The Effectiveness of Decarbonizing the Passenger Transport Sector Through Monetary Incentives

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Abstract

Passenger cars account for most road transportation emissions, and over 44% of overall transport sector emissions in the EU; it is the single largest sub-sector contributor among those in transport. Under the various agreements at the European level, countries in Europe have established policies to achieve the necessary reductions in the transport sector. A pair-wise comparison of common passenger vehicles sold in 2017 shows that fiscal incentives are effective at increasing acquisition of electric vehicles (EVs), and among the countries studied for comparison, Portugal and Italy provide the least incentives, and have the lowest targets for penetration of EVs. Acquiring EVs over conventional vehicles (ICEV) contributes to a 56% reduction of overall (well-to-wheel) emissions on a per kilometer traveled basis, based on new vehicle registrations in the EU in 2017, with studies suggesting the average reduction can be as high as 54-65% [1]. The carbon intensity of the electricity used to charge EVs will affect this reduction, and end-user behavior can have a further impact in decarbonization. Using Portuguese public charging data from 2017, a dynamic pricing mechanism dependent only on the hourly evolution of the carbon intensity of the electricity grid is proposed. The responsiveness of the users to the variable price is reflected by the market price elasticity of demand (PED), and the resulting reduction in demand can be approximated from the surcharge. The study finds that the proposed surcharging mechanism can reduce emissions by more than 17 tonnes per year while still achieving profits.
Keywords: *Electric vehicles, carbon intensity, price elasticity of demand, alternative fuels*

1. Introduction

In Europe, almost a quarter of greenhouse gas (GHG) emissions result from the transportation sector [2]. In 2017, 44.5% of overall transportation emissions result from passenger cars [3]. These transport emissions are dispersed, and not specific to a fixed location as can be said for other economic sectors that are primary sources of emissions. With the numerous forms of transportation that can be taken, decarbonization of the transport sector thus relies on technology development, as well as consumer behavior. The Kyoto Protocol set internationally binding emission reduction targets and sets a heavier burden on developed nations to achieve reductions under a principle of 'common but differentiated responsibilities' [4]. The Protocol identified some mechanisms to achieving decarbonization including the establishment of a carbon market (carbon taxes or cap and trade systems). These are often implemented at national levels, affecting businesses and stakeholders immediately below these levels of governance.

A carbon tax is a tax on GHG emissions and gives firms an incentive to reduce pollution; also referred to as a Pigouvian[1] tax. The idea is to impose a cost on negative externalities caused by activities which are not typically reflected in the private cost, such as emitting carbon dioxide into the atmosphere for the production of a good [5]. Another way to control GHG emissions is done through emissions trading systems (ETS). Emissions trading sets a limit on the amount of emissions that can be created across a group of sources such as a country, or sector. Each stakeholder creating emissions in the scope of the emissions trading 'market' is allocated a limit or 'cap' of emissions and can trade these 'rights for emitting'; hence a common way to refer to these mechanisms is as a 'cap and trade' system.

The EU ETS is the world's first major carbon market and remains its largest, operating in the entire EU-28 plus Iceland, Lichtenstein, and Norway [6]. Approximately 11,000 energy intensive installations in the power generation and manufacturing industry sectors are covered by the System representing 45% of the EU's GHG emissions. The EU ETS was established with the goal to achieve 20% reduction of GHG emissions in the entire EU from the base year, and it has already reached this target.

To supplement the ETS, Europe has employed the Effort Sharing Decision (ESD) with binding annual GHG emission targets starting in 2013 addressing sectors not covered in the ETS. Member states have targets which apply toward transport, buildings, agriculture, and waste sectors, thus accounting for the remaining 55% of the EU's GHG emissions, not covered in the ETS [7]. To achieve the desired reductions across the sectors in the EU ESD, the European Commission recommends a shift away from transportation reliant on fossil fuels among other measures. As of 2016 the targets for 2020 under the ESD have already been surpassed by 18 EU Member States, in addition to the 10% reduction in the EU overall [8]. These supra-national measures are a testament to how mechanisms toward decarbonization in the form of Pigouvian taxation (carbon tax), cap and trade systems (like the ETS), and shared commitments and goal-setting (like the ESD) have thus far been successful in achieving the carbon reduction targets established by the EU and should be used at levels below government.

Tax incentives and subsidies can result in tax revenue loss at government levels. At the business level, carrying out initiatives for decarbonization must make economic sense for the business to remain viable; hence the need for effective business models that prioritize environmental considerations and decarbonization, without sacrificing profits. This work contends that government policy and fiscal mechanisms aimed at vehicle electrification for decarbonization of the transport sector have proven to be effective, but as of yet, businesses have been slower to implement mechanisms to incentivize consumer choice toward sustainable behaviors, even though they can prove to be a useful level to implement such mechanisms due to their direct relationship with end-users/consumers. Pigouvian-type mechanisms have not been implemented at the business level because businesses fear losing money, however, this paper demonstrates that this may not be the case under a Pigouvian pricing model imposed on EV charging. Under this theoretical model developed for the Portuguese public charging network, further reduction of EV emissions are achieved, informing consumer behavior toward cleaner energy preferences, and without eroding profits for charging station operators.

The scope of this work considers the passenger vehicle subsector (M1 category vehicles) of the overall transport sector. Although vans (N1 category vehicles) are also a closely related segment of passenger vehicles, they are outside the scope of this work, due to lack of substitutes in these segments. European policies are focused on as resulting from European policies are a high level of transparency and the ability to publicly access large databases for the work across several countries in the EU-28. Portugal is of interest in this study due to the development of their harmonized public EV charging infrastructure while their incentives toward EV acquisition are low.

This work adds to the body of literature by: (i) examining policy and incentives toward the acquisition of EVs utilizing the most up-to-date market data and (ii) proposing a model for the direct coupling of emissions intensity with price in order to influence user behavior and studying its implications to emissions and profits. Chapter 2 discusses the current context of the passenger transport sector policy and market and a literature review of work done on related topics to this work. The data and methods used are presented in Chapter 3. Chapter 4 presents the results and a brief discussion, and Chapter 5 presents the conclusions and implications from a broader perspective.

2. Background and Literature Review

2.1 European Policy Toward Passenger Cars

The main EU legislation toward reducing CO_2 emissions from passenger vehicles is Regulation (EC) No 443/2009 passed in 2009 [9]. This

[1] Named for Arthur Pigou (1877 – 1959) [5].

legislation recognizes the reductions target established with the Kyoto Protocol (1997). The Legislation establishes the target of reaching emissions of 130 g CO_2/km for the average of the new car fleet by 2012. The Regulation improves the monitoring and reporting requirements for EU Member States for the CO_2 emissions of new vehicles purchased every year. Article 8 of the Regulation establishes that on a yearly basis, commencing in 2010, each Member State records and transmits data of vehicles registered within the country over the course of the year, developing a publicly available CO_2 monitoring database which is used in this study [9], [10]. In 2017, the average emissions of new cars sold was 118.5 g CO_2/km, achieving the 130 g CO_2/km target. Since monitoring started in 2010, average emissions across EU vehicle fleets have decreased by 16% [11].

Regulation (EU) No 333/2014 amends the 2009 regulation by setting a target of achieving emissions of 95 g CO_2/km for the average of the new car fleet by 2020, and further clarifies some of the objectives from Regulation (EC) No 443/2009 toward 2020. The amended regulation also recognizes that the lack of alternative fuel[2] infrastructure could be an obstacle to the market uptake of low-emission vehicles and therefore encourages the build-up of infrastructures to "facilitate the work of market forces and contribute to economic growth in Europe" [12]. Regulation (EC) No 443/2009 and Regulation (EU) No 333/2014 contain some of the most relevant and pertinent aspects toward the development of national policies, and thus, the development of the market to what was seen in 2017 vehicle sales.

The Alternative Fuel Infrastructure Directive 2014/94/EU (AFID) on the deployment of alternative fuels infrastructure establishes a regulatory framework for the necessary infrastructure for several alternative fuels to address the barrier laid out in Regulation (EU) 333/2014 regarding the pairing of infrastructure to allow 'market forces' to further the adoption of alternative vehicles. The AFID establishes a target of one EV charging point per every ten EVs by 2020 [13]. Under the AFID National Policy Frameworks (NPFs) are defined by each Member State to outline targets, objectives, and supporting actions for the development of the alternative vehicle market; those pertaining to Plug-in Electric Vehicles (PEV) are shown in Table 1.

and indicate that Portugal estimates to have the lowest share of vehicles, and a high sufficiency of available charging with two vehicles per public charger currently, and at maximum, a projection of under six vehicles per public charger.

2.2 Passenger Vehicle Market Context

Over 15 million M1 type passenger vehicles were sold in the EU-28, with about 2.9% from alternative fuel vehicle (AFV) purchases, and over 224,000 EVs were sold including battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs) [10]. Globally, over one million EVs were purchased in 2017, crossing the three million EV mark of the overall car stock. Figure 1 demonstrates how the 2017 vehicles purchased within the selected countries is split between internal combustion engine vehicles (ICEV) and AFVs.

