# Cross-price elasticities of demand on electric vehicles, by prices and taxes of gasoline vehicles

## Korspriselasticitet av efterfrågan på elfordon, beroende på bensin fordons priser- och skatter

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**Abstract:**

The purpose of the thesis is to estimate the cross-price elasticities of demand on electric vehicles by gasoline vehicle taxes and gasoline prices in six different countries with electric vehicle markets. This is to examine whether a government's incentives have any effect on the demand for electric vehicles, and if so by how much. The countries chosen are Sweden, Norway, Germany, USA, China and Japan where each country's demand and price changes during the time period 2016 - 2020 is studied. The investigation derives a logarithmic linear function that is applied in order to estimate the relevant elasticities from a panel data regression. The used data is on demand and prices of electric vehicles, prices of gasoline vehicles, prices of gasoline, taxes on gasoline vehicles and finally the GDP per capita in each of the countries. The demand of electric vehicles is the dependent variable which is divided into two datas; new registered electric vehicles per 100 000 capita and the market share of new registered electric vehicles compared to the total number of new registered light vehicles. The result shows that the demand of electric vehicles during the time period is mainly dependent on the gasoline vehicle prices and GDP per capita, whilst the other variables were examined to be non-significant. One explanation for the high insignificance in the study could be due to too few observations in the data set.

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# 1. Introduction

During the last decade, the demand for electric vehicles has increased enormously (EV-volumes). Ten years ago, electric vehicles had to resist a lot of complaints. Now, ten years later, it has started to slowly become the new normal. In line with new requirements regarding environmental policies, many countries have started their work for a phase-out of fossil fuel vehicles which has benefited the electric vehicle, EV, market (Wappelhorst., & Cui. 2020). As a result, actions are taken by the governments around the world in order to achieve these requirements and environmental goals, and climate advisors want the taxes to increase more (Fleetnews, 2020). The government incentives taking place are partly related to tax-policies, where taxes on gasoline vehicles, car-ownership and gasoline are examples of taxes being adjusted. The figures below represent the development of the electric vehicle market. Figure 1.1 shows the amount of sold battery electric vehicles, BEV, during the last decade, implying that the demand of BEV has increased exponentially in the past years. Figure 1.2 presents the percentage share of sold battery electric vehicles of the total amount of sold light vehicles.

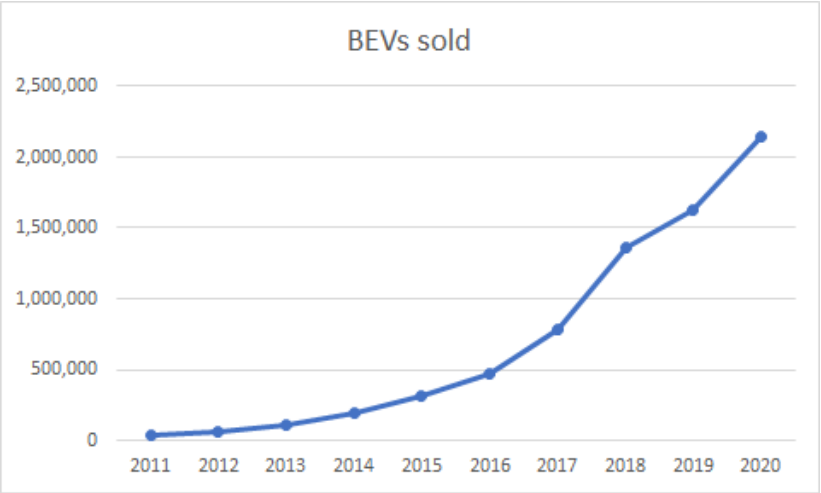


**Figure 1.1** ***Total amount of battery electric vehicles sold each year (source: EV-volumes)***

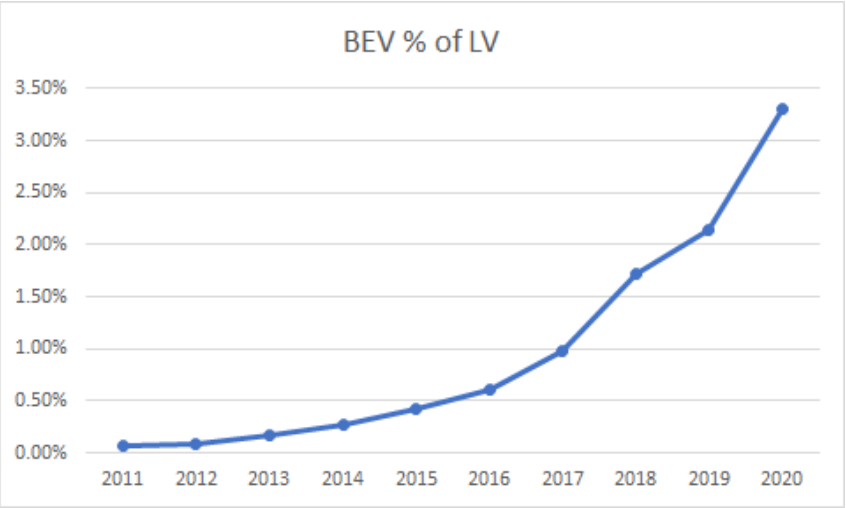


**Figure 1.2** ***Percentage share of battery electric vehicles sold compared to light vehicles sold, each year (source: EV-volumes)***

However, stated by Prud'homme & Koning, before costs and efficiency improvements are taken into place, the EV market would require huge subsidies (Prud'homme & Koning, 2012). Another policy that might impact EV demand is taxes on gasoline vehicles, since it leads to a relatively lower purchase cost of electric vehicles, because of a higher price on gasoline cars. It is interesting to do research on whether this policy will have an impact on EVs demand and how the impact would look like. Regarding taxes on gasoline vehicles, the prices of the gasoline itself could have an impact on the EVs demand in different countries. It further seems interesting to understand if high prices on gasoline in a country will contribute to a larger EV market share within the country.

