

# **The Influence of Public Charging Infrastructure Deployment and Other Socio-Economic Factors on Electric Vehicle Adoption in France**

Bassem Haidar<sup>1,2,\*</sup>, Maria Teresa Aguilar Rojas<sup>3</sup>

<sup>1</sup> Groupe PSA, Route de Gisy, 78140 Vélizy-Villacoublay, France

<sup>2</sup> Université Paris-Saclay, CentraleSupélec, Laboratoire Genie Industriel, 3 rue Joliot-Curie, 91190  
Gif-sur-Yvette, France

<sup>3</sup> Université Paris Dauphine-PSL, Place du Maréchal de Lattre de Tassigny, 75016 Paris, France

\* Corresponding author (bassem.haidar@centralesupelec.fr)

**Abstract:** Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) offer a promising choice to replace fossil-fuel dependent Internal Combustion Engine Vehicles with a low-emission transport solution. To overcome barriers hindering the purchasing activity, governments, automotive manufacturers, and charging infrastructure operators have deployed market-boosting initiatives. Here, we analyze the influence of socio-demographic, technical, and economic factors on the BEV and PHEV markets, separately, in French departments from 2015 to 2019, using fixed- and random-effects panel data regressions. We find BEV/PHEV models numbers and the gasoline price positively associated with both BEV and PHEV adoption. Contrary to slow-and-normal charger density, fast, ultrafast chargers and financial incentives boost the BEV market. Regarding the PHEV model, only fast charger density had a significant and negative influence on the sales from all charging powers densities. Based on the results, policy recommendations are discussed for the automotive industry, the charging operator, and the local authorities.

**Keywords:** Charging Infrastructure, Electric Vehicle, Incentives, Panel Data Modelling, Technology Adoption

**JEL Codes:** C01, C33, R48, R58, L62, O18, Q55

## 1. Introduction

Greenhouse gas (GHG) emissions contribute to the climate change phenomenon of the Earth's surface and the atmosphere. In Paris, from the 30th of November 2015 to the 12th of December 2015, the 21st Conference of Parties on Climate Change was held, resulting in a signature of a historical agreement of 196 countries to undertake ambitious efforts to combat climate change by reducing the emissions of these greenhouse gasses. This agreement required all parties to put forward their best efforts through “nationally determined contributions” (UNFCCC Secretariat, 2015). France has set itself the ambitious goal to reduce CO<sub>2</sub> emissions and the dependency of petroleum products from the transport sector by 20% by 2020, to bring them back to the level they had in 1990.

Plug-in Electric Vehicles (PEV) have noteworthy potential to reduce petroleum dependency and GHGs emissions related to the road transportation sector towards global decarbonization (Hainsch et al. 2021). PEVs encompass Battery Electric Vehicles (BEV), which use the electricity stored in the battery as a primary energy source, and Plug-in Hybrid Electric Vehicles (PHEV), which use both fossil fuel and battery as sources of energy. If the electricity is produced using renewable energy sources, the Greenhouse Gas emissions from transportation are significantly lower than fossil-fuel based transport. While this technology's adoption has been rapidly increasing over the last decade, their market share remains in most countries restrained by socio-techno-economic barriers (Egbue and Long 2012). The reasons for the slow uptake of EVs are generally divided into technical (charging time, limited BEV range), economic (PEV purchase, electricity, and fuel prices), awareness (client behavior towards new inventions, charging stations visibility, number of PEV models), and socio-demographic factors (age, education, income, environmentalism, and urbanity degree) (Egbue and Long 2012; Sierzchula et al. 2014; Tran et al. 2012). To overcome these obstacles, governments applied national and local, monetary, and non-monetary policies for all the EV supply chain members: supply and demand (Sykes and Axsen 2017).

In France, PEVs presented around 2% of total vehicles sales in 2020 (Automobile Propre 2020a). To boost market share, the local authorities, such as municipalities, contributed to making EVs more attractive to consumers by offering financial subsidies of a maximum of 5000€ to each driver switching to electric mobility additionally to tax exemption, free parking, and access to bus lanes. Some clients could benefit from additional local incentives from municipalities, such as Ile-de-France, Marseille, and Nice. Since the lack of charging infrastructure still presents a barrier to growth in the EV market, national and local authorities

in France boosted the deployment of this infrastructure by both installing more on-street chargers (e.g. Corri-door project) and offering up to 50% of the cost of the charger for both private and public usage (e.g. ADVENIR project).

While the study on the influence of government policies has received widespread attention in the literature (Hardman 2019; Jenn et al. 2018; Münzel et al. 2019), only limited investigation has been carried out about the potential impact of the charging infrastructure on demand for BEV/PHEV (Morganti et al. 2016). Besides, since the market-booster factors' influence differs significantly between countries, as consumer behaviour varies (Münzel et al. 2019), the French local-based case study is lacking. This paper seeks to fill the gap by assessing the privately-purchased BEV and PHEV market shares, separately, using a fixed-effect and random-effect panel data regressions on a local level in France from 2015 to 2019, taking into account the charging infrastructure deployment of different power speeds (slow chargers with 0-15 kW power, normal chargers with 16-40 kW, fast chargers with 41-80 kW, and ultra-fast chargers with more than 80 kW), and other socio-economic factors. To the best of our knowledge, our study is the first to isolate the impacts of local-level incentives and four charging speeds, on the rate of adoption of BEVs and PHEVs in France.

To address these research gaps, data, gathered for each French department using a variety of governmental and press sources, are used to determine what factors significantly affect BEV and PHEV purchasing activity. Based on the results, this paper ends with policy recommendations for automotive manufacturers, charging infrastructure operators and public authorities to boost both markets.

The rest of this paper is organized as follows. Section 2 presents an extensive overview of econometrics studies on PEV adoption. In Section 3, we describe the data and methodology used. Section 4 details the BEV and PHEV models' regression results, followed by robustness checks in Section 5. Conclusions and policy recommendations are provided in Section 6.

## **2. Literature review**

The study of electric-vehicle adoption using empirical studies has a limited history due to the relatively recent introduction of these types of vehicles on the market. In the following, we identify, based on papers analyzing PEV (BEV and PHEV) adoption in different countries

during various periods, the factors that could boost the market. We will neglect other research papers focusing on AFVs (HEV, FCEV)<sup>1</sup>.

