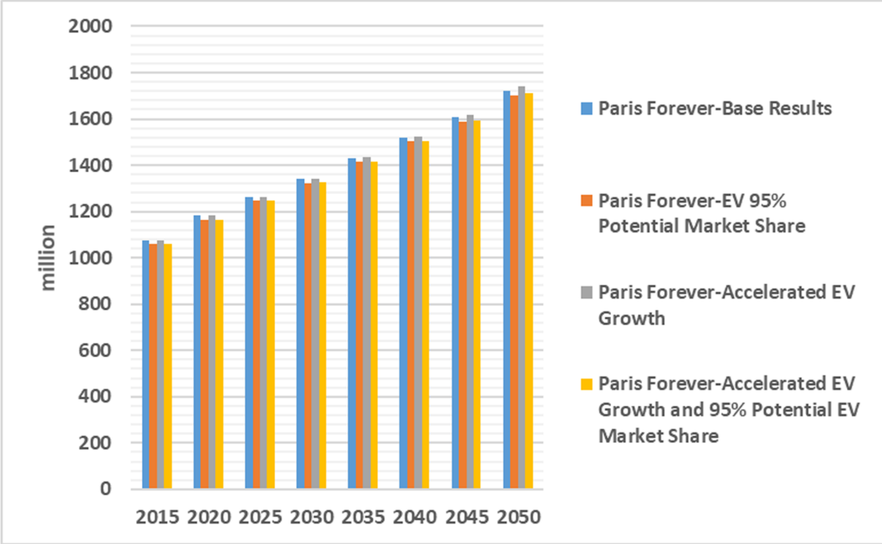

Fig. 9. Global LDV stock with accelerated EV growth and higher potential share for EV in the Paris Forever scenario.

At a regional level, Karkatsoulis et al. (2017) provide the results of simulations for the EU-28 that show in 2030 about 3% of EVs in total passenger car stock in a reference scenario and about 11% in a decarbonization scenario (with LDV technology change driven by CO2 emission standards for passenger cars). In 2050 these shares are about 7% in a reference scenario and 71% in a decarbonization scenario. In comparison, in our *Paris Forever* scenario the EV share is about 10% in 2030 and about 33% in 2050. The difference is impacted by the scenario design. In contrast to the scenarios that are driven either by electrification mandates or by emission standards, our study focuses on assessing the economic competitiveness of LDV types based on economy-wide emission reductions.

We performed a sensitivity analysis where we explored the impacts of accelerated government support to EV penetration (parameterized in the model by 15% reduction in EV cost in comparison to the base case) and higher potential share of EVs in providing total household transportation services (increased from 80% to 95%, see a related discussion in Section 2 about a reduction in the share of ICE1 from 20% to 5%). While total LDV stock is not significantly affected (Fig. 9), the global stock of EVs is projected to grow significantly in these scenarios (Fig. 10). In 2050, the global EV stock is about 660 million in the base settings of the *Paris Forever* scenario. With higher potential share of total personal mobility, they grow to about 800 million. With accelerated government

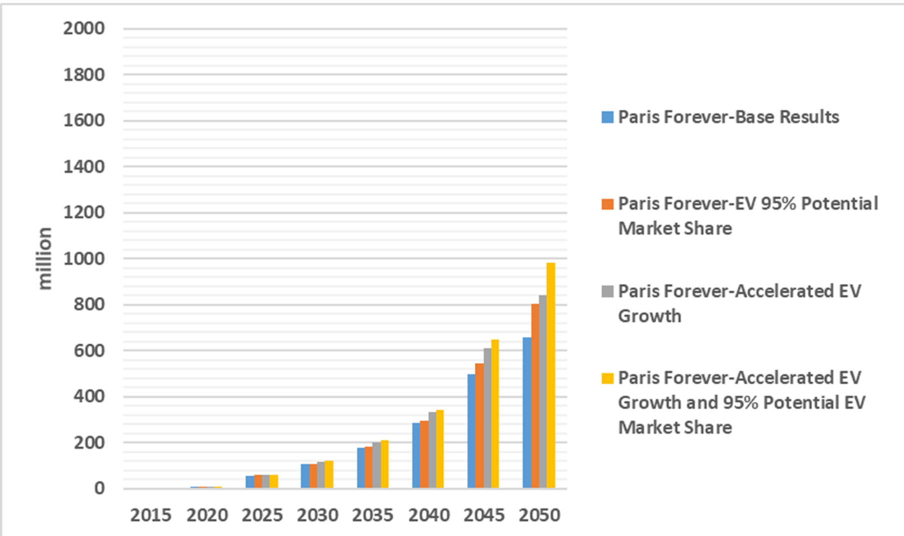

Fig. 10. Global EV stock with accelerated EV growth and higher potential share for EV in the Paris Forever scenario.

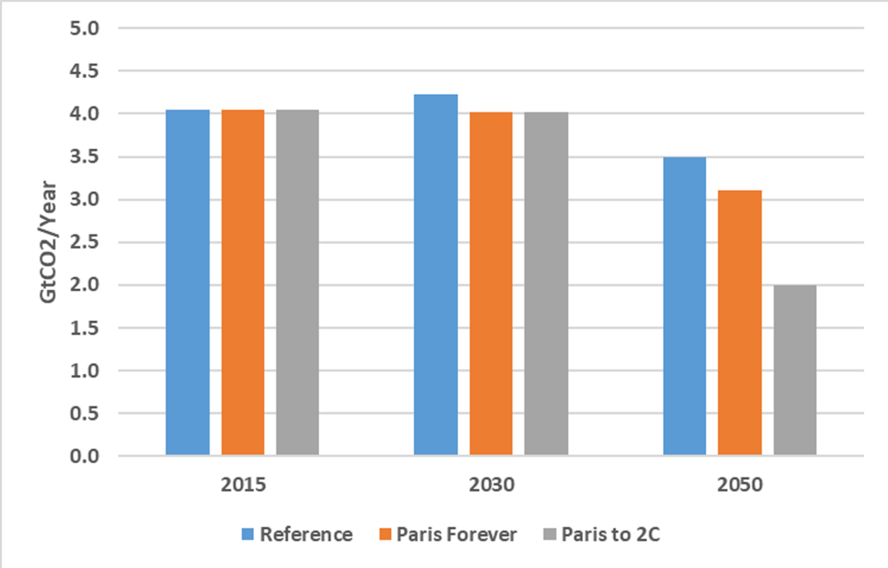

Fig. 11. Global CO_2 emissions from LDVs in different scenarios.

support, EVs stock in 2050 is about 840 million. With a combination of higher potential share and accelerated government support, the EV stock is about 980 million. Total LDV fleet is affected by the overall resulting cost of mobility services and stays in the range 1.7–1.74 billion in 2050.