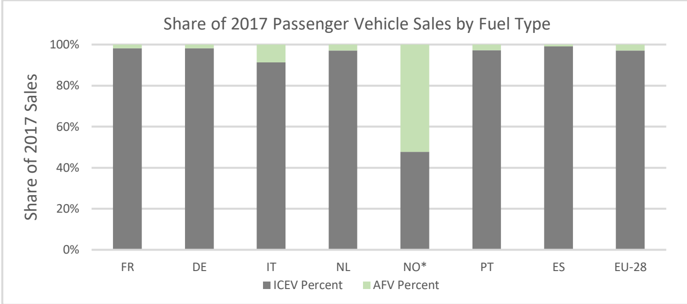

*Figure 1. Shares of passenger vehicle sales between ICEVs and AFVs (*Note: Norway is not included in the EU-28) [10], [15].*

The International Energy Agency (IEA) New Policies Scenario[3] projects that the number of electric light-duty vehicles on the road will reach 125 million by 2030 [14]. AFVs of all types are identified under European policy as a means of reducing emissions from the transport sector, and this, in part, helps to remain technology neutral and promote a wide variety of technical solutions toward reducing carbon emissions, and thus an overall landscape of AFVs has been presented. The remainder of this work focuses on electric vehicles.

2.3 Literature Review

2.3.1 Effectiveness of emissions reductions

Research on vehicle electrification has identified how the replacement of an ICEV with an EV leads to emission reductions illuminating the importance of EV acquisition. By reviewing the Well-To-Wheel (WTW)[4] emissions of EVs versus ICEVs, the reduction in air pollution (through the elimination of TTW/tailpipe emissions) is immediately realized. Capturing the entire WTW emissions is done by Kromer and Heywood (2007), where they compare the WTW emissions of several vehicle technologies based on current available technologies, and technologies that will be available in 2030, demonstrating how EVs can lead to reductions in GHG emissions from 54-65%[5] on a per-km basis [1]. The WTT emissions of conventional fuels (petrol and diesel) is quantified by a JRC study by Edwards et al. (2014) demonstrating that WTT emissions of petrol and diesel equate to 13.67 g CO_2/MJ and 15.28 g CO_2/MJ, respectively (in terms of Mega Joules of the final fuel produced) [16].

2.3.1 EV Charging Optimizations and Models

Optimizing EV charging can have an impact on the profit, emissions, and strain on the electric system. A common theme in these studies is the need (as well as difficulty) of quantifying transport behavior. Driving behavior, stochastic demands, and/or driving requirement as it impacts EV charging is discussed or is a component in several studies [17]–[22]. Concerning the technical aspects and grid demands, 'demand response' is a mechanism used by electricity suppliers to engage consumers to shift their electricity demand, typically during peak hours, to reduce stress on the electricity grid [23]. This can be done through variable pricing or rebate mechanisms that penalize or incentivize energy use reduction during peak hours. Shepero and Munkhammar (2017) develop a model

Table 1. Current state and National Policy Frameworks (NPFs) of a few Member States for PEV [13].

Country	Vehicles			Public Infrastructure			
	Current Situation [a]	*Future Estimate*	*Future Share (%)*	*Current Situation* [a]	*Target*	*Current Sufficiency*[b]	*Projected Sufficiency*
France	*118,663*	*960,000*	*2.19*	*16,081*	*35,000*	*7.38*	*27.43*
Germany	*87,914*	*1,000,000*	*2.14*	*18,078*	*43,000*	*4.86*	*23.26*
Italy	*11,663*	*45,000-130,000*	*0.11-0.32*	*2,205*	*6,500-19,000*	*5.29*	*6.92-6.84*
Netherlands	*115,502*	*140,000*	*1.47*	*10,400*	*17,844*[d]	*6.47*	*7.85*
Norway[c]	*212,705*			*11,195*		*19*	
Portugal	*2,258*	*14,000*	*0.23*	*1,126*[d]	*2,394*	*2.01*	*5.85*
Spain	*12,883*	*38,000-150,000*	*0.14-0.54*	*1,754*	*-*	*7.34*	

[a] From EAFO, 2017
[b] Reaching the stated target of a maximum of 10 PEVs per charging position
[c] Norway not in EU and thus no NPF is submitted. All data is from EAFO database, 2018
[d] Public network only

[2] Alternative fuel describes any fuel other than petrol or diesel (referred to as 'conventional fuels') for powering motor vehicles such as natural gas (NG), methanol, liquefied petroleum gasoline (LPG), or electricity.
[3] Considers announced policies as well as existing ones.
[4] Common accounting methodology for capturing emissions from Well-to-Tank (WTT), or the emissions from production, refining, transport, and distribution of a fuel (conventional or electricity), and Tank-to-Wheel (TTW) which are tailpipe emissions resulting from the vehicle's power-train technology [63].

[5] The study, "*Electric Powertrains: Opportunities and Challenges in the U.S. Light-Duty Vehicle Fleet*", measured GHG emissions on a WTW basis of powertrain types at the time of study (2006) and projections for performances (2030) of BEVs, HEVs, Diesel, and ICEVs. The study resulted in equivalent carbon emissions of the following: 2006 ICE = 251.7 g CO_2/km; 2006 BEV = 115.6 g CO_2/km; 2006 HEV = 87.3 g/km.

for the charging load profiles to generate EV charging data for grid studies and planning by using data from several charging stations in Sweden. On average, users charge more than the average daily Swedish driving distance in a typical charging session, indicating the ability to charge less [19]. Mullan et al. (2011) studies the impact of EV loads on the electricity grid in Western Australia demonstrating that structured tariffs and demand management to alter charging behaviors will achieve significant benefits [24].

With regard to economic and cost considerations, Aabrandt et al. (2012) utilizes fleet tracking data to develop a prediction model to minimize charging costs based on hourly electricity prices for proposed smart charging algorithms [20]. Hu et al. (2011) proposes an approach to optimize the charging schedule of an EV fleet with the goal of minimizing the cost of charging based on electricity spot price over the course of a typical day [18]. Mohamed et al. (2014) develops a smart charging algorithm that can be implemented at a car park with the target optimization to minimize the total cost of charging by managing the power allocated to each EV [25]. Dong and Lin (2012) examine the impact of public charging infrastructure on PEVs demonstrating that a more mature public charging infrastructure further increases energy cost savings for plug-in hybrid electric vehicle (PHEV) drivers [21]. Goebel (2013) identifies the 'business value' or savings potential that electricity retailers can realize by utilizing information and communication technology (ICT) to implement controls on PEV charging in California [26]. Luo et al. (2018) discusses the issues with stochastic dynamic pricing and energy demands for EV service providers and proposes a multi-objective optimization framework to determine retail charging prices and the appropriate amount of electricity to purchase from the wholesale market by utilizing a linear regression model to estimate EV charging demands [22].

From an environmental point-of-view, Saber and Venayagamoorthy (2010 & 2011) study the operation of EVs that can provide energy to the electricity grid as well as being a consumer of electricity providing added benefits as 'gridable vehicles' (GV). This capability is modeled in a smart grid utilizing algorithms to optimize the utilization of these GVs and with the focus on reducing emissions and increasing penetration of renewable energy sources (RES) [27] [28]. In addition, some of the referenced studies do mention the integration of renewables when considering optimal charging, however, the focus is usually in regards to permitting the integration of intermittent renewables [22], the integration of photovoltaics in the developed algorithms [25], or the effectiveness that decarbonizing the electric grid would have on reductions through PEVs [21]; as opposed to explicitly optimizing charging for the purpose of reducing emissions as the primary objective.

A common theme among the studies of EV charging is the focus on grid demand and cost, and indeed, several studies address the two together in search of a techno-economic optimal solution. The minority of studies focuses on reducing emissions based on the behavior of a country's electricity grid, and studies in this point of view are more recent (since the 2010s), indicating that it is more recently becoming a focal point.

2.3.2 *Social, Micro-and Macro-economic Factors*

The price elasticity of demand (PED) describes how a party responds to a change in price. Demand is usually negatively affected by price, in that an increase in price corresponds to a decrease in demand. The PED is therefore calculated as the percent change in price divided by the percent change in demand.

$$PED = \frac{\%\ change\ in\ demand}{\%\ change\ in\ price} \tag{1}$$

Several uncertainties can affect the PED in terms of electricity demand for EVs, and people face limitations in their decisions for charging which correspond to 'bounded rationality'[6] as originally described by Simon (1955) [29]. Koroleva et al. (2014) is currently aiming to capture how EV charging behavior would shift through a theoretical experiment (using stated preference data), aiming to quantify the PED of electricity for EVs under a flat tariff, time-of-use tariff, and a real-time tariff[7] [30]. The study identifies some key uncertainties facing consumers that affect the PED including: price uncertainty, range anxiety, travel need uncertainty, and social influence.