The first article focusing on the PEV market share is Sierzchula et al. (2014). The authors analyzed the relationship between governmental incentives, socio-economic factors, and 30 national electric-vehicle market shares in 2012, using a country-based multiple linear regression analysis. They found financial incentives, charging infrastructure, and the local presence of production facilities to significantly affect a country's electric vehicle market share. Results suggest that charging infrastructure was the strongest related factor to electric vehicle adoption. However, they pointed out that neither financial incentives nor charging infrastructure could ensure high electric vehicle adoption rates. Plötz et al. (2016) analyzed the country-based market shares of both BEV and PHEV market shares in different European countries and state-based PEV stock in the United States using a Pooled OLS regression with data from 2010 to 2014 every year. Their results show that economic factors such as income and gasoline prices are mandatory in analysing policies since they could explain PEV adoption rates variance. Besides, both direct and indirect incentives positively affect PEV adoption, based on empirical PEV market data from the U.S. and Europe. They concluded that the effects of different factors, such as the electricity price, and public charging infrastructure remain open for further research.

Another group of publications used the stepwise linear regression<sup>2</sup> to analyze the PEV adoption. Mersky et al. (2016) analyzed the impact of socio-demographic factors (population, average kilometers travelled), economic factors (income), and EV infrastructure (number of charging points) on the BEV yearly sales in Norway from 2010 to 2013 on both regional and municipal level. The authors excluded financial incentives (tax benefits) since they were offered on a national level, and non-financial incentives (free parking) since data was not available. Results showed that charging infrastructure is the most powerful predictor for BEV sales share. Wang et al. (2017) explored the key factors that promote EVs by using a Partial Least Squares (PLS) structural equation analysis to analyze the BEV and PHEV city-level sales in China, taking into account incentive measures and socio-demographic data between 2013 and 2014. The result shows that the density of charging infrastructure, license fee exemption, no driving restriction, and priority to charging infrastructure construction lands are the four most important factors to promote EVs. This paper recommends that local municipalities or

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<sup>1</sup> AFV: Alternative Fuel Vehicle; HEV: Hybrid Electric Vehicle (could not be charged using an external charger); FCEV: Fuel Cells Electric Vehicle

<sup>2</sup> It should be noted that stepwise linear regression has been criticized for yielding over-confident predictors (Harrell 2001; Münzel et al. 2019)

governments should strengthen the charging infrastructures as preferential policy by solving the problems related to civil construction, grid connections, and smart grids. Hall and Lutsey (2017) zoomed into the role of charging infrastructure deployment, mainly level 2 and DC chargers per capita, and socio-economic factors such as income, financial incentives, and population density, on BEV and PHEV adoption in 15 countries in 2016, using stepwise regression. They concluded that normal and fast charging infrastructure deployment and financial incentives significantly impact both BEV and PHEV market shares. Slowik and Lutsey (2017) analyzed BEV and PHEV sales data from 200 U.S. areas for 2016 using a stepwise multiple linear regression analysis. They showed that financial incentives, charging infrastructure deployment, and the variety of PEV models are the most critical factors for PEV adoption. Similarly, after analyzing the BEV sales of the U.S. states in 2013, Jin et al. (2014) concluded that state electric vehicle incentives, carpool lane access, and emission testing exemptions play a significant role in reducing the effective cost of ownership and drive electric vehicle sales. Vergis and Chen (2015) examined the correlation between social, economic, geographic, and policy factors on both battery and plug-in hybrid electric vehicle adoption across U.S. states in 2013. After applying a stepwise regression on state-level PEV market shares, their results showed that the significant variables are the consumer attribute variables (education, awareness of electric vehicles), geographic variables (average winter temperature, population density), variables related to the cost of energy (gasoline and electricity costs) and the ability to access charging infrastructure away from home. The variables that significantly influence PHEV market shares are market characteristics (the number of available PHEV models), incentives (financial and non-financial incentives), and average winter temperatures.

The third group of papers took advantage of their data's panel structure and built a panel data regression considering the temporal evolution. Gallagher and Muehlegger (2011) applied time and state fixed effects on BEV sales per capita on a quarterly U.S. state-level from 2000 to 2006, taking into account different socio-demographic (mean age, female percentage, education level), and economic (income, gasoline prices, incentives) variables. They found evidence that hybrid vehicle adoption is positively affected by incentives, income, and gasoline prices. Clinton and Steinberg (2019) applied the same model by adding charging infrastructure and electricity price covariates on the BEV sales per capita of the U.S. states between 2010 and 2015. Their findings indicate incentives offered as state income tax credits do not have a statistically significant effect on BEV adoptions. Jenn et al. (2018) found that financial incentives have a significant and positive effect PEV sales after analyzing monthly U.S. state-

level data for 2010 to 2015, including fixed effects for time-varying, regional, and vehicle model-specific factors, using a Generalized Method of Moments (GMM) to estimate their regression. Also, they included a lagged-dependent variable to account for suspected endogeneity in their model. Endogeneity could be present due to a higher motivation for governments to incentivize PEVs in states where their demand is already higher. Wee et al. (2018) analyzed semi-annual state-level newly registered EV by make, from 2010 to 2015, and state-level policies using a panel data regression. They pointed out that an additional 1000€ of subsidies could increase sales by 5 to 11%. Based on quarterly EV sales and charging station deployment in 353 metropolitan areas in the U.S. from 2011 to 2013, S. Li et al. (2017) found that sales incentives substantially affect EV sales. Also, results showed that the effect would be more significant if the subsidy had been directed toward charging infrastructure instead. Soltani-Sobh et al. (2017) conducted a cross-sectional/time –series panel analysis on the EV sales in the U.S. from 2003 to 2011, using socio-demographic (degree of urbanity, vehicle mileage travelled) and economic (income, gas prices, electricity prices, financial incentive) factors. The results showed that electricity prices were negatively associated with EV adoption, while urban roads and government incentives positively affected states' electric vehicle market share. Plötz et al. (2017) analyzed data on yearly PEV sales from 30 European countries from 2010–2016 using a panel data regression, controlled for several other influencing factors such as income and fuel prices. They concluded that income, diesel prices, and both direct and indirect subsidies influence PEV adoption positively. Using a fixed-effects regression model, X. Li et al. (2017) studied the impacts of seven factors on EV densities from fourteen countries between 2010 and 2015. The authors found that the percentage of renewable energies in electricity generation, the number of charging stations, the education level, the population density have apparent and positive impacts on the demands, contrary to the GDP per capita and urbanization. The gasoline price affects the demands for BEVs (battery electric vehicles) more than that for PHEVs (plug-in hybrid electric vehicles). Münzel et al. (2019) reviewed econometric studies on the effect size of purchase incentives and analyzed data on PEV sales from 32 European countries from 2010 to 2017 using panel data regression. They used as control variables both monetary and non-monetary incentives, socio-economic variables, such as electricity and diesel prices, and slow and fast charging infrastructure. They found that energy prices and financial incentives influence PEV adoption positively.