The resulting CO_2 emissions from LDVs are presented in Fig. 11 (regional information for economy-wide and LDV CO_2 emissions is provided in Appendix D). In 2015 they were at the level of about 4 Gt CO_2, which accounts for about 12% of total global CO_2 emissions. In the *Reference* scenario, LDV CO_2 emissions grow by about 5% by 2030, then fuel efficiency improvements bring the emissions down to about 3.5 Gt CO_2 in 2050. In the *Paris Forever* scenario, the emissions are reduced to 3.1 Gt CO_2 in 2050, while the *Paris to 2 °C* scenario achieves a reduction to about 2 Gt CO_2 in 2050. Calculating carbon intensity of LDVs (i.e., annual CO_2 emissions per vehicle) shows that it is reduced by about 70% from 2015 to 2050 in the *Paris to 2 °C* scenario, which is achieved by a combination of more efficient ICEs and a large penetration of electrified vehicles.

While in this paper we focus on the global economy-wide and LDV CO_2 emissions because CO_2 is a well-mixed gas and the climate impacts are determined by a coordinated policies for emissions mitigation and the resulting global CO_2 emission profiles, it is worth noting that both economy-wide and LDV emissions from a combination of four main regions (USA, EU, China, and India) currently account for about two-thirds of the corresponding global emissions. A leadership in electrification of LDV fleets in these major regions may provide a substantial advantage and set the path for other regions for an accelerated decarbonizing of their transportation systems.

Reducing emissions is not only about climate change, but also about improving local conditions. Air pollution effects are more visible now with more severe health and productivity implications. Moving toward low-carbon modes of transportation will help improve both climate and air pollution impacts. Additional research is needed to expand the analysis of the country-specific and air pollution impacts. The scenarios considered in this study show some potential trajectories for achieving low emission goals. Realization of the aggressive *Paris to 2 °C* scenario would need a substantial increase in policy development and coordination in comparison to the current path of country-specific actions. However, it is possible that even more aggressive actions are necessary, which would call for a faster transition to low-emitting options than in our scenarios.

4. Conclusion

The details of the data on regional stocks of vehicles (for the 2005–2015 period) and relative costs of light-duty internal combustion vehicles (ICE), plug-in hybrid vehicles (PHEV) and battery electric vehicles (BEV) are important to support calibration of global energy-economic models. The global number of private light-duty vehicles increased by about 45% in ten years, from 735 million in 2005 to 1,072 million in 2015. China has been the fastest growing market, where the light-duty vehicle stock has increased from 20 million in 2005 to 140 million in 2015, a 7-fold increase. In 2015, about one-quarter of the global stock of light-duty vehicles is in the European Union, about 23% is in USA, and 13% is in China. USA and China are also the leading countries in terms of the stock of electric vehicles.

Based on the data that we develop for this study, we provide illustrative projections of the deployment of regional light-duty vehicle (including electric vehicle) stock up to 2050. We employ the MIT EPPA model and find that global LDV stock will reach 1.6–1.8 billion by 2050 from 1.07 billion in 2015. Global EV stock is projected to reach 585–825 million by 2050 from about a million in 2015. At this level of market penetration, EVs would constitute one-third to one-half of the overall LDV fleet by 2050 in different scenarios, with the stricter carbon constraints implied in the *Paris to 2 °C* scenario leading to the largest EV share. The electric vehicle share of the LDV fleet grows substantially by 2050 in all scenarios. But it is significantly larger in the most aggressive climate policy case (50% of the global vehicle fleet in the *Paris to 2 °C* case compared to 33% in the *Reference* case). Our modeling suggests that EV uptake will vary across regions. China, the U.S., and Europe remain the largest markets in our study timeframe, but the EV presence is projected to grow in all regions.

Our scenarios show an importance of future refinement of EV representation in energy-economic models. At the same time, it shows that ICE vehicles may still be the main mode of private transportation for many decades to come. Our methodology can be used in economy-wide models to refine their projections of transportation demand, energy use, and the resulting emissions under different scenarios of technological advances, economic development, and stringent climate policies.

In the *Paris to 2 °C* scenario, while the global LDV fleet grows by about 50% by 2050, global CO_2 emissions from LDVs in 2050 are cut by half compared to 2015 emissions and by more than 40% compared to the *Reference* case. Note that our model projects lower vehicle emissions in 2050 compared to 2015 even with no further policy action (i.e., in the *Reference* case), because gains in fuel economy and a growing market share of electric vehicles offset projected increases in fleet size and vehicle kilometers traveled. In contrast, current Paris commitments, by themselves, produce only an 11% reduction in LDV emissions relative to the *Reference* case. Global carbon intensity of LDVs are reduced by about 70% from 2015 to 2050 in the *Paris to 2 °C* scenario. Overall, our scenarios suggest that electrification of light-duty vehicles can be a substantial, but partial contributor to climate change mitigation.

