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Representing a Deployment of Light-Duty Internal Combustion and Electric Vehicles in Economy-Wide Models

Abbas Ghandi and Sergey Paltsev

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This reprint is intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

—*Ronald G. Prinn and John M. Reilly,*
Joint Program Co-Directors

Representing a Deployment of Light-Duty Internal Combustion and Electric Vehicles in Economy-Wide Models

Abbas Ghandi¹ and Sergey Paltsev¹

Abstract: Representing the fleet of light-duty vehicles (LDV) in economy-wide models is important for projections of transportation demand, energy use, and the resulting emissions. We describe a methodology for incorporating the private transportation details into economy-wide models and, using an example of the MIT Economic Projection and Policy Analysis (EPPA) model, provide a description of calibrating the model to the data. We provide the results both for light-duty internal combustion engine (ICE) vehicles and electric vehicles (EV). For the EV fleet, both plug-in hybrid vehicles (PHEV) and battery electric vehicles (BEV) are considered. First, for initial calibration we provide a consistent representation of the historic data at the level of regional disaggregation of the EPPA model. We find that the global LDV stock increased by about 45% in ten years, from 735 million in 2005 to 1.1 billion in 2015. China has been the fastest growing market, where LDV stock increased from 20 million in 2005 to 140 million in 2015, a 7-fold increase. Second, we assess relative costs of ICE, PHEV, and BEV vehicles. Based on consumer prices (top-down approach) and battery pack/vehicle components cost estimates (bottom-up approach) in USA, PHEVs are about 30-60% more expensive than ICEs and BEVs are about 40-90% more expensive than ICEs. Finally, we apply our methodology for a long term projection of LDV stock. We find that global LDV stock is projected to grow from 1.1 billion vehicles in 2015 to 1.8 billion in 2050, while global EV stock is growing from about a million in 2015 to about 500 million in 2050. Our methodology can be applied in other energy-economic models to test a sensitivity of the results to different input assumptions and specifications.

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¹ MIT Joint Program on the Science and Policy of Global Change, Massachusetts Institute of Technology, 77 Massachusetts Ave, Cambridge, MA 02139, USA

1. Introduction

Understanding the future trends in providing private mobility services is crucial for projecting fuel use and emissions. Light-duty (i.e., cars and light trucks) vehicles (LDV) provide a substantial source of fuel demand and the resulting greenhouse gas (GHG) emissions—in USA, they 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 CO₂-equivalent (MtCO₂e), 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 important tools for projecting future energy use and GHG emissions, but usually these models provide projections at an aggregated level of sectoral representation of economy, with private transportation usually combined with other sectors (IPCC, 2014; EPA, 2017b). Traditional datasets like the Global Trade Analysis Project (GTAP) dataset (Aguilar *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). The goal of our paper is to provide a consistent approach for representing the LDV transportation in CGE models. We follow the methodology developed in Paltsev *et al.* (2004, 2005) and Karplus *et al.* (2013) and further develop the approach by providing an updated assessment of the stocks of private internal-combustion and electric LDVs and their total fuel use in 2005–2015,

creating top-down (i.e., based on manufacturer suggested retail prices, MSRP) and bottom-up (i.e., based on individual components of a vehicle) calculations of the relative costs of ICEs, plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV), and discuss the future trends in the relative costs of ICE, PHEVs and BEVs.

Despite the importance of an adequate representation of private transportation in energy and emission scenarios, the corresponding data with a global coverage for a stock of LDVs, their miles-driven and fuel use are sparse. In addition, data from different sources are often inconsistent due to their different approaches for reporting and different definitions of what is “a private light-duty vehicle”. We provide a discussion of the ways to achieve consistent representation of LDVs, assess the historic data from different sources and provide a methodology of calibrating the data to the regions of the MIT Economic Projection and Policy Analysis (EPPA) model (Chen, *et al.*, 2016). Our approach can be used by other modeling teams to represent the characteristics of the private LDVs in different modeling platforms.

The paper structure is as follows. Section 2 introduces the main transport-related features of the EPPA model. In Section 3, we discuss our methodology for estimating the stock number of light-duty vehicles at EPPA regional aggregation and summarize our calibrating of EPPA with regards to refined oil data. Our estimation of the relative costs of ICE/PHEV/BEV is presented in Section 4. Section 5 provides the results from EPPA model for the total stock of light-duty vehicle projection in addition to total stock of battery electric and plug-in hybrid vehicles projection. Section 6 concludes.

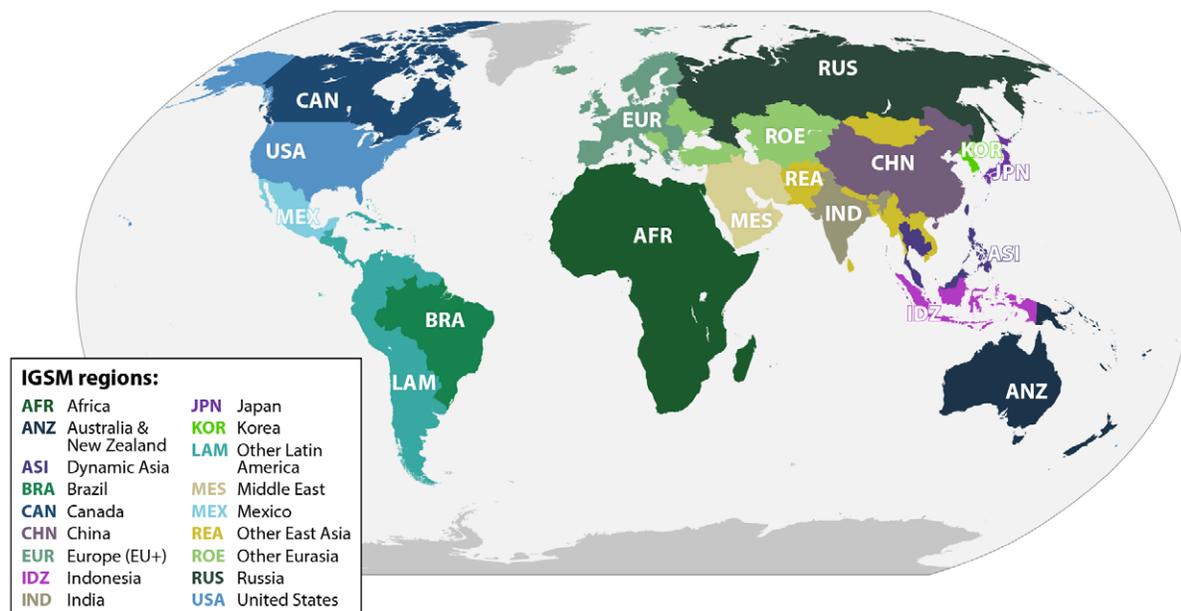


Figure 1. EPPA Model Regional Coverage

2. Private Transportation Details in the EPPA Model

For illustration of our approach for representation of 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). **Figure 1** provides a map and a list of regions of the EPPA model (a complete list of regional disaggregation of the EPPA model is provided in Appendix A). The procedures described in our paper can be applied for different regional aggregating schemes.

We also describe how the household transportation sector is introduced in 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 (Figure 1). The EPPA model has 33 sectors (**Table 1**), including several advanced technology sectors parameterized with supplementary engineering cost data. The model includes representation of CO₂ and non-CO₂ (methane, CH₄; nitrous oxide, N₂O; hydrofluorocarbons, HFCs; perfluorocarbons, PFCs; and sulphur hexafluoride, SF₆) 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 CO₂. The model also tracks major air pollutants (sulphates, SO_x; nitrogen oxides, NO_x; black carbon, BC; organic carbon, OC; carbon monoxide, CO; ammonia, NH₃; 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 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

Table 1. 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 Production	COAL
Oil Production	OIL
Refining	ROIL
Natural Gas Production	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	ELEC: windgas
Wind combined with biofuel backup	ELEC: windbio
Coal with CCS	ELEC: igcap
Natural Gas with CCS	ELEC: ngcap
Advanced Nuclear Electricity	ELEC: anuc
Advanced Natural Gas	ELEC: ngcc
Private Transport: Gasoline & Diesel Vehicles	HTRN: ice
Private Transport: Plug-in Hybrid Vehicles	HTRN: phev
Private Transport: Battery Electric Vehicles	HTRN: bev
Commercial Transportation	TRAN
First-Generation Biofuels	BIOF
Advanced Biofuels	ABIO
Oil Shale	SOIL
Synthetic Gas from Coal	SGAS

for vehicle miles traveled (VMT), a representation of fleet turnover, and opportunities for fuel use and emissions abatement, including representation of electric 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).