To sum up, we completed and adapted the literature review table provided by Münzel et al. (2019) in Table 1, by adding the articles of (X. Li et al. 2017; Münzel et al. 2019; Soltani-

Sobh et al. 2017) and by eliminating the articles discussing the evolution of EVs that could not be charged using an external charger, such as HEV and FCEV. Table 1 summarises the discussed papers, their case studies (countries, period), methodologies, datasets, and the used control variables. We found that the independent variable is generally measured by the PEV market share and is analyzed using a variety of regression models such as OLS, panel, and stepwise. Various social, demographic, economic, and technical control variables were used, primarily monetary and non-monetary incentives, income, energy prices, population density, and charging infrastructure deployment. While many articles in the literature zoomed into the impact of different covariates, the research gap, which we will try to fill in this paper, remains on the influence of different power charging infrastructure deployment on PEV adoption in France, on a department<sup>3</sup>-level approach and using a panel data regression. We also aim to evaluate how the studied factors vary between the BEV and PHEV markets.

### **3. Data and methodology**

#### **3.1.Data**

Our study is based on various datasets, gathered from different sources, in order to estimate the influence of different socio-techno-economic factors on the BEV and PHEV market shares. In this section, we detail the data used as explanatory and response variables for these models. We collected this dataset from different sources for the 95 French departments, from 2014 to 2019. Table 3 contains the summary statistics of the data used in our study, as well as the sources, and the name and description of the variables used in the model.

##### **3.1.1. Dependent variable: BEVs and PHEVs market shares**

To address the PEV adoption trend in French regions, we based ourselves on the yearly car registration shares of both BEVs and PHEVs in 95 departments in France from 2015 to 2019 (French Ministry of Ecological Transition 2020). It should be noted that we discarded five overseas departments (in French, *départements d'outre mer*)<sup>4</sup>. We were only interested in PEV market shares of privately-purchased vehicles and neglected other types of vehicles such as taxis. The collected dataset is balanced without any missing values in any years and departments. Figure 1 in Appendix A provides an overview of both BEV and PHEV market

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<sup>3</sup> In the administrative divisions of France, the department (*département*) is one of the three levels of government under the national level, between the administrative “regions” and the “communes”. France is composed of 13 regions, 95 departments, and 34670 communes.

<sup>4</sup> The five overseas departments excluded from our study are: Guadeloupe, French Guiana, Martinique, Mayotte and La Réunion.

share evolutions in the French departments, from 2015 to 2019. The BEV market share's evolution varies from 1% to more than 12%, and for the PHEV market share fluctuates from 0% to more than 7%.

Table 1 Overview of econometric studies presented in the literature review (adapted from (Münzel et al. 2019))

Author (Year)	Observations	Time resolution	Vehicle Type	N	Method	Dependent variable	Covariates																	
							Financial incentives	Non-Financial incentives	Charging infrastructure (Private)	Charging infrastructure (Public)	Charging infrastructure (Workplace)	Income	Education	Gasoline price	Electricity price	Population density	Mileage	Unemployment rate	Percentage of female	Environmentalism	Number of available vehicles models	Renewable Energy production		
Clinton & Steinberg (2019)	United States (State level)	2010-2015, Monthly	BEV	3864	Fixed Effect panel data regression	Sales per capita	NA	-	+	+			+	+	+	-				+	+			
Jenn et al. (2018)	United States (State level)	2010-2014, Quarterly	PEV	18644	Fixed Effect panel data regression/LDV Model with GMM estimator	Absolute sales	NA	NA																
Jin et al. (2014)	United States (State level)	2013, Yearly	BEV	50	Stepwise linear regression	Sales share	0	0	0	0			+											
Gallagher & Muehlegger (2011)	United States (State level)	2000-2006, Quarterly	PEV	4630	Fixed Effect panel data regression	Sales per capita	+						+	+	+						+			
Hall & Lutsey (2017)	15 countries	2016, Yearly	PHEV, BEV	350	Stepwise linear regression	Sales share	0		0	0							0							
Li et al. (2017)	United States (Metro areas)	2011-2013, Yearly	PEV	14563	OLS and GMM regressions	Absolute sales	+		+	+			+		+						+			
X. Li et al. (2017)	14 countries	2010 to 2015, Yearly	PHEV, BEV	84	Fixed Effect panel data regression	EV density				+		NA	+	+		NA								+
Mersky et al. (2016)	Norway (Municipality level)	2000-2013, Yearly	BEV	163/20	Stepwise linear regression	Sales per capita	0	+	+	+		NA					-	NA						
Munzel et al. (2019)	A global review and 32 European countries	2010 to 2017, Yearly	PEV	189/226	Fixed Effect panel data regression	Sales share	+					+		-	+									
Plotz et al. (2016)	12 European countries and the United States	2010-2014, Yearly	PEV	35/125	Pooled OLS regression	Sales share and Stock per capita	NA	+		+		NA		+	-									
Sierzchula et al. (2014)	30 countries	2012, Yearly	PEV	30	Pooled OLS regression	Sales share	+			+		-	+	-	-	+					+	+		
Slowik & Lutsey (2017)	United States (State level)	2016, Yearly	PHEV, BEV	200/50	Stepwise linear regression	Sales share	0	0		0	0												0	
Soltani-Sobh et al. (2017)	United States (State level)	2003 to 2011, Yearly	PEV	171	Fixed and random Effect panel data regression	Sales share	+					+		+	-	+	+							
Vergis & Chen (2015)	United States (State level)	2013, Yearly	PHEV, BEV	50	Stepwise linear regression	Sales share	+	+		+			+	+	-	+	-				+	+		
Wang et al. (2017)	China (City level)	2013-2014, Yearly	PHEV, BEV	41	Stepwise linear regression	Sales per capita	0	0		+		0												
Wee et al. (2018)	United States (State level)	2010-2015, Yearly	PHEV, BEV	1952-4287	Multi-level Fixed Effect regression	Absolute sales	+	-		-		+		+	-	+	+							

« + » positive impact, « - » negative impact, « NA » Not Available impact, « 0 » not reported  
 Colors indicate the significance level: 'light grey': low significance, 'grey': modest significance, 'dark grey': high significance, 'white': no significance  
 Adapted from: (Münzel et al. 2019) by adding the articles of (X. Li et al., 2017; Münzel et al., 2019; Soltani-Sobh et al., 2017) and by eliminating the articles discussing the evolution of Hybrid EV (HEV) and Flex-Fuel Vehicles (FFV).