Real-time pricing represents a direct and efficient demand response mechanism to shift electricity demand, and in a review by Bloustein (2005) on customer response to variable pricing, the average elasticity is -0.14 for all customers in their electricity usage [31]. Hössinger et al. (2017) studies the PED for fuel demand through a situational stated preference survey; the results of this study indicate that short term elasticities can range from -0.12 to -0.35 and long-term elasticity can range from -0.25 to -0.69[8] [32]. It is thus clear that the PED, even for ICEV fuels which have a long history, is not explicitly agreed upon in the body of literature, an issue that is more pronounced when dealing with newer alternative fuels. Koroleva et al. (2014) hypothesizes that higher uncertainty about future price diminishes the PED in the ongoing experiment being conducted on this topic [30].

Range anxiety[9] and a perceived lack of infrastructure for refueling are barriers toward the acquisition of EVs and influence the charging decision by users. According to a survey conducted by the European Commission (EC) on drivers in Europe[10], range anxiety and lack of infrastructure ranked second and third (after price) as the largest barriers to purchasing an AFV [33]. Studies of user response to range anxiety are limited. Frankie et al. (2012) experimentally studies range anxiety through a field study and survey and the findings suggest that with how developed electric mobility systems are, issues with range are indeed a psychological barrier, and not a technical one. Those in the study stated that they would prefer to have a buffer range of at least 25 km and would frequently charge the car to 'top-up' the battery while on a trip to increase their reserve, even following short trips [34]. These uncertainties about range or availability of refueling infrastructure can affect the choice of whether to charge at a given instance.

Related to range anxiety of the vehicle is the uncertainty of the user's travel needs. On average, Europeans drive between 40 km and 80 km per day and complete 2.9 trips on the high end [35]. The need for immediate gratification as described by Donoghue and Rabin (2000) can explain how users will behave to manage this uncertainty of their need. For small-scale day-to-day decisions, like whether or not to charge an EV at a given instant, the costs of not charging now (including the uncertain future monetary costs as well as the current psychological costs of an uncertainty about range) can be outweighed by the certainty and immediate gratification of charging now and assuring the ability to drive now [36]. Therefore, these affects may be expected to reduce an EV user's PED for electricity.

Social influence is also tied to the influence of behaviors, including those pertaining to environmentally-conscious ones. Kormos et al. (2015) experimentally demonstrates that when individuals are provided messages about the sustainable transportation behaviors of others, the individuals improve their behaviors more effectively than those who are asked to improve transportation behaviors, but are not provided with messages about how others have done with the same task [37]. Social influence occurs for the reasons defined by Herbert C. Kelman (1958) whose work pioneered the understanding of this concept and the reasons for which individuals are influenced by the behaviors of their peers [38]. Price elasticity can therefore be affected by positive or negative information about the performance of peers. Specifically, PED for electricity can be affected if users are aware of their environmental performance compared to their peers.

Accounting for all the above social and macroeconomic considerations toward how users will react toward different signals, the PED can be both increased and decreased by socio-economic factors. Without complete understanding of the PED for electricity for EVs, it is not a fixed input, and the present study does not treat it as such. Therefore, in quantifying how a variable pricing model can affect the 2017 baseline public charging demand, a range of PEDs are explored to understand the sensitivity of

[6] Describes decision-making behavior under three constraints: a limited amount of information, a limited capacity to evaluate each alternative, and a limited amount of time in order to make a decision; thus, decision-makers under 'bounded rationality' choose alternatives that are satisfactory as opposed to globally optimal) [29].

[7] In the study, the terminology used describes 'flat tariff' as constant throughout the day, 'time of use tariff' offers high prices in peak times between 7am and 6pm, and 'real time tariff' the price changes every hour, reflecting the wholesale market price of electricity [30].

[8] Long-term elasticities are typically higher or 'more elastic' because individuals can make other arrangements to accommodate the price increase. For example, in the long-term (>1 year) a fuel consumer can make a decision to purchase a vehicle that is more fuel efficient and require less fuel for the same amount of travel.

[9] Refers to the fear of a limited driving distance.

[10] The survey study was conducted in France, Germany, and Italy which covers almost half of the whole EU population and can be considered mature when it comes to the use of alternative fuels [33].

the realized outcomes toward PED. A range of PEDs is also useful as the author hypothesizes that in the near term the uncertainties described above will lead toward a much more inelastic PED (closer to -0.12) as the infrastructure is being developed and EV technology is being accepted by the public. Whereas in the long term, the author hypothesizes that PEDs will become more elastic (closer to -0.69) as social influence, environmental consequences, ubiquitous infrastructure for charging, and new technologies will become well accepted by the public. Although these hypotheses will not be tested within this study, this premise will be utilized to discuss the results obtained from the model.

3. Data and Methods

3.1 Vehicle Pair Choice Criteria

A pair-wise comparison is utilized to compare the differences across vehicle segments and country markets as demonstrated by Lévay et al. (2017) in a study that was done utilizing data until 2014; henceforth this study will be referred to as LDT for brevity [39]. The comparison of absolute sales of vehicles across multiple segments and countries would not be as useful for comparison because larger and more developed markets that yield more sales cannot be compared with smaller markets to draw accurate conclusions about the effectiveness of the EV acquisition incentives. Further discrepancies can be excluded as described in LDT.

Table 2. EV – ICE vehicle pairs for analysis

EV Vehicle	ICEV Vehicle	Vehicle Segment
Renault Zoe (BEV)	*Renault Clio (Petrol)*	*Small*
Volkswagen e-Golf (BEV)	*Volkswagen Golf (Diesel)*	*Medium*
Nissan Leaf (BEV)	*Honda Civic (Petrol)*	*Medium*
Mitsubishi Outlander PHEV (Petrol/Electric)	*Mitsubishi Outlander (Petrol)*	*Large*

As EVs are the more nascent market offering, the most popular EVs in 2017 were chosen and then the ICEV pair to each vehicle followed [40]. Vehicle pairs were chosen to be aesthetically similar. Furthermore, as demonstrated by Verhoef et al. (2007) brand loyalty in the vehicle market is very high and therefore, the vehicle pairs were chosen from the same manufacturer as much as possible [41]. Table 2 shows the vehicle pairs used for the analysis. Following these criteria, three out of the four vehicle pairs were also studied in LDT with the addition of the Volkswagen Golf vehicle pair which was included due to the increased popularity in Europe of the Volkswagen e-Golf. The year of first production or introduction of the vehicles should be prior to 2017 or earlier so that it was available for purchase throughout 2017 and already known on the market; all vehicles were introduced by 2012; newest vehicles were the e-Golf and the Mitsubishi Outlander PHEV, introduced in 2011 and 2012, respectively.

3.2 Vehicle Data Collection, Incentives, Sales, and TCOs

Table 3 provides an overview of the basis of calculation of fiscal duties, and some benefits for EVs and ICEVs. The vehicle total cost of ownership (TCO) and incentives were calculated for each vehicle in Table 2 to conduct the comparison. The calculation of the TCO and of the incentives are the same as is done by LDT. The TCO summarizes all present and future costs and revenues (from resale) of an investment over its lifetime. As opposed to only comparing its purchase price, this provides a more complete picture of the economic value of the investment. Since fuel cost savings from EVs are only realized during the operation period, they cannot be seen in the purchase price alone, and thus comparing TCOs is a more accurate representation of one's economic position. The TCO was calculated with the following equation,

$$TCO = P + VAT + T_r - S + PV(T_c) + PV(F) - R \tag{2}$$

Where P is the net price, VAT is the value added tax, T_r is the one time acquisition tax (registration tax and others at the time of purchase), S is the subsidy given upon purchase, $PV(T_c)$ is the present value of annual taxes on vehicle ownership (circulation or ownership tax), $PV(F)$ is the present value of fuel and/or electricity costs for vehicle operation, and R is the resale value of the vehicle; all in units of currency (EUR or other). The same assumptions from LDT are used: vehicles travel 12,000 km per year, 4-year ownership, and a discount rate of 1%. The incentives were classified as the fiscal incentives toward the acquisition of the EV over its ICEV pair. Incentives were defined with the following equation,

$$Incentive = S + (VAT_{ICEV} - VAT_{EV}) + (T_{r,ICEV} - T_{r,EV}) + (PV(T_{c,ICEV}) - PV(T_{c,EV})) \tag{3}$$

Although vehicle pairs were chosen as similar as possible, certain characteristics of the vehicles will still differ which serve as a basis for tax calculations including power, weight, engine capacity, etc. as described in Table 3. To control for these differences, incentives are defined as direct fiscal incentives toward EVs which are beyond those that ICEVs benefit from. For example, if a country exempts EVs from annual circulation taxes, the present value of the circulation tax paid by the ICEV over its lifetime is thus counted as the incentive. The same assumptions used in TCO calculations are used in calculations of the incentives.