The GTAP data, which is the source for the underlying data for the EPPA model in a base year, does not provide the details on household transportation. To calibrate the EPPA model, additional data on the stocks of private light-duty vehicles, expenditures on fuel, vehicle and services, cost of alternative vehicles (such as PHEV and BEV) are needed for all 18 regions of the model. **Figure 2** provides an illustration of the data requirements in addition to those represented in the GTAP dataset. Aggregate consumer expenditures on private transportation should be divided into expenditures on fuel, vehicle and services. Energy in the EPPA model is tracked in value terms (i.e., expenditures) and physical terms (exajoules or tonnes of oil equivalence). To represent competitiveness of alternative vehicles, the so called “mark-ups” (i.e., relative costs) are needed because they provide information that drives the economic decisions about expanding the fleet of vehicles of different types. In the next sections we describe the process of providing the data for these requirements. We start with providing a consistent assessment of the number of LDVs.

3. Number of Private Light-Duty Vehicles

3.1 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 2**) report either “passenger cars” or “light-duty vehicles” categories, but in many cases they use different definitions of light-duty vehicle. We evaluated numerous data sources and in **Table 2** we identify five

major datasets: BMI Research¹, International Organization of Motor Vehicle Manufacturers (OICA)², 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.

We also explored the data used in the analysis by the U.S. government entities. **Table 3** 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 2**.

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 **Appendix B** we provide a short description of other primary data sources: IEA MoMo, IHS Polk and Ward’s.

- 1 A Fitch Group Company (<http://www.bmiresearch.com/>).
- 2 The International Organization of Motor Vehicle Manufacturers is known as the “Organisation Internationale des Constructeurs d’Automobiles” (OICA).

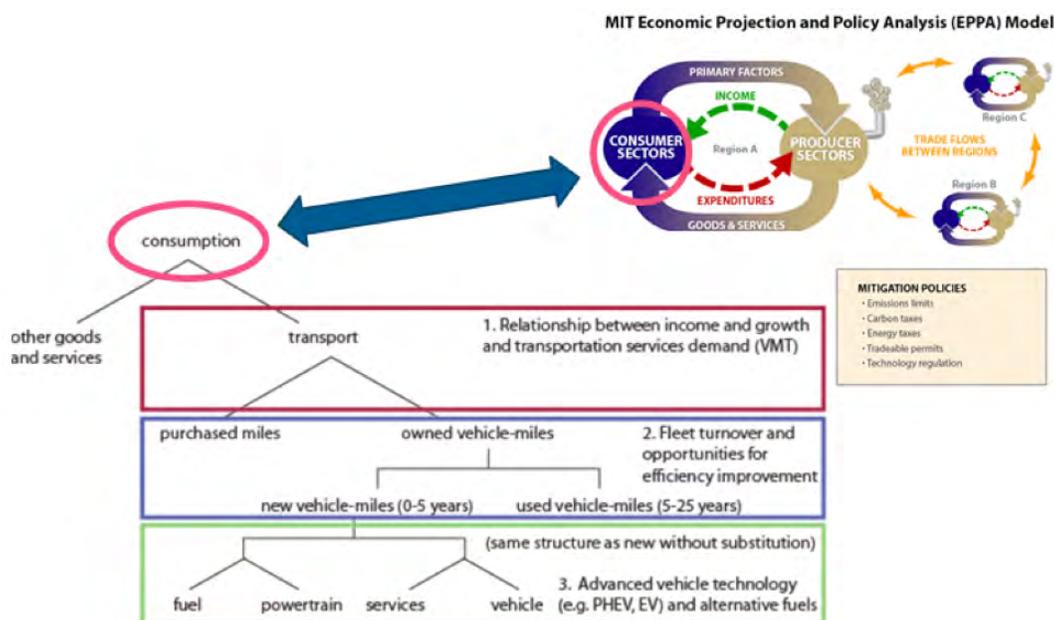


Figure 2. Schematic overview of the household transportation details and the circular flow of goods and resources in the EPPA model

Table 2. 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*
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)

* Partially based on states' vehicle registration records and Polk (US DOT Federal Highway Administration, 2017)

Table 3. 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/Regions 2004 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

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).

3.2 Number of LDVs

Table 4 summarizes our summary for the number of light-duty vehicles in each of EPPA's 18 regions in 2005, 2010, and 2015. In Appendix C we provide a detailed 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

Table 4. Stock of Private Light-Duty Vehicles (million vehicles) in the EPPA Regions

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	20.50	60.18	141.48
EUR	233.44	246.70	261.90
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	14.30	21.15	26.94
REA	3.12	4.80	7.22
ROE	19.74	26.72	33.27
RUS	25.57	34.35	44.25
US	215.52	224.56	242.42
Global	735.27	869.19	1072.31

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. These numbers include EVs (regional numbers for EVs are provided in Section 4).

3.3 Refined Oil Consumption

To evaluate refined oil consumption by LDVs, we use the GTAP data for the total use of oil by households. Some of the oil in final consumption is not used for transportation (e.g., for heating), therefore, we apply the region-specific shares (see Table 5) for use in personal transportation from Karpplus (2011). Consistent with our approach for classification of private LDVs, 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. The refined oil consumption in transportation for the EPPA regions is reported in Table 5.

Table 5. LDV Refined Oil Use (EJ) in 2004, 2007 and 2011 and Share of Household Transport in Total Household Refined Oil Consumption (%).

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	0.90	0.85
BRA	0.76	0.80	1.01	0.90
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	0.60	0.68	0.81	0.45
JPN	1.63	1.52	1.41	0.83
KOR	0.37	0.37	0.37	0.80
LAM	1.14	1.21	1.31	0.85
MES	0.79	0.88	0.91	0.32
MEX	0.91	0.99	1.00	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

4. BEV/PHEV Markup Estimation

We begin this section with a brief overview of the BEV/PHEV global markets in terms of stocks in 2015–2017. We then discuss our methods for estimating the “Markups”, or the relative costs of BEV/PHEV to ICE vehicles. We provide an assessment based on a “Top-Down” approach (based on MSRP) and a “Bottom-Up” approach (based on the cost of car components). Our discussion also includes a review of the reported estimates for BEV battery pack costs for 2015–2030. We use this data to derive the relative cost of ownership of BEVs and PHEVs to the cost of ownership of an ICE vehicle.

4.1 EV Global Market Status

The stocks of EVs are growing rapidly in many countries. Table 6 presents the data for EV stocks in 2015–2017 for the EPPA model regions. We develop regional numbers (that combine PHEVs and BEVs) from IEA (2018) reports and additional country statistics. China, USA and EUR have the largest number of EVs. In 2017, China had 1.2 million EVs, USA had 0.76 million and Europe had 0.74 million. The global number of EVs almost tripled in two years, it grew from 1.2 million in 2015 to 3.1 million in 2017.

To represent a composition of EV sales, we divide BEVs into medium range (up to 100 miles) and long range (up

Table 6. EV (BEV+PHEV) Stock in 2015-17 in EPPA regions (thousand vehicles)

EPPA Region	2015	2016	2017
AFR	3.6	6.1	10.0
ANZ	4.6	7.5	13.2
ASI	4.2	6.7	11.0
BRA	0.2	0.3	0.7
CAN	17.7	29.3	46.0
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	6.0	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	9.0	15.2
USA	404.1	563.7	762.1
Global	1239.5	1982.1	3109.1

to 300 miles) vehicles. PHEV vehicles are divided into low range (up to 10 miles in all electric mode) and extended range (up to 40 miles in all electric mode). Using 2017 monthly cumulative sales volume in USA (InsideEVs, 2018), we summarize in **Figure 3** the data for the sales volumes combining all makes/models into two BEV groups and two PHEV groups. To illustrate the best-selling categories, in Figure 3 we show the sales volumes for four categories of EVs in different colors. The BEV sales in 2017 were 73,444 for the long range and 31,515 for the medium range. The PHEV sales in 2017 were 41,474 for the low range and 45,882 for the extended range. In USA, the majority of BEVs sold in 2017 are the long range vehicles, while for PHEVs the shares of sales of the low range vehicles and the extended range vehicles are about the same. For other EPPA regions we use the data from IEA (2018).

To represent the EV penetration dynamics for the future projections in the EPPA model, we specify the rate of EV adoption based on data for conventional hybrid (non-plug in Toyota Prius) vehicle penetration over the period 1998 to 2008 (Karplus *et al.*, 2010). Based on data from Carsalesbase (2018), **Figure 4** shows the cumulative sales of different EVs from the time of their introduction to the market. A non-plug-in 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 (Davis *et al.*, 2016).

As can be seen from Figure 4, medium range BEVs (Nissan Leaf) extended range PHEVs (Chevy Volt), low range PHEVs (Toyota PHEV Prius) and non-plug-in hybrid Toyota Prius have followed a similar path in terms of cumulative sales in their first few years after their introduction to the market.³ In **Figure 5**, 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.⁴ Figure 4 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 tech-

3 These findings are consistent with Davis *et al.* (2016).

4 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).