## 1.2 Purpose

Are government incentives really a good way to increase the EV demand and phase out the gasoline vehicles? Since governments are implying different incentives in order to eliminate fossil fuel vehicles, and increase the demand of electric vehicles, it would be important to understand how the incentives impact the EV demand. Therefore, the goal of this paper is to investigate if, and by how much, the demand of EVs is affected by gasoline vehicle prices and government incentives such as gasoline prices and gasoline vehicle taxes. This study is therefore a contribution to whether government incentives do have a big impact on the EV industry or not, which could be of interest for decision makers, companies with involvement within the market, and others interested in the subject.

Further, cross-price elasticities of demand on electric vehicles by the variables gasoline prices, gasoline vehicle prices and gasoline vehicle taxes will be determined within the paper in order to understand how strongly the demand of EVs is affected by these factors, along with some other interesting factors. The study is focusing on battery electric vehicles, and will for simplicity use the term EV instead of BEV further.

# 2. Background

Countries' carbon awareness has increased in later decades where the governments' interest in implementing a greener environment has been growing. The Paris Agreement has been one way to consider low carbon awareness by limiting the increasing average global temperature which is affected by CO2 emissions, partly from gasoline vehicles. (Mulvaney, 2019). Therefore, governments are taking responsibility to implement different solutions and policies that contribute to a greener world. One environmentally friendly option is to make the transportation consistent with electric vehicles primary, within the near upcoming decades (Ning, Run-Lin, and Ya-Fei 2015). This option can be reached by implementing policies that contribute to increasing the EV market and industry. Governments have a crucial position in the electric vehicle case and can support the EVs industry growth by tax reliefs, incentives, reduction of production costs and subsidies for electric vehicles by a form of financial support (Penev, Ivan, 2011).

However, the world faces a reality where the demand side of gasoline vehicles is greatly above the demand of electric vehicles (Lovedy, 2019). An important aspect that makes this demand gap maintain is the low carbon awareness amongst the populations, mainly low education by consumers regarding electric vehicles. Further, there is a certainly main decisive aspect that affects the EVs demand. The high prices have been discovered to be one main reason why consumers still purchase gasoline vehicles. According to consumers, the main precondition of purchasing an electric vehicle is that prices of gasoline vehicles and electric vehicles would be close to each other (Penev, Ivan, 2011).

Therefore, the purchase price of the vehicle is of major importance when looking at the vehicle demand (Coffman, Bernstein & Wee, 2017). Regarding the government incentives, the study by Coffman showed mixed findings, with some difficulties finding a clear

conclusion. The relative fuel price was also stated not to be a significant predictor of the EV market share, regarding conclusions based on findings using data from 2012, where one can argue that the EV market was in a very early adopting state.

# 3. Previous literature

There are different studies about how different policies and developing aspects have an impact on EV demand and supply. The demand and supply sides are further investigated in different market areas. One study investigates how technology improvement and tax reliefs have an impact in the market demand for EVs, and shows that it has a positive effect during optimal equilibrium where the demand of electric vehicles increases (Gong, Wang & Cheng, 2020). Considering that study, the tax relief on electric vehicles by taxes on gasoline vehicles will be a specified investigation in this study that complements the previous literature of the subject.

Another article studies the economic and environmental impact of tax incentives on internal combustion gasoline vehicles. The implied tax incentives in the study are supposed to act as subsidies and tax reliefs of electric vehicles, and the author of the article concludes that the tax incentives of gasoline vehicles will relatively reduce the costs of purchasing an electric vehicle. As a result the study identified an increase in EVs demand and an increase in sales of EVs with elasticity of 1,3 (Shiyu, 2018). This implies a possibility that the investigation for the purpose of this study will imply that incentives by the government lead to a smaller price gap between gasoline vehicles and electric vehicles, which increases the impact on EVs demand.

Further on, there have been previous stated-preference studies on EV demand describing the EV market as an emerging technology market (Carley, Siddiki & Crotty, 2019) and are dividing the consumers in different categories, innovators - early adopters - early majority - late majority - laggards (Coffman, Bernstein & Wee, 2017) . The study from 2019 by Carley et al stated the consumers for BEVs to be in the early adopters category between the years 2011 and 2017, when the study took place, and argued that the market will eventually expect an acceleration in the rate of adopters for the future. The study also shows a lack of influence for public policies on plug-in electric vehicle demand. However it is only looking at the intent to purchase, and not real behaviour, which can differ in these kinds of questions. It is also

only looking at a two-time period, and not a panel-dataset with annual documentation (Carley, Siddiki & Crotty, 2019).