Average 2017 electricity prices were obtained from the European statistics website (Eurostat) for EU Member States [8]. The average electricity price was used to calculate the cost of the fuel for electric vehicle propulsion for cost-comparison with ICEVs. Diesel and petrol prices were taken from the European Automobile Manufacturers' Association (ACEA) Tax Guide [42]. Fuel prices for Norway were obtained from myLPG.eu, a repository of fuel prices across Europe [43]. Vehicle net prices were taken from manufacturer websites in the respective countries. Due to differences in how prices are listed from company websites, the VAT and other taxes might have already been included, thus they had to be subtracted from the listed price on company websites to get the net price of the vehicle without any duties. An important value in the TCO is the resale value of the car, the term R in Equation (2). Several online marketplaces were consulted before deciding to use OOYYO (www.ooyyo.com) to do a manual search for vehicles that exhibited the expected qualities at the time of resale considering the assumptions made (12,000 km per year and 4 years old). Since two vehicles were released very close to the target model year (Volkswagen e-Golf and Mitsubishi Outlander PHEV), there was a very small availability of these used vehicles through the platform, and thus these vehicles (and their ICE pair vehicle) were excluded from the TCO

Table 3. Basis of calculation of fiscal duties and benefits for passenger vehicles in 2017

Country	VAT, % (EV/ICEV)	Subsidy[a]	Registration Duties		Ownership/Circulation Duties	
			EV	*ICEV*	*EV*	*ICEV*
France	*20/20*	*€6000 (1000)*	-[b]	*CO_2, kW*	-[b]	*CO_2*
Germany	*19/19*	*€4000 (3000)*	*€26*	*€26*	-[b]	*CO_2, engine cc*
Italy	*22/22*	-	*kW*	*kW*	-	*kW*
Netherlands	*21/21*	-	-[b]	*CO_2[c]*	-[b]	*region, CO_2, wt[c]*
Norway	*0[b]/25*	-	-	*wt, CO_2, NOx,*	-[b]	*fuel type*
Portugal	*23/23*	*€1125 (562.50)*	*€100*	*€100*	-[b]	*CO_2, engine cc[c]*
Spain	*21/21*	*€5500 (5500)*	-	*CO_2*	*kW*	*kW, fuel type*

[a] In Euros, PHEV values in ()
[b] EVs exempt, PHEVs are not.
[c] Diesel vehicles subject to additional surcharge

calculation. Figure 2 summarizes these used and net prices.

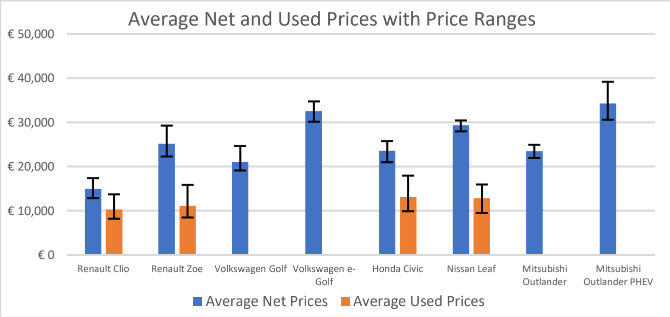

Figure 2. Average net and used prices with price range bars used for the study.

The primary source for passenger vehicle market data is the 2017 CO_2 monitoring database provisional data [10]. The data cleaning procedure described in Thiel et. al (2015) who worked with earlier iterations of the database—from 2010 to 2014—was utilized for the subset of data pertinent to this study [44]. For Norwegian vehicle registration data, public data from the OFV (Norwegian transport authority) was used and certain data was interpolated from the public data [15].

3.3 Surcharge pricing model for EV charging

3.3.1 Working Principle

The model aims to promote the use of less carbon-intense electricity and therefore reduce the WTT emissions from EVs. The main principle of the model is to develop a price signal, or surcharge, based on the degree to which the electric carbon intensity (CI) exceeds a baseline value. The Portuguese public charging demand, electricity generation sources, and electricity wholesale market prices are used to quantify the effectiveness from a profit and emissions reduction standpoint. An analogous mechanism is employed by Uber™ the ride-hailing app with its 'Surge Price'. When demand for rides increases, and the supply of drivers may not be enough to satisfy the demand, a surcharge is communicated to the users [45]. Customers either pay more for their ride, or decide not to take it, thus relieving strain on the system. The application of this principle for EV charging in this study thus employs a penalty when charging behavior is not sustainable, and the model thus reduces the charging demand at periods where electricity is more carbon intense.

3.3.2 Model and inputs: carbon intensity, wholesale price, and baseline charging data

A multiplier value or surcharge is calculated based on a defined baseline. In the case of this model, the baseline was defined as the Portuguese gross average intensity in 2017 which was attained from data from the European Network of Transmission System Operators (ENTSO-E)[11] [46]. The emissions resulting from the produced electricity were calculated using the most recent IPCC emissions factors (EF) that reflect global warming potential [47]. The 2017 gross average CI is calculated as,

$$baseline = \frac{2017\ Total\ emissions\ from\ power\ generation\ sources\ [g\ CO2\ eq]}{2017\ Total\ energy\ generated\ [kWh]} \qquad (4)$$

The 2017 gross average CI was 304.836 g CO_2 eq/kWh[12]. The surcharge could then be calculated on a scaled value between the hourly CI of the Portuguese grid versus the baseline. The maximum value of an average day was used as the maximum value of the surcharge scale and assigned a 100% surcharge, and the values in between were calculated based on this scale. The general equation for the surcharge value is thus:

$$S_h = \begin{cases} \dfrac{CI_h - baseline}{CI_{max} - baseline}, & for\ CI_h > baseline \\ 0, & for\ CI_h \leq baseline \end{cases} \qquad (5)$$

Where S_h is the surcharge value at any hour h, CI_h is the hourly carbon intensity at the hour, and CI_{max} is the maximum carbon intensity of an average day. Although this was done with 2017 values, once *baseline* and CI_{max} values are chosen, the model can be applied in real time for any CI, making this model applicable for implementation today. The price at every hour is calculated based on the surcharge and can be represented with the equation,

$$P_h = T_h\ x\ (1 + S_h) \qquad (6)$$

With T_h representing the tariff at the hour and can be constant (in the case of a flat tariff), or variable (in the case of real time tariffs).

Electric Carbon Intensity

The CI of the electricity grid is the amount of greenhouse gas emissions released to generate one unit of electricity (usually expressed in g CO_2eq/kWh). The ENTSO-E database provides hourly generation data from fuel sources. Moro and Lonza (2017) study the impacts on carbon intensity in EU Member States and their effects on the emissions of EVs on a WTW basis, and underline the importance of quantifying the emissions intensity of transmission electricity as imported electricity contributes to the final CI of the electricity used [48]. Therefore ENTSO-E data for Portugal, and for Spain—Portugal's only electricity trading partner[13]—was used from the resource. From each electricity generation source, the emissions resulting from each fuel source can be calculated using the IPCC values for emissions intensity shown in Table 4. As can be seen from the table, the choice of accounting method to use, whether direct emissions or lifecycle emissions can have a large effect on the results of the CI of the electricity grid. The direct emissions are used in this analysis (WTT methodology) since LCA emissions encompass a fixed amount (from the building of plants and equipment for example) that are not realized in real-time, and thus, the direct emissions give a more accurate comparison of electricity when used as a fuel for EVs and thus, a better comparison to emissions attained by an ICEV.

Table 4. Direct and lifecycle emissions factors from different fuel sources [47][49][50][51][52].

Fuel Source	2014 IPCC aggregated results, direct emissions (median) [g CO_2/kWh el]	2014 IPCC aggregated results, Lifecycle emissions (median) [g CO_2/kWh el]
Coal - PC	*760*	*820*
Natural Gas	*370*	*490*
Diesel/Oil	*668*[ab]	*778*[a]
Waste Incineration	*795*[ac]	-
Combined Cycle	*120*	*200*
Biomass	*n.a.*[d]	*230*[e]
Nuclear	*0*	*12*
Geothermal	*0*	*38*
Hydro	*0*	*24*
Wind	*0*	*12*
Solar PV	*0*	*48*
CSP	*0*	*27*

[a] Not included in the 2014 IPCC aggregated results from literature
[b] Calculated using data on emissions from combustion sources per unit of thermal energy and a thermal efficiency of 40% as per IPCC sources [81] [82]
[c] Calculated direct emissions based on 2006 IPCC data on GHG emissions from waste to energy [80] [83].
[d] No value listed by IPCC for direct emissions, although the direct emissions are positive and substantial, burning biomass must be taken into a wider consideration for the GWP due to their behavior as a carbon sink while growing.
[e] Although it is listed as positive, Biomass lifecycle results can actually be negative depending on the bounds of the study because they are a carbon sink before being combusted for energy; there is no single acceptable value for biomass, and technology, bounds, methodology are all important factors to consider.