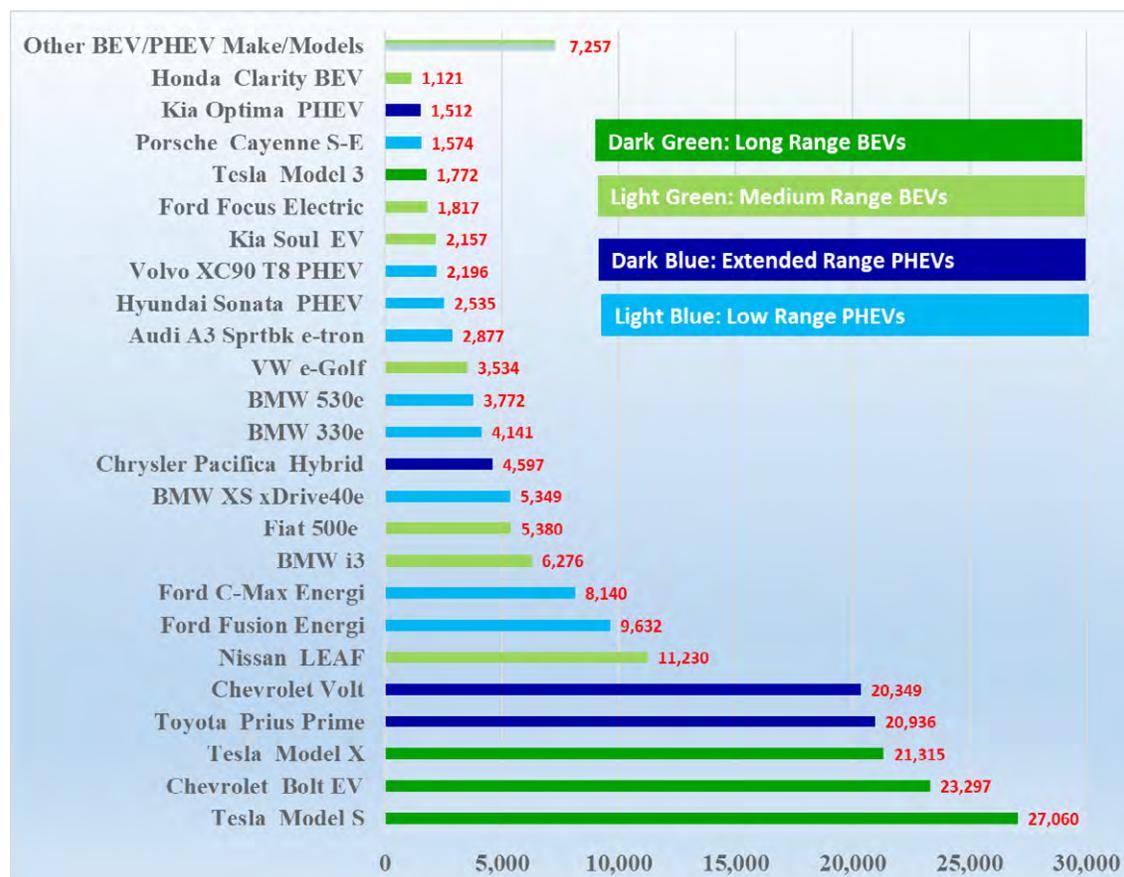


Figure 3. 2017 Annual Sales of EVs in USA. Data Source: InsideEVs (2018).



Figure 4. Market Penetration Rates-Tesla Model S, Nissan Leaf, Chevy Volt, Prius PHEV and Prius (HEV) and Chevy Bolt, based on monthly sales data from Carsalesbase (2018)

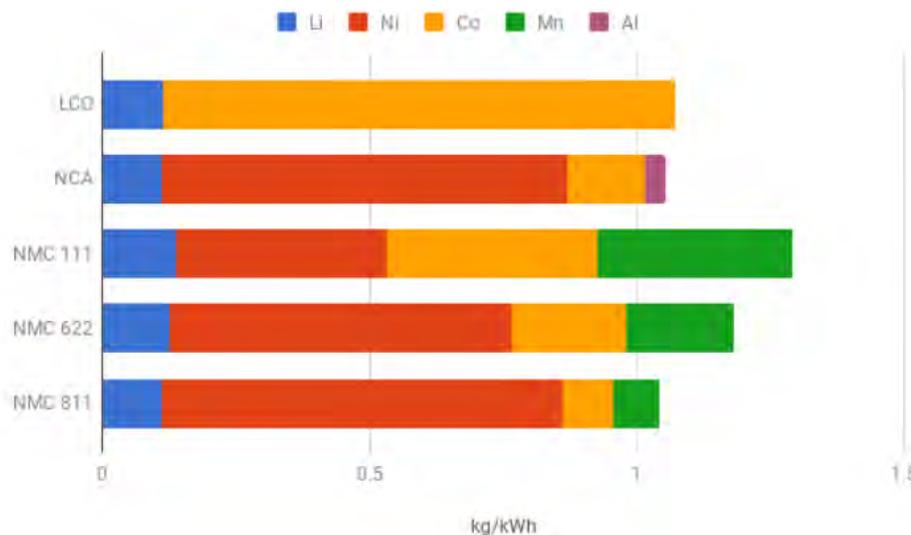


Figure 5. Comparison of different raw materials in different battery chemistries. (Research Interfaces, 2018)

nology-specific factor in the EPPA model (Karplus *et al.*, 2010). Once substantial experience with new technology is gained, the limitation on the speed of adoption is gradually removed as described in Morris *et al.* (2014).

4.2 BEV/PHEV Top-Down Markup Estimation

4.2.1 PHEV Top-Down Markups

For relative costs we use USA data because the data for other regions is more difficult to obtain. Further research is needed to incorporate more region-specific details. In determining the markups for PHEVs, we distinguish between two general

groups of PHEVs based on their all-electric range and their battery size. As previously discussed, we divide PHEVs into two groups: *Low Range PHEVs* and *Extended Range PHEVs*. **Table 7** provides the characteristics of these two groups.

The *Low Range PHEVs* have on average a smaller battery pack and a more powerful ICE engine. They also have one electric motor. This group includes vehicles such as BMW 330e, Mercedes C350, Ford C-Max Energi and Ford Fusion Energi. In contrast, the *Extended Range PHEVs* models have a larger battery pack, higher all electric range and less powerful ICE engine. Most of the cars in this group

have two electric motors. Examples for the extended range group are Prius Prime and Chevy Volt.

Table 8 provides key information about the representative PHEVs in each group. We have considered Ford Fusion Energi as a representative PHEV for the low range because it has a comparable ICE model from the same manufacturer, and it has the highest sales volume in its group in 2017. For the extended range group, we have chosen Chevy Volt as one of the two best selling cars in their group in 2017 in addition to Toyota Prime Prius. For each representative PHEV and the comparable ICE model from the same manufacturer, we provide their 2017 MSRPs. As listed in Table 8, the PHEV markup with respect to ICEs is in the range from 1.45 to 1.58. These numbers do not consider the U.S. Federal tax incentives.

Based on a battery size, different vehicles are eligible for different Federal incentives. For example, Ford Fusion Energi is eligible for \$4,000 Federal tax credit while Chevy Volt qualifies for \$7,500. In general, Federal tax credit for PHEVs varies from \$2,500 to \$7,500. Federal income tax

credit will start to phase out once a manufacturer reaches 200,000 number of cumulative sold of BEV/PHEV. With Federal tax incentives, the resulting markups are lower. They are in the range between 1.23 and 1.27 (Table 8).⁵

4.2.2 BEV Top-Down Markups

For BEVs, we identify two groups by considering their range, which we call as the *Medium Range* and the *Long Range* groups. The medium range BEVs have an average 33 kWh battery size and the range of about 100 miles. The long range BEV group has a 68 kWh battery size and the range of about 250 miles. We consider Nissan Leaf, Ford Focus EV for the medium range BEVs and Chevy Bolt for the long range BEVs because they are the top sellers in their respective categories. **Table 9** lists MSRPs and the resulting markups for the medium and long range BEVs.

While Ford has Focus as a comparable ICE to Focus EV, for Nissan Leaf and Chevy Bolt we choose Honda Civic

⁵ For representation in the EPPA model we add \$1,000 for a Level 2 home charger to the cost of the car.