The EV market was to some extent expected to soon reach the mainstream market in 2019 (Rubens, 2019). It could be possible that the market today in 2021 is beginning to reach a new broader type of consumers. Due to this and the presented above, it would be appropriate to conduct a new study with the purpose of this thesis on the electric vehicle market demand.

## 3.1 Theory

This part will explain the economic theory and econometrics used behind the analysis of the electric vehicle demand. Firstly, the demand curve will be briefly explained along with theoretical explanations for related models like indifference curves. Further, the econometric framework will be explained, such as the concept of panel data and regression analysis.

### 3.1.1 Demand function

Figure 3.1.1 is showing a classic market model with a demand and supply curve. In this market model, the intersection between the demand curve and the supply curve are showing the optimal market outcome for price and quantity. Focusing on the demand curve, there are different factors that can both cause movement along the demand curve, and factors that can result in shifts of the demand curve, according to economic theory.

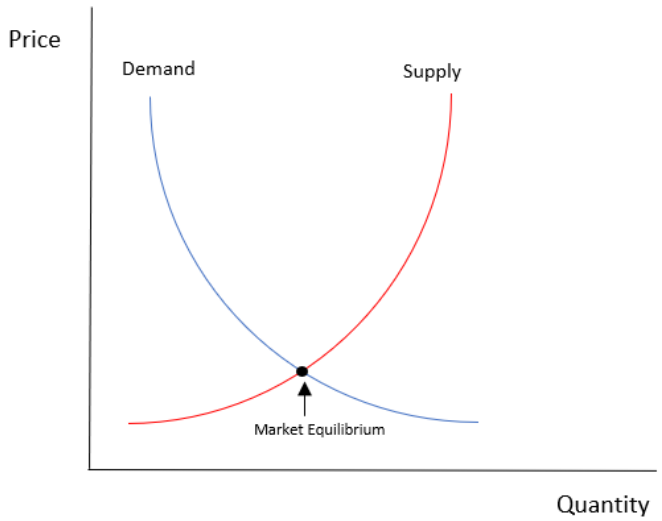


**FIGURE 3.1.1** ***Demand and supply curves***

The factors responsible for shifts in the demand curve related to this study could for example be income or price of substitute goods (both these are positively correlated to the demand). The price of a complementary good on the other hand does have a negative effect on the demand curve, and therefore the price of a complementary good for a substitute good should affect the demand positively. This would mean that a rise in fuel price would have a positive effect on the EV demand. An example of a complementary good to EV could be a charging station, while an example of a substitute could be a fuel vehicle. These demand shifts explained are resulting in a change of the equilibrium. Adding up all the demand curves together, we are facing the aggregate market demand (Kenton, 2021a, 2021b).

The figure below shows an example of a positive demand shift, which could be caused by for example a higher price on its substitute-good. The market demand then does a parallel shift to the right, making the consumers now having a higher level of quantity and price willing to pay of the investigated good.

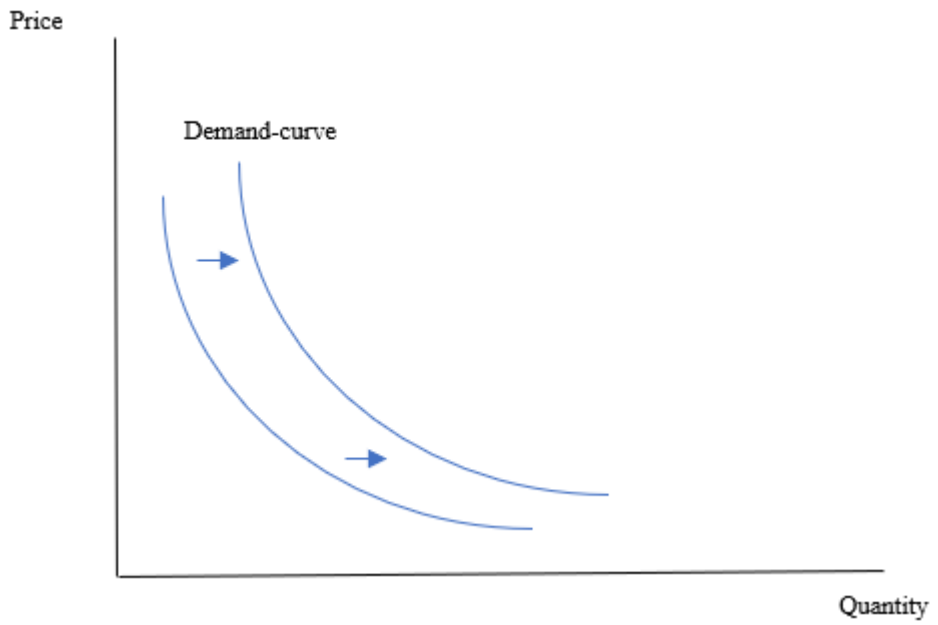


**FIGURE 3.1.2** ***Demand curve***

Considering the economic theory, our demand curve depends on GDP per capita, prices of substitute goods and prices of complements to the substitute goods - gasoline vehicle and

gasoline, which should all affect the market demand of the chosen good - electric vehicles. The general demand expression will therefore be given by:

$$D\,(P_{it},\ Q_{it},\ Y_{it},\ P_{sit},\ P_{scit}) \qquad (3.1)$$

*Where*

$D$ is the demand

$P_{it}$ is price of the good in year t, country i

$Q_{it}$ is quantitative of the goods sold in year t, country i

$Y_{it}$ is GDP per capita in year t, country i

$P_{sit}$ is price of substitute in year t, in country i

$P_{scit}$ is price of complement to substitute in year t, country i

For the purpose of this study, each factor of the demand expression above will be replaced with the relevant variables that have been used during the investigation. Therefore, the factors will be given by:

