Tax cuts for electric vehicles : Do the benefits outweigh the costs?

A welfare analysis of the purchase tax exemption for battery electric vehicles in the Netherlands

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The usual disclaimer applies.

Abstract

With the potential to help tackle climate change, air pollution and oil dependency, electric vehicles have been embraced by governments worldwide as a viable alternative to internal combustion engine vehicles. Purchase tax incentives are among the most popular instruments used to stimulate the electric vehicle uptake in many jurisdictions. This present research provides a theoretical framework based on random utility theory to estimate the marginal welfare impact of these taxes. Based on vehicle registration data in the Netherlands during 2000-2017, this study shows that the purchase tax exemption offered by the Dutch government to private battery electric vehicles resulted in a net welfare loss of up to €130 million in 2017, or €800 per car. The analysis presented in this paper focuses on the environmental externalities associated with the vehicle production and end-of-life phases, which have been ignored in previous impact evaluations of similar financial incentives for electric vehicles. The paper provides yet another perspective to examine the impact of the vehicle purchase tax incentives and calls for a reconsideration of using these instruments to promote the consumer adoption of electric vehicles.

Keywords – electric vehicles, welfare analysis, tax incentives

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1 Introduction

Despite a sharp contraction in the global car sales amid the COVID-19 pandemic, electric vehicles (EVs[1]) remain a growth market with over 3 million units sold in 2020, quadrupling in just five years.[2] EVs have increasingly been embraced as a viable alternative to fossil-fuel cars, a solution to mitigate the transport sector's contribution to global climate change, local air pollution and oil dependency. The European Union, for example, aims to have at least 30 million zero-emission cars on its roads by 2030. This is a step toward curbing the carbon footprint of the transport sector by 90 percent by 2050, as outlined in the European Green Deal (European Commission, 2020). Over the past decade, governments across the world have offered generous tax cuts to accelerate the market diffusion of EVs. In many places, these incentives have proved effective in boosting the share of EVs in the passenger car fleets. However, their cost-effectiveness to reduce CO_2 emissions and their net social benefits can be questionable.

This present research investigates the welfare effects of the vehicle purchase tax (BPM) exemption for battery electric vehicles (BEVs) offered by the Dutch government. The paper develops a theoretical framework based on random utility theory (McFadden, 1986) to measure the marginal welfare effect of the vehicle purchase tax, including the environmental costs from vehicle production and end-of-life phases. Based on new private car registration data from 2000 to 2017 in the Netherlands, the empirical analysis of this paper shows that the social welfare loss in 2017 could reach between €30.7 million and €130 million, or between €190 and €800 per car—the wide range is attributable to the large divergence between the lower and upper levels of the environmental prices of CO_2 and air pollutants. This welfare loss is a result of the significant environmental costs during the vehicle production and end-of-life phases, which to the best of my knowledge, have not been incorporated in the impact evaluation of EV tax incentives in the existing literature. These external costs do not vary with vehicle use. Whether a car is used for ten or fifteen years, or whether it is driven daily or twice a week, the environmental costs from this car's production and end-of-life phases remain unchanged. Therefore, in theory, these

[1] The abbreviation "EV" in this paper refers to both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs).

[2] https://www.theguardian.com/environment/2021/jan/19/global-sales-of-electric-cars-accelerate-fast\-in-2020-despite-covid-pandemic

externalities should be internalized by the vehicle purchase tax, which penalizes vehicle purchases, as opposed to vehicle use. The calculation for this part of the marginal welfare effect shows that a €1,000 increase in the purchase tax on BEVs in the Netherlands will increase social welfare by approximately €44 - 90 million.

The remainder of this paper is organized as follows. The next section provides a comparison in terms of externalities between EVs and their conventional counterparts - the internal combustion engine vehicles (ICEVs). Section 2 also presents an overview of the literature assessing the impact of EV purchase incentives. Section 3 elaborates on the main research question of this present study, and Section 4 presents the analytical framework to answer this research question. Section 5 describes the data and the empirical methodology to quantify the welfare effects of the vehicle purchase tax exemption. Section 6 discusses the results and caveats of the present study as well as recommendations for future research. Section 7 concludes.

2 Back ground & Literature review

2.1 An overview of EVs vs ICEVs in externalities

Road transport incurs significant externalities in terms of congestion, accidents, noise nuisance, air pollution and climate change that are often difficult to internalize fully. Quantifying these external costs is complex, because they are under the influence of various factors related to the number of potentially affected people, such as driving time of the day (day or night, rush or non-rush hours) and driving location (urban or rural). The magnitudes of these externalities also depend on the size and weight of the vehicles, and more importantly, their fuel types (gasoline, diesel and electricity).

2.1.1 Congestion

Congestion externality occurs when an additional vehicle reduces the speed of the other vehicles using the same road, thus increasing their travel time. This externality is estimated to make up the largest share of the external costs of a vehicle (over 65% according to Jochem et al. (2016)). The main component of this externality—the value of travel time loss, varies across drivers' income and their travel purposes, among others. Obtaining a reasonable estimate for this cost is thus challenging. Using different area model specifications, CE Delft (2019) estimates that the car marginal congestion cost in the Netherlands ranges from €0.19 per vehicle-kilometer (vkm) in a near-capacity motorway in an inter-urban area to €0.89 per vkm in an over-capacity urban non-trunk road. However, as an additional car entering a road, be it powered by fuel or electricity, incurs the same congestion cost on other cars, EVs fare similarly to their conventional counterparts in terms of congestion externality.

2.1.2 Accidents

With regard to traffic accidents, EVs might have a higher marginal external cost than their conventional counterparts, because they are typically heavier—around 5% to 35% heavier than equivalent ICEVs (OECD, 2020) and in a multi-vehicle crash, a heavier car is likely to increase the fatality and injury risks (Van Ommeren et al., 2013). Nevertheless, the relationship between vehicle weight and traffic safety is subject to numerous other factors and thus remains debated. On the one hand, EVs can be associated with higher accident risk to cyclists and pedestrians, given their quietness when running at low-speed (Stelling-Kończak et al., 2015). However, this accident risk is minimal, based on empirical findings from a field study conducted in Berlin by Cocron et al. (2011). On the other hand, less severe accidents at top speeds are more likely associated with EVs because they cannot reach the maximum speeds of gas-guzzlers, or because EV drivers may be reluctant to drive fast to save energy. Similar to congestion externality, CE Delft (2019) differentiates the marginal external accident cost estimates by driving location and road condition. The estimates for the EU-28 ranges from €-cent 0.25 per passenger-kilometer (pkm) on motorways to €-cent 1.4 per pkm on urban roads. These estimates are the same for EVs and ICEVs.

2.1.3 Noise nuisance

When it comes to noise nuisance, EVs are often thought to be better than conventional cars. However, in the usual traffic, this externality from EVs does not differ significantly from gas-guzzlers. According to RIVM (2010), at low speed, an EV can be 10 times less loud than an equivalent ICEV, but at high speed, the difference is insignificant, as the noise coming from the interaction between the tyres and road dominates the propulsion noise. Jochem et al. (2016) argue that the quiet feature of EVs becomes useful only in urban traffic, during nighttime and at low speed. CE Delft (2019) gives the same marginal external noise cost estimates for EVs and ICEVs. These estimates for the EU-28 range from €-cent 0.004 per pkm in dense traffic during the daytime in rural areas to €-cent 2.1 per pkm in thin traffic in the nighttime in urban areas.

2.1.4 Environment: air pollution and climate change

2.1.4.i Vehicle-use phase

With respect to environmental externalities, EVs appear to trump conventional cars during the vehicle-use phase, since EVs produce no tailpipe emissions of CO_2, NOx, particulate matter ($PM_{2.5}$ and PM_{10}) and other toxic air pollutants generated from the combustion of fossil fuels. Nevertheless, EVs produce more particulate non-exhaust emissions from the wearing of tyres, brakes, and roads and the re-suspension of dust, compared with typically lighter ICEVs, as these non-exhaust emissions are influenced by vehicle weight. A recent report, OECD (2020) points out that these non-exhaust emissions have surpassed exhaust emissions to become the dominant source of particulate matter in Europe's road transport, as its fleet has become more electrified. This study estimates that heavier EV models may emit up to 8% more $PM_{2.5}$ relative to equivalent ICEV models. Simulations under the scenario of low adoption of EVs show that global non-exhaust $PM_{2.5}$ will rise by 53.5% in 2030 compared with its 2017 level. These non-exhaust emissions have so far remained unregulated.

2.1.4.ii Well-to-tank

For ICEVs, most greenhouse gases (GHG) and air pollutants are emitted during the vehicle-use stage (i.e. the tank-to-wheel or TTW). Meanwhile, for BEVs, most emissions occur during electricity production stage (i.e. the well-to-tank or WTT). The kind of electricity that goes to charge EVs' batteries is critical to determining their carbon footprints in the well-to-wheel (WTW) stage which combines the WTT and TTW stages. Moro and Lonza (2018) provide the WTW estimates for a representative EV in all European countries, taking into account their different electricity generation mixes. The estimated GHG emissions of a typical BEV during the WTW stage stand around 90 gram CO_2-equivalent per kilometer (gCO_2eq/km) in the Netherlands where natural gas and coal generation dominate (2013 data). This estimate is only 10 gCO_2eq/km in Sweden, where most electricity comes from nuclear and hydro-power, but 235 gCO_2eq/km in Latvia, an importer of coal-generated electricity from neighboring countries. For comparison with ICEVs, the GHG emission level during the WTW stage is 145 gCO_2eq/km for a typical diesel vehicle and 178 gCO_2eq/km a gasoline car. These figures demonstrate the importance of the electricity generation mix to determine the environmental benefits of EVs during the WTW phase. Driving EVs yields no environmental benefits in Latvia, but a great deal in the Netherlands and even more so in Sweden.

Although the rising share of renewable sources in electricity mix can reduce the WTT emissions of EVs, more EVs on the roads will put extra pressure on the electricity demand. Global electricity demand is predicted to increase six-fold from 2019 level if EVs' share of the global fleet grows to 7% by 2030 (IEA, 2020a). The magnitude of the rise in electricity demand is by no means non-negligible, but it is important to consider this rise not only in absolute terms, but also in peak loads caused by EV charging (Kapustin and Grushevenko, 2020). Charging activity often takes place at the start of the working day, coinciding with the morning peak of electricity consumption, or in the evening at home, right during the evening peak. This raises concerns over the stability of the electricity grid, which is prone to even more volatility amid the rising share of renewable sources in global electricity generation mix.