Table 7. PHEVs Categorization

PHEV Categorization	Battery Size Average (kW)	All EV Range Average (miles)	ICE Engine Output Average (hp)	Number of Electric Motors	Vehicle Examples
Low Range All Electric Mode PHEVs	7	17	167	1	BMW 330e Mercedes C350 Ford C-Max Energi Ford Fusion Energi
Extended Range All Electric Mode PHEVs	14	39	98	2	Prius Prime Chevy Volt

Table 8. PHEV Markup Estimates

PHEV	PHEV Model	Comparable ICE	MSRP ICE		MSRP PHEV	Markup wrt ICE
Low Range All Electric Mode PHEVs	2017 Ford Fusion Energi	2017 Fusion ICE	\$22,120	With Fed Tax Credit	\$27,120	1.27
				Without Fed Tax Credit	\$31,120	1.45
Extended Range All Electric Mode PHEVs	2017 Chevy Volt	2017 Malibu	\$21,680	With Fed Tax Credit	\$25,700	1.23
				Without Fed Tax Credit	\$33,200	1.58

Table 9. BEV Markup Estimates

BEV	BEV Model	Comparable ICE	MSRP ICE		MSRP BEV	Markup wrt ICE
Medium Range	Nissan Leaf	2017 Honda Civic	\$19,900	With Fed Tax Incentive	\$22,490	1.18
				Without Fed Tax Incentive	\$29,990	1.56
Long Range	Chevy Bolt	2017 Subaru WRX	\$26,995	With Fed Tax Incentive	\$29,995	1.15
				Without Fed Tax Incentive	\$37,495	1.43

and Subaru WRX as comparable ICEs, respectively. We made these choices based on two factors: torque (lb-ft) and curb weight (lbs). Honda Civic has a 162 lb-ft torque and 2742 lbs curb weight, which is a close match to Nissan Leaf with 187 lb-ft torque and 3307 lbs curb weight. We choose Subaru WRX as a comparable ICE to Bolt. The reason is in terms of curb weight, Bolt’s curb weight at 3391 lbs is close to Subaru WRX at 3563 lbs. In addition, Bolt and Subaru WRX have torque in the range of 266 to 290 lb-ft. The resulting markups are in the range of 1.43–1.56. Considering the Federal tax credit of \$7,500, the range of markups is 1.15–1.18 as also listed in Table 9.

4.3 BEV/PHEV Bottom-Up Markup Estimation

4.3.1 Representative BEV/PHEV

In order to check our top-down markup estimation provided in Section 4.2, we consider a bottom-up approach using the cost of the vehicle components. According to the U.S. National Academy of Sciences (NAS, 2013), a representative BEV with 100 miles range requires a battery pack of 26 kWh. For a 300 mile range BEV, the battery size needs to be increased to 78 kWh. Consistent with the NAS categorization, we have considered Nissan Leaf, BMW i3 and Ford Focus EV in the 100-mile range category, and Bolt and Tesla Model S in the 300 mile group. In **Table 10** we provide the average battery sizes and the ranges of these vehicles. They are 33 kWh and 105 miles for the medium range BEVs and 68 kWh and 246 miles for the long range BEVs.

For PHEV, NAS (2013) distinguishes between the all-electric ranges of 10 miles (low range) and 40 miles (extended range). They require battery sizes of 4 and 20 kWh, correspondingly. For these categories we have considered BMW 330e, Mercedes C350, Ford C-Max Energi and Ford Fusion Energi in the low range category and Prius Prime and Chevy Volt in the extended range category. In Table 10 we also provide the average battery sizes and the ranges

of these vehicles. They are 7 kWh and 17 miles for the low range PHEVs and 14 kWh and 39 miles for the extended range PHEVs.

4.3.2 Issues Related to Battery Pack Cost Estimates

One of the main components for the bottom-up 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 is for a battery cell or a battery pack. Battery packs include the 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, which rely more on less expensive Nickel as opposed to more expensive Cobalt.

Table 10. BEV/PHEV Categorization

BEV/PHEV	Battery Size (kWh) NAS, 2013	All Electric Range (Mile) NAS, 2013	Battery Size (kWh) Our approach	All Electric Range (Mile)	Representative Vehicles
BEV Medium Range	26	100	33	105	2017 Nissan Leaf 2017 Ford Focus EV 2017 BMW i3
BEV Long Range	78	300	68	246	2017 Chevy Bolt 2017 Tesla Model S 75D
PHEV Low Range	4	10	7	17	2017 BMW 330e 2017 Mercedes C350 2017 Ford C-Max Energi 2017 Ford Fusion Energi
PHEV Extended Range	20	40	14	39	2017 Prius Prime 2017 Chevy Volt

The composition of different batteries is shown in Figure 5. 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, 2017). 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.

4.3.3 BEV Battery Pack Cost Estimation

In Figure 6, 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 Figure 6) takes

into consideration only the estimates for 2015, and it yields 330 \$/kWh. The red line on Figure 6 represents the average estimates for 2014, and it yields for 500 \$/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.

4.3.4 2020–2030 BEV Battery Cost Projection

Table 11 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 and Green (2018) 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. Based on these projections, we provide in Figure 7 our adopted values for 2020–2030. The PHEV

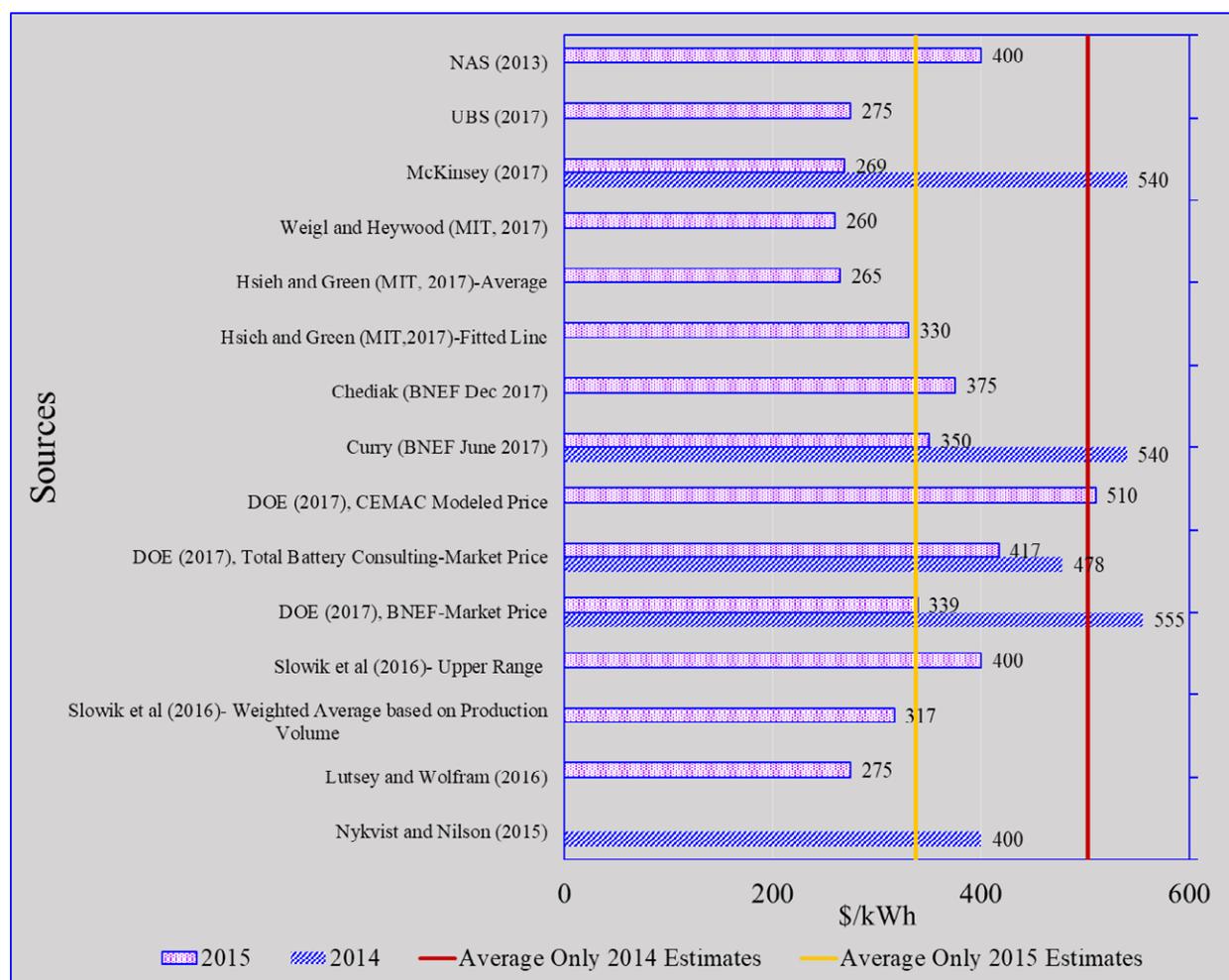


Figure 6. Summary of BEV Battery Pack Cost Estimates 2014-2015

The chart includes estimates from NAS (2013), UBS Evidence Lab (2017), McKinsey&Company (2017), Hsieh and Green (2017), Chediak (2017), Curry (2017), DOE (2017), Slowik et al. (2016), and Nykvist and Nilsson (2015).

battery pack cost is higher by 60 \$/kWh. **Tables 12 and 13** list the total battery pack cost considering the size of the battery in BEVs and PHEVs of different types.