$D$ is the demand for electric vehicles

$P_{it}$ is price of electric vehicles in year t, country i

$Q_{it}$ is quantity of electric vehicles sold in year t, country i

$Y_{it}$ is GDP per capita in year t, country i

$P_{sit}$ is price of gasoline vehicles in year t, country i

$P_{scit}$ is price of gasoline in year t, country i

### 3.1.2 Indifference Curves

When measuring the choices between two goods, economic theory often makes use of indifference curves. The indifference curves are based on individuals preferences and budget limitations, and are together representing the market preferences between two chosen goods. In our case, this would be between electric vehicles and gasoline vehicles. The indifference curves cannot intersect each other, since each curve represents a new level of indifference, where you are indifferent to the distribution between the goods along the indifference curve.

Intersecting curves would therefore demolish the theory of being indifferent. The highest level of indifference to achieve when still being on the budget constraint, is the distribution of the two goods preferred by the market (Banton, 2021). The slope of the indifference curves shows how the market perceives the worth and substitution between the two goods. The slope of the budget constraint depends on the price of the two goods, while a change in income would lead to a shift in the budget constraint.

An example of a general indifference curve with two goods is represented in Figure 3.2 below. The preferred distribution in the example is given by the black dot in the figure.

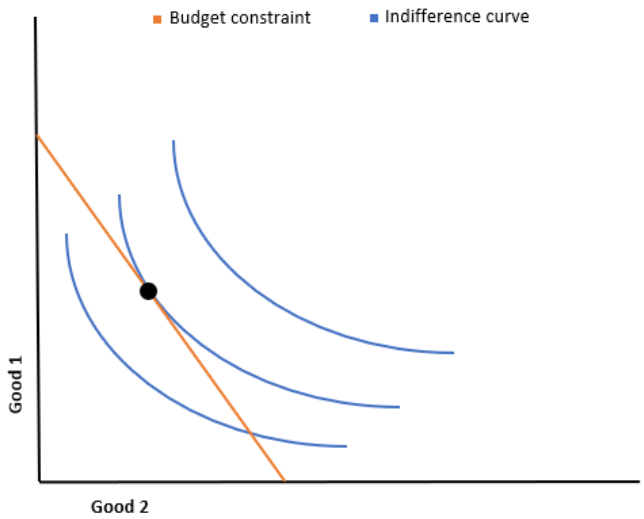


**Figure 3.2 -** ***Indifference curve***

# 4. Methodology

For this study, data will be collected in order to compute values of observations that will be examined to estimate the cross-price elasticity of demand on electric vehicles by gasoline vehicle taxes and gasoline prices. The theoretical part consists of the econometric model panel data regression that will be used for the purpose of the thesis. The econometric approach will apply to a logarithmic linear function with coefficients that estimates for elasticities, and will therefore be relevant to use during this study since the study investigates different elasticities. A panel data is used in this study mainly because the investigation computes for six different countries during a five year interval and there will therefore be observations for both years and countries, which preferably then could be applied to a panel

data.

## 4.1 Scope and Limitations

The chosen countries for the investigation are China, Japan, Sweden, Norway, Germany and US, during the interval of 2016 to 2020. The chosen time period was decided based on the EV market's start of its growth, which was mainly in a half decade ago where the amount of new registered electric vehicles increased rapidly until today. The reason behind the choice of the countries was that each of the chosen countries had a relatively large EV market compared to the rest of the world, which made them interesting to involve in this study (EV-Volumes, 2021). The chosen countries are all well developed, and among the highest in their continent based on country-development (World Population Review). This creates an opportunity to understand the EV markets in well-developed countries which is relevant since electric vehicles are innovative developing vehicles. A specific reason for the choices of the countries, focusing on Germany, the US and China, is that they belong to the world's largest economies (Eurostat, 2020).

Further, every country in this study has differences in their country size, culture, governance, population and environment awareness. Those factors are mainly important when investigating the electric vehicle market demand since they all together make each country unique with different willingness to purchase electric vehicles. For instance, people with bigger awareness of environmental questions and CO2 emissions are more likely to purchase electric vehicles, which have been considered when choosing countries for this study (Evexperts, 2017).

However, because of limitations for time and data access when completing this study, not every interesting country could be chosen. Because of that, in countries with relatively similar electric vehicle markets, only one of the countries was chosen for investigation, while rest markets had to be excluded. As an example, England and Germany implied indicators of having a relatively similar EV market (EV-Volumes). Therefore only Germany was included for the investigation. That decision was based on the fact that Germany had a higher well-developed index, which, along with the arguments above, would be more relevant to add in this study (World Population Review).

The study investigates the elasticities on demand of electric vehicles by different variables. For the purpose of the investigation, the most valuable variables that are considered to affect the demand of electric vehicles in the electric vehicle industry and in every country were included. The included variables are; prices of electric vehicles, prices on gasoline vehicles, prices on gasoline, taxes on gasoline vehicles, the real GDP per capita. Every variable is included for each year and each country. However, some other variables that might have affected the demand are excluded because of modeling purposes. The determined variables in this study include the variables that must be included for our model purpose.