The more reliance on renewable generation necessitates vast energy storage capabilities to cover demand in peak hours. This is where much hope has been put in EVs to be used as not only a means of transport but also an energy storage that can feed energy back into the grid through Vehicle-To-Grid (VTG) systems. Although the feasibility and economics of VTG remain replete with uncertainties (Shirazi et al., 2015), one thing for sure is that the system only works on a large-scale basis with a high number of EVs. This implies that each EV can potentially generate a positive externality associated with technology innovation and energy security, which even the most fuel-efficient ICEV cannot.

2.1.4.iii Vehicle production and end-of-life phases

In addition to the electricity generation process, EV production stage has considerable environmental impacts. Compared with conventional cars, EVs require more copper, nickel, critical raw materials and rare earth elements, the extraction of which is energy-intensive and likely to cause adverse human health and ecosystem impacts (EEA, 2018). The manufacturing of lithium-ion battery packs is mainly responsible for the higher environmental impacts of EVs within the vehicle-production phase (Kim et al., 2016). As roughly half of emissions associated with battery manufacturing comes from the electricity used, this environmental impact depends on the electricity generation mix of the manufacturing place of the batteries (ICCT, 2018) . European EVs mostly have their batteries manufactured in Japan and South Korea, where the electricity mix is similar to the European average. In the future, a greater share of batteries may come from China where the mix remains heavily reliant on fossil fuels (ICCT, 2018). Kim et al. (2016) estimate that BEV production results in 1.3-2 times more GHG emissions than a comparable conventional car. Likewise, Rangaraju et al. (2015) find that the emissions of NOx , SO_2 and PM from EV production can reach 1.5-2.5 times higher than ICEVs. Since all the steps within the vehicle-production phase (i.e. raw material extraction, vehicle component production and assembly) take place across many different countries with varying levels of stringency with respect to environmental regulations and taxation, these environmental impacts may be only partially, if not at all, taxed .

During the end-of-life phase, the environmental impacts of EVs and ICEVs do not differ considerably. Most of the life-cycle assessments (LCA) suggest that this phase is not a large contributor to the vehicle life-cycle impacts (EEA, 2018), although research focused on this phase is highly sensitive to assumptions about the potential for reusing and recycling BEVs. These are the areas where data remain distinctly lacking.

Assessing all the above externalities in the context of Germany, Jochem et al. (2016) conclude that EVs only offer some advantages in climate change, air pollution and noise reduction compared with conventional cars in congested inner-cities where the current European policies seek to get rid of cars. Noting that congestion dominates the external costs of a vehicle, the authors question the justification of a rising number of EVs on the road, which further intensifies transport externality. Similarly, Holtsmark and Skonhoft (2014) raise concerns over the high EV uptake per capita in Norway, particularly the failure of EVs to substitute ICEVs: citizens may purchase EVs as second cars and even worse, use EVs instead of public transportation.

In all, the above discussion offers an extensive, albeit not comprehensive, overview of how EVs compare with ICEVs in terms of externalities, with a focus on the environmental impacts. Most LCAs conclude that BEVs have lower GHG emissions than ICEVs throughout their lifespans (EEA, 2018). Taking a life-cycle oriented view covering the impacts of not only the vehicle-use phase, but also the production and end-of-life phases is critical to draw a valid comparison.

2.2 Policy instruments to promote EV uptake

Despite the recent rise in new sales, EVs still hold a humble share in the current global car fleet—only 1% of total stock in 2019 (IEA, 2020b). Diffusing EVs into the market has encountered various technical and economic barriers such as limited driving range and high purchase prices. According to a meta-analysis of studies using stated preference data (Dimitropoulos et al., 2013), a BEV with a 160 km range must be priced US$17,000 lower to be competitive with a comparable gasoline vehicle. Meanwhile, the availability of charging stations in public venues and along highways in most countries, except Norway and the Netherlands, remains inadequate. While the fast-charging facilities are slowly developed, EVs are at another disadvantage, as they take considerably more time to charge, compared with a few minutes to fill up a gas tank.

To increase the attractiveness of EVs, governments worldwide have intervened with a suite of demand-pull incentives. For example, EVs receive preferential access to high-occupancy vehicle lanes and parking spaces in several U.S. states, to bus lanes in Norway and license plates in Chinese provinces. In additional to these non-financial incentives, subsidy programs that vary in design, scope and magnitude have also been in place to stimulate EV adoption. In the U.S. and Canada, rebates on purchase prices, income tax credits, toll waivers or parking fee exemptions have been popular forms of subsidies to promote EV uptake.

Over the past recent years, the Dutch government has invested substantially in charging facilities, making the Netherlands currently in the global top 2 in public charging deployment per vehicle.[3] By 2030, only zero-emission passenger cars can be sold in the country. BEVs have been exempt from motor vehicle tax (MRB) and purchase tax (BPM) since 2010 and will remain so until 2024 at the earliest. Company BEVs, typically owned by leasing companies and provided to employees by their employers, are subject to an additional income tax rate (bijtelling) of 4% of their net list price, instead of 22% as in the case of non-BEV cars, with a cap on the first €50,000 of the vehicle's net list price in place since 2019. A subsidy scheme in the Netherlands gives €4,000 for purchasing or leasing a new EV and €2,000 for a used one starting from July 2020.

2.3 Impacts of EV financial incentives

A rich body of literature has examined the cost-effectiveness and welfare effects of EV financial incentives, using stated preference (SP) and revealed preference (RP) data from various car markets.

Using panel data of quarterly EV model sales in the U.S. metro areas during 2011-2013, Li et al. (2017) investigate the federal income tax credit's cost-effectiveness, defined as

[3] https://theicct.org/sites/default/files/publications/EV-charging-metrics-aug2020.pdf

public dollar costs per EV sold. This study focuses on the indirect network effects between public charging station availability and EV sales to isolate the effect of public investment in charging facilities from the effect of public spending on the tax credit program, using instrumental variables (IV). In particular, the authors instrument for the number of public charging stations with the number of grocery stores and supermarkets, arguing that while these venues do not have a direct impact on EV sales, they are well related to charging points, as charging facilities tend to be installed near supermarkets. To instrument for the cumulative sales of EVs, the authors use a set of current and past annual gasoline price variables, which they argue to be exogenous to charging station deployment, whereas related to EV purchases: in areas where gasoline are much more expensive than electricity, consumers would gain more from fuel cost savings by switching to EVs and thus have stronger incentives to buy EVs. Their IV regression shows that a 10% rise in the number of public charging stations would boost EV sales by about 8%, while a 10% rise in EV stock would boost charging station deployment by only 6%. Their simulation of the tax credit program finds that the almost $1 billion program contributed to 40% of the total EV sales, but the indirect network effect was responsible for a significant 40% of that growth in sales. Due to the strong indirect network effects on EV demand and the low level of price elasticity among early adopters, the authors suggests that if the $1 billion were used to build charging stations in lieu of subsidizing EV purchase, the number of EV sales would have doubled. Therefore, the public spending's cost-effectiveness would double as well.

Another study on the cost-effectiveness of EV tax incentives, Azarafshar and Vermeulen (2020) make use of the variation in the rebate rates across time and Canadian provinces to quantify the causal impact of Canada's EV rebate program. The authors employ a eneralised Linear Model regression on panel data of monthly vehicle registrations between September 2012 and December 2016. The regression includes a set of fixed effects to account for the heterogeneity in provincial preferences for vehicle models, the availability of models across time, and consumers' time-varying preferences for vehicle models. Using the estimated demand parameters, the authors predict the EV sales that would have been made in the absence of the rebates, and find that only 35% of EV purchases made during the studied period could be attributed to the rebate program. Using the counterfactual estimates together with data on the models' fuel efficiency, average lifespan of cars and distance driven in Canada, the authors calculate how much gasoline was saved thanks to the rebates and convert this saving into CO_2 reduction. The rebate cost per ton of CO_2 savings over 10 years stands around C$700 for BEVs and C$850 for PHEVs. Noting that the Canadian government's cost of carbon is C$30 per ton, the authors conclude that the rebate program is not cost-effective.

Both the above studies employ a vehicle choice model based on the standard logit framework set out by Berry (1994) based on a strong assumption of the independence of irrelevant alternatives (IIA). In an attempt to relax the IIA assumption, Sheldon and Dua (2019) employ a mixed logit model on a cross-sectional data of new vehicle purchases in 2015. This dataset is split into 90 subgroups based on observed consumer characteristics (i.e. income, education, age, environmental attitudes and geographical residence). Random coefficients, whose values within a subgroup follow a certain distribution, are introduced to four selected vehicle attribute variables in the estimating equation. The authors then use the estimated parameters to establish the own-and cross price elasticity of demand for different models and predict their market shares at different level of subsidies. Sheldon and Dua (2019) find that 17% of EV sales are attributable to the federal tax credits, which is much lower than the 40% found in (Li et al., 2017).

Xing et al. (2021) also employ the mixed logit model in another assessment of the cost-effectiveness of the US' federal income tax credits for EV purchases. In addition to the market-level sales data during 2010-2014, the authors make use of second-choice data (i.e. consideration set) from a survey of new EV car buyers. This dataset helps identify unobserved consumer preferences conditional on observed consumer characteristics. Following Berry et al. (1995)'s mixed logit model, Xing et al. (2021) introduce four random coefficients to allow for unobserved preferences for four selected vehicle attributes, which relaxes the IIA assumption. Running counterfactual simulations based on their estimated vehicle choice model, the authors find that roughly 70% of consumers would have bought EVs even without the tax credits. These consumers might have placed a higher value on the environment, or simply could afford these more expensive vehicles. They are the so-called "non-additional" or "free-riders" (Chandra et al., 2010), as they receive windfalls from the tax credits without having to change their behaviors, thus adding cost to the policy. Xing et al. (2021) suggest that to be more cost-effective, the tax credits should target low-income households.

The above papers assessing EV tax incentives from the cost-effectiveness perspective focus on the public dollar costs per vehicle induced or per ton of CO_2 reduced. Their recommendations include spending more on charging facilities (Li et al., 2017), targeting low-income households (Xing et al., 2021) or those that drive a lot, live in rural areas, or currently own old and polluting cars (Sheldon and Dua, 2019). The cost-effectiveness analysis takes as given that the government will spend an amount of public money on one or more instruments to achieve a goal. From a political perspective, this is sensible and even essential. This type of analysis compares the costs of these instruments, but does not question the goal. Welfare analysis, however, questions the optimality of the goal. This type of analysis investigates how the instruments will result in a net gain or loss in consumer surplus, producer surplus, government revenue and externalities. From an economics perspective, welfare analysis is more extensive. It is likely to yield different conclusions from cost-effective analysis, particularly when the goal is not socially optimal. However, which approach is more valuable from the political viewpoint is not definite.