Acknowledgement

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Appendix A. . Description of the EPPA model

The EPPA model (Paltsev et al., 2005; Chen et al., 2016) offers an analytic tool that includes a technology-rich representation of the household transport sector and its substitution with purchased modes, as documented in Karplus et al. (2013). The model captures interactions between all sectors of the economy, accounting for changes in international trade. Data on production, consumption, intermediate inputs, international trade, energy and taxes for the base year of 2007 are from the Global Trade Analysis Project (GTAP) dataset (Narayanan et al., 2012). The GTAP dataset is aggregated into 18 regions (information about regional aggregation is provided in Fig. 1 and Table A1). The EPPA model has 33 sectors (Table A2), including several advanced technology sectors parameterized with supplementary engineering cost data. The model includes representation of CO_2 and non-CO_2 (methane, CH_4; nitrous oxide, N_2O; hydrofluorocarbons, HFCs; perfluorocarbons, PFCs; and sulphur hexafluoride, SF_6) greenhouse gas (GHG) emissions abatement, and calculates reductions from gas-specific control measures as well as those occurring as a byproduct of actions directed at CO_2. The model also tracks major air pollutants (sulfates, SO_x; nitrogen oxides, NO_x; black carbon, BC; organic carbon, OC; carbon monoxide, CO; ammonia, NH_3; and non-methane volatile organic compounds, VOCs); however, different impacts of local air emissions in cities and on the countryside are not considered. The data on GHG and air pollutants are documented in Waugh et al. (2011).

From 2010 the model solves at 5-year intervals, with economic growth and energy use for 2010–2015 calibrated to data and short-term projections from the International Monetary Fund (IMF, 2018) and the International Energy Agency (IEA, 2017). The model includes a representation of the household transport sector and its substitution with purchased modes of public transportation, including aviation, rail, and marine transport (Paltsev et al., 2004). Several features were incorporated into the EPPA model to explicitly represent household transport sector detail (Karplus et al., 2013). These features include an empirically-based parameterization of the relationship between income growth and demand for vehicle miles traveled (VMT), a representation of fleet turnover, and opportunities for fuel use and emissions abatement, including representation of plug-in hybrid electric (PHEV) vehicles. The opportunities for fuel efficiency improvement are parameterized based on data from the U.S Environmental Protection Agency (EPA, 2010; EPA, 2012) as described in Karplus (2011), Karplus and Paltsev (2012), and Karplus et al. (2013). Additional information about the details of the EPPA model can be found in Chen et al. (2016) and Paltsev et al. (2018).

Table A1
Composition of the regions in the EPPA model.

Country	Region	Country	Region	Country	Region	Country	Region	Country	Region
Afghanistan	REA	Congo (Zaire)	AFR	India	IND	Morocco	AFR	Sierra Leone	AFR
Albania	ROE	Cook Islands	ANZ	Indonesia	IDZ	Mozambique	AFR	Singapore	ASI
Algeria	AFR	Costa Rica	LAM	Iran	MES	Myanmar	REA	Slovakia	EUR
American Samoa	ANZ	Croatia	ROE	Iraq	MES	Namibia	AFR	Slovenia	EUR
Andorra	ROE	Cuba	LAM	Ireland	EUR	Nauru	ANZ	Solomon Islands	ANZ
Angola	AFR	Cyprus	EUR	Israel	MES	Nepal	REA	Somalia	AFR
Anguilla	LAM	Czech Republic	EUR	Italy	EUR	Netherlands	EUR	South African Republic	AFR
Antigua & Barbuda	LAM	Denmark	EUR	Jamaica	LAM	Netherlands Antilles	LAM	Spain	EUR
Argentina	LAM	Djibouti	AFR	Japan	JPN	New Caledonia	ANZ	Sri Lanka	REA
Armenia	ROE	Dominica	LAM	Jordan	MES	New Zealand	ANZ	Sudan	AFR
Aruba	LAM	Dominican Republic	LAM	Kazakhstan	ROE	Nicaragua	LAM	Suriname	LAM
Australia	ANZ	Ecuador	LAM	Kenya	AFR	Niger	AFR	Swaziland	AFR
Austria	EUR	Egypt	AFR	Kiribati	ANZ	Nigeria	AFR	Sweden	EUR
Azerbaijan	ROE	El Salvador	LAM	Korea	KOR	Niue	ANZ	Switzerland	EUR
Bahamas	LAM	Equatorial Guinea	AFR	Korea, Dem.Ppl.Rep	REA	Norfolk Islands	ANZ	Syria	MES
Bahrain	MES	Eritrea	AFR	Kuwait	MES	Nothern Mariana Islands	ANZ	Taiwan	ASI
Bangladesh	REA	Estonia	EUR	Kyrgyzstan	ROE	Norway	EUR	Tajikistan	ROE
Barbados	LAM	Ethiopia	AFR	Laos	REA	Oman	MES	Tanzania	AFR
Belarus	ROE	Falkland Islands	LAM	Latvia	EUR	Pakistan	REA	Thailand	ASI
Belgium	EUR	Faroe Islands	ROE	Lebanon	MES	Palestine	MES	Timor-Leste	REA
Belize	LAM	Fiji	ANZ	Lesotho	AFR	Panama	LAM	Togo	AFR
Benin	AFR	Finland	EUR	Liberia	AFR	Papua New Guinea	ANZ	Tokelau	ANZ
Bermuda	LAM	France	EUR	Liechtenstein	EUR	Paraguay	LAM	Tonga	ANZ
Bhutan	REA	French Guiana	LAM	Lithuania	EUR	Peru	LAM	Trinidad and Tobago	LAM
Bolivia	LAM	French Polynesia	ANZ	Luxembourg	EUR	Philippines	ASI	Tunisia	AFR
Bosnia and Herzogovina	ROE	Gabon	AFR	Libya	AFR	Poland	EUR	Turkey	ROE
Botswana	AFR	Gambia	AFR	Macau	REA	Portugal	EUR	Turkmenistan	ROE
Brazil	BRA	Georgia	ROE	Macedonia	ROE	Puerto Rico	LAM	Turks and Caicos Islands	LAM
Brunei	REA	Germany	EUR	Madagascar	AFR	Qatar	MES	Tuvalu	ANZ
Bulgaria	EUR	Ghana	AFR	Malawi	AFR	Reunion	AFR	Uganda	AFR
Burkina Faso	AFR	Gibraltar	ROE	Malaysia	ASI	Romania	EUR	Ukraine	ROE
Burundi	AFR	Greece	EUR	Maldives	REA	Russia	RUS	United Arab Emirates	MES
Cambidoa	REA	Greenland	LAM	Mali	AFR	Rwanda	AFR	United Kingdom	EUR
Cameroon	AFR	Grenada	LAM	Malta	EUR	Saint Helena	AFR	United States	USA
Canada	CAN	Guadeloupe	LAM	Marshall Islands	ANZ	Saint Kittis and Nevis	LAM	Uruguay	LAM
Cape Verde	AFR	Guam	ANZ	Martinique	LAM	Saint Lucia	LAM	Uzbekistan	ROE
Cayman Islands	LAM	Guatemala	LAM	Mauritania	AFR	Saint Pierre & Miquelon	LAM	Vanuatu	ANZ
Central African Republic	AFR	Guinea	AFR	Mauritius	AFR	Saint Vincent and Grenadines	LAM	Venezuela	LAM
Chad	AFR	Guinea-Bissau	AFR	Mayotte	AFR	Samoa	ANZ	Vietnam	REA
Chile	LAM	Guyana	LAM	Mexico	MEX	San Marino	ROE	Virgin Islands, British	LAM
China	CHN	Haiti	LAM	Micronesia	ANZ	Sao Tome and Principe	AFR	Virgin Islands, U.S.	LAM
Cote d'Ivoire	AFR	Honduras	LAM	Moldova	ROE	Saudi Arabia	MES	Wallis and Futuna	ANZ
Colombia	LAM	Hong Kong	CHN	Monaco	ROE	Senegal	AFR	Yemen	MES
Comoros	AFR	Hungary	EUR	Mongolia	REA	Serbia	ROE	Zambia	AFR
Congo	AFR	Iceland	EUR	Montserrat	LAM	Seychelles	AFR	Zimbabwe	AFR