### 4.1.1 Two dependent variables

The elasticity of demand will be investigated by two different determinant dependent variables; both a quantitative demand and a percentile demand. The quantitative demand is given by the amount of new registered electric vehicles per 100 000 capita by a specific year, and the percentile demand is given by the share of new registered electric vehicles out of total new registered light vehicles, in a specific year. The dependent variables are referred to as *new registered electric vehicles per 100 000 capita* and *market share electric vehicles* respectively. For simplicity, the thesis can further call the share of new registered electric vehicles out of total new registered light vehicles for simply EV share/market share.

The reason behind why it is interesting to make the investigation by these two dependent variables is that it will set perspectives to the study. The fact that country A has a bigger amount of new registered vehicles per 100 000 capita than country B might therefore not necessarily mean that country A also has a larger market share of electric vehicles than country B. For example, USA had by amount of registered cars per 100 000 capita a total of 77.42 during 2020 while China had 76.07 ones during the same time period. On the other hand, China’s market share of electric vehicles during 2020 was 4.88 % while USA's market share was 1.76 % during the same time period (EV-Volumes). Even though the USA exceeds China by registered cars per 100 000 capita, it was clear that China had a larger market share of electric vehicles than the USA and therefore it can make clearer differences by implying both dependent variables.

### 4.1.2 Panel Data regression

Panel data is the main basis to the econometric investigation and the most relevant one to approach. Since the observations are determined both by country and year, a panel data regression is managed through the study. Panel data must be applied for both a panel id and a time variable. In this case, the panel id is given by countries and labeled as *countryid* while the time variable is given by years and labeled as *year*. Further, the variables in the panel data is categorized by dependent variables and independent variables - where the dependent ones are the variables that are considered as affective to the dependent variable.

## 4.2 Regression analysis

The chosen logarithmic linear model can generally be applied for pooled OLS or Fixed Effect/Random Effect. In order to apply pooled OLS, the linear regression in the panel data must fulfill five assumptions. Those are; (1) Linearity, (2) Exogeneity, (3a) Homoscedasticity and (3b) Non-autocorrelation, (4) Independent variables are not Stochastic and (5) No Multicollinearity. If assumption (2) and/or (3) is violated, it will be more suitable to apply one of the econometric models Fixed Effect or Random Effect (Brugger, 2021, 6 january). The case of this study does not fulfill assumption (2) and therefore one of Fixed and Random Effect will be applied.

The difference between the Fixed Effects and Random Effects model is how you perceive the country's specific effect. In the Fixed Effects model, you are using the specific effect inside the model, as the intercept. While in the Random Effects model, you keep the country's specific effects outside the model, as an error term. Specifically, if you expect the covariance between the specific country effect and the variables used to be zero (or close to zero), then the fixed effects model would be preferred. Otherwise, the Random Effects model is favored. The choice of model will therefore affect the assumptions made in the thesis (Kalita, India., 2013). The general equations for Fixed Effect and Random Effect are presented in equation (4.1) and (4.2) below.

*Fixed-Effects model:*

$$y_{it} = \alpha_i + x_{it}\beta + e_{it} \text{ for } t = 1,\ldots,T \text{ and } i = 1,\ldots,N \qquad (4.1)$$

$$Where: \ \widehat{\alpha_i} = \bar{y} - \bar{x}_i\hat{\beta}$$

*Random-Effects model:*

$$y_{it} = x_{it}\beta + (\alpha_i + u_{it}) \text{ for } t = 1,\ldots,T \text{ and } i = 1,\ldots,N \qquad (4.2)$$

$$Where: \ Cov\,(\alpha_i, x_{it}) \neq 0 \text{ and } e = (\alpha_i + u_{it})$$

*Where*,

$y$ =*outcome/dependent variable*

$x$ =*independent variable*

$\beta$=*Coefficient of variable x*

$u$ =*error term*

$e$ =*error term* $(\alpha_i + u_{it})$

$\alpha_i$= *Country specific effects*

$i$=*Country*

$t$=*year*

### 4.2.1 Hausman Test

In order to choose between Fixed Effect and Random Effect, a test can be applied in the study that helps to estimate what regression is most suitable for the study. The test is called Hausman Test and is runned in STATA for the purpose of deciding which of the regressions to choose. The result that is generally aimed is a positive number since it clearly indicates which model would be the most suitable one to choose between Fixed Effect and Random Effect. When the Hausman-test shows a relatively high p-value, the null hypothesis is accepted and the random effect is preferred. Otherwise, the fixed effect is preferred (Brugger, 2021).

### 4.2.2 Breusch and Pagan Lagrangian Multiplier Test

A Breusch and Pagan Lagrangian multiplier test can be conducted in order to determine whether to use an OLS or random variable model. IF the Lagrangian multiplier test does show significance, it implies that there are significant differences across units, and the RE model is preferred over OLS (Stata, 2013).