Holland et al. (2016) study the welfare effects of the U.S.' federal purchase subsidy in terms of environmental benefits throughout vehicle lifespans. The authors define net welfare from buying a car as the sum of expected utility less expected pollution damage, and builds a framework to obtain a "second-best" subsidy which equals the difference in marginal damages per mile driven by a gasoline vehicle and a comparable EV. Incorporating spatially detailed emissions, the study shows that the environmental externalities from driving EVs are spatially heterogeneous, thereby advocating for a regionally differentiated EV policy with higher subsidy in urban areas and lower subsidy—or even tax in rural remote places. The authors argue that only in these urban areas would driving an EV generate a net welfare gain. This argument is an interesting divergence from the recommendation by Sheldon and Dua (2019) who focus on the cost-effectiveness of the same program and advocate offering more incentives to EV drivers in the rural areas. Overall, a second-best nationwide subsidy for an EV, according to Holland et al. (2016), is a tax - not a subsidy - of US$427. The authors also find that these environmental externalities are heavily driven by local air pollution. If the environmental benefit is restricted in CO_2 reduction only, a subsidy would be justified.

Another welfare analysis in terms of environmental benefits, Dimitropoulos et al. (2016) evaluate the Dutch *bijtelling* incentives for EV company cars. The study uses SP data from a survey on lease drivers. The advantage of this type of data compared with revealed preference data are four-fold. First, the choice set stays limited with a tractable number of alternatives designed by the researchers. Second, EV-specific attributes such as driving range and recharging time, usually excluded in RP data, can be included in SP survey data, enabling the estimation of the willingness to pay for these attributes. Third, the attributes of the alternatives stay orthogonal by design, avoiding the complex IV method to address the multicollinearity between vehicle attributes and price as in Berry et al. (1995); Adamou et al. (2014) for instance. For the vehicle choice estimation, Dimitropoulos et al. (2016) use the panel latent class model which relaxes the IIA assumption of the traditional logit model and the distributional assumption of the random parameters in the mixed logit model. The latent class model assigns everyone with a probability to a class with a certain preference. The latent class model also enables an easier computation of consumer surplus at the individual level, which captures the social benefit associated with the tax base rate reduction. It also helps calculate the implicit subsidy per company car, which captures the social costs. The authors find that the social costs outweigh the social benefits as a result of the reduced *bijtelling* for BEVs, resulting in an annual welfare loss of €42 – 95 million.

Albeit various advantages, SP data are prone to several biases such as hypothetical bias, strategic bias or starting pointing bias, as they come from choice experiments (Brown, 2019). Studies solely based on SP data are, therefore, not apt for forecasting purposes and to some extent, for policy impact evaluation due to scaling problems. A more recent study on the impact of the CO_2-dependent *bijtelling* on the Dutch company EV market, van Eck et al. (2019) make use of RP data on vehicle registration during 2011-2016 and lease car driver characteristics. Identifying 196 unique combinations of brand, model and fuel type of vehicles in the dataset, the authors assume each consumer is faced a choice set of 196 alternatives. Their vehicle choice model, based on a multinomial logit model, shows that the preferential *bijtelling* rate for EVs led to fewer petrol cars and more EVs, diesel and hybrid electric vehicles (HEVs) sold on the lease car market over the studied period. They conclude that this policy was effective but not a cost-effective instrument to reduce CO_2 due to substantial foregone tax revenues. They point to the unintended consequence of local air pollution, arguing that incentives solely based on vehicles' CO_2 emission level can be a subsidy for diesel cars in disguise.

Overall, there is still much room in the literature for welfare analysis of EV tax incentives that not only evaluate their CO_2 impacts, but also other environmental impacts such as air pollutants. Given many financial incentives are offered at the point of sale (ie. purchase tax, purchase rebates), the environmental impacts in question should include those from the vehicle-production and disposal phases, which do not vary by vehicle use. In the context of the Netherlands, the private car market, which accounts for roughly the same number of annual new car registrations as company cars (BOVAG & RAI Vereniging, 2020), would also benefit from further studies.

3 Research question

This present study investigates what are the net welfare gains from the Dutch zero vehicle purchase tax (BPM) for BEVs.

Over the past decade, the BPM policy has experienced several changes. Before 2010, BPM was around 40% of the net list price—price after BTW (the Dutch value added tax). From 2010, BPM followed a step function of vehicle's CO_2 emission level (gram per kilometer, g/km) plus 27.4% of the net list price. This figure went down to 19% in 2011 and 11% in 2012. Since 2013, the BPM has been solely determined by type-approval CO_2 emissions (Belastingdienst, 2020). BEVs have been exempted from BPM since 2010.

Unlike the motor road tax (MRB) which varies with the vehicle ownership duration (in addition to its weight) or the fuel tax which varies with the vehicle use, BPM is a one-off tax on the purchase of a vehicle. Therefore, the social benefits and costs associated with this tax do not vary with vehicle use. The environmental costs that this tax should internalize are the one-off emissions from the vehicle-production and disposal phases. The benefits are the gain in the consumer surplus as lower prices allow more people to buy these vehicles.

Comparing the social benefits and costs associated with the BPM tax exemption for BEVs is relevant to economics, the discipline that advocates for the use of tax to address externality. In this present research, I focus on the externalities that the vehicle purchase tax seeks to internalize—that is, the environmental impacts from vehicle production and end-of-life phases. This is the key difference between this present research and earlier studies. As discussed in Section 2, the externalities of different vehicle types vary across different phases, with benefits of EVs realized most during the vehicle-use phase. Noting that the BPM is imposed at point of sale, would the BPM exemptions for BEVs be welfare-enhancing after all?

This research question is highly relevant to society as well. Tax reduction and exemption is a loss of government income. In 2020, this loss amounted to nearly €340 million in the Netherlands (Government of the Netherlands, 2020). Quantifying the welfare impacts of this tax exemption for BEVs is instructive for policymakers to choose an appropriate instrument to deliver more social benefits than costs.

4 Analytical framework

The analytical framework to quantify the welfare effects of EV tax incentives in this paper relies on random utility theory (McFadden, 1986). Consumer n is faced with a choice set of different vehicle types i and assumed to purchase the vehicle type j that gives the greatest utility U_{nj}. This utility level consists of a deterministic part V_{nj} and unobserved part ε_{nj}. Consider the case of a representative consumer, suppressing the subscript n, the utility associated with buying vehicle type j becomes

$$U_j = V_j + \varepsilon_j, \tag{4.1}$$

with the deterministic utility:

$$\begin{gathered} V_j = \alpha p_j + \theta \tau_j \ + X_j' \beta \\ (with\ \alpha, \theta < 0). \end{gathered} \tag{4.2}$$

Parameters α and θ denote the marginal disutilities of price and tax respectively, and β the marginal utility of vehicle attributes such as horsepower, size, brand, fuel consumption among others. X_j' is a vector of relevant attributes.

The vehicle purchase tax is denoted as τ_j, which in this framework, is independent of the vehicle price p_j. This has been the case with the Dutch BPM since 2010 when this tax rate started being CO_2-dependent, as opposed to being solely percentages of the vehicle net list price. From 4.2 , the partial derivative of V_j with respect to τ_j is

$$\frac{\partial V_j}{\partial \tau_j} \ = \ \theta. \tag{4.3}$$

Another assumption inherent in this framework is the independence of the vehicle price with respect to the vehicle tax. This assumption implies that manufacturers do not increase their EV prices in an attempt to reap windfall from the tax cuts. Full pass-through of vehicle tax benefits to consumers is a plausible assumption as evidenced from the literature on the incidence of vehicle incentives. For example, in a study on tax incentives for Toyota Prius, comparing transaction prices just before and after each time the tax changed, Sallee (2011) finds that there were minimal movements in the transaction prices less the subsidy amounts. Although there could be gradual changes, the majority of the subsidies, as Sallee (2011) explains, might have passed through to consumers because during the nascent adoption stage of new technology, automakers would want to keep the prices low to attract more consumers and gain initial market shares. In another study using transaction-level data, Muehlegger and Rapson (2018) also find that consumers captured around 80-90% of California's subsidy program for new EV purchases by low- and middle-income consumers. In case the assumption of no incidence of vehicle incentives is violated, the (cost-) effectiveness of the EV policy would be overestimated. However, this violation would not affect the welfare analysis of the policy.

The term ε_j in 4.1 is the difference between U_j - the utility consumer obtains by purchasing vehicle type j and V_j - the utility the researcher measures using observed attributes of vehicle type j. The distribution of ε_j is assumed to be of type I extreme value (Train, 2009), which leads to the well-known logit formula:

$$P_j = \frac{e^{V_j}}{\sum_i e^{V_i}}. \tag{4.4}$$

This formula gives the probability of vehicle type j being selected among all available vehicle types i. This probability equates to the market share of vehicle type j. The partial derivative of the market share of vehicle type j with respect to the deterministic utility associated with buying it is

$$\frac{\partial P_j}{\partial V_j} = \frac{e^{V_j}}{\sum_i e^{V_i}} - \left(\frac{e^{V_j}}{\sum_i e^{V_i}}\right)^2 = P_j \left(1 - P_j\right). \tag{4.5}$$

From 4.3 and 4.5, the marginal effect of vehicle tax τ_j on its own market share is dependent on the market share itself:

$$\frac{\partial P_j}{\partial \tau_j} = \frac{\partial P_j}{\partial V_j} \frac{\partial V_j}{\partial \tau_j} = P_j \ (1 - P_j \ )\theta. \tag{4.6}$$

I assume the vehicle market to be perfectly competitive and the supply of different vehicle types perfectly elastic. This is a reasonable assumption, given the small size of the Dutch car market (Dimitropoulos et al., 2016) Also, it is consistent with the previous assumption of zero incidence of EV tax benefits. This assumption implies zero producer surplus, and thus social welfare is the difference between total consumer surplus and total external cost.