4.3.5 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). 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 \$/kWh and 7 \$/kWh. Based on the assumed motor sizes, in **Table 14** 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 a 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

Table 11. 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. Also by linking production volume and battery pack cost
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). Also we assume 20 million annual BEV sales in 2030 for this calculation
UBS Evidence Lab, (2017)	-	130	-	NMC811 total battery pack cost
Hsieh & Green, (2018)	-	-	130	Least Cost Scenario
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	

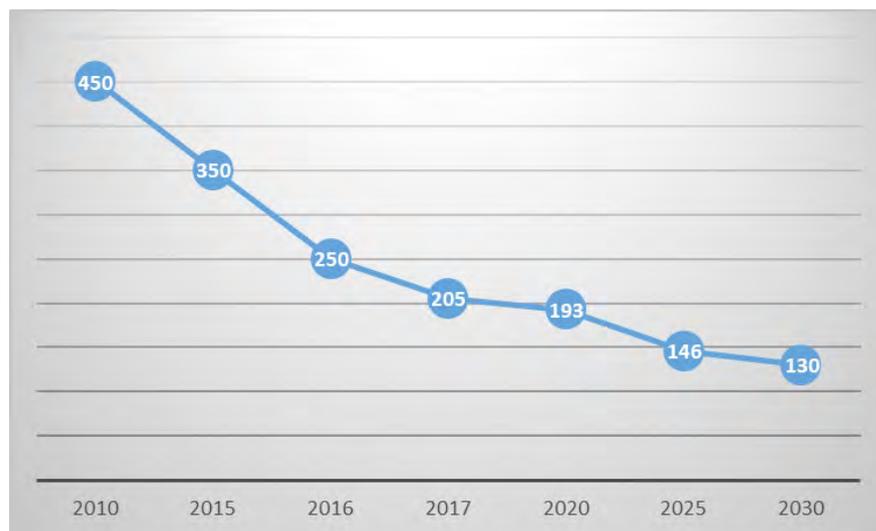


Figure 7. BEV Battery Pack Cost Projection

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.

4.3.6 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, including the 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 15 summarizes the total incremental cost estimates relative to the ICE vehicle. 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.

4.4 Top-Down/Bottom-Up Markup Summary

Table 16 provides a summary of the relative costs of BEV/PHEV to ICE vehicles with and without government support. We also compare the results that are based on top-down and bottom-up approaches. Without government support, our top-down and bottom-up approaches result in comparable markups for a medium range BEV of around 1.6. For the long range BEV, our bottom-up approach suggests much higher markup of around 1.9, while the top-down method suggests the 1.4 markup. In this group we considered Chevy Bolt as a representative vehicle. One potential explanation for a difference in the markups is that some car companies are either “forgone profits on their BEVs or pass along the markup differences to buyers of other vehicles in their portfolio (DOT and EPA, 2018). For the low range PHEV, two approaches result in the markup of 1.3 to 1.4. For the extended range PHEV the markups are also close—1.45 from the bottom-up approach and 1.6 from the top-down approach.

In Table 16 we also provide the results of the markup calculation when the government support of \$7,500 for all BEVs and the extended range PHEVs. The level of support for the low range PHEVs is the based on the size of the battery. Here we have considered \$4,000. The government support decreases the markups by 12% to 24%, but the differences between top-down and bottom-up approaches are in a similar range as without government support.

Table 12. BEV \$/kWh and Total Battery Cost (\$)

Trend 2010-2030

	BEV Battery Cost		
	per kWh	Medium Range (33 kWh)	Long Range (68 kWh)
2010	450 \$/kWh	\$14,700	\$30,375
2015	350 \$/kWh	\$11,433	\$23,625
2020	193 \$/kWh	\$6,305	\$13,028
2025	146 \$/kWh	\$4,769	\$9,855
2030	130 \$/kWh	\$4,247	\$8,775

Table 13. PHEV \$/kWh and Total Battery Cost \$

Trend 2010-2030

	PHEV Battery Cost		
	per kWh	Low Range (7 kWh)	Extended Range (14 kWh)
2010	510 \$/kWh	\$3,749	\$6,936
2015	410 \$/kWh	\$3,014	\$5,576
2020	253 \$/kWh	\$1,860	\$3,441
2025	206 \$/kWh	\$1,514	\$2,802
2030	190 \$/kWh	\$1,397	\$2,584

Table 14. Electric motor cost estimates (\$)

Range:	Electric Motor Cost			
	PHEV		BEV	
	Low	Extended	Medium	Long
2010	1573	2536	1874	2959
2015	1393	2240	1698	2680
2020	1197	1919	1504	2374
2025	1035	1653	1341	2115
2030	884	1407	1184	1867

Table 15. Incremental cost for BEV and PHEV (\$)

Range:	Incremental Cost			
	PHEV		BEV	
	Low	Extended	Medium	Long
2010	7191	11342	15044	31804
2015	6276	9686	11601	24775
2020	4927	7230	6279	13871
2025	4419	6325	4580	10440
2030	4269	6079	3901	9112

Table 16. Bottom-Up versus Top-Down BEV/PHEV Markup Summary

Markups	BEV		PHEV	
	Medium Range	Long Range	Low Range	Extended Range
<i>Without Federal Tax Incentive</i>				
Bottom-Up Cost	1.58	1.92	1.28	1.45
Top-Down	1.56	1.43	1.45	1.58
<i>With Federal Tax Incentive</i>				
Bottom-Up Cost	1.21	1.64	1.10	1.10
Top-Down	1.18	1.15	1.27	1.23

5. Light-Duty Vehicle Projection

As an illustration of our approach, we incorporated the derived data for the number of vehicles, fuel use and the markups into the EPPA model to make a projection of LDV and EV stocks up to 2050. We use the scenario of economic growth and energy and climate-related policies from the MIT Joint Program Outlook that assumes the implementation of the Paris Agreement pledges (MIT Joint Program, 2016). We combined PHEVs and BEVs into a representative EV and assumed a gradual decrease in the cost of batteries (as in Figure 7) and a gradual decrease in government support to EVs, which is eliminated by 2025.

As shown in **Figure 8**, we find that in this illustrative scenario a global LDV stock reaches about 1.8 billion by 2050 from 1.07 billion in 2015. The regions with the largest numbers of the LDV stock in 2050 are Europe (370 million), USA (330 million), China (300 million) and India (100 million). These four regions’ total LDV stock in 2050 represent 60% of the global LDV. The number of LDVs in these four regions in

2050 is about the same as the total global number of LDVs in 2015. Among these four regions, India is projected to have the highest growth of 71% from 2015 to 2050, followed by China with a 52% growth, Europe with 30% growth, and USA with 26% growth from 2015 to 2050.

In terms of EV deployment, **Figure 9** shows that by 2050, the global EV (BEV+PHEV) stock is projected to reach about 500 million cars (from about 1 million cars in 2015). USA, China and Europe will each have around 10% of the global stock of EVs in 2050, so these three regions are projected to have a third of global EVs in 2050. Globally, EVs in 2050 are about a quarter of total LDVs. While our scenario is based on one plausible development, we stress an illustrative nature of our calculations because the results depend on many assumptions about economic development and policy. While our goal in this paper is to describe the method for refining the input data for energy-economic models, our approach allows the researchers to perform scenario analysis with respect to alternative assumptions.