### 3.1.2. Technical factors

To investigate the effect of the recent deployment of charging infrastructure on PEV adoptions, we collected the number of semi-public and public chargers per department and per power from the official French data website (French data official site 2020). Unfortunately, we did not have the installation date for every charging station. Therefore, in order to build the backward evolution trend of the infrastructure deployment from 2014 to 2018, we applied the percentage increase, collected from (EAFO 2020), equally to these departments. Chargers with 0-15 kW power are considered as *slow*, with 16-40 kW as *normal*, with 41-80 kW as *fast*, and more than 80 kW as *ultra-fast*.

For the results section, it should be noted that chargers, with different powers, do not share the same price, charging tariffs, or availability. Table 2 details the charger's price, the tariffs, and the charging durations and fees for a 50-kWh BEV and a 17-kWh PHEV.

Table 2 Charging costs of different charging powers (Source: chargemap.com)

					<i>50 kWh BEV</i>		<i>17 kWh PHEV</i>	
<b>Charging speed</b>	<b>Charging power</b>	<b>Charger's price</b>	<b>Availability</b>	<b>Charging pricing system</b>	<b>Charging duration</b>	<b>Charging fees</b>	<b>Charging duration</b>	<b>Charging fees</b>
<b>Slow charger</b>	3-7 kW	2000€	At-home, on-street ( <i>Cities</i> )	1 €/hour sometimes free	11 hours	11 €	4 hours	4 €
<b>Normal charger</b>	22 kW	4000€	On-street, points of interest (supermarkets), ( <i>Cities</i> )	1.5€/first hour 0.2€/min after	2.7 hours	20 €	0.9 hours	1.2 €
<b>Fast charger</b>	50 kW	25000€	On-street, points of interest (supermarkets), ( <i>Cities</i> )	2€/access 0.4€/min	1.2 hours	25 €	0.4 hours	10 €
<b>Ultrafast charger</b>	150 kW	40000€	<i>Highways</i>	4€/access 0.8€/min	0.4 hour	30 €	0.15 hour	12 €

### 3.1.3. Economic factors

As mentioned in the literature review, several economic factors could stimulate PEV purchasing activity. First, financial incentives, such as local subsidies, could help overcome the vehicle's high cost (Slowik and Lutsey 2017). In our case, French departments have established different consumer incentives for adopting EVs. Information on local subsidies was gathered from departments and municipalities' websites and press reviews to provide as much accuracy as possible. These local financial incentives vary between 0€ and 5000€, based on the department and the year. We consider that a consumer purchasing a PHEV could benefit up to

50% of the incentives given to BEV adopters. Since the French government offered additional direct subsidies to PEV adopters equally on the territory, we did not take into account these national incentives. Additionally, BEVs are exempt from either 50% or 100% of the total registration fee in specific departments during this study period. The difference between BEV and ICEV registration fees is considered in our study. This difference can be understood as the tax benefit of purchasing a BEV and will capture the monetary savings in taxes of a BEV compared to a conventional vehicle. We gathered this data from various sources, including press articles (Le Figaro 2015, 2016, 2017, 2018, 2019). Registration fee exemption for PHEV adopters depends on the emissions cap of each vehicle. Since we do not know the distribution of PHEVs that are exempted per department, we decided not to consider this incentive for PHEVs. No reliable source was found for other local monetary and non-monetary incentives (free parking, access to restricted traffic zones, access to bus lanes), making it impossible to include them in our study.

Previous research suggests that energy costs played a crucial role in boosting the PEV purchasing activity and were found to affect switching into electric mobility firmly (Gallagher and Muehlegger 2011; S. Li et al. 2017; Plötz et al. 2016; Vergis and Chen 2015). First, we calculated the yearly average gasoline prices per department using daily gasoline prices that were gathered from the website of the French ministry of economy and finance (French Ministry of Economy and Finance 2020a) for the studied period.

Additionally, we grouped the average amount of income declared per household to the tax authorities from 2014 to 2018 (French Ministry of Economy and Finance 2020b), since, as stated in the literature, it has a significant direct influence on PEV sales (Gallagher and Muehlegger 2011; Jin et al. 2014; S. Li et al. 2017).

Finally, in order to adjust for the effects of inflation/deflation during our period of analysis, we divided all the economic covariates by the GDP deflator, by considering 2015 as the base year (World Bank 2020)<sup>5</sup>.

#### 3.1.4. Socio-demographic factors

As described in the literature review section, socio-demographic factors could influence the adoption of PEVs, namely age, sex, education level, population density, and

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<sup>5</sup> The GDP deflator measures the change in prices for all goods and services in an economy. Constant prices are obtained by dividing nominal prices (the prices in a given year) to the GDP deflator (for a base year). Then, constant prices reflect the value of goods, with respect to a base year, correcting by the effects of inflation.

environmentalism (Clinton and Steinberg 2019; S. Li et al. 2017; Soltani-Sobh et al. 2017; Vergis and Chen 2015). Thus, we gathered socio-demographic data from the official French data website, for every department, to study their impact on departmental PEV adoption: the population density (INSEE 2020a), the average age (INSEE 2020b), and the average unemployment rate (INSEE 2020c).

Besides, we included a public availability factor, measured by the number of available BEV and PHEV models, which could significantly impact the PEV sales (Sierzchula et al. 2014; Vergis and Chen 2015).

Table 3 Summary statistics of covariates

Variable	Variable description	Years	Unit	N	Mean	St. Dev.	Min	Max	Sources
<i>Dependent variables</i>									
$PEV_{ms\ BEV}$	BEV market share	2015-2019	-	475	0.014	0.005	0.002	0.045	(French Ministry of Ecological Transition 2020)
$PEV_{ms\ PHEV}$	PHEV market share	2015-2019	-	475	0.004	0.003	0.0004	0.023	
<i>Socio-demographic Covariates</i>									
$d_{population}$	Population density	2015-2019	People/km <sup>2</sup>	475	587.326	2449.442	15	21014	(INSEE 2020a)
$age$	Average age	2015-2019	-	475	42.29	2.67	35	48	(INSEE 2020b)
$unemployment_{rate}$	Unemployment rate	2015-2019	-	475	8.9	2.165	5.05	22	(INSEE 2020c)
<i>Availability Covariates</i>									
$nb\ models_{BEV}$	Number of available BEV models	2015-2019	-	475	21	4,152	18	29	(Avem 2020)
$nb\ models_{PHEV}$	Number of available PHEV models	2015-2019	-	475	28.2	12.573	16	52	
<i>Economic Covariates<sup>6</sup></i>									
$subsidies_{BEV}$	Subsidies for purchasing a BEV	2015-2019	€	475	672	1432	0	5000	(Automobile Propre 2020b; Beev 2019; Charente Libre 2016; CompteCO2 2015; Nicematin 2017)
$subsidies_{PHEV}$	Subsidies for purchasing a PHEV	2015-2019	€	475	336	716	0	2500	
$diff_{taxes}$	Difference in registration taxes	2015-2019	€	475	35	40.6	0	51	(Le Figaro 2015, 2016, 2017, 2018, 2019)
$p_{gasoline}$	Gasoline price (SP95)	2015-2019	€/l	475	1.416	0.071	1.302	1.759	(French Ministry of Economy and Finance, 2020)
$income$	Average amount of income declared per household	2014-2018	€	475	24461.35	3751.4	19249	44794	(French Ministry of Economy and Finance 2020b)
<i>Technical Covariates</i>									
$d_{slow\ chargers}$	Slow chargers density	2014-2018	charger/km <sup>2</sup>	475	0.103	0.786	0.001	11.61	(EAFO 2020; French data official site 2020)
$d_{normal\ chargers}$	Normal chargers density	2014-2018	charger/km <sup>2</sup>	475	0.033	0.114	0.001	1.381	
$d_{fast\ chargers}$	Fast chargers density	2014-2018	charger/km <sup>2</sup>	475	0.002	0.007	0	0.076	