Following (Small and Rosen, 1981), given the standard logit assumptions, the expected consumer surplus of the representative consumer associated with the set of alternatives i is the logarithm of the denominator of the choice probability. This consumer surplus conveniently takes a closed form:

$$CS = \frac{1}{\alpha} \, ln \sum_{i} e^{V_i}. \tag{4.7}$$

With N consumers in the market, total consumer surplus becomes $TCS = N * CS = \frac{N}{\alpha} \, ln \sum_i e^{V_i}$. Taking the partial derivative of the total consumer surplus with respect to the utility of choosing vehicle type j, we have

$$\frac{\partial TCS}{\partial V_j} = \frac{N}{\alpha} \frac{e^{V_j}}{\sum_i e^{V_i}} = \frac{N}{\alpha} \, P_j. \tag{4.8}$$

From 4.3 and 4.8, the marginal effect of vehicle tax τ_j on total consumer surplus is a function of P_j, or the market share of vehicle type j:

$$\frac{\partial TCS}{\partial \tau_j} = \frac{\partial TCS}{\partial V_j} \frac{\partial V_j}{\partial \tau_j} = \frac{N}{\alpha} P_j(\theta) = \frac{\theta N}{\alpha} P_j. \tag{4.9}$$

With N consumers in the market, there are $Q_j = NP_j$ vehicles of type j being purchased. From 4.6, the marginal effect of τ_j - the tax on vehicle type j on Q_j - the quantity of purchased vehicles of the same type becomes

$$\frac{\partial Q_j}{\partial \tau_j} = N \frac{\partial P_j}{\partial \tau_j} = NP_j \, (1 - P_j)\theta. \tag{4.10}$$

The external cost of vehicle type i is assumed to depend on its quantity $c_i \, (Q_i \,)$. Therefore, the total external cost associated with the set of alternatives i is $TEC = \sum_i c_i \, (NP_i \,)$. The marginal effect of vehicle tax τ_j on total external cost associated with the set of alternatives i is

$$\frac{\partial TEC}{\partial \tau_j} = \frac{\partial c_j}{\partial Q_j} N \frac{\partial P_j}{\partial \tau_j} + \sum_{i \neq j} \frac{\partial c_i}{\partial Q_i} N \frac{\partial P_i}{\partial \tau_j}. \tag{4.11}$$

This equation breaks down the effect of τ_j on total external cost into two parts : (i) $\frac{\partial c_j}{\partial Q_j} N \frac{\partial P_j}{\partial \tau_i}$ is the effect of τ_j on its own-market share; and (ii) $\sum_{i \neq j} \frac{\partial c_i}{\partial Q_i} N \frac{\partial P_i}{\partial \tau_i}$ is the effect of τ_j on the market shares of the other vehicle types in the set. This second part exists because of the substitution effect among different alternatives in the choice set. For instance, when the tax on BEVs decreases, the probability of a BEV being purchased increases. Some of the consumers that would have purchased other types such as ICEVs, HEVs or PHEVs now opt for BEVs instead. As probabilities sum to one over all vehicle types, an increase in the probability of one type must dovetail with a decrease in probability of the other types.

The choice probabilities under the logit model also have a special property of independence from irrelevant alternatives, or IIA—that is, the relative odds of choosing j over i are the same no matter what other types are available. This property can be demonstrated in the ratio $\frac{P_i}{P_j}$:

$$\begin{aligned} \frac{P_i}{P_j} &= \frac{\frac{e^{V_i}}{\sum_j e^{V_j}}}{\frac{e^{V_j}}{\sum_i e^{V_i}}} = \frac{e^{V_i}}{e^{V_j}} \\ Hence: P_i &= \frac{e^{V_i}}{e^{V_j}} P_j = e^{V_i - V_j} P_j . \end{aligned} \tag{4.12}$$

The marginal effect of vehicle tax τ_j on the market shares of other types $i \neq j$ is

$$\begin{aligned} \frac{\partial P_i}{\partial \tau_j} = \frac{\partial P_j}{\partial \tau_j} e^{V_i - V_j} + \frac{\partial \left(e^{V_i - V_j}\right)}{\partial \tau_j} P_j &= P_j (1 - P_j) \theta \frac{e^{V_i}}{e^{V_j}} + e^{V_i - V_j} \frac{\partial(-V_j)}{\partial \tau_j} P_j \\ &= P_j (1 - P_j) \theta \frac{P_i}{P_j} + \frac{P_i}{P_j} (-\theta) P_j \\ &= (1 - P_j) \theta P_i - \theta P_i \\ &= -\theta P_j P_i . \end{aligned} \tag{4.13}$$

Plugging 4.6 and 4.13 into 4.12, we have

$$\frac{\partial TEC}{\partial \tau_j} = \frac{\partial c_j}{\partial Q_j} N P_j \, (1 - P_j) \, \theta - \sum_{i \neq j} \frac{\partial c_i}{\partial Q_i} N \; \theta P_j P_i \quad . \tag{4.14}$$

From 4.9 and 4.14, the marginal welfare effect of vehicle type j tax, $\frac{\partial W}{\partial \tau_j}$ is

$$\frac{\partial W}{\partial \tau_j} = \frac{\partial TCS}{\partial \tau_j} - \frac{\partial TEC}{\partial \tau_j} = \frac{\theta N}{\alpha} P_j \quad - \frac{\partial c_j}{\partial Q_j} N P_j \, (1 - P_j) \, \theta + \sum_{i \neq j} \frac{\partial c_i}{\partial Q_i} N \; \theta P_j P_i$$

$$= \theta N P_j \; [\frac{1}{\alpha} \; - \frac{\partial c_j}{\partial Q_j} (1 - P_j) + \sum_{i \neq j} \frac{\partial c_i}{\partial Q_i} P_i \;].$$

$$Hence: \frac{\partial W}{\partial \tau_j} = \theta N P_j \; [\frac{1}{\alpha} \; - \frac{\partial c_j}{\partial Q_j} + \sum_{i} \frac{\partial c_i}{\partial Q_i} P_i \;]. \tag{4.15}$$

This equation shows that the marginal welfare effect of the tax on vehicle type j depends on the marginal disutilities of price and tax (α and θ), the number of consumers in the market (N) as well as the market shares and the marginal external costs of all vehicle types in the choice set.

The marginal external cost of vehicle type j ($\frac{\partial c_j}{\partial Q_j}$) appear twice in this marginal welfare function: (i) first on its own and (ii)second in the sum of the products of the market shares and marginal external costs of all vehicle types in the choice set $\sum_i \frac{\partial c_i}{\partial Q_i} P_i$. Since $P_i < 1$, the first part dominates the second, and since $\theta < 0$, the marginal external cost of vehicle type j has a positive sign in this marginal welfare function. This sign reflects the effect of the tax τ_j on the quantity of j and others. As the tax on type j decreases, more vehicles of type j will be purchased. As the external cost of a vehicle type depends on it quantity, marginal external cost of vehicle type j is added to the effect of the tax τ_j. Since all the choice probabilities sum up to one, the more vehicles of type j are purchased, the fewer purchases of vehicles of other types. Therefore, in the marginal welfare effect, the marginal external costs of other types have negative signs (noting $\theta < 0$).

5 Data description & Empirical methodology

5.1 Data

The two datasets used in this paper come from the RDW (Rijksdienst voor het Wegverkeer), the official vehicle registration authority of the Netherlands. The first dataset, which has been pre-processed by the PBL, contains micro-data on 8.3 million vehicle registrations, each of which includes the vehicle's plate number (unchanged throughout its lifespan), its date of first registration, list price and purchase tax (BPM). The characteristics of each vehicle such as brand and model name, engine type, horse power, curb weight, wheelbase, rear axle, fuel consumption and CO_2 emissions, among others, constitute the major part of this dataset. The second dataset contains records on the ownership of each vehicle—individual or company (anonymized identifier) from when the vehicle was first registered to 2017-end. A vehicle, whether a private car or company car, can change hands many times throughout its lifespan, so this is a big dataset of over 67 million observations. Each observation includes an ownership type reference: B a car stocked by a dealer,N for a private car and R a company car or a business car[4]. The starting date and ending date of each ownership are also given in each observation. The plate number is the unique identifier of a certain vehicle across these two datasets.

The first task is to determine which cars in the vehicle characteristic dataset had been first purchased as private cars. I merged these two datasets by a combination of plate number and registration date and obtained two subsets of observations that only have either R or N as ownership type references. Filtering out all the B observations which neither influence nor assist with the identification of these cars, I merged again the remaining observations, which are associated with multiple ownership types, with the original ownership dataset, but this time, by plate number only. Grouping this newly-merged dataset by plate number, I then filtered out the observations containing the earliest starting date for each car and a holding duration of minimum 30 days. This was to avoid a situation when a car changed hands so quickly from a company to a private driver. From these observations, I filtered those with distinct plate numbers and homogeneous ownership type references to obtain

[4]This is a registration made by a company, but whether the car is mostly used for private trips (a company car) or not (a business car) is unknown.

the third subset. The remainder included observations of the same plate number and registration date but mixed ownership references (both R and N) and those with holding duration lasting less than 30 days. I took further cleaning steps and finished with a dataset of approximately 5.2 million private cars, which are used in this analysis.

Table 5.1 provides the descriptive statistics of the newly merged dataset. The *netlistprice* was constructed from subtracting the corresponding VAT portion from the list price variable in the dataset. According to BOVAG & RAI Vereniging (2020), The Dutch VAT tax on passenger cars increased from 17.5% to 19% in January 2001 and then to 21% in October 2012. The *listprice* variable suffers from a lot of missing values, around 200,000 of which were then recovered by using the average price of vehicles from the same brand, model, year, segment, engine type and CO_2 level. However, the large number of remaining missing values is still a major drawback of this dataset.