Table A2
Sectors in the EPPA model.

Sectors	Abbreviation
Energy-Intensive Industries	EINT
Other Industries	OTHR
Services	SERV
Crops	CROP
Livestock	LIVE
Forestry	FORS
Food Processing	FOOD
Coal	COAL
Crude Oil	OIL
Refined Oil	ROIL
Natural Gas	GAS
Coal Electricity	ELEC: coal
Natural Gas Electricity	ELEC: gas
Petroleum Electricity	ELEC: oil
Nuclear electricity	ELEC: nucl
Hydro Electricity	ELEC: hydro
Wind Electricity	ELEC: wind
Solar Electricity	ELEC: solar
Biomass Electricity	ELEC: bele
Wind combined with gas backup Electricity	ELEC: windgas
Wind combined with biofuel backup Electricity	ELEC: windbio
Coal with CCS Electricity	ELEC: igcap
Natural Gas with CCS Electricity	ELEC: ngcap
Advanced Nuclear Electricity	ELEC: anuc
Advanced Natural Gas Electricity	ELEC: ngcc
Private Transportation: Gasoline & Diesel Vehicles	HTRN: ice
Private Transportation: Plug-in Hybrid Vehicles	HTRN: phev
Private Transportation: Battery Electric Vehicles	HTRN: bev
Commercial Transportation	TRAN
First-Generation Biofuels	BIOF
Advanced Biofuels	ABIO
Oil Shale	SOIL
Synthetic Gas from Coal	SGAS

Appendix B. . Data sources on LDV stock and number of LDVs in the EPPA model regions

B1. Data sources

The task of evaluating the global and regional numbers of private (household-owned) light-duty vehicles (LDV) is not as simple as seems because a "private LDV" is not a well-established category. Many transportation-focused datasets (see Table B1) report either "passenger cars" or "light-duty vehicles" categories, but in many cases they use different definition of the light-duty vehicle. We evaluated numerous data sources and in Table B1 we identify five major datasets: BMI Research[5], International Organization of Motor Vehicle Manufacturers (OICA)[6], International Energy Agency (IEA) Mobility Model (MoMo) data (IEA, 2017b), IHS Polk (IHS, 2016) and Ward's (WARDSAuto, 2016). OICA data at a country-level are available publicly. Other datasets require special access.

Table B1
Primary Data Sources on the Number of Light-Duty Vehicles.

Data Source	Transport Parameter	Data Input
BMI Research	Passenger Vehicle Fleet	Government Statistics; Federal Highway Statistics[1]
OICA (Organisation Internationale des Constructeurs d'Automobiles)	Registered Vehicles on Road (Passenger separate from commercial)	Government Statistics; Ward's (US); Fourin
International Energy Agency (IEA) Mobility Model (MoMo)	Light-Duty Vehicle Stock	Government Vehicle Registrations (Country Level); Polk (IHS Markit)
Polk (IHS Markit)	Passenger Cars	Vehicle Registrations
Ward's World Motor Vehicle Data	Total Vehicles in Operation by Country	IHS Automotive (US); Auto Associations and other Vendors (International)

[1] Partially based on states vehicle registration records and Polk (US DOT Federal Highway Administration, 2017).

[5] A Fitch Group Company (http://www.bmiresearch.com/).

[6] The International Organization of Motor Vehicle Manufacturers is known as the "Organisation Internationale des Constructeurs d'Automobiles" (OICA).

Table B2
US Agencies Engaged in Transport Related Analyses and their Data Sources.

Data Source	Transport Parameter	Data Input
US Energy Information Administration (EIA)	Light-Duty Vehicle Stock	Polk (IHS Markit)
Oak Ridge National Lab Transport Energy Data Book	Vehicles per Thousand People	Ward's (Other Countries/Regions2004 and 2014)
US Department of Transportation (DOT)	Light-Duty Vehicle	Highway Statistics (States Vehicle Registrations)
US Environmental Protection Agency (EPA)	Passenger Cars	IHS Automotive Vehicle Registrations

Table B3
Comparing Number of Passenger Cars for EPPA Composite Regions from BMI and OICA.