[11] Data collected and given every hour.
[12] By comparison the EI of electricity in the EU as a whole in 2016 was 314.188 g $_{CO2}$ eq/kWh. This accounts for 1022.699 Tg $_{CO2}$ eq released from public electricity and heat production and gross electricity production of 3255.05 TWh according to EEA and Eurostat sources [53], [54]. See Table 5 for further reference on comparative CI values.

[13] Refers to the fact that electricity interconnections (where electricity is exchanged between countries) for Portugal only connect with Spain. This is in contrast to interior European countries like France, Germany, or Switzerland which may have as many as three or four countries that electricity is exchanged with.

Using the EF, the total CI from each form of generation and at each hour can be calculated and totaled for both Spain and Portugal as,

$$CI_{gen}(h) = \frac{\sum_n (EF_n \times GEN_{h,n})}{\sum_n GEN_{h,n}} \tag{7}$$

Where, EF_n is the emissions factor of the nth power generation unit, and at a given hour, $GEN_{h,n}$ is the energy generated from the nth power generator source. The result of Equation (7) is thus the sum of emissions across all power generation unit types over the total amount of energy generated by the country, calculated at every hour. To go from CI of generation to CI of end use, transmission of imported energy must be accounted. If energy is exported, this does not affect the CI[14], and the CI of end use is equal to the CI of transmission. When energy is imported, the CI of the imported electricity should be accounted for as,

$$CI_{use}(h) = \begin{cases} CI_{h,gen}, & for\ TRANS_h \le 0\ (exporting) \\ \frac{(CI_{h,gen}\ x\ \sum_n GEN_{h,n}) + (CI_{h,trans}\ x\ TRANS_h)}{TRANS_h + \sum_n GEN_{h,n}}, & for\ TRANS_h > 0\ (importing) \end{cases} \tag{8}$$

Where $TRANS_h$ represents the total amount of energy exchanged between countries and $CI_{h,\text{trans}}$ is the CI of generation of the transmitting country where the energy is being received from. The final CI in the distribution grid at every hour in 2017 is calculated with Equation (8), yielding 8760 data points. The hourly values on an 'average day' used in the analysis is the average of each hour across 365 days of the year calculated as,

$$CI_{ave,use}(h) = \frac{\sum_d CI_{h,use,d}}{365} \tag{9}$$

Where Equation (9) is calculated for each hour in a day (0 to 23) to attain a single, 'average day'. Comparative values of CI for the countries in this study are shown in Table 5.

Applying the same methodology to the day-ahead wholesale electricity price, the hourly evolution of the cost of electricity is parsed into an 'average day' which is used to quantify the electricity cost.

Table 5. Comparative results of CI of gross electricity production [48], [53], [54].

Entity	2016 Emissions from Electricity and Heat [Tg], (Source: EEA [53])	2016 Electricity production [TWh], (Source: Eurostat [54])	Resulting entity-wide average CI [g/kWh]	Moro and Lonza (2017) Comparison [48] [g/kWh]
EU28	1022.67	3255.05	314.18	340
France	35.10	556.18	63.10	66
Germany	302.88	649.12	466.60	485
Italy	76.37	289.77	263.55	358
Netherlands	55.24	115.17	479.63	479
Norway	1.70	149.66	11.37	-
Portugal	15.02	60.28	249.09	295
Spain	58.75	274.78	213.81	248

Portuguese EV Charging Data

Table 6 summarizes the most used charging stations in Portugal. Salisbury (2016) demonstrates the effect of ambient temperature on the consumption rate of an electric vehicles [55]. Utilizing the nominal temperatures in Portugal from the study, and an AC/DC conversion rate of 0.86 as shown by Sears et. al (2014), a consumption rate of 0.14 kWh/km is used [56]. This also agrees with the arithmetic mean of electricity consumption rates for the new EV stock acquired in Portugal in 2017 (0.136 kWh/km) found in the European vehicle registration database [10]. Therefore, the higher consumption rate of 0.14 kWh/km is conservative to quantify the travel range added to EVs.

Table 6. Relevant data of public top 10 charging stations in Portugal in 2017.

Station	# of Chargers	2017 charging events	Average Energy [kWh]	Average Range added [km]	Average Time [min]	Average Power [kWh/h]
Station 1	3	7,960	11.47	81.92	25	27.65
Station 2	3	7,494	8.67	61.93	20	25.60
Station 3	3	7,002	11.21	80.07	27	25.42
Station 4	3	7,023	12.75	91.07	26	28.55
Station 5	3	5,202	13.04	93.14	29	26.81
Station 6	3	4,572	12.72	90.86	28	27.81
Station 7	3	4,297	10.74	76.71	26	25.19
Station 8	3	3,858	9.97	71.21	27	22.65
Station 9	2	3,044	4.44	31.71	102	2.77
Station 10	3	3,442	11.44	81.71	28	25.10
Top 10	29	53,894	10.65	76.04	34	26.76
POR Total	977	225,122	9.74	69.57	105	13.38

Portuguese daily driving distances can be as low as 49 km/day [57], thus the average range added at stations of nearly 70 km is more than required for average daily travel, indicating the reduction in electricity charged is possible while still satisfying EV user needs, similar to the finding of Shepero and Munkhammar (2017) for Swedish charging behavior mentioned in Chapter 2.3.1 [19].

The power from each charging station was recorded in 15-minute intervals by summing the power of the charging events that were occurring at each quarter hour (ending at :00, :15, :30, and :45). Parsing the data into these discrete values allowed for a manageable-sized database for the demand profile as the database is large to begin with. Figure 3 provides a schematic of how the resulting curve was collected every 15 minutes with the blue lines representing the actual data (start time, end time, and electricity charged), and the average power value for the charge (above the blue line) is calculated based on this electricity exchanged over the duration of the charge. The same hour at one station over three days is shown as an example.

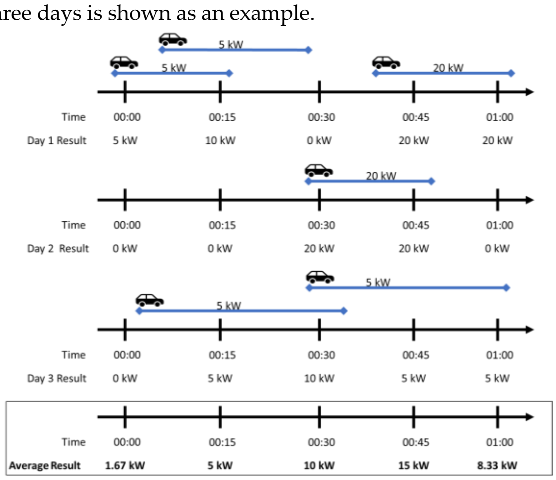

Figure 3. Schematic of the methodology for collecting the charging power for different charging durations.

There are drawbacks to this method, as start and stop times fall differently across the 15-minute time stamps. The error was calculated according to Equation (10) resulting in an error of 1.3%, well within an acceptable range, and thus verifying that this data-processing methodology does not greatly alter the electricity demand.

$$error = \frac{Calculated\ Energy - Given\ Energy}{Given\ Energy} = \frac{28{,}592.14}{2{,}193{,}157.13} = 0.0130 \tag{10}$$

Again, as was done with the CI of the electricity grid and the wholesale price, an 'average day' over the course of the year can be developed analogous to Equation (9), where Figure 3 is the depiction of this methodology. Replacing the emissions intensity with power demanded yields Equation (11).

$$CL_{ave}(t) = \frac{\sum_d CL_{t,d}}{365} \tag{11}$$

Where the average charging load at time, t, is represented by $CL_{ave}(t)$, $CL_{t,d}$ is the charging load at a specific time for a specific day, and thus the average at this hour for every day in 2017 and develop the demand curve. The price elasticity of demand (PED) describes the behavior of the entire market, and thus it is better applied to the average demand of the market on an 'average day'. A surcharge affects individual users and situations differently. For example, if the PED is -1.0 and the hourly surcharge is 33%, this corresponds to an expected market demand reduction of 33% during that hour, however, a 33% reduction in market demand cannot be expressed on a one-day demand profile for one station where there may have been two vehicles charging. The problem in reducing the demand by 33% from two individuals charging becomes clear as on an instance-by-instance basis, the decision for the individual is binary: to charge or not to charge. Conversely, if the average day over the course of the year demonstrates that the power demanded at 12pm is 30 kW, this is spread out over customer demands at that hour across the year, and across many stations, and it is more accurate to say that if faced with the same constraints, 33% of the customers in the market who charged at that hour of the day, will decide not to at that hour, and the 'average day' power thus becomes 20 kW at 12pm. The idiosyncrasies faced in an instance-by-instance bases are accounted for when using average data.