Table 5.1: Descriptive statistics of private cars in the Netherlands in 2000-2017

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
bpm	5,251,425	4,544.9	4,094.5	0	2,083	5,984	182,960
netlistprice	2,535,971	18,355	18,274.4	405	10,377	22,230	528,407
weight	5,251,425	1,133.9	250.6	605	940	1,293	3,268
enginecylcap	5,246,965	1,538.5	459.1	599	1,229	1,796	8,285
wheelbase	5,251,348	2,546.6	149.7	1,810	2,450	2,650	3,970
rearaxle	5,250,921	1,472.3	65.2	1,200	1,430	1,520	1,920
horsepower	5,247,159	75.9	28.7	18	55	88	570
CO2	5,127,309	153.2	39.5	0	127	176	570
fuelconsumption	5,133,339	6.4	1.6	0	5.2	7.3	25

Figure 5.1: Private car registrations by engine types

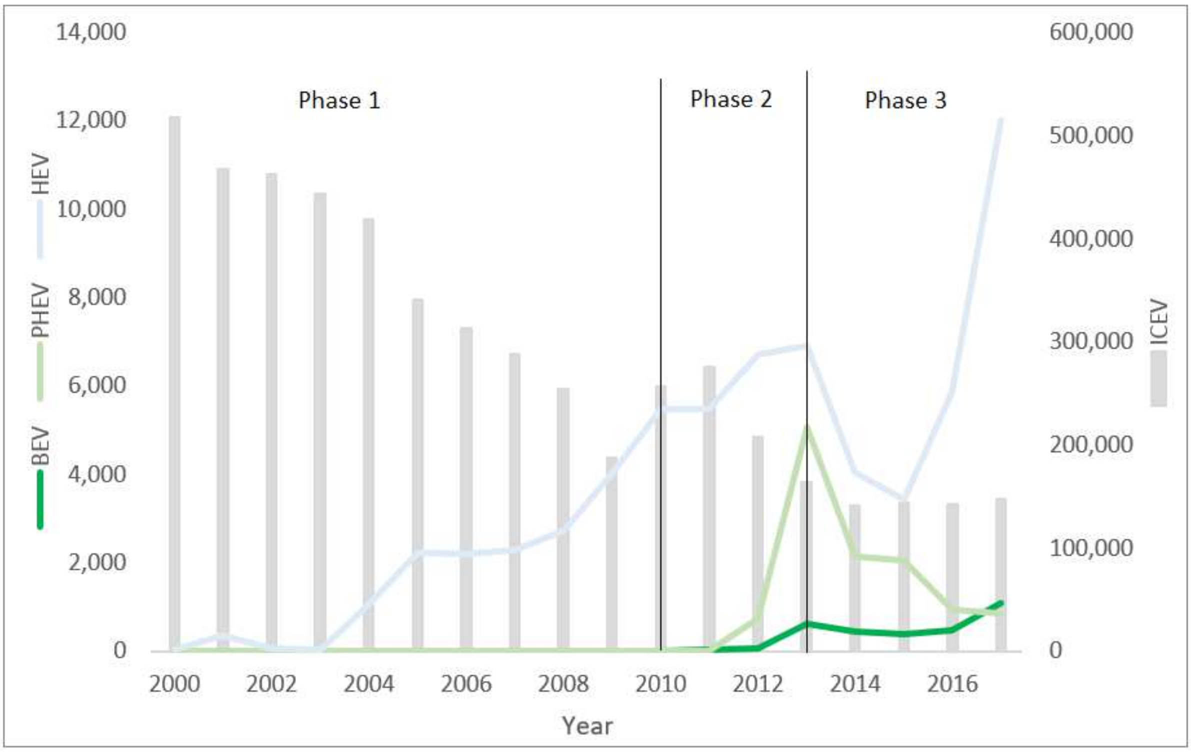


Figure 5.1 provides the distribution of private car registrations by year during 2000-2017. These cars are grouped into four engine types : BEV, PHEV and HEV (with numbers of registrations against the left vertical axis) and ICEV (the right vertical axis). Although declining dramatically—by roughly five-fold over the period , ICEVs still dominate the private car market. HEV registrations increased steadily from 2003, but started to decline in 2013 only to pick up again in 2015. Meanwhile, PHEV and BEV had a late start. Registrations of PHEV spiked in 2013 and then levelled off, whereas BEV registrations slowly picked up. Over this period, the BPM experienced several changes as outlined in Section 3. The milestones of these major changes are marked in Figure 5.1.

To study the impact of the tax benefits on EVs with the framework described in Section 5, I created a panel dataset from the existing dataset. The cross-sectional units are the four engine types and the time dimension at weekly level. I used the median values (as opposed to mean values to avoid extreme outliers) of each characteristic from vehicles with the same engine type for each week. The next sub-section discusses the assumptions and empirical strategy to analyse this panel dataset.

5.2 Empirical methodology

To estimate the marginal disutility of price and tax (parameters α and θ in 4.15), I first attempted to estimate the vehicle type demand function by using the multinomial logit model (MNL). The use of MNL would require identifying the choice set each consumer might have faced. To do this, van Eck et al. (2019) identify 196 unique combinations of brand, model and fuel types from their vehicle registration dataset and assume the choice set facing each consumer has 196 alternatives. This choice set is unrealistic, as hardly anyone can consider such a large number of choices. Moreover, this identification would not be particularly useful for my analysis, since vehicles would ultimately aggregated into four engine groups. Instead, I used a method similar in spirit to what (Berry, 1994) proposes to circumvent the nonlinear instrumental problems. Taking the logarithm of equation 4.4, we have

$$ln(P_j) \;=\; V_j - ln(\sum_i e^{V_i}) + \varepsilon_j. \tag{5.1}$$

To drop the logsum term $ln(\sum_{it} e^{V_{it}})$, Berry (1994) take the difference in the logarithms of market shares of alternative j and the outside good $j = 0$ (i.e. not buying a new vehicle).

$$ln(P_j) - ln(P_0) \;=\; ln(\frac{P_j}{P_0}) = \; V_j + \varepsilon_{jt}. \tag{5.2}$$

Adamou et al. (2014) follow this strategy and add the time subscript t:

$$ln(P_{jt}) - ln(P_{0t}) \;=\; ln(\frac{P_{jt}}{P_{0t}}) = \; V_{jt} + \varepsilon_{jt}. \tag{5.3}$$

By so doing, Adamou et al. (2014) make an implicit assumption that the choice sets are equal over the years, which is not a realistic assumption. Also, obtaining the "outside good" market share is tricky, since we do not observe the potential market size which includes those that want to buy a car but do not purchase one. Total market size can be set as the number of households in the market (Berry et al., 1993; Adamou et al., 2014), although this might be an overestimation in the Dutch context. Alternatively, total market size can be estimated to be the sum of new and old car sales, for example. In the literature, the outside good term is often dropped from the regression with varied justifications. Weber (2019) holds that the outside good is absorbed by the year fixed effects, hence regressing the log market share of alternative j via year fixed-effects regression. Similarly, Azarafshar and Vermeulen (2020) argue that tax rebates would not incentivize consumers to shift preferences from not buying a vehicle at all into buying a new EV vehicle. These authors provide a test for this argument by estimating the extensive margin effects of the rebates on total vehicle sales in each Canadian province, controlling for province- and time-specific unobserved factors. Their estimation results show no significant effect of the rebates on the aggregate sales, invalidating the possibility that those that would not have bought any new vehicle in the absence of the rebates would choose to buy new EVs in the presence of the rebates. Based on this finding, Azarafshar and Vermeulen (2020) set the dependent variable to be the log of model-specific market share, instead of the log-odds ratio of buying a new EV relative to buying no new vehicle.

To avoid estimating the potential market size and making further assumptions regarding the outside good, I take the difference in the logarithms of the market shares of two alternatives j and i. Since these two belong to the same choice set, the logsum terms are cancelled out:

$$ln(P_{jt}) - ln(P_{it}) \quad = V_{jt} - V_{it} + \varepsilon_{jt} - \varepsilon_{it}.$$

The logarithms of market shares of the two vehicle types can thus be modelled by standard linear regression methods with the regressors being the differences in prices, taxes and attributes of these two types:

$$ln(P_{jt}) - ln(P_{it}) \quad = \alpha(p_{jt} - p_{it}) + \theta(\tau_{jt} - \tau_{it}) \ + \beta(X'_{jt} - X'_{it}) + (\varepsilon_{jt} - \varepsilon_{it}). \tag{5.4}$$

The term $(\varepsilon_{jt} - \varepsilon_{it})$ can break down into three components: (i) a pair-specific term $(\epsilon_j - \epsilon_i)$, which captures unobserved factors that differ across pairs $(j; i)$ and but are constant over time (e.g. consumers' preference for EVs as green vehicles as opposed to ICEVs as environmentally-unfriendly means of transport); (ii) a time component λ_t capturing unobserved factors that are constant across pairs but evolve over time (e.g. easiness to charge EVs, which has improved steadily over time with the increasing availability of charging stations) and (iii) an idiosyncratic error term $(\nu_{jt} - \nu_{it})$ capturing time-varying and pair-varying unobserved factors. This idiosyncratic error term may also capture the unobserved behavioral effect of the difference in the tax rates applied on vehicle types which varies over time and across pairs.

We want to estimate α, θ and β, or the effects of the differences in prices, taxes and attributes, on the differences in the (logarithm) market shares of a vehicle type pair, holding constant the unobserved pair characteristics $(\epsilon_j - \epsilon_i)$ and unobserved time effects λ_t. The key identifying assumption rendering fixed-effect estimators consistent is the zero conditional mean of the error term given the regressors and the pair and time fixed effects. This implies that the term $(\nu_{jt} - \nu_{it})$ must be uncorrelated with $(p_{jt} - p_{it})$, $(\tau_{jt} - \tau_{it})$ and $(X'_{jt} - X'_{it})$, controlling for the pair-specific and time-specific effects. This assumption may not be met, because price differences might well be related to differences in many vehicle attributes that must be excluded from the regression due to their high correlations with the price. This endogeneity problem means that the fixed-effect estimator of the price might be biased.

The most common solution to this problem is to employ instrumental variables (IV). For instance, using nested logit to estimate a vehicle type demand, Adamou et al. (2014) use the sum of each vehicle attribute characteristic (i.e. horsepower CO_2 emission level and engine capacity) and of the constant term over all competing products belonging to the same nest as an IV for price. The IV-estimated price coefficients across three model specifications are between 2 and 7 times higher than those estimated by OLS. The authors use two levels of aggregation of their dataset: (i) at the aggregated level, a product is specified by the model and engine type, resulting in 729 unique products; and (ii) at the disaggregated level, models were broken down into different categories of engine displacement, doubling the number of unique products. By comparison, my unit of analysis is vehicle types by engine—that is, more aggregated than commonly seen in the literature (e.g. by model or a combination of brand and model). Furthermore, the dependent variable and all regressors in this present study are in difference form. Therefore, the omitted variable bias might be less pronounced than in Adamou et al. (2014).