EPPA Composite Regions	Data Source	2005	2010	2015	Number of Countries Included	Decision Summary
AFR	BMI Passenger Car Fleet	12.39	19.46	25.60	23	OICA for all years due to higher coverage of the countries in the data.
	OICA Passenger Cars	15.19	20.75	26.54	32	
ANZ	BMI Passenger Car Fleet	13.18	14.67	16.22	2	OICA for all years due to higher coverage of the countries in the data.
	OICA Passenger Cars	13.32	14.74	16.78	4	
ASI	BMI Passenger Car Fleet	12.60	19.96	27.09	4	OICA for all years due to higher coverage of the countries in the data.
	OICA Passenger Cars	19.17	23.17	30.78	5	
EUR	BMI Passenger Car Fleet	224.79	244.04	257.43	30	OICA for all years due to higher coverage of the countries in the data.
	OICA Passenger Cars	233.44	246.70	261.90	30	
LAM	BMI Passenger Car Fleet	10.56	24.21	30.60	17	OICA for all years due to higher coverage of the countries in the data.
	OICA Passenger Cars	20.37	27.74	35.74	26	
MES	BMI Passenger Car Fleet	13.34	20.74	34.38	12	OICA for all years due to higher coverage of the countries in the data.
	OICA Passenger Cars	17.06	23.06	33.96	14	
REA	BMI Passenger Car Fleet	2.07	3.92	6.23	7	OICA for all years due to higher coverage of the countries in the data.
	OICA Passenger Cars	3.12	4.80	7.22	6	
ROE	BMI Passenger Car Fleet	18.04	24.67	31.34	10	OICA for all years due to higher coverage of the countries in the data.
	OICA Passenger Cars	19.74	26.72	33.27	13	

We also explored the data used in the analysis by the U.S. government entities. Table B2 summarizes key US entities and agencies, which provide transport related analyses and the main sources of the data used in U.S. government reports. In many cases, the assessments are based on the data from the primary sources listed in Table B1.

Our analysis of the available data resulted in our reliance on the BMI Research and the OICA datasets for the following reasons. First, both sources have extensive global coverage that allows us to calculate the number of LDV for all 18 regions of the EPPA model. Second, these two datasets are mostly relying on different sources, which allows for cross-checking. For example, BMI Research relies on the data from the Federal Highway Administration for its US estimates, which in part is based on state vehicle registrations and Polk (US DOT Federal Highway Administration , 2017). On the other hand, the OICA has relied on WARD's data for its US estimates (OICA, 2017).

In terms of car classifications, the OICA passenger car database (OICA, 2017) states that vehicles in use are "composed of all registered vehicles on the road". OICA defines passenger cars as "road motor vehicles, other than a motor cycle, intended for the carriage of passengers and designed to seat no more than nine persons (including the driver). The term "passenger cars" therefore covers taxis and hired passenger cars, provided that they have fewer than ten seats. This category may also include pick-ups or microcars (i.e., those that do not require a permit to be driven) (OICA, 2017).

The reported data from BMI Research are for passenger vehicle fleet. BMI Research defines passenger vehicle fleet as "officially registered road motor vehicles with at least four-wheels, designed for the purpose of carrying nine or fewer passengers (including the driver) and with a gross vehicle weight (GVW) of less than 3.5 tons. These include saloons, estates, coupes, convertibles, MPVs and SUVs and excludes quad bikes. Vehicles must be officially registered with national traffic authorities." (BMI Research, 2017).

B2. Number of private LDVs: EPPA composite regions

We separated our discussion for those EPPA regions that consists of several countries and those that represent individual countries. At first, we look at the composite EPPA regions. These include Africa (AFR), Australia and New Zealand (ANZ), Higher-Income Asia (ASI), Europe (EUR), Latin America and Caribbean (LAM), Middle East (MES), Rest of East Asia (REA) and Rest of Eurasia (ROE).

Table B3 provides the data for those EPPA regions that consist of aggregated countries. It also lists the number of countries for each EPPA composite region that each of the two databases cover. In almost all of the EPPA composite regions, the OICA covers more countries than the data from BMI. As a result, we opt to use OICA data for these EPPA composite regions. In only two EPPA composite regions, OICA number of covered countries is either equal or less than the number from BMI. These two regions are Europe (EUR) and

Table B4
Number of Passenger Cars for EPPA Country/Regions.

EPPA Country/Regions	Data Source	2005	2010	2015	Decision Summary
BRA	BMI Passenger Car Fleet	26.31	37.19	49.82	OICA for all years just to be consistent with most of our other EPPA countries and composite regions even though OICA estimates are much lower in all years.
	OICA Passenger Cars	18.93	26.89	35.47	
CAN	BMI Passenger Car Fleet	18.28	20.27	22.13	OICA for all years for consistency. OICA and BMI estimates are very close.
	OICA Passenger Cars	18.12	20.27	22.07	
CHN	BMI Passenger Car Fleet	20.50	60.18	141.48	BMI for all years. See the sub-section on China.
	OICA Passenger Cars	21.69	62.07	136.34	
IDZ	BMI Passenger Car Fleet	5.08	8.89	13.42	OICA for all years for consistency. OICA and BMI estimates are very close.
	OICA Passenger Cars	5.08	8.89	13.48	
IND	BMI Passenger Car Fleet	10.32	17.11	30.19	OICA for all years just to be consistent with most of our other EPPA countries and composite regions even though OICA estimates are much lower in all years.
	OICA Passenger Cars	7.63	13.27	22.47	
JPN	BMI Passenger Car Fleet	57.09	58.35	62.09	OICA for all years for consistency. OICA and BMI estimates are very close.
	OICA Passenger Cars	57.09	58.35	60.99	
KOR	BMI Passenger Car Fleet	11.12	13.63	16.56	OICA for all years for consistency. OICA and BMI estimates are very close.
	OICA Passenger Cars	11.12	13.63	16.56	
MEX	BMI Passenger Car Fleet	14.30	21.15	26.38	OICA for all years for consistency. OICA and BMI estimates are very close.
	OICA Passenger Cars	14.30	21.15	26.94	
RUS	BMI Passenger Car Fleet	–	34.35	48.11	OICA for all years due to higher coverage of the years with data.
	OICA Passenger Cars	25.57	34.35	44.25	
USA	BMI Passenger Car Fleet	136.57	130.89	112.86	Both OICA and BMI estimates are low due to exclusion of light trucks. See the section on the US.
	OICA Passenger Cars	132.91	129.05	122.32	

Rest of East Asia (REA).