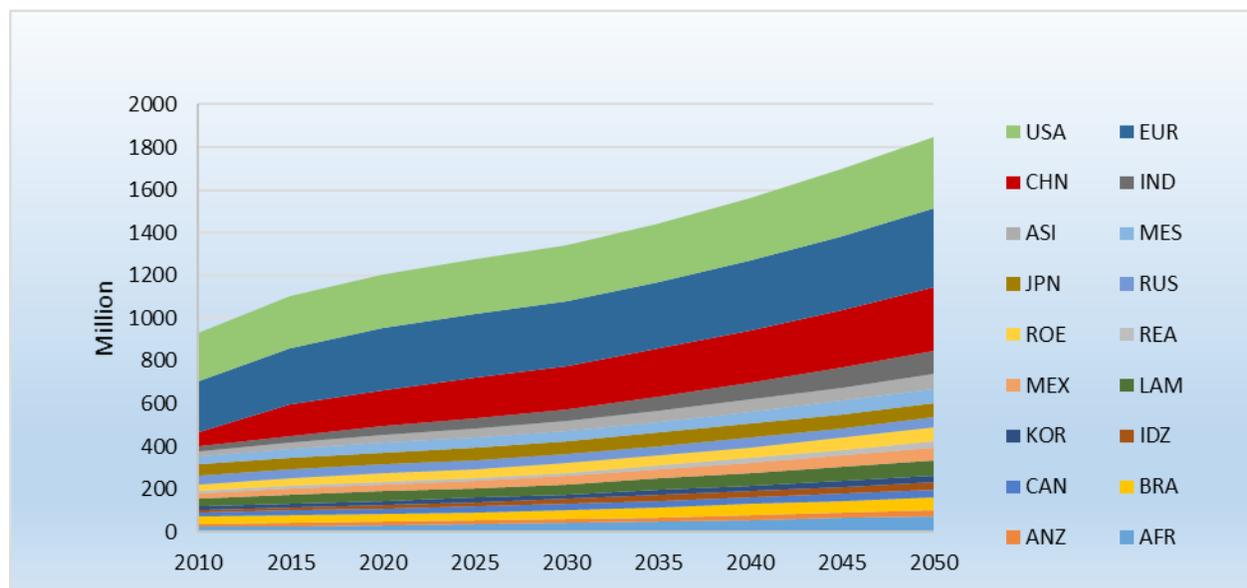


Figure 8. Regional LDV Deployment

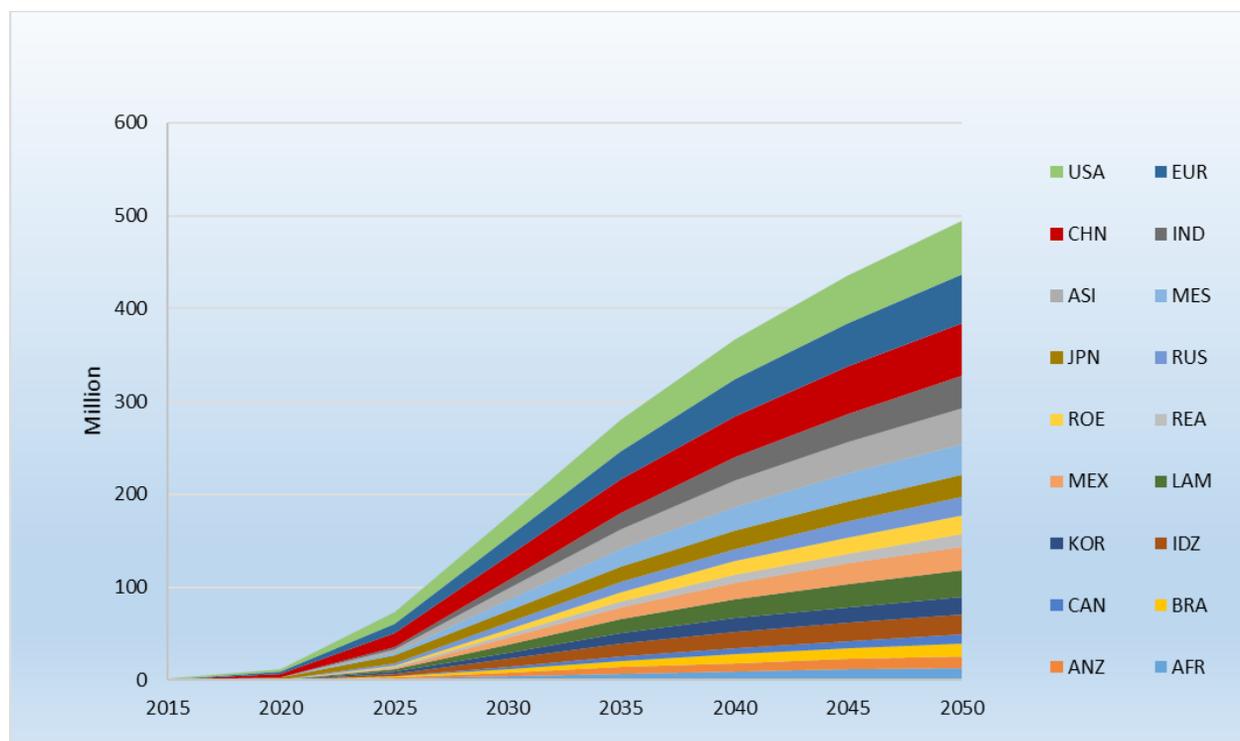


Figure 9. Regional EV Deployment

6. 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. Currently (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 consumer prices (top-down approach) and battery pack/vehicle components cost estimates (bottom-up approach) in USA, PHEVs are about 30–60% more expensive than ICEs and BEVs are about 40–90% more expensive than ICEs (depending on the vehicle type), when Federal incentives are not included. Availability of the data for other regions is limited. Additional research is warranted to provide region-specific characteristics of the vehicles and government incentives towards the alternative vehicles.

Based on the data that we develop for this study, we also provide an illustrative projection of the deployment of regional light-duty vehicle (including electric vehicle) stock up to 2050. We employ the MIT EPPA model and find that the global LDV stock will reach 1.8 billion by 2050 from 1.07 billion in 2015. Global EV stock is projected to reach 500 million by 2050 from about a million in 2015. Our scenario shows 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.

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Appendix A. Composition of the regions in the EPPA model

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

Appendix B. Other databases for car stocks

B.1 International Energy Agency Mobility Model (IEA-MoMo)

The Mobility Model (MoMo) is a technical-economic database spreadsheet and simulation model that enables detailed projections of transport activity, vehicle activity, energy demand, and well-to-wheel GHG and pollutant emissions according to user-defined policy scenarios to 2050. The MoMo covers road (passenger), rail, air and shipping (freight) as the main modes of passenger and freight transport. The historic portion of the model covers 1975 to 2015 (or 1990 to 2015 for certain countries). As noted in the MoMo documentation, the IEA-MoMo is using Polk (IHS Markit) as one of its primary data sources. MoMo divides the world into 29 regions including several specific countries as listed below: USA, Canada, Mexico, Brazil, France, Germany, Italy, United Kingdom, Japan, Korea, China and India (Cazzola & Teter, 2016). The IEA (2017) is based on a version of MoMo that “comprises of 27 countries and regions, which are aggregated into four Organisation for Economic Co-operation and Development (OECD) regional clusters and 11 groups of non-OECD economies” (IEA, 2017a).

B.2 Polk (IHS Markit)

IHS Polk is a primary data source on all sorts of vehicle attributes including the vehicle stock at the global level. IHS Polk products are used by top agencies such as the EIA and the IEA. IHS Polk is the only data source that has confirmed to us that they have data with global coverage on the number of private household-owned light-duty vehicles. IHS Polk data are based on registration records that the company purchases in many countries followed by rigorous data cleaning and validation. The registration records include vehicle identification number, owner name and address, title information and other data. As a result, while they have data on the ownership of all LDVs they cover at country-level, they also have data on vehicle attributes. In addition to vehicles in operation, IHS Polk tracks and provides data on new and used vehicles registration (IHS, 2016).

B.3 WARD's Auto

WARD's Auto is another key data source since its products are used by several agencies including the OICA and Oak Ridge National Laboratory. WARD's World Motor Vehicle Data Book incorporates WARD's data on annual sales and production of around 50 countries between 1970–2014/2015. WARD's Auto tracks sales for all of the world's primary vehicle markets, the number of vehicles on the road, and the split between car and commercial vehicle (total truck) for those vehicles. In terms of fuel consumption and miles traveled, WARD's Auto only tracks US totals (WARDSAuto, 2016).

Appendix C. Number of LDVs in the EPPA model 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).

C.1. Number of Private LDVs: EPPA Composite Regions

Table C1 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 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.

C.2. Number of Private LDVs: Individual countries in EPPA

The EPPA model includes the following regions that consist of individual countries: Brazil, Canada, China, Indonesia, India, Japan, Korea, Mexico, Russia, and USA. **Table C2** provides the data for these regions. In five of these regions, OICA and BMI estimates are fairly close. As a result, we choose the OICA data for the purpose of 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.

For Brazil, our consultations with experts on Brazilian auto market led us to a choice of OICA numbers for this country. For India, we chose BMI estimates based on industry

experts' feedback suggesting the higher range of the estimates. In contrast to most parts of the world, USA have a large portion of the private household-owned light-duty fleet that is composed of trucks. As a result, none of the two sources' estimates for the US is close to the historic number of private LDVs.

C.3. China

As mentioned, BMI and OICA estimates show inconsistencies in their reported number of passenger cars for 2015. Since BMI Research lists annually published Chinese Statistical Yearbook (CSY) in addition to their in-house calculation as their main two sources of primary data, we take a closer look at the vehicle classification in China by various Chinese agencies, including the CSY, as summarized in Appendix D.

For this study, we follow CSY classification as we find that its definition is more consistent with BMI's general definition. As shown on **Table C3** for 2015, BMI reports 141.68 million passenger cars in China. This estimate is very close to 2015 total of 140.99 million private vehicles (including both passenger vehicles and trucks) as reported in Chinese Statistical Yearbook 2016 and shown in Table C3. As a result, the closeness of the BMI and CSY estimates suggest that between the BMI and OICA, it is reasonable to follow BMI's estimation for all years for the purpose of updating and calibration of EPPA model.