## 4.3 Model and general function

The model that will be used for the purpose of the thesis is a logarithmic linear function which will be demand based and will be applied with logged data, both of dependent and independent variables. Applying logarithms to linear function makes it easier to estimate the elasticities of the study since the elasticities can be directly read from the logarithmic linear function. The coefficient estimations of a logarithmic linear function when running a regression will be the estimated elasticities (Lundberg, 2009). The definition of a logarithmic linear function in our investigation will be given by equation (4.3) below:

$$ln\, C_{EV} = \beta_0 + \beta_1 ln\, P_{EV} + \beta_2\, ln\, P_G + \beta_3\, ln\, Y + \beta_4\, T_G + \beta_5\, P_f + e \qquad (4.3)$$

where:

$C_{EVj}$ is consumptions of electric vehicle yearly

$P_{EV}$ is real price of electric vehicle

$P_G$ is real price of regular gasoline vehicle

$Y$ is the real GDP per capita

$T_G$ is the tax on gasoline vehicle

$P_f$ is the gasoline price

$e$ is the residual

The coefficients estimations of $\beta_1$, $\beta_2$ $\beta_3$, $\beta_4$, $\beta_5$ are the electric vehicle price elasticity, cross-price elasticity by gasoline vehicle price, income elasticity, cross-price elasticity by

taxes on gasoline vehicles, and cross-price elasticity by gasoline prices respectively. Therefore, $\beta_4$ and $\beta_5$ will be considered as the coefficients that are most interesting one for the purpose of the thesis in this investigation, since they estimate the cross-price elasticity of demand on electric vehicles by taxes on gasoline vehicles and by gasoline prices.

The logarithmic linear function will be applied to panel data with panel id and a time variable. "Country" from our data is chosen as our panel id in our panel data, whilst "Year" from our data is chosen as the time variable. The variables $P_{EV}$, $P_G$ ,$Y$ , $T_G$ and $P_f$ are the control variables while $C_{EV}$ is the dependent variable of the logarithmic linear function.

## 4.4.Cross-price elasticity

Elasticity describes how a change in one economic variable affects another variable. The elasticity is defined as the ratio between the percentage changes in each variable. There are various types of elasticities that can be measured, where one of them is the cross-price elasticity. Cross-price elasticity (CPEoD) presents how the demand on one product will be affected by a price change of another product. The CPeoD formula is estimated as following:

CPEoD =

(% change in quantitative demand for good B)

÷

(% change in taxes on good A)

The calculation for the cross-price elasticity is given by the percentile change in quantitative demand for one product (good B), divided by the percentile price change of the other product (good A) (Hayes 2021).

The relevant elasticity for this study is the cross-price elasticity which in this case measures how the demand on electric vehicles is affected by other variables, such as taxes on gasoline vehicles and gasoline prices.

Implementing the equation in this study, good A (in numerator) and B (in denominator) must be replaced with relevant variables from the investigation. For example, when estimating the cross-price elasticity of demand on EVs by gasoline vehicle taxes, it will be assumed that product B is the electric vehicle and product A is the taxes on gasoline vehicles during this estimation. Therefore, replacing those in both numerator and denominator, the cross-price elasticity will be given by:

CPEoD =

(% change in quantitative demand for electric vehicles (good B))

÷

(% change in taxes on gasoline vehicles (good A))

Moreover, in our model of logarithmic linear function, the cross price elasticity is given by $\beta_4$ in equation (4.3). Therefore, we will consider the estimation of the coefficient by the panel data regression as the cross-price elasticity. That cross price elasticity, with coefficient given by a logarithmic linear function is given in a formula shown below:

$$\text{CPEoD} = \frac{\partial \ln C_{EV}}{\partial \ln T_G} = \frac{\partial C_{EV}}{\partial T_G} \text{x} \frac{T_G}{C_{EV}} = \beta_2 \qquad (4.4)$$

where we make use of the logged function, ln, since the values of the variables will be logged in the logarithmic linear function (4.3) (Lundberg, 2009).

The cross-price elasticity of demand between electric vehicles and gasoline vehicle taxes tells how the demand, by *amount per 100 000 capita* and *market share*, on electric vehicles will change when the gasoline vehicle tax changes keeping all else constant. Moreover, depending on what goods are involved in cross-price elasticity, the sign will tell how those two goods are connected to each other. If the sign is positive, meaning the value is positive (+), then the two goods are substitutes which implies that demand for electric vehicles increases if the substitute, which is tax on gasoline vehicles, will increase. If the sign is negative, meaning the value is negative (-), then the two goods are complements because the demand for electric

vehicles decreases if the substitute, which is tax on gasoline vehicles, increases (Hayes 2021).

## 4.5 Other elasticities of demand

The logarithmic linear functions coefficients observe more elasticities than only the cross-price elasticity, which will also be investigated and computed in this study. Below there will be a presented explanation of each relevant type of elasticity that will be computed for this study. All the elasticities are of demand for electric vehicles and will be computed for both dependent variables, *new registered electric vehicles per 100 000* capita and *market share electric vehicles*. Therefore, consider through reading that the demand of estimation will be given both by amount and by market share.

### 4.5.1 Cross-price elasticity by gasoline vehicle price

The logarithmic linear function model will compute for second cross-price elasticity, that differs from the first one that the investigation focuses on. This cross-price elasticity of demand is given by the price of the gasoline vehicle, and therefore it shows how the demand on electric vehicles will change when the prices of the gasoline vehicles change, keeping all else constant. The sign of this cross-price elasticity is as the sign of cross-price elasticity by gasoline vehicle taxes that was explained above; if the sign is positive then the goods are substitutes, and if it is negative then the goods are complements (Hayes 2021).