For EUR, both sources cover 30 countries in 2015. However, in 2005 and 2007, the BMI source is missing data on Norway and Romania. The two sources' differences are around 9 million in 2005 to 6 million in 2007. The differences reduce to around 3 million in 2010 and about 1 million in 2015. This suggests that exclusion of Norway and Romania number of vehicles in 2005 is a likely factor for BMI's lower estimates.

For the Rest of Asia (REA), BMI covers seven countries compared to OICA's coverage of six nations. However, even with smaller number of countries covered, OICA estimates are consistently higher than the BMI's. That is due to OICA's higher estimates for Pakistan and Bangladesh in all years. As a result, we also rely on the OICA's estimates for the REA region.

The EPPA model includes the following regions that consist of individual countries: Brazil, Canada, China, Indonesia, India, Japan, Korea, Mexico, Russia, and USA. Table B4 provides the data for these regions. In five of these regions, OICA and BMI estimates are close. As a result, we choose the OICA data for updating the EPPA model and for consistency with the data choice for the EPPA composite regions. These five regions include Canada, Indonesia, Japan, Korea and Mexico. For Russia, we also choose OICA due to lack of data for selected years from the BMI. However, OICA and BMI estimates are not consistent for Brazil, China, India, and USA. Additional information is provided in Ghandi and Paltsev (2019).

Appendix C. . Issues related to the battery pack cost estimates

One of the main components for the vehicle/component-based approach is the cost of the car battery. Battery pack cost estimates from different sources often lack specifics to make a proper comparison between studies. In particular, it is not always stated if the cost for a battery cell or a battery pack. Battery pack includes thermal management system, module housing, module control, battery management system, pack housing and the battery cell. Battery cost sometimes is referred as a cost of battery cell rather than the whole battery pack. The difference in cost is in the range of 40% (Slowik et al., 2016) to 45% (Zamorano, 2017). In our analysis, we provide the estimates for the whole battery pack.

Another important distinction is batteries for PHEVs versus batteries for BEVs. The battery packs used in PHEVs are smaller but with higher density, which increases the cost per kWh. According to Wolfram and Lutsey, (2016) additional cost of PHEV battery pack (relative to BEV battery pack) is 60 $/kWh.

Battery cell chemistry is also important. Lithium-ion batteries are dominant in EVs. They are differentiated by their cathode materials: Nickel Cobalt Aluminum-NCA (Tesla Model S), Lithium Manganese Oxide-LMO (Nissan Leaf 2015), Lithium Iron Phosphate-LFP (Chinese BEV manufacturers) and a more recent chemistry known as Nickel Manganese Cobalt -NMC (Tesla Model 3, Bolt, New Leaf) (Slowik et al., 2016). In turn, NMC battery cell chemistry has three variations. Currently, manufacturers rely on NMC111 that refers to the 1:1:1 ratio in kg/kWh between Nickel, Manganese and Cobalt. However, the industry's trend is towards NMC622 and NMC811 that rely more on less expensive Nickel as opposed to more expensive Cobalt.

The composition of different batteries is shown in Fig. C1. In our analysis, the battery pack $/kWh estimate reflects the evolution of different battery composition over time. In 2015, we represent NCA battery chemistry as the dominant chemistry in 2015 (Hsieh & Green, 2019). In 2020, we consider NMC111 chemistry as the dominant. Over time, the chemistry of batteries is expected to move towards NMC811 (UBS Evidence Lab, 2017), and we also make a similar assumption.

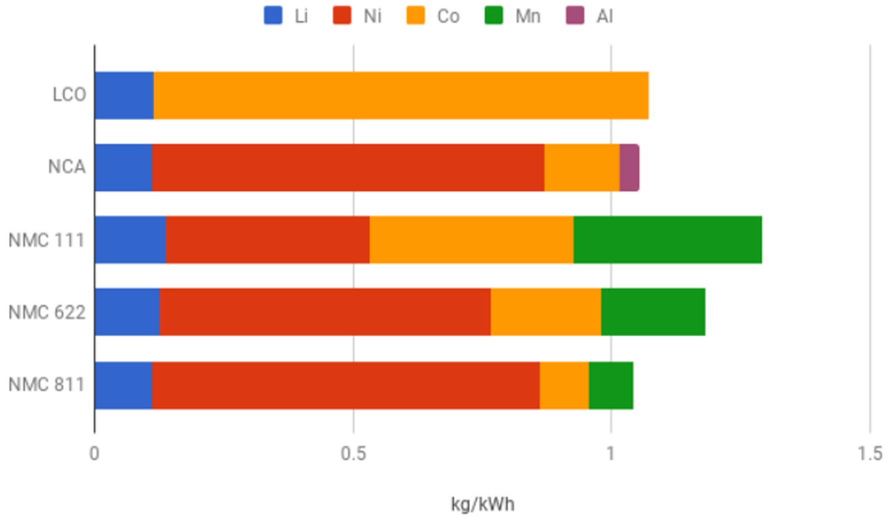

Fig. C1. Comparison of different raw materials in different battery chemistries. (Research Interfaces, 2018).

Appendix D. . Additional results for CO_2 emissions

See Table D1–D6.

Table D1
LDV CO_2 Emissions in Reference Scenario ($MtCO_2$).