<sup>6</sup> The deflator is considered in the economic covariates

### 3.2. Methodology

Based on the literature, we chose the panel data regression for the analysis of PEV adoption<sup>7</sup>. This methodology provides various benefits and overcomes some limitations related to time-series and cross-section studies (Kennedy 2003). Panel data overcome unobserved heterogeneity between departments, resulting from the variation of some unmeasured factors that affect people's behaviour in different departments and reduce the problem of multicollinearity. Also, panel data generate more variation between multicollinear variables by combining the variation across departments with variation over time (Soltani-Sobh et al. 2017). Both fixed-effects and random-effects are used to estimate the BEV (with one-way error components) and PHEV market shares (two-way error components). The one-way fixed-effects regression defines unobservable specific effects for each department studied, and therefore, captures variances within departments. It also considers the influence and the significance of each explanatory covariates over time, averaged across all the departments in the dataset (Stock and Watson 2003). The two-way fixed effects regression not only defines unobservable specific effects for each department, but also for each year. We also conducted a random-effects model, which considers variation across different departments and/or years. These intercepts are considered a part of the error term.

Since the logarithmic form is highly recommended when the dependent variable is a percentage because it ensures the residuals' normality (Sprei, 2018; Wooldridge, 2012), we studied the logarithmic form of the new registered BEV and PHEV market shares for the different departments in France. Our analysis accounts for infrastructure availability because users will not buy vehicles they cannot recharge. However, charging infrastructure operators await a meaningful market share of vehicles so that charging stations become a profitable business. This is called “the chicken-egg electric mobility problem”, where each party awaits the other before acting. To avoid endogeneity problems coming from the simultaneity between PEV market shares and the installation of charging infrastructure, we studied the influence of the lagged form of charging infrastructure departments densities of slow-and-normal speed combined, fast and ultrafast speeds on BEV/PHEV market shares. In other words, we consider the effect of charging infrastructure densities for the year ‘ $t-1$ ’ on the market shares of the year

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<sup>7</sup> Using the ‘plm’ package of R (Croissant et al. 2020)

' $t$ '. Thus, charging densities, in chargers/km<sup>2</sup>, for each lagged year (i.e., 2014 to 2018) are considered. We transform the slow-and-normal chargers' density to the logarithmic form in order to linearize the model. To avoid the loss of observations with zero values, we transformed the fast and ultrafast chargers densities using  $\ln(x + \sqrt{1 + x^2})$  (Busse et al. 2010). We denote such transformations as  $\tilde{d}_{fast\ chargers}$  and  $\tilde{d}_{ultra-fast\ chargers}$  for the fast and ultrafast chargers' densities, respectively. In addition, we added the subsidies for BEVs/PHEVs, respectively, and the difference in taxes, which are measured in Euros/BEV for every department. We include the number of available models for BEVs and PHEVs to capture the influence of PEV availability on purchase. Gasoline price is included in €/litre. Our model also investigates the impact of socio-demographic-economic factors: income (in thousands of Euros) for the year ' $t-1$ ', the population density in people/km<sup>2</sup>, the average age of the population, and the unemployment rate.

We used department-fixed effects, and random effects panel data regressions to analyze the impact of charging infrastructure deployment and other socio-economic factors separately on both BEV and PHEV market shares, per department in France, from 2015 to 2019. Equation (1) describes the model:

$$\begin{aligned} \log(PEV_{i,t,z}) = & \beta_1 \log(d_{slow,normal\ chargers_{i,t-1}}) + \beta_2 \tilde{d}_{fast\ chargers_{i,t-1}} + \beta_3 \tilde{d}_{ultra-fast\ chargers_{i,t-1}} + \beta_5 subsidies_{i,t,z} \\ & + \beta_6 diff\ taxes_{i,t,z} + \beta_7 nb\ models_{t,z} + \beta_8 p_{gasoline_{i,t}} + \beta_9 income_{i,t-1} + \beta_{10} d_{population_{i,t}} + \beta_{11} age_{i,t} \\ & + \beta_{12} unemployment_{i,t} + \gamma_{i,z} + \mu_{t,z} + \varepsilon_{i,t,z} \end{aligned} \quad (1)$$

Observations in our sample are Independent and Identically Distributed<sup>8</sup>, the subscript  $i$  denotes the department (from 1 to 95),  $t$  denotes the year (from 2015 to 2019), and  $z$  denotes the vehicle type (BEV or PHEV).

For each variable, we determined the regression coefficients  $\beta$ . The term  $\gamma_{i,z}$  corresponds to the department fixed effect, while  $\mu_{t,z}$ , represents the year fixed effect (which only applies for  $z = PHEV$ ).  $\varepsilon_{i,t,z}$  is the random disturbance term.

#### 4. Results

As previously shown in Equation (1), we applied department-fixed effects (plus year-fixed effects on the PHEV model) and random effects regression models on both BEV and

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<sup>8</sup> The errors are Independent and Identically Distributed if they meet the following two criteria: (1) Independence: The errors are independent, which implies that there is no correlation between consecutive residuals in time series data. (2) Homoscedasticity: The errors have constant variance conditional on the explanatory variables.

PHEV market shares. The results are presented separately for the BEV (Section 4.1) and PHEV models (Section 4.2). It should be noted that the number of models and the subsidies covariates depends on the vehicle type, and the difference in registration taxes covariate is omitted from the PHEV model.