The other option that we have explored is CSY's reported number of LDVs in all years instead of the BMI's. CSY reports number of LDVs as a summation of mini and small private passenger vehicles in addition to private mini and light trucks. As shown in Table C3, the reported number of LDVs for 2015 is 137.70 million which is lower than the BMI 2015 estimates (141.48 million).

CSY's lower estimates compared to BMI's could be explained by the CSY's exclusion of large and medium passenger vehicles in addition to heavy and medium trucks for the total of 2.97 million vehicles in 2015. Exclusion of private-owned large and medium passenger vehicles in addition to private-owned heavy and medium trucks is inconsistent with our objective of model update and calibration based on historic private household-owned LDVs. Therefore, we argue that it is still reasonable to choose BMI over CSY LDV estimates. As another justification of deciding to use BMI's estimate is the BMI's potential underestimating of the number of passenger fleet in China. The reason is that BMI Research's general definition of passenger fleet considers motor vehicles for the purpose of carrying nine or fewer passengers with a gross vehicle weight less than 3.5 metric tons or 3.86 US tons. In summary, we find BMI's estimates for China more inclusive and consistent with our methodology for other regions in terms of types of vehicles.

Table C1. Comparing Number of Passenger Cars for EPPA Composite Regions from BMI and OICA

EPPA Composite Regions	Data Source	2005	2010	2015	# 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	

Table C2. 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	

In addition, as discussed, BMI's estimates for 2005, 2010 and 2015 are close to CSY's private vehicles.

C.4. USA

In **Table C4** we provide estimates by both BMI and OICA. Both sources' estimates are far below the actual number of private household-owned LDVs. That is due to the unique feature of the US auto market that has a large market share of SUVs and light trucks as private passenger vehicles. This unique feature is in part due to the consequences of exemption of light trucks from the CAFE standards that Congress passed in 1975 (Sperling and Gordon, 2009). To address this issue, we take a closer look at available sources of data from the US Federal agencies. However, as we explain in Appendix D, US state agencies' motivation and objectives on vehicle classification are not all the same. Therefore, we

provide some details on vehicle classifications adopted by different agencies in the US in Appendix D.

In our calculation of the total private household-owned light-duty vehicles, we follow EPA/NHTSA/Oak Ridge classification of these vehicles. This means that we enforce Oak Ridge methodology and reasoning on the EIA reported data in order to calculate the number of private household-owned light-duty vehicles. Therefore, we start with the EIA reported data on the total number of light-duty vehicles and we subtract total stock of fleet LDVs from total stock of LDVs. We also add the total number of commercial light truck. This way we could include private household-owned class 2b light trucks following Oak Ridge analysis of class 2b vehicles and assume that majority of the stock of class 2b vehicles including large pickups, SUVs and Vans are owned and operated by private households in the US. Table C4 summarizes these calculations.

Table C3. China Stock Number of Private Light-Duty Vehicles

China (in Million)	2005	2010	2015
BMI Passenger Car Fleet	20.50	60.18	141.48
OICA Passenger Cars	21.69	62.07	136.04
Chinese Statistical Yearbook Private Vehicles (Passenger and Truck)	18.48	59.39	140.99
Chinese Statistical Yearbook Private Passenger Vehicle	13.84	49.90	127.37
Chinese Statistical Yearbook Private LDV (Mini/Small Passenger & Mini/Light Truck)	16.15	55.69	137.70

Table C4. US Number of Private Light-Duty Vehicles

US Number of Vehicles (Millions)	2005	2010	2015	Explain
Total LDV Stock	220	228	240	Total stock include total car stock and total light truck stock
Total Car Stock	136	129	121	
Total Light Truck Stock	85	99	119	All trucks weighing 8,500 pounds or less
Fleet Car Stock	6	5	6	
Fleet Light Truck Stock	5	5	5	
Total Fleet Vehicles	11	10	11	Includes all fleets of 10 or more
Commercial Light Trucks	7	7	13	Commercial trucks from 8,501 to 10,000 pounds
Total Private LDV	216	225	242	Total LDV plus Commercial Light Trucks minus Fleet Cars and Fleet Light Trucks

Appendix D: Light Duty Vehicle Classification

D.1. China

We divide the Chinese vehicle classification systems into four groups. The first group is led by the National Bureau of Statistics of China and its annual data publication through CSY. The second group consists of China Association of Automobile Manufacturers (CAAM) and the China Automotive Technology Association Research Center (CATARC). Third group of vehicle classification in China is based on fuel economy regulations implemented by the Ministry of Industrial and Information Technology of China. And finally the fourth group represents vehicle emission standards that are issued by the Ministry of Environmental Protection and Standardization Administration of China. **Table D1** summarizes the four groups of vehicle classification and the motivation for each group.

In the CSY, vehicles are categorized into two broad groups of private passenger car and private trucks. CSY also reports total number of civil and special vehicles, separately. Civil vehicles include commercial-used passenger cars and trucks

in addition to those owned by the government agencies. All other vehicles are considered for special uses and they include municipal and military fleet (Huo et. al, 2007). Since 2002, CSY reports four sub-categories for each of the private passenger cars and trucks (Huo and Wang, 2012). The data for these categories are presented in **Table D2**.

The second group of classification is led by the China Automotive Technology and Research Center and Chinese Automotive Manufacturers Association. Starting 2005, the two institutes report production and sales volume of passenger and commercial vehicles. Passenger vehicles include passenger cars, minivans (less than 9 seats) and SUVs. This classification is consistent with what Chinese regulators consider as M1 vehicles. Commercial vehicles consist of more than 9-seat passenger vehicles and all trucks (Huo & Wang, 2012).

Ministry of Industrial and Information Technology of China (China MIIT), the agency in charge of the implementation

Table D1: China Vehicle Classification Summary

Agency/Institute	Classification Purpose	Date Implemented	Classification Details	Sources
National Bureau of Statistics of China	Chinese Statistical Yearbook-Table 16-21 Possession Private Vehicles	2002 (Category Updated)	Passenger Vehicles (large, medium, small, mini) Trucks (heavy, medium, light, mini)	NBS
China Association of Automobile Manufacturers (CAAM) China Automotive Technology Association Research Center (CATARC)	Production and sales volume of passenger and commercial vehicles	2005	Passenger vehicles include passenger cars, minivans (less than 9 seats) and SUVs. Commercial vehicles consist of more than 9-seat passenger vehicles and all trucks	Huo <i>et al.</i> , (2007)
Ministry of Industrial and Information Technology of China	Fuel economy regulations	2010	Passenger cars, minivans and sport-utility vehicles <ul style="list-style-type: none"> • M1 (fewer than 9 seats and lighter than 3,500 kg) • M2 (nine or more seats and weighing 5,000 kg or less) • M3 (nine or more seats and heavier than 5000 kg) Trucks <ul style="list-style-type: none"> • N1 (GVW less than 3,500 kg), • N2 (GVW between 3,500 and 12,000 kg) • N3 (GVW above 12,000 kg) 	Huo <i>et al.</i> (2012)
Ministry of Environmental Protection and Standardization Administration of China	Vehicle Emission Standards	2016	Type 1 vehicles include M1 vehicles with fewer than 6 passenger-seats and GVW less than 2.5 Metric tons Type 2 vehicles are all other light-duty vehicles	TransportPolicy (2017) ICCT (2017)

Table D2: Total Number of Private Passenger Vehicles and Trucks 2005-2015 (in millions). (China National Bureau of Statistics, 2016)

Indicators	2005	2010	2015
Possession of Private Vehicles	18.48	59.39	140.99
Possession of Private Passenger Vehicles	13.84	49.90	127.37
Possession of Private Large Passenger Vehicles	0.08	0.09	0.08
Possession of Private Medium Passenger Vehicles	0.51	0.61	0.29
Possession of Private Small Passenger Vehicles	10.80	45.93	124.32
Possession of Private Mini Passenger Vehicles	2.46	3.26	2.68
Possession of Private Trucks	4.52	9.32	13.31
Possession of Private Heavy Trucks	0.63	1.41	1.74
Possession of Private Medium Trucks	1.00	1.41	0.87
Possession of Private Light Trucks	2.43	6.33	10.61
Possession of Private Mini Trucks	0.46	0.17	0.09
Possession of Private Other Vehicles	0.12	0.18	0.31
LDV	16.15	55.69	137.70

of fuel economy regulations since 2010,⁶ uses a somewhat different vehicle classification. The agency considers passenger cars, minivans and sport-utility vehicles as one group and trucks in a separate group.⁷ For both groups, the agency follows a categorization system based on the vehicles Gross Vehicle Weight (GVW). The agency divides passenger cars, minivans and sport-utility vehicles into three sub-groups of M1 (fewer than 9 seats and lighter than 3,500 kg), M2 (nine or more seats and weighing 5,000 kg or less) and M3 (nine or more seats and heavier than 5000 kg). Similarly, the regulator has three sub-categories for trucks: N1 (GVW less than 3,500 kg), N2 (GVW between 3,500 and 12,000 kg) and N3 (GVW above 12,000 kg). (Huo et. al, 2012c)