6 Results & Discussion

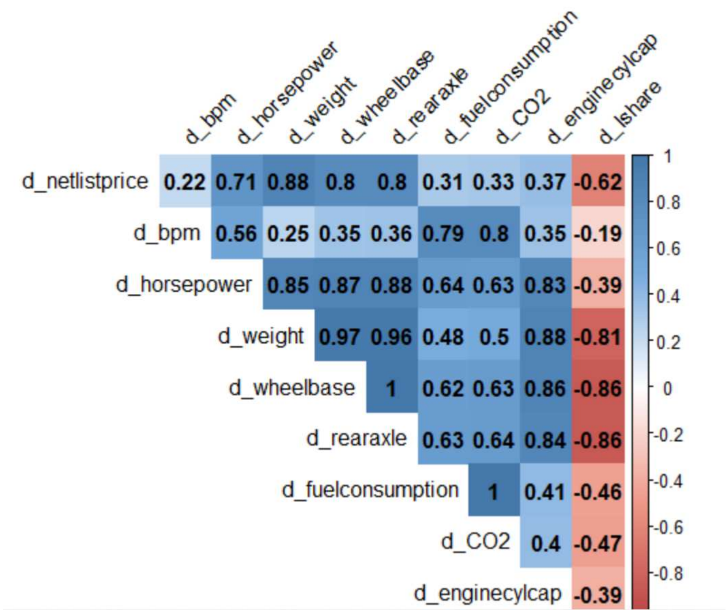
6.1 Descriptive statistics

To implement the empirical strategy described in Section 5, I computed the differences between BEV and each of the other types and obtained the descriptive statistics and correlation matrix:

Table 6.1: Descriptive statistics of key variables

Variable	N	Mean	Std. dev.	Min.	25%	Median	75%	Max.
d_netlistprice	1926	-2968.71	26476.06	-99149	-21157.8	-15941.7	14407.11	107233
d_bpm	2139	-2693.89	2056.9	-17833	-4226.46	-2811.96	-469.07	4835
d_horse_ power	1254	-65.9	21.9	-190	-76.5	-71.752	-61.8	77
d_weight	2139	-503.13	826.42	-2018.5	-1220	-1061.44	336.67	2056
d_wheelbase	2139	-1311.77	1439.98	-2960	-2573.87	-2501.84	110.057	2960
d_rearaxle	2139	-748.285	827.19	-1645	-1480	-1455.77	50.83	1700
d_fuel_ consumption	2137	-4.82	1.69	-14.7	-5.84	-4.93	-4.36	0
d_CO2	2139	-114.43	41.275	-349	-138.96	-114.77	-104.68	0
d_enginecylcap	1186	-1537.93	278.419	-3564	-1669.25	-1567.83	-1477.25	1339
d_lshare	2139	-2.254	5.86	-16.96	-6.99	0	2.794	9.48

Figure 6.1: Correlation matrix for 2000-2017 dataset



The correlation matrix shows substantial correlations between *d_ netlistprice* and *d_ weight*, *d_ wheelbase* and *d_ rearaxle*. These high correlations are expected, because bigger cars tend to be more expensive. Meanwhile, *d_ bpm* is highly correlated with *d_fuelconsumption* and *d_ CO2*, because the BPM tax was dependent on vehicle CO_2 emission level, which is contingent on fuel consumption. Adding these variables together in one regression will thus lead to multicollinearity problem, which will affect the interpretation of the estimated coefficients of our two variables of interest: *d_ netlistprice* and *d_ bpm*. However, there is no correlation between these two variables, thus including them both in a regression will not compromise the interpretation of their estimated coefficients.

6.2 Estimation results

Table 6.2: Regression results

	Dependent variable: d_lshare					
	OLS		Fixed-effects			
	(1)	(2)	(3)	(4)	(5)	(6)
d_netlistprice	-0.077***	-0.079***	-0.057***	-0.011***	-0.013***	-0.001
	(0.005)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)
d_bpm	0.619***	0.616***	0.964***	-0.195***	-0.195***	-0.067***
	(0.025)	(0.025)	(0.038)	(0.016)	(0.016)	(0.025)
d_horsepower	0.085***	0.085***	0.030***	0.008***	0.007**	-0.014***
	(0.006)	(0.006)	(0.007)	(0.003)	(0.003)	(0.003)
d_enginecylcap	-0.005***	-0.005***	-0.004***	0.002***	0.002***	0.003***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
pair fixed-effects	no	no	no	yes	yes	yes
month fixed-effects	no	yes	no	no	yes	no
year fixed-effects	no	no	yes	no	no	yes
Observations	1,002	1,002	1,002	1,002	1,002	1,002
Adjusted R^2	0.728	0.730	0.814	0.951	0.952	0.961
F-test for pair fixed-effects				2248.1*** (df1 = 2, df2 = 995)		

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses.

Table 6.2 presents the results from linear regression analysis. Only *d_ horsepower* and *d_ enginecylcap* are included as control variables, because the others are highly correlated with the two variables of interest. Column (1) provides the estimates from the OLS regression as the base specification. The month (month of the year) fixed-effects do not appear to have any significant effects, as estimates in column (2) do not differ much from the base estimates. Meanwhile, the year fixed effects seem to absorb some variations in both the variables of interest as shown in column (3). The estimated coefficients of the d_bpm variable, or parameter θ, have unexpected sign across the first three specifications. θ has the expected negative sign only when the pair fixed-effects are included, indicating that the difference in BPM tax variable and the pair fixed-effects are highly related. This indication makes sense because the BPM varies across the vehicle types and equals 0 for BEVs. Comparing specification (4) with the base OLS (1), much of the price effect is absorbed in the pair fixed-effects. The F-test for individual effects confirms the pair fixed-effects model (4) is better than the OLS. When the pair fixed-effects are controlled for, the estimated α declines by seven-fold, θ has the negative sign as expected and the model fit also improves (adjusted-R^2 increases from 0.73 and 0.82 to 0.95). Adding the month fixed-effects in specification (5) does not substantially improve the model fit or change the estimates for both our variables of interest. Meanwhile, adding the year fixed-effects in specification (6) crowds out the effects of these variables.

In the preferred specification (4), the estimated θ is approximately 20 times larger than α. As both vehicle net list price and vehicle tax have the same units (€'000), this indicates that controlling for vehicle type, horsepower and engine capacity, consumers are 20 times more sensitive to the BPM tax than the vehicle price. This behavioral effect of tax is substantial, indicating consumers' strong aversion to the vehicle purchase tax BPM. This also implies that the tax is an effective instrument to influence consumer choices.

6.3 Estimates for marginal external costs

Vehicle purchase tax is a one-off payment. It is not a tax on the ownership or the use of the vehicle. Thus the externalities meant to be internalized by this tax do not vary by the length of the ownership or the extent of driving made by the vehicle. Based on the discussion on the various environmental impacts throughout the lifespan of a vehicle in Section 2, the externalities relevant for the vehicle purchase tax are those associated with the vehicle production and end-of-life phases.

To obtain the estimated marginal external costs ($\frac{\partial c_i}{\partial Q_i}$ in 4.15) from vehicle production and end-of-life phases of the four vehicle types under study, I collated the relevant emissions output (Table 6.3) from the GREET 2 Model (Argonne National Laboratory, 2020), the most comprehensive and updated database for life-cycle-assessment of various vehicle technologies. The model offers estimates for five propulsion technologies—ICEV, HEV, PHEV, BEV and Fuel cell vehicle (FCV). The last type is not included Table 1 due to the very low uptake of this technology in the Dutch car market. The GREET 2 simulates vehicle-cycle energy use and emissions from raw material recovery, vehicle component production, assembly, disposal and recycling. Two main vehicle material compositions are evaluated in the model—lightweight and conventional. I focus only on the estimates of conventional material vehicles, since the use of lightweight materials in car manufacturing is still in its infancy. Six major GHGs and pollutants from vehicle production and end-of-life phases include CO_2, NO_x, PM_{10}, $PM_{2.5}$, CH_4 and CO.

Table 6.3: Emissions from vehicle production and end-of-life phase (kg)

	ICEV	PHEV	BEV	HEV
CO_2	5,678.14	6,771.31	6,261.66	5,832.70
NOx	6.91	8.50	7.80	7.15
PM_{10}	2.63	3.36	3.27	2.85
$PM_{2.5}$	1.22	1.47	1.35	1.32
CH_4	12.59	14.40	13.53	12.77
CO	19.53	21.71	18.86	20.58

Table 6.4: Environmental prices for average atmospheric emissions in the EU28 (€$_{2015}$/kg emission)

	Lower	Central	Upper
CO_2	0.022	0.057	0.094
NOx	9.97	14.8	22.1
PM_{10}	19	26.6	41
$PM_{2.5}$	27.7	38.7	59.5
CH_4	0.673	1.74	2.91
CO	0.0383	0.0526	0.0918

Table 6.5: Estimated marginal external costs during vehicle production and end-of-life phases (€$_{2015}$)

	ICEV	PHEV	BEV	HEV
Lower	286.60	348.84	324.92	299.66
Upper	904.87	1,093.58	1,016.58	940.65

Next, I obtained the environmental prices of these emissions from the Environmental Prices Handbook (CE Delft, 2018), which provides the upper, central and lower pollutant level values (Table 6.4). The ranges in these estimates are indicative of the uncertainties in how much people value environmental quality. The upper and lower values are recommended to be used in social cost-benefit analysis (CE Delft, 2018). Finally, I multiplied the estimates in Table 6.3 and Table 6.4 to obtain the marginal external costs from vehicle production and end-of-life phases of the four vehicle engine types reported in Table 6.5.

Table 6.6: Vehicle statistics in 2017

	Sales	Market share	Avg. netlistprice	Avg. BPM	Avg. horsepower	Avg. engine
ICEV	146,910	91.34%	21,265	4,262	81.1	1262.3
PHEV	848	0.53%	39,008	1,569	113.6	1792.4
BEV	1,077	0.67%	54,079	0	40.0	703.0
HEV	12,012	7.47%	31,864	1,376	110.0	1648.2
Total(N)	160,847					

6.4 Welfare effects

As the instrumental variable techniques are out of scope for this present study, I adjusted the OLS estimates of coefficients on price and tax by a multiplier of 3 to obtain the estimates that might have been generated with an IV technique: $\alpha = (-0.011) * 3 = -0.033$ and $\theta = (-0.195) * 3 = -0.589$.

Plugging the estimates of α and θ, and the vehicle statistics in 2017 (Table 6.6) into the equations of total consumer surplus and total external costs in Section 5, I obtain a net welfare loss of €30.7 million using the lower values of the marginal external costs in 6.5 and €130.6 million using the upper values. These values correspond to €190 to €800 per car. Plugging these estimates into the marginal welfare effect function 4.15, I conclude that for every €1,000 increase in the BPM tax on BEV, social welfare will increase by approximately €94 million.