Looking at relationships between individual variables can help to highlight dynamics that are not evident in linear regression models. Table 5 in Appendix B contains the correlation coefficients of all variables. The largest cross-correlation coefficient among a pair of independent variables is 0.929 (between the different charging infrastructure densities). We confirm the severity and magnitude of multicollinearity between the different charging infrastructure variables by considering the size of the Variance Inflation Factor (VIF). To correct for multicollinearity, we used the logarithmic form of a variable that groups both the densities of slow-and-normal charging infrastructure. The absence of severe collinearity is then established, resulting in VIF values below 5.0, indicating our explanatory variables' independence. Besides, we suspect the presence of heteroscedasticity in our models. Based on the studentized Breusch-Pagan test, we reject the null hypothesis that standard errors are homoscedastic<sup>9</sup>. Since we have lagged variables in our model, we analyze for the presence of autocorrelation by performing the Breusch–Godfrey test for serial correlation in panel models. Test results conclude for the presence of autocorrelation in both BEV and PHEV models<sup>10</sup>. Hence, in what follows, we report the heteroscedasticity and autocorrelation robust standard errors. Therefore, multicollinearity, heteroscedasticity, and autocorrelation problems are corrected for both BEV and PHEV models. Also, in order to decide between Pooled OLS or fixed-effect, and Pooled OLS or random-effect models, we applied several statistical tests. Based on the Lagrange-Multiplier test and the F test of individual effects, we reject the null hypothesis to adopt the Pooled OLS model (p-value close to 0 for BEV and PHEV models)<sup>11</sup>.

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<sup>9</sup> Studentized Breusch-Godfrey test results: p-value = 0.002203 for the BEV model; p-value = 0.04841 for the PHEV model.

<sup>10</sup> Breusch–Godfrey test results: chisq = 84.016 and p-value < 2.2e-16 for the BEV model; chisq = 67.993 and p-value = 2.679e-13 for the PHEV model.

<sup>11</sup> Lagrange multiplier test results for pooled versus random effects model: chisq = 545.01, p-value < 2.2e-16  
F test results for pooled versus fixed effects: F = 19.273, p-value < 2.2e-16

#### 4.1. BEV model regression

We perform department-FE and RE regressions, with one-way error components<sup>12</sup>, including different social, demographic, technical, and economic factors to estimate their impact on BEV market shares. Table 4 displays the results of these models.

The FE model (model 1) presents high goodness-of-fit measure ( $R^2 > 63\%$ , F-statistic  $> 57$ ), representing a high explanatory power of our models. The variables that have a positive and significant effect on the  $\log(BEV_{ms})$  are ultrafast charging density, subsidies, the difference in registration taxes, the number of BEV models, and gasoline price. Therefore, an increase in these covariates is associated with an increase in the BEV market share. Income, the population density, the average age, the unemployment rate, and slow, normal, and fast chargers' densities have no significant effect on BEV adoption.

The relationship between the economic factors and the market share, namely subsidies, the registration tax exemption, and the gasoline price, is as expected. To clarify, a person receiving up to 5000€ subsidies, additional to the 5000€ national subsidies, and paying zero registration fees has a higher chance of purchasing a BEV. Besides, since higher gasoline prices increase the trip cost of ICEVs and decrease the utility of this type of vehicle, they could potentially motivate consumers to switch to BEVs, leading to lower traveling costs and higher market shares.

Additionally, the  $\beta$  coefficient on the number of BEV models available on the market, corresponding to the availability factor, is positive and statistically significant at a 1% level. Providing a variety of models on the market by the automotive industry will enhance the client's availability and, consequently, result in higher BEV sales.

Regarding the charging infrastructure deployment, we studied the impact of the lagged and logarithmic form of the public charging infrastructure densities on the  $\log(BEV_{ms})$ . Only ultrafast power coefficient was statistically significant at a 1% level with a  $\beta$  coefficient of 4.59, meaning that an increase of 1 percentage point in ultrafast chargers will lead to an increase of 4.59 percentage points in the BEV sales in the following period. Since slow, normal, and fast chargers are generally available in cities, regression results, in Table 4 show that BEV adopters

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<sup>12</sup> We test for time fixed effects by adding a time trend to the model and using the F-test for individual panels. The null hypothesis states that no time effect is needed. Tests results show that for the BEV model no time effect is needed (F-test:  $F = 2.5753$ ,  $p\text{-value} = 0.05$ ). We also performed the Breusch Pagan LM two-sided test for balanced panels and confirmed the previous results (BEV model:  $\text{chisq} = 0.583$ ,  $p\text{-value} = 0.4451$ ).

are mainly equipped with at-home chargers, since chargers installed in cities have no significant effect on the BEV adoption activity. Alternatively, ultrafast chargers, located on highways, are a potential solution for long-distance trips, such as holiday trips. Therefore, results show that BEV adopters are convinced by ultrafast charging to solve these types of trips. This result is justified by (EVBox 2020), where most respondents (55 % of BEV drivers) privilege the usage of ultra-fast chargers available on highways.

Regarding the RE model (model 2), it presents high goodness-of-fit measure ( $R^2 > 58\%$ , F-statistic  $> 643$ ), resulting in a high explanatory value of our models. The RE model results are similar to those of the FE model, except for the effect of income, slow-and-normal, and fast charger densities. The income covariate's effect becomes positive and significant on the BEV sales at a 5% level. Interesting results are further concluded regarding the charging network: a one percentage point increase in the deployment of fast chargers (*slow-and-normal chargers*) will lead to an increase of 6.9 percentage points (*a decrease of 0.038 percentage points*) of the BEV sales since it is significant at a 5% (1%) level. The trade-off could explain these results between charging powers and fees is elaborated in Table 3 and among chargers powers located in cities, the drivers are interested in spending the minimum charging duration, even with higher charging fees for fast chargers than lower speeds. For instance, a 50-kWh BEV driver prefers to pay 25€/event for using a fast charger and wait 1.2 hours, compared to paying 20€/event for normal chargers (*11€/event for slow chargers*) and spend 2.7 hours (*11 hours*). These conclusions come in line with the results of a recent European study conducted by EVBox (EVBox 2020), where 46% of PEV drivers are willing to pay more for fast public charging. By comparing the regression coefficients, the influence, in absolute terms, of fast chargers density ( $\beta=6.9$ ) is greater than slow-and-normal chargers density ( $\beta=0.038$ ).

Finally, to decide between fixed or random effects, we ran a Hausmann test where the null hypothesis is that the preferred model is RE. The data does not provide enough evidence to reject the null hypothesis (RE model) at a 7% level (chisq = 18.389, p-value = 0.07298). However, we must acknowledge that RE models' main assumption (the unobserved variables are assumed to be uncorrelated with all the observed variables) is contested in practice. FE models tend to be more convincing for policy analysis than RE (Wooldridge 2016).