The fourth group represents vehicle emission standards that are issued by the Ministry of Environmental Protection and Standardization Administration of China.⁸ The standards apply to Type 1 and Type 2 vehicles. Type 1 vehi-

cles include M1 vehicles with fewer than 6 passenger-seats and GVW less than 2.5 Metric tons. Type 2 vehicles are all other light-duty vehicles which also include the N1 light commercial vehicles. The regulation divides Type 2 vehicles into three sub-categories based on the vehicles reference mass (TransportPolicy.net, 2017; ICCT, 2017)

D.2. USA

In the United States, at least five Federal agencies and one state agency are engaged with the regulation of light-duty vehicles. These include US Department of Transportation (US DOT) Federal Highway Administration (FHWA) and US DOT National Highway Traffic Safety Administration (NHTSA); US Oak Ridge National Laboratory (Oak Ridge); US Environmental Protection Agency (EPA); US Department of Energy, Energy Information Administration (EIA); and California Air Resources Board (CARB). These agencies can be divided in to three groups in terms of their adopted classification of light-duty vehicles. The first group consists of NHTSA, EPA, CARB and Oak Ridge. The EIA and FHWA's distinct classifications make them recognizable as our second and third groups.

In what follows, we first provide a summary for each group's classification of light-duty vehicles. We, in particular, give a particular attention to the first group's classification due to its relevance to Corporate Average Fuel Economy (CAFE) standards. Then, we summarize our reasoning in choosing Group 1 classification, as listed below, for our EPPA model update and calibration.

6 For the first phase of the policy in 2010, the agency required demonstration of fuel-consumption rate labels for all new M1 and M2 (with GVW below 3,500 kg) and N1 vehicles. The fuel-consumption rates are issued by the agency following vehicles lab testing.

7 The 2010 regulation is an update to earlier regulatory development starting 2004 when the agency introduced its two-phase national fuel consumption standards for new passenger vehicles based on their gross vehicle weight in 16 sub-categories for M1 vehicles. (Wang et al., 2006)

8 The MEP regulation of emissions from new light-duty vehicles, trucks and heavy trucks started in 2000 through China I emission standards. (Kishimoto, et al., 2017)

D.2.1. Group 1: NHTSA, EPA, CARB and Oak Ridge

Since 2009's adoption of updated CAFE standards, EPA and NHTSA have had two joint rulemakings. The first joint rulemaking was in May 2010 covering vehicle model years (MYs) 2012–2016 and the second one was in October 2012 for MYs 2017–2025. The objective of the regulation is to double fuel efficiency and reduce the GHG emissions of light-duty vehicles by half compared to MY 2008 by 2025. The new regulation also requires the EPA to perform midterm evaluations (MTEs) of the GHG standards for MYs 2022–2025. Based on EPA's MTE, the NHTSA will then revisit the GHG standards for MYs 2022–2025. EPA and NHTSA joint activities are also supported by CARB. The collaboration with CARB and the state agency's commitment to the new standards allows automakers to plan for single fleet in all US territories. (EPA; Cal Air Resources Board; NHTSA, 2016)

As shown in **Figure D1** and following the implementation of updated CAFE standards in 2010, the EPA and NHTSA consider two broad categories of cars and trucks in their classification of light-duty or personal vehicles. Two important changes in this new classification are the treatment of small SUVs and "medium-duty passenger vehicles (MD-PVs), those SUVs and passenger vans with gross vehicle weight ratings between 8,500 and 10,000 pounds." These distinctions are based on regulatory reasons addressing the CO₂ emissions and CAFE standards. In particular, this new vehicle classification is to "to match the Corporate Average Fuel Economy (CAFE) methodology. Under CAFE, small, two-wheel drive sport utility vehicles will be held to the same standards as cars. The Environmental Protection Agency has defined these vehicles as Car SUVs." This means that EPA has re-classified "many small and mid-sized, 2-wheel drive sport utility vehicles (SUVs) from the truck category

to the car category." In addition, the EPA now considers medium-duty passenger vehicles (GVW between 8,500 and 10,000 lbs) in the light-duty truck category as opposed to previous classification in the heavy-duty vehicle category (EPA, 2016).

D.2.2. Group 2: EIA

The Energy Information Administration (EIA) considers vehicles weighing less than 8,500 lbs (automobiles, motorcycles, and light trucks) as light-duty vehicles (LDVs) (Energy Information Administration, 2017c). EIA reports total stock of LDV and total stock of fleet LDV in two separate supplementary tables as part of their Annual Energy Outlook (AEO) publications (U.S. Energy Information Administration (EIA), 2017b). EIA's treatment of trucks with gross vehicle weight of 8,501 to 10,000 lbs makes its classification distinct from the EPA, NHTSA, CARB and Oak Ridge. In particular, while the for mentioned agencies consider trucks of GVW 8,501 to 10,000 lbs as medium-duty passenger vehicles and include that in light-duty vehicle classification, the EIA considers this group of vehicle as commercial light trucks. The agency reports data on commercial light trucks as part of AEO fleet supplementary tables separate from LDVs. The agency also assumes that that "class 2b vehicles are to be used primarily for commercial purposes." (EIA, 2017a)

D.2.3. Group 3: Federal Highway Administration (FHWA)

Starting 2007, US DOT Federal Highway Administration (FHWA) has started using a new vehicle classification not compatible with earlier years and also different from other US agencies. The FHWA vehicle classification is based on vehicles' wheel base (short and long) as opposed to having

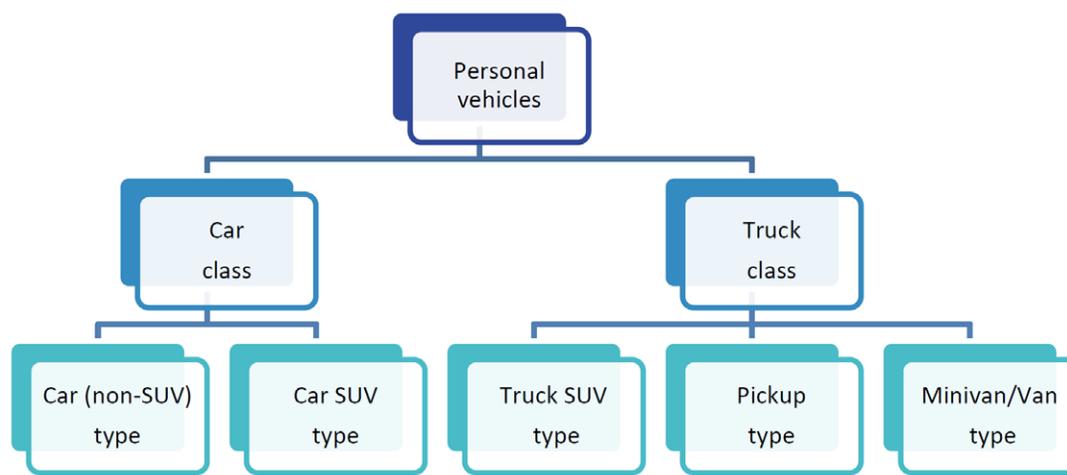


Figure D1. EPA-NHTSA Light-Duty Vehicle Classification (EPA, 2016)

gross vehicle weight (GVW) as a determinant factor. FHWA's *Light duty vehicle, short wheel base* includes passenger cars, light trucks, vans and sport utility vehicles with a wheelbase (WB) equal to or less than 121 inches. The new category *Light duty vehicle, long wheel base* consist of large passenger cars, vans, pickup trucks, and sport/utility vehicles with wheelbases (WB) larger than 121 inches.

D.3. EPPA Model Classification

As noted, our main objective is to provide a consistent approach in calculating the number of private light duty vehicles in each EPPA region including the United States. Among the above mentioned groups, only the EIA provides total stock of LDV and total stock of fleet LDV in two separate supplementary tables as part of their Annual Energy Outlook (AEO) publications. This makes it possible to calculate for the US the number of private household-owned light duty vehicles with only one caveat. The caveat is the EIA's treatment of commercial light truck as a distinct category in just the AEOs LDV fleet tables. EIA's definition of commercial light trucks include trucks known as class 2b with GVW between 8,501 to 10,000 lbs (EIA, 2017a). Similarly, Oak Ridge National Lab divides class 2 trucks (6000–10,000lbs) into class 2a (6,000–8,500 lbs) and class 2b (8,501–10,000 lbs) (Davis and Truett, 2002). However, in contrast to EIA's terminology for the class 2b truck as commercial light trucks, Davis and Truett (2002) suggest that in recent years (up to year 2000 that the study covers), most class 2b trucks have been sold to private household for non-commercial use.

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