### 4.5.2 Cross-price elasticity by gasoline prices

Last elasticity that the logarithmic linear function model computes for is a third cross-price elasticity of demand, but in this case it is given by the gasoline prices. The cross-price elasticity of demand by gasoline prices shows how much the demand of electric vehicles will change when, keeping all else constant, the prices of gasoline changes. The sign of this elasticity indicates repeatedly the same as for the other explained cross-price elasticities above. Therefore, if the sign is positive then the goods will be substitutes, while if the sign is negative the goods will be complements instead (Hayes 2021).

### 4.5.3 Own Price Elasticity

The own price elasticity of demand is a n elasticity that presents how the demand of a product will change when the price of the product itself changes. In this case the elasticity measures how the demand on electric vehicles changes by the price changes of the electric vehicles themselves. This elasticity shows how a change in price of electric vehicles will affect the demand on electric vehicle when keeping all else constant. Theoretically, the sign for this elasticity is supposed to be negative because of the negative demand slope which indicates that there appears to be a lower demand when the product's price increases (Lundberg 2009). Figure 3.1 represents the negative demand slope for this study.

### 4.5.4 Income elasticity

The income elasticity of demand is an elasticity that presents how the demand of a product is affected by changes in the income, keeping all else constant. The income can be measured by different measurements, such as income per capita & GDP per capita (Hayes, 2021). For the purpose of the study, the income elasticity is computed on demand on electric vehicles by real income per capita. This will indicate how a change in the real income per capita might affect the demand of electric vehicles.

# 5. Data collection

The data collection was completed by research and data accesses from websites and databases. A limited scope of observations was determined for this study since the data access was limited during this investigation for the purpose of the thesis. The data was collected for each of the determined variables in the study, which are prices of electric vehicles, prices on gasoline vehicles, prices on gasoline, taxes on gasoline vehicles, the real GDP per capita and new registered electric vehicles per 100 000 capita. All data has been collected or converted into EURO.

## 5.1 Data decisions

Different decisions and determinants had to be considered and done during the collection of our data. This part of the paper will present the background of the data decisions for the variables in this study.

### 5.1.1 New registered electric vehicles per 100 000 capita and share of new registered electric vehicles on total amount of vehicles

The elasticity of demand is investigated with respect to two different dependent variables, *new registered electric vehicles per 100 000 capita* and *market share of electric vehicles*. The dependent variables consist therefore of both a quantitative demand of new registered EV per 100 000 capita and a percentile market share of electric vehicles in each country during each year. The total electric vehicle demand was collected from the database EV-volumes. The data for the population in the different countries is collected from United Nations database *World Population Prospects* from 2019. The population for 2020 are therefore based on estimates. From this collected data, the amount of new registered electric vehicles per capita were then calculated. The result was then multiplied by 100 000, because of the small measurement (Indeed, 2021). After multiplying by 100 000, the result is now given by per 100 000 capita instead. Further on we will call this variable EVdensity instead of EV per 100 000 capita, for simplicity. So when referring to EVdensity, it means the new registered electric vehicles per 100 000 capita.

The percentile demand is given by the market share of electric vehicles, also collected from EV-volumes. The data accounts for all light vehicles, which consists of passenger vehicles and light commercial vehicles.

### 5.1.2 Gasoline prices

Data of gasoline prices in each country was collected from Bloomberg (Bloomberg, 2020). Due to time limitations, the mean value of each year was not calculated. Instead, the data was collected using the prices from the second quarter each year 2016-2020.

### 5.1.3 GDP per capita

The data for the variable GDP per capita was collected from The World Bank's database for each year from 2016 to 2019 (The World Bank, 2021). Since this study was done in May of 2021, there were yet no numbers of real income per capita for the same year, 2020. Therefore we collected an estimated GDP per capita for the year 2020, collected from IMF (IMF, 2021). IMF was used for the estimated values of 2020 since the World Bank's database did not provide any estimates for future years. Moreover, IMF did not have all the values for the previous years. Based on that, we therefore used two different sources for the actual and estimated values.

The decision was made to use real GDP instead of nominal GDP in order to have data adjusted to inflation. By that decision our results should be strengthened by taking into account inflation, especially relevant since last year, 2020, had an increase in inflation of most countries which had an effect on the purchases for those countries and therefore an effect on GDP was identified (CaixaBank Research, 2021). Further, real GDP is impacted only by changes in quantitative outputs and not only by price changes (Lumen, 2021), which is relevant for us since we partially analyze whether the quantity of new registered cars per 100 000 capita are impacted by gasoline prices. The GDP per capita was collected with constant prices using the countries' local currencies. The amount for each country was then conducted to EURO using our chosen exchange rates (see appendix).

### 5.1.4 Taxes on gasoline vehicles

Data of taxes on gasoline vehicles in each country and each year was calculated through a worldwide tax guide from ACEA, for each year. The ACEA tax guide is based on official information from each country, with sources and contact information for each country's representatives. A research in ACEAs documents was done and calculations were used by considering our chosen exchange rates (see appendix). The taxes were calculated based on different car specifications, such as motor sizes and CO2 emissions. It was therefore obligatory to base the tax calculations on one specific car. We choose to base the calculations on the Volkswagen Golf 130hp. This car model was chosen based on the fact that it is one of the most purchased cars in the world of all time (AutoGuide, 2012). Further, Volkswagen was ranked the largest car company in the world by the Fortune top 500 list in 2020 (Car logos,

2021). Within the Volkswagen car-line, the Golf has been one of the most popular car models between 2017 and 2020 which made it relevant to use (Wagner, 2021).