The net welfare loss from BPM tax exemption on private BEVs is a result of the tax's failure to internalize the external cost of BEV production and disposal phases. The BPM in its current form is only dependent on CO_2 emission from vehicle-use phase, which is zero for BEVs. However, BEV drivers already enjoy the benefit of the zero CO_2 emissions from BEVs during the vehicle-use phase, as they pay no fuel tax. The BPM tax exemption only make BEVs less expensive for consumers, hence creating some consumer surplus gain, while leaving their externalities during the vehicle-production and end-of-life phases unaddressed.

The findings from this paper suggest that BPM exemption for BEVs, albeit effective in increasing BEV adoption, is not a welfare-enhancing policy. Strictly speaking, to internalize the external costs from vehicle production and end-of-life phases, BEV buyers should pay a higher BPM tax than conventional cars. To increase BEV adoption without creating a welfare loss, the appropriate policies should focus on the vehicle-use (WTW) stage where BEVs yield more environmental benefits than ICEVs. These can be an increase in the fuel taxes, or a vehicle mile traveled (VMT) tax differentiated by engine types.

While this present study only focuses on the Dutch private car market, its findings also shed lights on the company car market. The *bijtelling* treatment for company cars has already caused a social welfare loss, as it leads to purchases of more expensive cars and more kilometers driven (Gutiérrez-i Puigarnau and Van Ommeren, 2011) than would be the case for private cars. In 2017, the *bijtelling* rate (percentage of net list price) applied on EV company cars is 4%, much lower than the rate imposed on non-EVs (22%). Using the average net list price of a BEV in 2017 (Table 6.6), the difference of 18% would amount to €9,700 of tax loss per company BEV, which is twice the amount of BPM loss per private BEV. This implies that welfare loss from company car tax reduction for BEVs can even exceed the estimated welfare loss from the BPM exemption for private BEVs found in this present study and the estimated average welfare loss per company car between €70 and €159 found in Dimitropoulos et al. (2016).

6.5 Caveats and avenues for further research

The present study has ample room for improvement. First, its theoretical framework and empirical analysis are based on the IIA assumption which implies unrealistic substitution patterns among different vehicle type choices. With further data on the drivers' characteristics such as income, age, residential location, and perhaps, the consideration set as in Xing et al. (2021), the mixed logit model or latent class model will yield more convincing results due to their relaxed IIA assumption. That being said, as shown in van Eck et al. (2019), the mixed logit model may not necessarily outperform the standard multinomial logit model. van Eck et al. (2019) use the mixed logit model to control for unobserved behavioral factors, but this model fails to generate the expected signs for the estimates of the variables of interest (i.e. fuel cost and lease cost of company cars). Ultimately, their preferred estimates come from the standard multinomial logit model.

Second, the present analysis does not make full use of the given micro dataset, due to the high aggregation level of the data—at the engine-type level, that finally go to the vehicle demand estimation. The choice of this aggregation level was driven by the available estimates of the environmental impacts from the vehicle-production and disposal phases, which are only at the engine-type level. If these estimates are available at a more disaggregated level (i.e. by vehicle attributes such as weight, segment, horsepower or driving range), the detailed variations at the vehicle-level of the micro dataset will be of more use.

Third, this analysis ignores a potential ramification of point-of-sale incentives such as the BPM exemptions—that is, the reduction in the average life of vehicles, hence an increase in vehicle production. Further research on how a purchase tax can affect vehicle holding duration can provide insights into this unintended effect of the incentives.

Last, the welfare analysis in this paper also does not factor in EVs' potential positive externality with respect to the vehicle-to-grid innovation and energy security as discussed in Section 2. Albeit still laden with uncertainties, the network effect of EVs can be substantial. Including this positive externality will make the welfare analysis more comprehensive.

7 Conclusion

With a welfare framework based on random utility theory and a regression-type empirical analysis on revealed preference data, this present study provides evidence of the net welfare loss from the Dutch purchase tax exemption for battery electric vehicles. The social cost analysis in this paper focuses on the environmental externalities associated with the vehicle-production and end-of-life phases, which have been excluded from the impact assessment of similar financial incentives in the existing literature. This research can be strengthened with further data on the socio-economic characteristics of the Dutch private drivers and more advanced econometrics techniques that can relax its assumptions about the substitute patterns among different vehicles. More disaggregated estimates of the marginal external costs during the vehicle-production and end-of-life phases can enable the present study to make the most out of the available micro dataset. The findings from this study call for a reconsideration of using purchase tax incentives to promote EV adoption.

Though electric cars have been existing for as long as gas-guzzlers, they kept a low profile in the last century and has only gained relevance over the recent decade. This revival was largely driven by the increasing pressure of GHG emissions, air pollution and oil dependency in many developed and emerging markets. Given the announced goals and plans of governments across the world, the transition from a predominantly fuel-powered vehicle fleet to an electrified one is bound to accelerate in the next decade. Purchase tax incentives, albeit not a cost-effective instrument to reduce GHG emissions as shown in the existing literature, will remain a popular tool for policymakers to stimulate the uptake of EVs. This present study contributes another perspective to examine the impact of this instrument and suggests a different form of tax incentives, specifically during the vehicle-use phase, to deliver net welfare gain in terms of environmental benefits.

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Appendix

A1 R code for the empirical analysis

```
library(data.table)
library (dplyr)
library(stargazer)
library(lfe)
library(plm)
devtools::install_github("joachim-gassen/ExPanDaR")
library(ExPanDaR)
library(corrplot)

priv <- fread("../data.csv")
###########construct dates###############
priv$year <- format(as.Date(priv$dt1streginnl, format="%d/%m/%Y"),"%Y")
priv$month <- format(as.Date(priv$dt1streginnl, format="%d/%m/%Y"),"%m
   ")
priv$week <- format(as.Date(priv$dt1streginnl, format="%d/%m/%Y"),"%Y-W
   %V")
time <- cbind(priv$week,priv$month)
time <- data.frame(time)
########### recover missing values of net list price ###########
priv <- priv%>%
  group_by(brand,model,year,vehsegment,propulsiontype,
   emissco2combi_g_km)%>%
  mutate(newlistprice=median(listprice,na.rm=TRUE))

priv$newlistprice <- ifelse(is.na(priv$listprice),priv$newlistprice,
   priv$listprice)
priv$netlistprice <- ifelse(priv$dt1streginnl<  "2001-01-01",0.825*
   priv$newlistprice,
                              ifelse(priv$dt1streginnl>="2001-01-01" &
   priv$dt1streginnl<"2012-10-01",0.81*priv$newlistprice,
                                     0.79*priv$newlistprice))
priv$netlistprice <- priv$netlistprice/1000

##################rename variables#################
priv <- priv %>%
  rename(bpm=bpm_paidvehregtax,
    weight= massemptyveh,
    horsepower=power_kw,
    rearaxle = vehrearaxl,
    fuelconsumption=fuelconscombi_l_100km,
    CO2 = emissco2combi_g_km ,
    enginecylcap = enginecylcap_cc,
  )
priv$bpm <- priv$bpm/1000
###############construct chosen#########################
priv$chosen <- priv$propulsiontype
priv$chosen[priv$chosen=='Alcohol']<-'ICEV'
priv$chosen[priv$chosen=='CNG']<-'ICEV'
priv$chosen[priv$chosen=='Diesel']<-'ICEV'
priv$chosen[priv$chosen=='Diesel Electric']<-'ICEV'
priv$chosen[priv$chosen=='Double Combustion Other']<-'ICEV'
priv$chosen[priv$chosen=='Electric']<-'BEV'
```

```
priv$chosen[priv$chosen=='Electric Gasoline']<-'ICEV'
priv$chosen[priv$chosen=='Gasoline']<-'ICEV'
priv$chosen[priv$chosen=='LPG']<-'ICEV'
priv$chosen[priv$chosen=='Hybrid Diesel Electric']<-'HEV'
priv$chosen[priv$chosen=='Hybrid Electric Gasoline']<-'HEV'
priv$chosen[priv$chosen=='Hybrid other']<-'HEV'
priv$chosen[priv$chosen=='Plug-in Hybrid Diesel Electric']<-'PHEV'
priv$chosen[priv$chosen=='Plug-in Hybrid other']<-'PHEV'
priv$chosen[priv$chosen=='Plug-in Hybrid Electric Gasoline']<-'PHEV'
priv <- priv[priv$chosen!="Hydrogen_Fuel_Cell",]

####################### Sales by type by year#############
des <- as.data.frame(table(priv$chosen,priv$year))
bev <- subset(des,Var1=="BEV")
icev <- subset(des,Var1=="ICEV")
phev <- subset(des,Var1=="PHEV")
hev <- subset(des,Var1=="HEV")
des2 <- matrix(data=NA, nrow=18, ncol = 4)
colnames(des2) <- c("BEV","PHEV", "HEV", "ICEV")
des2 <- data.frame(des2)
des2$BEV <- bev$Freq
des2$ICEV <- icev$Freq
des2$PHEV <- phev$Freq
des2$HEV <- hev$Freq
des2 <- t(des2)
des2 <- data.frame(des2)
colnames(des2) <- c(2000:2017)
fwrite(des2,"year1.csv")
############################PANEL DATA###########
g_priv <- priv%>%
  group_by(week)%>%
  summarise(totalcount = n())%>%
  ungroup()

priv_median<-
  priv%>%
  group_by(week,chosen)%>%
  summarise(count = n(),netlistprice=median(netlistprice,na.rm = TRUE),
            bpm=median(bpm,na.rm = TRUE),
            horsepower=median(horsepower,na.rm = TRUE),
            weight=median(weight,na.rm = TRUE),
            wheelbase=median(wheelbase,na.rm = TRUE),
            rearaxle=median(rearaxle,na.rm = TRUE),
            fuelconsumption=median(fuelconsumption,na.rm = TRUE),
            CO2=median(CO2,na.rm = TRUE),
            enginecylcap=median(enginecylcap,na.rm=TRUE),)%>%
            ungroup()

priv_median<- left_join(priv_median, g_priv,by ="week")
priv_median$market_share <- priv_median$count/priv_median$totalcount
priv_median$l_share <- log(priv_median$market_share)
priv_median$count <- NULL
priv_median$totalcount <- NULL

########ICEV
b_ice<- priv_median[!priv_median$chosen=="PHEV",]
b_ice<- b_ice[!b_ice$chosen=="HEV",]
b_ice_g<-
```

```
  b_ice%>%
  group_by(week)%>%
  summarise(n=n())%>%
  ungroup()

b_ice<- left_join(b_ice, b_ice_g,by ="week")

b_ice_1 <- subset(b_ice,n=="1")

setDT(b_ice_1)
substract0 <- function(x){
  if (class(x) == "numeric"){
    0-x
  } else {
    x
  }
}

b_ice_1[, names(b_ice_1) := lapply(.SD, substract0)]
b_ice_1 <- subset(b_ice_1, select=-c(chosen,n))

b_ice_2 <- subset(b_ice,n=="2")

b_ice_2$netlistprice <- ifelse(b_ice_2$chosen=="ICEV",-
    b_ice_2$netlistprice,b_ice_2$netlistprice )
b_ice_2$bpm <- ifelse(b_ice_2$chosen=="ICEV",- b_ice_2$bpm,b_ice_2$bpm
    )
b_ice_2$horsepower <- ifelse(b_ice_2$chosen=="ICEV",-
    b_ice_2$horsepower,b_ice_2$horsepower)
b_ice_2$weight <- ifelse(b_ice_2$chosen=="ICEV",- b_ice_2$weight,
    b_ice_2$weight)
b_ice_2$wheelbase <- ifelse(b_ice_2$chosen=="ICEV",- b_ice_2$wheelbase,
    b_ice_2$wheelbase )
b_ice_2$fuelconsumption <- ifelse(b_ice_2$chosen=="ICEV",-
    b_ice_2$fuelconsumption,b_ice_2$fuelconsumption )
b_ice_2$CO2 <- ifelse(b_ice_2$chosen=="ICEV",- b_ice_2$CO2,b_ice_2$CO2
    )
b_ice_2$ln_share <- ifelse(b_ice_2$chosen=="ICEV",- b_ice_2$l_share ,
    b_ice_2$l_share)
b_ice_2$rearaxle <- ifelse(b_ice_2$chosen=="ICEV",- b_ice_2$rearaxle ,
    b_ice_2$rearaxle)
b_ice_2$enginecylcap <- ifelse(b_ice_2$chosen=="ICEV",-
    b_ice_2$enginecylcap ,b_ice_2$enginecylcap)


b_ice_m <- b_ice_2%>%
  group_by(week)%>%
  summarise(netlistprice=sum(netlistprice),
            bpm=sum(bpm),
            horsepower=sum(horsepower),
            weight=sum(weight),
            wheelbase=sum(wheelbase),
            rearaxle=sum(rearaxle),
            fuelconsumption=sum(fuelconsumption),
            CO2=sum(CO2),
            enginecylcap=sum(enginecylcap),
            l_share=sum(l_share))%>%
    ungroup()
```

```r

icev <- bind_rows(b_ice_1,b_ice_m)
icev$pair <- "BEV_ICEV"

###################PHEV
b_ice<- priv_median[!priv_median$chosen=="ICEV",]
b_ice<- b_ice[!b_ice$chosen=="HEV",]
b_ice_g<-
  b_ice%>%
  group_by(week)%>%
  summarise(n=n())%>%
  ungroup()

b_ice<- left_join(b_ice, b_ice_g,by ="week")

b_ice_1bev <- subset(b_ice,n=="1"& chosen=="BEV")

b_ice_1non <- subset(b_ice,n=="1"& chosen=="PHEV")

setDT(b_ice_1non)
substract0 <- function(x){
  if (class(x) == "numeric"){
    0-x
  } else {
    x
  }
}

b_ice_1non[, names(b_ice_1non) := lapply(.SD, substract0)]

b_ice_1non <- subset(b_ice_1non, select=-c(chosen,n))
b_ice_1bev <- subset(b_ice_1bev, select=-c(chosen,n))


b_ice_2 <- subset(b_ice,n=="2")

b_ice_2$netlistprice <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$netlistprice,b_ice_2$netlistprice )
b_ice_2$bpm <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$bpm,b_ice_2$bpm )
b_ice_2$horsepower <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$horsepower,b_ice_2$horsepower)
b_ice_2$weight <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$weight, b_ice_2$weight)
b_ice_2$wheelbase <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$wheelbase, b_ice_2$wheelbase )
b_ice_2$fuelconsumption <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$fuelconsumption,b_ice_2$fuelconsumption )
b_ice_2$CO2 <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$CO2,b_ice_2$CO2 )
b_ice_2$ln_share <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$l_share , b_ice_2$l_share)
b_ice_2$rearaxle <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$rearaxle , b_ice_2$rearaxle)
b_ice_2$enginecylcap <- ifelse(b_ice_2$chosen=="PHEV",- b_ice_2$enginecylcap ,b_ice_2$enginecylcap)