#### 4.2.PHEV model regression

Like the BEV model, we perform department- and year-fixed effects and random effects panel data regressions, with two-way error components, including different social,

demographic, technical, and economic factors to estimate their impact PHEV market shares. Table 4 displays the results of both fixed and random effect models. That is, the confidence in explaining the PHEV demand is above 63% for the variables tested. Since different incentives are given to PHEV buyers, it should be noted that the difference in registration taxes is not included in the PHEV model, and the PHEV subsidies account for 50% of those offered to BEV adopters. Additionally, the number of available models covariate accounts for PHEV models only.

The FE model (model 3) presents high goodness-of-fit measure ( $R^2 > 71.7\%$ ,  $F\text{-statistic} > 93$ ). Covariates that significantly impact the PHEV adoption are fast chargers' density, the number of PHEV models, the price of gasoline, and the unemployment rate. The coefficients of the number of models and the price of gasoline are positive. Therefore, an increase in these covariates will result in more PHEV sales. Conversely, an increase in the fast chargers density and/or the unemployment rate has a negative impact on the PHEV sales. Other covariates, such as slow-and-normal charger density, ultrafast charger density, local subsidies, income, population density, and the average age, have no significant effect on the model.

Similar to the BEV model, the regression coefficients for the gasoline price and the number of available models are positive and significant at a 1% and at a 5% level, respectively. Higher gasoline prices increase the travelling cost of an ICEV, resulting in higher PHEV sales since this type of vehicle uses electricity as primary energy besides fossil fuel. Besides, results give evidence that releasing more PHEV models on the market could increase the PHEV market share because of the higher availability for this type of vehicle.

Regarding socio-demographic covariates, the unemployment rate coefficient is negative and significant at a 5% level. Presumably, unemployed people reduce their purchasing power, impacting PHEV sales negatively.

As for the charging infrastructure deployment, only fast chargers' density is significant and negatively affecting PHEV sales at a 5% level. Since a maximum 17 kWh battery could be installed in the PHEV as a second.

Table 4 Regression results of logarithmic form of BEV and PHEV market shares  $\log(\text{PEV})$

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*Dependent variable:*

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	Log BEV Market share		Log PHEV Market share	
	FE (1)	RE (2)	FE (3)	RE (4)
Log Slow-and-Normal Chargers Density	-0.025 (0.015)	-0.038*** (0.010)	0.024 (0.029)	0.101*** (0.011)
Log Fast Chargers Density	5.639 (3.583)	6.939** (2.958)	-5.858** (2.312)	-8.239*** (2.155)
Log Ultra-Fast Chargers Density	4.594*** (1.365)	4.094*** (1.043)	-0.782 (1.417)	-1.450 (1.228)
Subsidies	0.00002* (0.00001)	0.00002* (0.00001)	0.00001 (0.00003)	-0.00004 (0.00003)
Difference in Registration Tax	0.003*** (0.001)	0.003*** (0.001)	-	-
Number of Models	0.028*** (0.003)	0.026*** (0.002)	0.005** (0.002)	0.010*** (0.001)
Price of SP95	0.984*** (0.207)	0.773*** (0.191)	1.941*** (0.387)	2.863*** (0.225)
Income	0.00002 (0.0001)	0.00002** (0.00001)	0.00000 (0.0001)	0.0001*** (0.00001)
Population Density	-0.0002 (0.001)	-0.00001 (0.00001)	-0.0005 (0.001)	-0.00001 (0.00001)
Age	-0.019 (0.028)	0.002 (0.012)	0.006 (0.047)	-0.027** (0.013)
Unemployment	0.005 (0.037)	-0.030 (0.027)	-0.225** (0.089)	-0.004 (0.025)
Constant		-6.627*** (0.988)		-9.931*** (1.020)
Department FE	✓		✓	
Year FE			✓	
Observations	475	475	475	475
R <sup>2</sup>	0.633	0.582	0.717	0.679
Adjusted R <sup>2</sup>	0.528	0.572	0.638	0.672
F Statistic	57.795*** (df = 11; 369)	643.356***	93.847*** (df = 10; 370)	982.905***

Note:

\*p<10%; \*\*p<5%; \*\*\*p<1%

## 5. Robustness checks

We applied different robustness checks, such as omitting nineteen random regions, eliminating the years 2018 and 2019 to analyze the model on early PEV adopters, removing charging infrastructure covariates to identify their impact on our models, and clustering SE by department.

### 5.1. Robustness check 1: Removing random departments

As a robustness check, we examined the impact of omitting random 19 departments on the model; results are shown in Table 5 in Appendix C (models 2, 4, 6, and 8). It should be noted that the coefficients of the panel regression are an estimation of all the studied regions and are equally calculated for all the departments. We conclude that the model is robust since the estimation results of department-fixed effects and random-effects of both BEVs and PHEVs market shares do not significantly change in any coefficients or significance, except for the fast charging density for the BEV and PHEV models and the number of PHEV models.

### 5.2. Robustness check 2: Excluding departments with big cities

As a robustness check, we examined the results when omitting departments where the cities of Paris, Marseille, and Lyon are located<sup>13</sup>. Results are shown in Table 6 in Appendix C (models 2, 4, 6, and 8). We conclude that the model is robust since the estimation results of department-fixed effects and random-effects of both BEVs and PHEVs market shares do not significantly change in any coefficients or significance.

### 5.3. Robustness check 3: Removing 2018-2019 years

To focus on early BEV and PHEV adopters in France, we excluded the 2018-2019 data, 2017-2018 for lagged covariates (models 2, 4, 6, and 8). Results are shown in Table 7 in Appendix C. Regarding the BEV regression model, the coefficients and the control variables slightly changed, contrary to the significance levels that dramatically switched. Nevertheless, the associated  $R^2$  of both FE and RE plummeted, resulting in a non-robust model for early BEV adopters (from 50%-60% for the base model to around 15% for early adopters). For early adopters, the registration taxes exemption had a modest impact on the BEV adoption trend. These findings could be justified by the recent introduction of BEV on the market compared to 2015-2017. Concerning the PHEV regression model, the coefficient and the significance of the control variables additionally to the  $R^2$  modestly changed after excluding the dataset of the years 2018-2019. These findings could be warranted because after the driver's behavior will not significantly change since PHEV and ICEV share the same technological aspect: depending on fossil-fuel as a primary energy, additionally to the early PHEV release date before BEV technology.

In sum, the effect of charging infrastructure deployment and other socio-economic control variables is highly robust for the early adopters in the PHEV model and less robust for

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<sup>13</sup> The departments removed are Paris (75), Bouches du Rhône (13) and Rhône (69)

the early adopters in the BEV model. The reason behind these results could mainly be the customer behavior towards new inventions (BEV), and his/her adaptability with PHEV.