	2015	2020	2025	2030	2035	2040	2045	2050
USA	1054.0	1018.3	942.4	880.4	820.3	767.2	702.5	675.7
CAN	80.7	85.6	84.7	86.4	87.0	87.4	89.8	92.0
MEX	146.4	152.7	149.2	147.9	143.1	136.6	116.4	115.1
JPN	126.3	127.9	123.9	123.3	119.5	113.7	98.6	85.9
ANZ	49.5	53.0	53.5	54.6	55.0	53.8	45.7	43.9
EUR	577.9	566.4	526.6	495.8	472.2	444.0	402.0	385.0
ROE	41.3	45.1	45.3	45.9	46.8	48.1	48.7	50.6
RUS	124.0	124.9	121.6	117.6	114.6	109.3	95.1	93.9
ASI	113.0	128.8	137.8	144.9	145.7	141.0	116.8	119.7
CHN	796.4	930.7	976.2	972.2	927.2	846.3	769.0	709.0
IND	183.7	248.2	292.5	319.4	329.1	319.5	302.3	306.4
BRA	115.2	113.8	115.9	116.3	117.6	118.8	124.0	130.2
AFR	175.5	190.0	204.2	227.6	248.3	266.1	268.1	271.6
MES	140.3	147.2	143.6	136.4	132.8	126.2	115.5	109.9
LAM	173.6	172.2	172.9	179.4	181.4	179.7	147.6	133.9
REA	41.6	50.1	54.4	57.9	60.5	60.6	49.5	52.1
KOR	43.0	45.9	46.4	46.6	46.6	46.3	45.9	47.4
IDZ	62.3	75.1	80.8	80.8	80.4	77.1	72.1	71.1
World	4044.7	4275.8	4272.0	4233.4	4128.0	3941.8	3609.6	3493.6

Table D2
LDV CO_2 Emissions in *Paris Forever* Scenario ($MtCO_2$).

	2015	2020	2025	2030	2035	2040	2045	2050
USA	1054.0	1010.3	916.7	827.9	758.8	700.9	629.9	595.6
CAN	80.7	83.5	79.0	75.1	72.1	68.2	57.3	51.5
MEX	146.4	149.4	142.5	139.7	135.5	130.3	115.6	118.8
JPN	126.3	124.1	119.9	118.6	115.9	111.2	97.2	86.1
ANZ	49.5	52.0	51.6	50.6	50.1	48.1	39.5	38.7
EUR	577.9	567.4	522.3	471.3	439.0	404.1	351.0	318.0
ROE	41.3	45.1	45.5	45.8	46.3	47.2	46.4	47.2
RUS	124.0	123.6	120.0	115.8	113.5	109.9	101.6	101.7
ASI	113.0	129.2	139.1	143.9	144.1	139.5	117.2	120.2

(continued on next page)

Table D2 (*continued*)

	2015	2020	2025	2030	2035	2040	2045	2050
CHN	796.4	908.4	935.8	942.5	890.2	801.3	704.7	623.3
IND	183.7	249.3	295.6	325.5	337.3	329.7	324.2	322.6
BRA	115.2	113.9	87.8	79.7	73.0	61.4	34.4	24.5
AFR	175.5	189.6	203.8	226.6	247.8	265.9	271.0	278.5
MES	140.3	146.0	140.9	129.0	124.3	117.7	107.9	104.7
LAM	173.6	172.3	174.3	179.6	182.3	182.1	155.4	147.0
REA	41.6	50.1	54.6	58.3	61.0	61.6	52.3	55.8
KOR	43.0	45.3	45.2	43.8	43.1	41.5	38.7	38.5
IDZ	62.3	60.8	58.4	45.8	42.3	37.0	30.4	29.7
World	4044.7	4220.3	4132.9	4019.4	3876.8	3657.6	3274.6	3102.4

Table D3
LDV CO_2 Emissions in *Paris to 2C* Scenario ($MtCO_2$).

	2015	2020	2025	2030	2035	2040	2045	2050
USA	1054.0	1010.3	916.7	827.9	735.9	665.7	573.3	518.5
CAN	80.7	83.5	79.0	75.1	70.5	65.7	52.9	44.0
MEX	146.4	149.4	142.5	139.7	120.6	101.7	59.5	41.3
JPN	126.3	124.1	119.9	118.6	113.7	104.7	81.7	59.1
ANZ	49.5	52.0	51.6	50.6	47.0	42.4	29.0	26.3
EUR	577.9	567.4	522.3	471.3	439.5	403.9	346.8	310.1
ROE	41.3	45.1	45.5	45.8	41.9	39.6	34.1	31.1
RUS	124.0	123.6	120.0	115.8	98.5	85.0	59.0	43.7
ASI	113.0	129.2	139.1	143.9	130.6	112.2	61.0	55.1
CHN	796.4	908.4	935.8	942.5	694.9	533.4	389.2	298.5
IND	183.7	249.3	295.6	325.5	312.6	249.4	198.2	173.5
BRA	115.2	113.9	87.8	79.7	91.1	92.0	77.1	62.5
AFR	175.5	189.6	203.8	226.6	215.1	211.9	179.9	145.3
MES	140.3	146.0	140.9	129.0	106.3	88.8	63.7	45.4
LAM	173.6	172.3	174.3	179.6	159.4	142.0	85.0	64.0
REA	41.6	50.1	54.6	58.3	54.7	49.2	29.9	26.3
KOR	43.0	45.3	45.2	43.8	40.0	35.0	24.3	21.6
IDZ	62.3	60.8	58.4	45.8	52.5	44.8	32.7	28.0
World	4044.7	4220.3	4132.9	4019.4	3524.7	3067.4	2377.0	1994.0

Table D4
Economy-wide CO_2 Emissions in Reference Scenario ($MtCO_2$).

	2015	2020	2025	2030	2035	2040	2045	2050
USA	5153.6	5310.8	5101.8	4989.3	5060.9	5023.9	5004.9	4975.3
CAN	688.4	707.6	687.7	709.8	743.1	775.6	807.9	822.6
MEX	510.3	552.3	577.1	601.5	624.8	647.8	656.2	689.1
JPN	1284.3	1257.4	1170.1	1147.8	1108.4	1069.6	1030.3	994.7
ANZ	493.7	512.0	496.0	476.7	457.1	434.1	404.5	388.0
EUR	3517.8	3707.3	3733.0	3753.4	3747.7	3773.1	3866.8	3946.4
ROE	1334.4	1469.2	1641.0	1803.3	1980.1	2178.5	2366.3	2542.8
RUS	1517.7	1382.3	1295.9	1319.8	1312.3	1296.7	1288.2	1293.9
ASI	1158.7	1264.4	1379.6	1479.6	1542.8	1603.7	1650.8	1734.1
CHN	10402.1	12055.3	12853.0	13547.9	14025.3	14394.9	14859.2	14982.6
IND	2075.3	2557.2	2894.4	3094.5	3286.1	3478.7	3485.0	3745.0
BRA	485.9	483.2	512.5	571.3	639.7	712.3	804.1	904.2
AFR	1194.6	1252.7	1348.3	1481.0	1602.7	1735.5	1896.6	2072.4
MES	1466.3	1479.1	1540.5	1625.0	1717.4	1828.3	1969.3	2106.4
LAM	861.3	818.7	864.5	945.2	1027.2	1104.6	1157.2	1233.8
REA	480.5	585.4	724.3	848.5	986.5	1117.0	1231.7	1370.0
KOR	758.1	798.5	859.3	920.1	988.1	1065.3	1149.8	1217.9
IDZ	498.0	607.0	718.2	791.1	856.3	907.7	943.8	978.0
World	33880.9	36800.3	38397.1	40105.6	41706.2	43147.2	44572.5	45997.2