[14] All the electricity consumed within the country was generated within the country, and therefore, the EI in final usage is accounted for in the EI for generation.

3.3.3 Model calculations

Combining Equation (1) and Equation (6), the change in demand will be:

$$CL_{surcharge}(t) = (1 - S_t \times PED) \times CL_{initial}(t) \tag{12}$$

As can be seen from Equation (12), for a fixed PED, the reduced charging load, $CL_{surcharge}(t)$, is directly related to the surcharge, S_t, which already represents a percent change in the price. From the reduced demand curve, the hourly profits can be quantified as:

$$Profit_{PED}(t) = Revenue(t) - Cost(t) = P(t) \times CL(t) \times d - C(t) \times CL(t) \times d \tag{13}$$

Rearranging and substituting the identities of Equation (6) and Equation (12) for the surcharge price and demand under the surcharge, respectively, gives the general equation,

$$Profit_{PED}(t) = [CL(t) \times (1 - S(t) \times PED) \times d] \times [T \times (1 + S(t)) - C(t)] \tag{14}$$

Where t increases in 15-minute intervals, d = 0.25 hours, and PED is constant and unitless. T is constant (a flat base tariff is used) and measured in (EUR/kWh). S(t) is the unitless hourly surcharge evolution and C(t) is the hourly wholesale market price measured in (EUR/kWh). CL(t) is the initial charging load, measured in kW, which has been established as the 'average day' developed earlier. $C(t)$, $CL(t)$, and $S(t)$ are thus the 'average day' evolutions of cost, initial charging load, and surcharge value which vary with time. The resulting carbon emissions of the initial charging load and of the reduced charging load can thus be calculated to obtain the resulting reduction on an average day as,

$$Emissions(t) = EI_{ave,use}(t) \times CL(t) \times d \tag{15}$$

$$Total\ Reduction = \sum_t Emissions_{initial}(t) - Emissions_{surcharge}(t) \tag{16}$$

$$Total\ Reduction = d \times \sum_t EI_{ave,use}(t) \times [CL_{initial}(t) - CL_{surcharge}(t)] \tag{17}$$

Substituting the identity in Equation (12), and factoring out $CL_{initial}(t)$ results in,

$$Total\ Reduction = d \times \sum_t [EI_{ave,use}(t) \times CL_{initial}(t)] \times [1 - (1 - S(t) \times PED)] \tag{18}$$

With the resulting emissions at every hour individually calculated as in Equation (15) based on the emissions intensity at that time, $EI_{ave,use}(t)$, and the energy exchanged at that time, $CL(t) \times d$, or the power demand (in kW) times the duration of the charge (0.25 hours). The quantification of the emissions reduction under the model is thus calculated according to Equation (18), and it can be seen how the reduction only depends on the PED studied.

4. Results and Discussion

4.1 Fiscal Incentives and Sales of EVs

Following the pairwise comparison between EV and ICEVs the relationship between the incentives and sales is graphically depicted in Figure 4. In the figure, countries are identified by color, and each vehicle pair is denoted by a data-point, with shapes denoting the same pair.

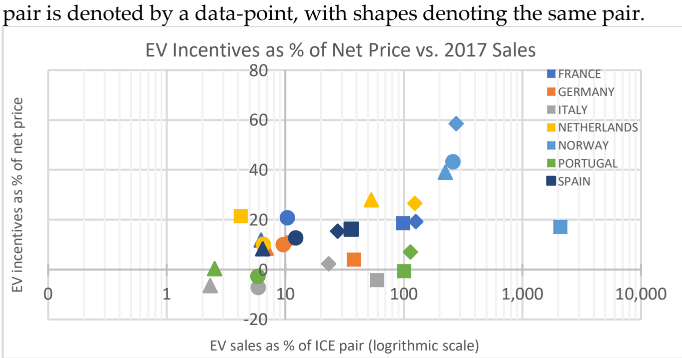

Figure 4. Incentives vs. 2017 sales; own elaboration.

Italy and Portugal are the only countries which have negative incentives, indicating that the economic incentive favors the acquisition of an ICE vehicle as opposed to its EV pair. There is a visible and expected direct relationship between incentives and sales indicating that as incentives (or benefits) increase, so do the sales (or quantity demanded) of the vehicle, thus demonstrating that the market responds to fiscal incentives. The market response to net price is depicted in Figure 5. As can be seen, the higher the relative net price of the EV with respect to its pair, the less popular this model is. The expected negative relationship between price and quantity is visible.

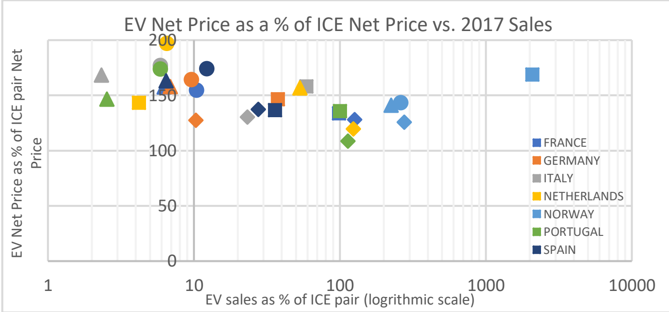

Figure 5. EV net price vs. sales; own elaboration.

Finally, the TCO of the vehicle pairs expressed as the EV TCO as a percent of the TCO of its ICE is depicted in Figure 6. Where the same general relationship seen in the net price is expected, although it is more difficult to see and there are several outliers in the data without a very distinct negative correlation as would be expected. Since net prices are much easier to interpret as a cost than the TCO (which requires foresight and assumptions on costs of fuel, ownership periods, usage, discount rates, and resale value), it makes sense that the correlation is much stronger between net price and sales than between TCO and sales. Although TCO is a better indicator of the economic position resulting from a choice between an EV and its ICEV substitute pair, net price is a better communicator of value for consumers. Further work can study more vehicle pairs, to verify this initial observation of the data.

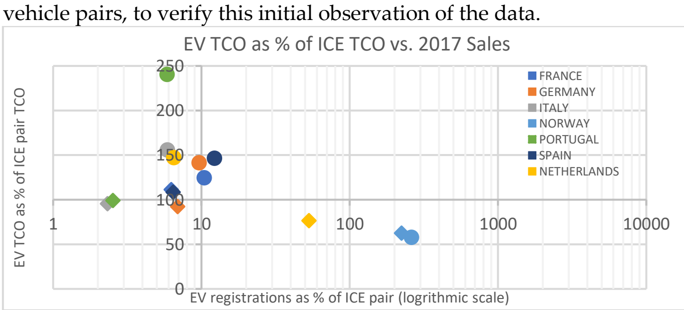

Figure 6. EV TCO as a % of ICE TCO vs. sales; own elaboration.

In essence, Figure 4, Figure 5, and Figure 6 illustrate that fiscal incentives are effective in promoting the acquisition of EVs and provides some insight into how price signals affect consumer decision-making in transportation.

Figure 7 demonstrates the comparison of vehicle WTW emissions with a distinction between WTT and TTW emissions.

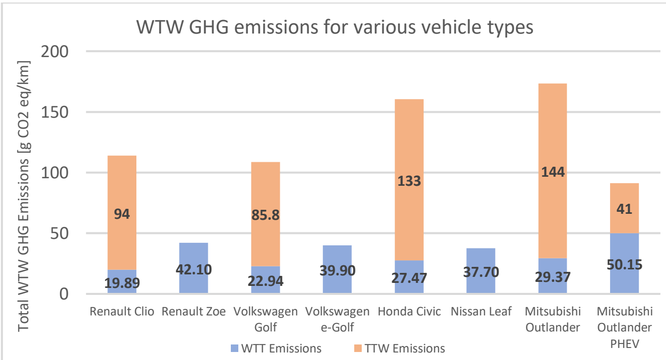

Figure 7. WTW GHG emissions resulting from various vehicles (a grid intensity of 314.18 g/kWh is used); own elaboration.

As demonstrated and expected, BEVs have no TTW emissions, and even the only hybrid vehicle (the Outlander PHEV) offers a large overall reduction in WTW GHG emissions compared to its ICE pair. In Figure 7, the CI of electricity is assumed as the EU average, however, in reality the CI of electricity is different in each country, even within Europe, and is different throughout the year having an impact on the WTW GHG emissions of EVs. For example, as demonstrated in Table 5, CI of the electricity grid in Europe can range from as low as 11.37 g CO_2 eq/kWh in Norway to as much as 479.63 g CO_2 eq/kWh in the Netherlands.