```

```
b_ice_m <- b_ice_2%>%
  group_by(week)%>%
  summarise(netlistprice=sum(netlistprice),
            bpm=sum(bpm),
            horsepower=sum(horsepower),
            weight=sum(weight),
            wheelbase=sum(wheelbase),
            rearaxle=sum(rearaxle),
            fuelconsumption=sum(fuelconsumption),
            CO2=sum(CO2),
            enginecylcap=sum(enginecylcap),
            l_share=sum(l_share))%>%
  ungroup()

phev <- bind_rows(b_ice_1non,b_ice_1bev,b_ice_m)
phev$pair <- "BEV_PHEV"
################HEV################
b_ice<- priv_median[!priv_median$chosen=="ICEV",]
b_ice<- b_ice[!b_ice$chosen=="PHEV",]
b_ice_g<-
  b_ice%>%
  group_by(week)%>%
  summarise(n=n())%>%
  ungroup()

b_ice<- left_join(b_ice, b_ice_g,by ="week")

b_ice_1bev <- subset(b_ice,n=="1"& chosen=="BEV")

b_ice_1non <- subset(b_ice,n=="1"& chosen=="HEV")

setDT(b_ice_1non)
substract0 <- function(x){
  if (class(x) == "numeric"){
    0-x
  } else {
    x
  }
}

b_ice_1non[, names(b_ice_1non) := lapply(.SD, substract0)]

b_ice_1non <- subset(b_ice_1non, select=-c(chosen,n))
b_ice_1bev <- subset(b_ice_1bev, select=-c(chosen,n))


b_ice_2 <- subset(b_ice,n=="2")

b_ice_2$netlistprice <- ifelse(b_ice_2$chosen=="HEV",-
    b_ice_2$netlistprice,b_ice_2$netlistprice )
b_ice_2$bpm <- ifelse(b_ice_2$chosen=="HEV",- b_ice_2$bpm,b_ice_2$bpm )
b_ice_2$horsepower <- ifelse(b_ice_2$chosen=="HEV",- b_ice_2$horsepower
    ,b_ice_2$horsepower)
b_ice_2$weight <- ifelse(b_ice_2$chosen=="HEV",- b_ice_2$weight,
    b_ice_2$weight)
b_ice_2$wheelbase <- ifelse(b_ice_2$chosen=="HEV",- b_ice_2$wheelbase,
    b_ice_2$wheelbase )
b_ice_2$fuelconsumption <- ifelse(b_ice_2$chosen=="HEV",-
```

```
    b_ice_2$fuelconsumption,b_ice_2$fuelconsumption )
b_ice_2$CO2 <- ifelse(b_ice_2$chosen=="HEV",- b_ice_2$CO2,b_ice_2$CO2 )
b_ice_2$ln_share <- ifelse(b_ice_2$chosen=="HEV",- b_ice_2$l_share ,
    b_ice_2$l_share)
b_ice_2$rearaxle <- ifelse(b_ice_2$chosen=="HEV",- b_ice_2$rearaxle ,
    b_ice_2$rearaxle)
b_ice_2$enginecylcap <- ifelse(b_ice_2$chosen=="HEV",-
    b_ice_2$enginecylcap ,b_ice_2$enginecylcap)


b_ice_m <- b_ice_2%>%
  group_by(week)%>%
  summarise(netlistprice=sum(netlistprice),
            bpm=sum(bpm),
            horsepower=sum(horsepower),
            weight=sum(weight),
            wheelbase=sum(wheelbase),
            rearaxle=sum(rearaxle),
            fuelconsumption=sum(fuelconsumption),
            CO2=sum(CO2),
            enginecylcap=sum(enginecylcap),
            l_share=sum(l_share))%>%
  ungroup()

hev <- bind_rows(b_ice_1non,b_ice_1bev,b_ice_m)
hev$pair <- "BEV_HEV"


################COMBINED#########
all <- bind_rows(icev,phev,hev)
all <- all %>%
  rename(
    d_netlistprice=netlistprice ,
    d_bpm=bpm,
    d_weight= weight,
    d_horsepower=horsepower,
    d_wheelbase=wheelbase,
    d_rearaxle=rearaxle ,
    d_fuelconsumption=fuelconsumption,
    d_CO2=CO2  ,
    d_enginecylcap=enginecylcap ,
    d_lshare=l_share)
ExPanD(df = all, cs_id = "pair", ts_id = "week")
all_numeric <-  subset(all,select = -c(week,pair,market_share))
col <- colorRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77AADD",
    "#4477AA"))
M2 <- cor(all_numeric, use='pairwise')
corrplot(M2, method="color", col=col(200),
         type="upper",
         addCoef.col = "black", # Add coefficient of correlation
         tl.col="black", tl.srt=45, #Text label color and rotation
       # hide correlation coefficient on the principal diagonal
         diag=FALSE
)
time$week <- time$X1
time$month <- time$X2
time$X1 <- NULL
time <- distinct(time,week,.keep_all = TRUE)
```

```
all <- left_join(all,time,by="week")
all$year <- format(as.Date(all$week, format="%Y-W%V"),"%Y")

ols <- lm(d_lshare~d_netlistprice+d_bpm+d_horsepower+d_enginecylcap,all
    )
lm2 <- felm(d_lshare~d_netlistprice+d_bpm+d_horsepower+d_enginecylcap|
    pair , data=all)
lm3 <- felm(d_lshare~d_netlistprice+d_bpm+d_horsepower+d_enginecylcap|
    year , data=all)
lm4 <- felm(d_lshare~d_netlistprice+d_bpm+d_horsepower+d_enginecylcap|
    month , data=all)
lm6 <- felm(d_lshare~d_netlistprice+d_bpm+d_horsepower+d_enginecylcap|
    year + month , data=all)
lm7 <- felm(d_lshare~d_netlistprice+d_bpm+d_horsepower+d_enginecylcap|
    pair + month  , data=all)
lm8 <- felm(d_lshare~d_netlistprice+d_bpm+d_horsepower+d_enginecylcap|
    pair + year , data=all)

stargazer(ols,lm4,lm3,lm2,lm7,lm8, type="html", out = "final.txt")
fixed <- plm(d_lshare~d_netlistprice+d_bpm+d_horsepower+d_enginecylcap,
     index="pair", model = "within", data=all)
pFtest(fixed, ols)
```