Table D5
Economy-wide CO_2 Emissions in *Paris Forever* Scenario ($MtCO_2$).

	2015	2020	2025	2030	2035	2040	2045	2050
USA	5153.6	4981.2	4331.5	3883.0	3875.6	3864.1	3861.0	3851.3
CAN	688.4	571.9	505.0	438.4	436.1	433.9	429.1	426.5
MEX	510.3	501.2	486.9	495.9	544.2	594.4	634.3	684.5
JPN	1284.3	1045.1	986.2	926.7	925.9	925.2	923.4	921.8
ANZ	493.7	459.3	423.8	362.6	354.6	342.5	332.4	327.4
EUR	3517.8	3715.0	3353.8	2628.7	2645.7	2657.4	2658.4	2658.9
ROE	1334.4	1490.6	1677.7	1676.8	1816.6	1974.9	2129.9	2287.2
RUS	1517.7	1270.2	1237.7	1411.4	1432.7	1425.2	1435.8	1448.3
ASI	1158.7	1288.5	1430.7	1351.6	1430.8	1508.8	1586.8	1673.1
CHN	10402.1	10091.0	10313.8	11515.5	11515.2	11514.8	11514.7	11514.6
IND	2075.3	2603.8	2949.1	3181.9	3396.7	3610.5	3849.4	3919.8
BRA	485.9	487.9	72.2	47.7	42.9	33.8	25.9	12.5
AFR	1194.6	1265.8	1390.1	1533.9	1655.3	1787.1	1970.4	2167.2
MES	1466.3	1493.6	1565.3	1407.3	1533.4	1654.3	1791.0	1931.0
LAM	861.3	832.5	901.0	936.8	1033.5	1130.0	1214.6	1325.4
REA	480.5	601.1	753.5	890.2	1028.5	1178.4	1317.8	1481.1
KOR	758.1	724.8	739.1	693.4	739.6	785.6	839.3	883.0
IDZ	498.0	217.4	188.3	150.0	165.4	176.3	178.7	199.5
World	33880.9	33640.7	33305.6	33531.7	34572.7	35596.9	36692.9	37713.0

Table D6
Economy-wide CO_2 Emissions in *Paris to 2C* Scenario ($MtCO_2$).

	2015	2020	2025	2030	2035	2040	2045	2050
USA	5153.6	4981.2	4331.5	3883.0	3319.5	3246.7	3145.1	2967.1
CAN	688.4	571.9	505.0	438.4	414.5	398.2	385.7	360.3
MEX	510.3	501.2	486.9	495.9	353.8	327.1	274.2	220.8
JPN	1284.3	1045.1	986.2	926.7	791.9	600.5	558.9	513.5
ANZ	493.7	459.3	423.8	362.6	262.6	246.4	219.2	199.3
EUR	3517.8	3715.0	3353.8	2628.7	2563.9	2569.3	2482.5	2419.3
ROE	1334.4	1490.6	1677.7	1676.8	1201.9	1162.2	1112.9	1037.7
RUS	1517.7	1270.2	1237.7	1411.4	655.2	590.5	521.6	351.8
ASI	1158.7	1288.5	1430.7	1351.6	1054.9	909.0	742.6	694.2
CHN	10402.1	10091.0	10313.8	11515.5	4104.3	3872.6	3717.0	3475.7
IND	2075.3	2603.8	2949.1	3181.9	1599.0	1278.7	1279.8	1283.9
BRA	485.9	487.9	72.2	47.7	206.2	217.6	216.3	227.3
AFR	1194.6	1265.8	1390.1	1533.9	957.3	952.5	943.8	877.5
MES	1466.3	1493.6	1565.3	1407.3	946.0	934.9	903.6	820.7
LAM	861.3	832.5	901.0	936.8	710.4	692.3	633.6	588.4
REA	480.5	601.1	753.5	890.2	574.8	574.6	568.4	550.9
KOR	758.1	724.8	739.1	693.4	599.1	575.9	512.6	509.1
IDZ	498.0	217.4	188.3	150.0	281.5	285.0	266.4	262.8
World	33880.9	33640.7	33305.6	33531.7	20596.8	19433.8	18484.2	17360.1

Appendix E. . Acronyms used in the paper

Acronyms	Description
BEV	battery electric vehicles
CAFE	corporate average fuel economy
CGE	computable general equilibrium
EPPA	Economic Projection and Policy Analysis model
EV	electric vehicles that includes both BEV and PHEV
FCEV	fuel cell electric vehicle
GTAP	Global Trade Analysis Project
ICE	internal combustion engine
IEA MoMo	International Energy Agency Mobility Model
LCO	Lithium Cobalt Oxide
LDV	light-duty vehicles

LFP	Lithium Iron Phosphate
LMO	Lithium Manganese Oxide
MPG	miles per gallon
MSRP	manufacturer's suggested retail price
$MtCO_2e$	million tonnes of CO_2-equivalent
NCA	Lithium Nickel Cobalt Aluminum Oxide
NMC	Lithium Nickel Manganese Cobalt Oxide
PHEV	plug-in hybrid vehicles
VMT	vehicle miles traveled

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