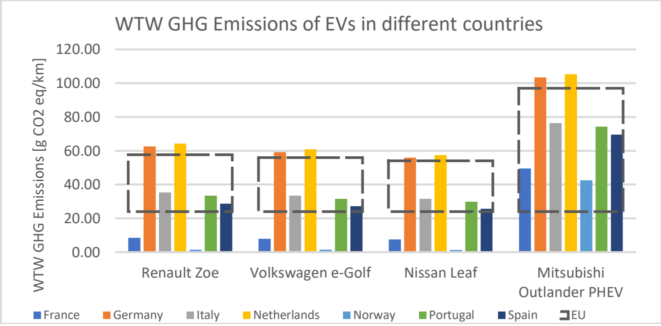

Figure 8. WTW GHG Emissions of EVs in different countries accounting for different CIs of electricity; own elaboration.

Figure 8 demonstrates how dependent EV emissions are on the CI of electricity. Low CIs (such as in France and Norway) contribute to large WTW reductions of more than 90%. While in countries like the Netherlands and Germany with higher CIs (>400), the reduction of emissions on a per km basis is as low as 40%. The main takeaway is that WTW emissions from EVs are hugely sensitive to the CI of electricity. Government incentives are an effective mechanism to promote the decarbonization of passenger transport as is uncovered by the relationship of incentives toward the acquisition of vehicles through this pairwise comparison of specific vehicles and the resulting WTW emissions reductions, and the CI of the electricity used to charge influences the quantification of these emissions.

4.2 Surcharge pricing model for EV charging

Figure 9 demonstrates the surcharge pricing evolution of an average day:

Figure 9. Evolution of average day carbon intensity of electricity (blue, left axis) and the resulting surcharge evolution (green, right axis).

The green line in the figure represents the incurred surcharge for charging an EV at that hour (refer to Equation (5)). Therefore, the black dotted lines identify times when the CI is below the baseline and no surcharge is applied. Figure 10 shows the wholesale electricity price for the Portuguese market and how the price fluctuates in comparison to the CI of the grid.

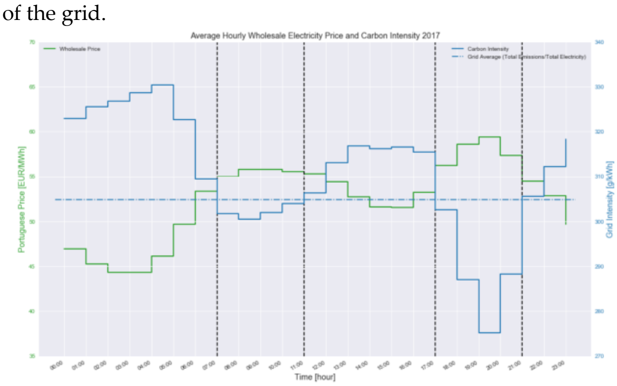

Figure 10. Hourly evolution of the wholesale price of electricity (green, left axis) in comparison to the CI of the Portuguese grid (blue, right axis) [46], [58].

As can be seen in Figure 10, the lowest valley in wholesale price aligns with the highest peak in CI and the highest peak in wholesale price aligns with the lowest valley of CI. The wholesale price closely follows the Portuguese consumer demand curve. This represents a contradiction as the mirroring of the wholesale price and CI indicates that if the objective was to optimize charging to reduce costs (and thus increase profits), this would have the opposite effect on the environmental aspect—preferring high CI electricity because it is also cheaper. A very low consumer demand of electricity can explain the peak in CI in the midnight to early morning hours. Although fossil fuel burning plants do not ramp up, they still end up supplying a greater percentage of the electricity consumed at this time due to such low demand. In essence, under the current paradigm, setting up a surcharge pricing mechanism with the purpose to shift user preferences toward low-carbon electricity would result in a preference of electricity during already existing peaks in electricity demand. Moving EV charging to the night hours is advantageous from the grid operation point of view, however, this model would encourage the reduction of charging demand during these hours due to the high CI. The author acknowledges the existence of this contradiction, and further elaborates on its implications in the conclusions.

The Portuguese EV public charging network average day is developed using the methodology depicted in Figure 3. The initial demand curve for an average day illustrates the baseline customer demand on an average day shown in blue in Figure 11. Assuming a price elasticity of demand equal to -0.12 and -0.69[15] the reduced demand curves in Figure 11 are developed (gray and red). No surcharge is applied between the black dotted lines; thus, it follows that during these times, the baseline charging demand is unchanged. For reference, the surcharge is superimposed on the graph to demonstrate the fluctuation in price. With a relatively inelastic response to the pricing surcharge, the demand is only reduced very slightly. The response can be seen much clearer when the PED is more elastic.

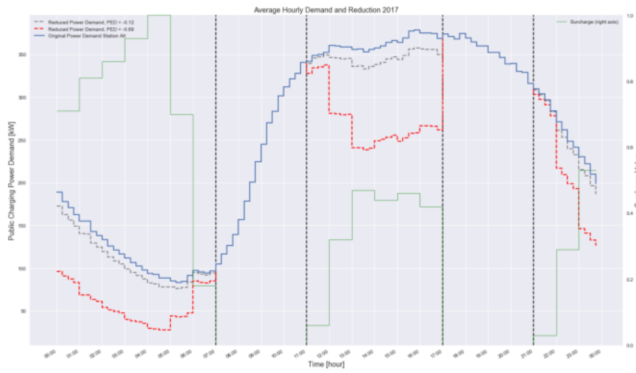

Figure 11. Resulting power demand curves superimposed with two PED values and hourly surcharge (green, right axis).

The emission reduction is elaborated in Figure 12 where it follows that the greater the reduction of demand (occurring at periods of high CI corresponding to the design of the surcharge), there is a pronounced effect on the resulting emissions from the electricity demanded by public charging. The more responsive (more elastic) the market is to the surcharge, the greater the emission reductions are. The hourly grid intensity is superimposed for reference.

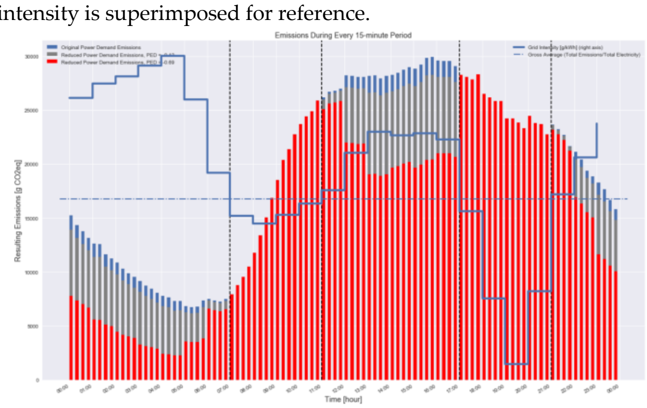

Figure 12. Resulting emissions reductions under the two PED paradigms.

Table 7 summarizes the results from the application of the surcharge model with the initial situation shown for comparison. Also included in

[15] The most inelastic, short-term PED for fuel demand found in Hössinger et al. (2017) was -0.12; the most elastic PED for fuel (which was a long-term elasticity) from the study was -0.69 [32].

the tables are the amount of energy exchanged from the initial demand profile and under different PED paradigms. Based on the amount of energy exchanged in the average day and the amount of emissions resulting from the CI of the grid when the energy was charged an 'effective CI' value can be calculated. Shown as the last column in Table 7. This effective CI does not differ much from the calculated 2017 gross average CI (304.836 g CO_2eq/kWh); even in the existing/initial situation, the change between the effective CI and the gross average CI is 0.78%, even though both the CI and demand fluctuate throughout the day. Thus, using average CI values from the electricity network are acceptable when quantifying the WTW emissions from EVs for policy analysis purposes, and high levels of granularity are not necessary; this is the same conclusion found in Jochem et al. (2015) to calculate the emissions resulting from EVs [59].

Table 7. Selected results of profits and emissions shown as a percentage of the initial situation with no surcharge applied.

Retail Price	Existing/ Initial	Price Elasticities of Demand					
		-0.12	-0.15	-0.2	-0.4	-0.6	-0.69
0.054	1.96	262.24%	244.90%	215.82%	98.98%	-17.35%	-69.90%
0.055	8.05	80.00%	74.78%	66.09%	31.55%	-3.11%	-18.76%
0.06	38.48	33.65%	31.57%	28.14%	14.35%	0.49%	-5.67%
0.08	160.22	24.32%	22.88%	20.48%	10.87%	1.27%	-3.05%
0.1	281.96	23.05%	21.69%	19.44%	10.40%	1.37%	-2.70%
0.2	890.66	21.90%	20.63%	18.50%	9.98%	1.46%	-2.38%
0.22	1012.40	21.84%	20.57%	18.44%	9.95%	1.46%	-2.36%
0.3	1499.36	21.69%	20.42%	18.32%	9.90%	1.47%	-2.32%
kWh	6086.98	-3.16%	-3.95%	-5.27%	-10.54%	-15.80%	-18.18%
t CO_2	1.870	-3.21%	-4.06%	-5.40%	-10.91%	-16.42%	-18.82%
CI,eff	307.21	-0.05%	-0.12%	-0.14%	-0.42%	-0.73%	-0.79%

Negative values indicate a reduction from the initial situation and are therefore not optimal from a profit point of view but are the desired result from an emissions point of view. It should be noted that a reduction in electricity sold (compared to the initial situation) still yields more profits than the initial flat-rate-tariff with no surcharge situation. This is relevant to an EV charging station operator who seeks to maximize profits and indicates the most optimal situation in the space. From the literature studied and the nascent stage of EV charging infrastructure and the public perceptions, the PED is expected to be inelastic in the short-term and much closer to -0.12 than -0.69. This behavior is favorable for the EV charging station operators to maximize their returns. As consumers become more accustomed to the technology, comfortable with its range, and the public charging infrastructure matures, more elastic behavior can be expected to be realized, closer to -1.0. Under this paradigm, consumer response to the surcharge is greater, and its coupling to the CI of the grid means that consumer response to clean energy increases.