#### 5.4. Robustness check 3: Removing charging infrastructure control variables

As a third robustness check, charging infrastructure control variables were excluded. The results, which are shown in Table 8 in Appendix C (models 2, 4, 6, and 8), showed slight variations in the coefficients and significance of the control variables of the BEV/PHEV regression models. Only a maximum of 2% of the variation in the goodness-of-fit was measured for all the models. While the charging infrastructure variables are essential predictors of BEV and PHEV sales, we can still confidently predict vehicle sales without considering the charging infrastructure densities.

#### 5.5. Robustness check 4: Clustering standard errors by department

We address the potential correlation of standard errors within groups in our data. Clustered standard errors allow errors to be correlated within clusters but not across clusters. Obtaining standard errors without clustering can lead to misleadingly small standard errors, narrow confidence intervals, and small p-values. Appendix C (models 2, 4, 6, and 8) comprised the results of the model with clustered SE in Table 9. Results slightly vary with respect to our base model. Only the coefficient for fast charging infrastructure density in the FE model becomes insignificant. The other variables in our model remain unchanged in the clustered model.

## **6. Conclusions and Policy Recommendations**

### 6.1. Conclusions

The target of this paper is to explore the impact of different socio-techno-economic factors across the PEV adoption activity in 95 French departments between 2015 and 2019 using department-fixed-effects and random-effects panel data regressions. Therefore, based on extensive literature, we gathered different datasets of factors potentially impacting BEV or PHEV sales, from various sources. We then chose to apply panel data models to investigate the evolution of BEV and PHEV purchasing activity separately. This study has different goals: First, we determine which socio-demographic, economic, technical, and availability factors could boost the electric mobility market. Second, we examine if these factors vary between BEV and PHEV markets separately. Third, we zoom into the French case study. Finally, we

identify the charging power with the most significant effect on the BEV and PHEV markets' evolution.

Our BEV and PHEV models present goodness-of-fit measures ( $R^2 > 63\%$ ). The results show that the variables contributing to the BEV market could differ from those of the PHEV market. We find that the densities of fast and ultrafast chargers, the subsidies, the registration taxes exemption, the number of BEV models, and the gasoline price have a positive and significant relationship with the BEV market share, contrary to the slow-and-normal charger density. Similar to the BEV model, the number of PHEV models and the gasoline price positively influence the PHEV market share, and their regression coefficients are significant. However, the density of fast chargers, the population density, and the unemployment rate are significantly but negatively affecting PHEV sales.

Regarding the socio-economic variables, results seem to be coherent with the literature, meaning that factors such as subsidies, taxes and gasoline prices, which have a significant influence on the BEV and PHEV market shares in our model, are similar to those detailed in Table 1. We contribute to this literature by considering the effect of the different charging speeds (slow, normal, fast and ultra-fast charging) in PEV adoption, and by analyzing the case of France using panel data regressions.

While some of the findings of this study were expected and despite the high resolution of our analysis, further studies are suggested in order to boost these models by taking into account other socio-techno-economic factors. Our model can only draw general conclusions since PEV market share in France represents less than 5%. It would be useful to perform a follow-up study in a more developed market. Moreover, we recommend further studies to consider the availability of at-home and at-work charging infrastructures of both the department of residence and work, the tariffs of public charging infrastructure, and the adaptability of charging infrastructure sockets and the vehicles<sup>14</sup>. We further urge upcoming research to account for local non-financial incentives that were not considered due to the lack of data. Additionally, the model does not capture the customer's psychological effect, which could be affected by the marketing campaign of both automotive manufacturers and charging infrastructure operators. The influence of additional electric mobility services are also not considered in our study, namely Vehicle-to-Grid, smart charging, and carsharing. Finally, the relationship between BEV and PHEV market shares are worthy of further study and refinement.

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<sup>14</sup> Some vehicles are not compatible with fast and ultrafast charging technology.

## 6.2. Policy recommendations

Based on the results of the model, this paper ends with providing some policy recommendations for the members of the PEV supply chain: the automotive industry, the charging operator, and government/local authorities.

First, we found that the number of available models on the market is positively correlated to PEV sales. It is recommended for the automotive industry to provide a variety of models on the market of different sizes, battery capacities/autonomies, styles, and designs. Indeed, various choices could increase the awareness towards clients, resulting in buying a BEV/PHEV.

Second, results show that deploying fast and ultrafast chargers could boost the BEV market, contrary to slow-and-normal chargers. Therefore, it is vital to review the charging infrastructure deployment. Charging infrastructure operators should consider a strategic plan while deploying chargers by providing public fast and ultrafast chargers, rather than slow-and-normal speeds. Also, since fast charging negatively affects the PHEV market, these operators should consider revising their charging tariffs/pricing method to attract these customers. We recommend operators provide different charging pricing methods and tariffs, taking into account a variety of BEV and PHEV types, with different battery sizes.

Finally, as discussed before, economic factors present promising opportunities for new policies to achieve low emissions goals. The gasoline price has significant and positive impacts on BEV and PHEV markets. Since economies could be achieved, especially on the cost of traveling if purchasing a PEV, governments should consider gasoline taxes as tools to encourage clients to buy PEVs. Similarly, results show that local subsidies and registration tax exemptions are two important reasons for BEV adoption. Local authorities should revise the subsidies for PHEV new adopters. By modifying these financial incentives and economic factors, local authorities and governments should expand their PEV markets and achieve their road electrification targets rapidly. Besides we recommend local authorities to concentrate their efforts on providing and/or increasing economic incentives (e.g. subsidies) to the instalment of fast and ultrafast public chargers, instead of providing incentives to the instalment of slow-and-normal public chargers.

**Acknowledgements:** The Armand Peugeot Chair in collaboration with Groupe PSA (Peugeot-Citroën), CentraleSupélec Engineering School (Université Paris-Saclay), Laboratoire Genie Industriel (LGI), and ESSEC Business School fund Haidar's thesis under the 'ANRT-CIFRE'

contract #2018/1162. The Université Paris Dauphine-PSL and the Governance Regulation Chair fund Aguilar's thesis under the PhD contract 30/17. We would like to thank Pascal da Costa, Jan Lepoutre, Fabrice Vidal, Yannick Perez, Andreas Markoulidakis, and Adélaïde Fadhuile for their precious help.

**Conflicts of Interest:** The authors equally contributed to this paper regarding study conception and design, data collection, analysis and interpretation of results, and draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript. The funders had no role in study design, data collection and analysis, decision to publish, or manuscript preparation.

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