The payback period can be calculated assuming a cost of 5,525 EUR/EVSE Charger [17], [60]. For the top three used stations in 2017, this results in a cost of 16,575 EUR/Station for the charging equipment (each has 3 ESVE chargers). The payback period based on the net profits made from each of the top three stations is shown in Figure 13. The marginal decrease in payback period is small after a unit price of 0.1 EUR/kWh, demonstrated by the levelling-off of the payback period after this point.

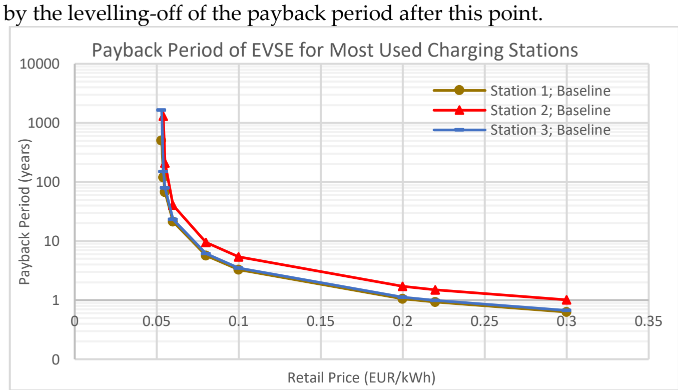

Figure 13. Payback periods of stations in Portugal; based on EVSE costs in [17], [60].

From this, a unit price for the electricity within the range of 0.1 to 0.22 EUR/kWh in the public EV charging infrastructure remains competitive to private charging and makes sense from a business standpoint from the visualization of payback periods for the most used stations in 2017. The application of the surcharge mechanism and the user response (PED) to the mechanism will also play a role, but it will be seen as a direct vertical shift of the graphs in Figure 13 while maintaining the same shape, thus the same logic applies for the price range of 0.1 to 0.22 EUR/kWh. Using the Portuguese PEV fleet acquired in 2017 the resulting per-km emissions of PEVs can be calculated as the product between the first two columns in Table 8.

Table 8. Emissions resulting from the Portuguese vehicle fleet accounting for various CI values and assumptions on yearly kilometers travelled [10].

Parameter	Gross Average	2017 actual	PED - 0.12	PED - 0.69
CI or CI,eff (gCO2/kWh)	304.836	307.21	307.06	304.78
Portuguese EV fleet Electricity Consumption	136.41 Wh/km			
Resulting EV Emissions (gCO2/km-vehicle)	41.58	41.91	41.89	41.58
Portuguese ICE fleet Emissions (gCO2/km-vehicle)	104.81			
Resulting per-km emission reduction (% less CO_2/km emitted)	60.33%	60.02%	60.03%	60.33
Absolute amount of emissions per EV (t CO2/year-vehicle)	0.49896	0.50292	0.50268	0.49896
Absolute amount of emissions from new EVs in sold 2017 (tCO2/year)	2,207.4	2,224.9	2,223.9	2,207.4
Reduction of EV emissions compared to the 2017 (tCO2/year)	n/a	0	- 1.0	- 17.5

The new passenger vehicle fleet in Portugal acquired in 2017 totals 4,424 EVs and 79,834 ICEVs [10]. With an average ICE fleet emission rate shown in Table 8 of 104.81 g CO_2/km-vehicle, the new ICE vehicle fleet would be expected to emit 100,408.8 t CO_2/year (1 t = 10^6 g), compared to the 2,224.9 t CO_2 released by EVs in 2017. This stems from the magnitude of the ICEV fleet compared with EVs, as well as the substantial reductions in WTW emissions per vehicle. The effect of promoting EV acquisition on decarbonization of passenger transport becomes clear. Further reductions of 17.5 t CO_2/year realized under this surcharge model are marginal in comparison, however, still achievable without additional costs, and only the reduction in realized profits to charging station operators, which do not have extreme detrimental effects on the payback period of the investment as demonstrated. Thus, the importance of policy toward acquisition, and business models promoting sustainable operation are complementary at decarbonizing the transport sector.

5. Conclusions

Acquisition of EVs as a substitute for ICEVs realizes immediate benefits and reductions in GHG emissions with the average European electricity mix. Comparing near substitutes of EVs and ICEs, a reduction of 40% of WTW emissions on a per-kilometer basis is realized with reductions greater than 90% in countries like France and Norway where a large portion of electricity is generated from non-fossil burning sources. For the entire EU fleet, the average reduction is 56%. To realize these benefits, fiscal incentives toward the acquisition of EVs have been widely established in Europe, and the combination of these incentives is well-perceived by consumers, resulting in an increasing uptake of EVs. As demonstrated through the effectiveness of carbon markets at the EU and national levels, Pigouvian fiscal mechanisms (taxes and pricing) have been successful at achieving decarbonization in economic sectors in which they are implemented, and thus further carbon reductions can be realized by implementing similar mechanisms for charging infrastructure pricing in order to develop user preferences for cleaner electricity, as measured through the CI of the electricity grid.

A model is developed to couple price for EV charging with the CI of the electricity. Under this model, users face a surcharge that is directly proportional to the amount of emissions their charge will cause (from the generation of the electricity) compared to the average value of 2017. If users are very affected by the surcharge, the reduction in electricity demanded at times when it is the least environmentally considerate to do so can result in a total abatement of 17.5 t CO_2 over the year, while maintaining positive operating profits for charging station operators; albeit at a slightly reduced level compared to the initial situation.

Many social factors for EV operation and charging exist which would likely push behaviors toward more inelastic behavior, making profit losses under more elastic behaviors non-existent, indicating a more advantageous situation in the near-term for charging station operators. The current and projected sufficiency of the Portuguese public charging network, and the transparency of the communication of price can help to allay the societal barriers laid out in Chapter 2.3.2. By basing the current price on a base tariff, users will have less uncertainty about future price if a surcharge exists at the current hour, and they should expect the surcharge to go to zero at some point in the future.

European transparency in electricity production is allowing closer and closer to real-time reporting of electricity sources (currently the ENTSO-E reports production values for the past hour between 15 and 20 minutes after the hour), allowing near real-time quantification of the CI at any given hour and thus facilitating the ability to quantify an 'effective CI' for users charging in the public charging grid, and in the future, of the individuals' home energy use; two sectors—transportation and energy—which account for the largest shares of GHG emissions. There is a lack of an effective communicator of the sustainability of consumer behavior to help inform of environmentally positive actions. The concept of an 'effective CI' is introduced which is a characterization of consumer electricity usage and the effective emissions that resulted from their demand. This can be utilized as an environmental score to gauge behaviors against others, characterize an individual's demand profile, and unlock benefits of user aggregation. Furthermore, this parameter can facilitate competition, and through the comparison with how other users' effective CI's compare, descriptive social norms can drive individual behavior to prefer using low CI electricity. Descriptive social norms such as these are effective in pushing users toward more sustainable behaviors in transportation [37].

As mentioned earlier, there is an inherent contradiction in the way the wholesale electricity price and carbon intensity behave, and the model encourages electricity usage at periods of low CI which are also periods where grid demand is high under the current paradigm. If the penetration of EVs is very high, this could lead to an over-loading of the grid and even greater demand peaks. If the electricity demand of a substantial portion of consumers is strongly driven by the CI (consumers with lower 'effective CI' scores), the production mix can yield a means to shift demand to times when it is beneficial for the grid, such as by injecting low-carbon electricity to the grid in the late-night to early-morning hours, to achieve a lower CI and encourage charging at these hours by those who are more responsive to this indicator. This may facilitate a new form of demand-side management driven by environmentally-coupled concerns, as opposed to solely price.

5.1 Limitations and Future Work

The primary limitation of the proposed surcharging mechanism is that it only discusses the reduction in demand. The effect of the surcharge at increasing demand at other times is not reflected. It is likely that there would be some increase at times when the surcharge is zero. An increase in demand at times of lower CI (and lower surcharge) would yield increased profits and reduce the effective CI, therefore, this limitation does not greatly affect the general outcomes of this work.

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