The calculations were based on each country's specific circumstances. For the US, the taxes differed from state to state, therefore California's tax policy was used to represent the taxes in the US. The scope of investigating the taxes for California is mainly done because of limitations when completing the study, such as data and time access limitations. The decision of studying specifically California is based on the fact that California has the largest market share of electric vehicles in the US and therefore the study will be able to include the largest representative state of EV market share within the country (EV-Volumes). Therefore, by investigating countries with EV markets around the world, there will be a mixture of countries representing different types of EV markets.

### 5.1.5 Electric and gasoline vehicle prices

Further, data of prices for electric vehicles and gasoline vehicles was collected. For this data collection, prices of a specific car or average prices of numbers of cars had to be found and determined. In order to base our variables and observations on the same car model, we had then to consider the argument from above that the computation of taxes had to be done based on one car model. Therefore the same car model, Volkswagen Golf 130hp, that was used to calculate gasoline tax price, was also used to collect gasoline vehicle price data. The prices of the gasoline vehicle Volkswagen Golf 130hp during each year between 2016-2020 was collected from Cars-Data. Further, the electric car price was based on a vehicle that fills the similarity to the gasoline vehicle Volkswagen Golf 130hp. The best vehicle to match similarity in car model and price class was the electric car Volkswagen E-Golf. We collected price data of Volkswagen E-Golf for each year between 2016-2020 from Cars-Data. A new Volkswagen E-Golf was not launched each year during our time period. For those years with no new updated E-Golf, we used the same price as the previous year's E-Golf.

# 6. Estimation results

This part of the paper will represent the results of the econometric estimations from the collected data. The econometric estimations are based on a panel data regression that were considered to be the most suitable for the purpose of the thesis. The regressions were made for two dependent variables - EVdensity and market share of new registered electric vehicles. The estimated coefficients from the regression are aimed to fulfill the cross-price elasticity estimates that can be read from the chosen logarithmic linear function. In order to apply the data for a logarithmic linear function, every variable except evshare was regenerated and logged before running the regressions.

## 6.1 Test Results

### 6.1.1 Hausman Test Results

The Hausman test was runned on the panel data for both variables in this study, *market share of electric vehicles* and *EVdensity*. The results came out differently for each dependent variable. When interpreting the results for the variable EVdensity, it shows a p-value of 0.0716. For the variable *market share of electric vehicles* the p-value was interpreted to 0.6053. The test results show that it would be preferred based on the Hausman test to apply the Random Effect model for the market share, since it rejects the null hypothesis at a 10% significance level. For the EVdensity, the fixed effect model is preferred, since it does not reject the null hypothesis.

Below in subheadings 6.2 and 6.3, both regressions Fixed Effect and Random Effect, for both dependent variables of *EVdensity* and *market share of electric vehicles,* are shown. This is done in order to compare the different effects with each other.

### 6.1.2 Breusch and Pagan Lagrangian Multiplier Results

The test result of our Breusch and Pagan Lagrangian multiplier test showed significance. That implies that there are significant differences across units, and therefore the Random Effect model will be preferred over an OLS. This test result is in line with what was expected and stated earlier.

## 6.2 Regression: EVdensity

This part represents the regressions of panel data with the dependent variable *EVdensity* which is labeled as log*newevpercapita* in our regression. The data in the panel data set is logged in order to fulfill the standards for the chosen model, logarithmic linear function model. As mentioned above, the results from the Hausman test were advantageous towards the Fixed Effect model for this dependent variable. This will therefore be taken into account when comparing the models. However, both Fixed Effect and Random Effect were regressed and analyzed. Table 6.2 presents the results for Random Effect regression and table 6.3 presents the result for the Fixed Effect regression, both to the logged dependent variable *EVdensity* - lognewevpercapita. The numbers without parentheses are the estimated coefficients.

| VARIABLES | lognewevpercapita |
|---|---|
| logfuelprice | 1.439 |
| | (1.301) |
| logevprice | 0.584 |
| | (2.158) |
| logfuelcarprice | 13.20*** |
| | (4.269) |
| lognewcartax | 0.677 |
| | (0.560) |
| loggdppercapitaconstantprices | 0.611 |
| | (0.610) |
| Constant | -149.9** |
| | (63.25) |
| Observations | 30 |
| Number of countryid | 6 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 6.2** Regression Random Effect of *new registered electric vehicles per 100 000 capita*

| VARIABLES | lognewevpercapita |
|---|---|
| logfuelprice | 2.705 |
| | (1.789) |
| logevprice | -1.592 |
| | (2.145) |
| logfuelcarprice | 10.13** |
| | (4.075) |
| lognewcartax | 1.892 |
| | (1.427) |
| loggdppercapitaconstantprices | 8.147** |
| | (3.621) |
| Constant | -184.1** |
| | (72.45) |
| Observations | 30 |
| Number of countryid | 6 |
| R-squared | 0.580 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 6.3** Regression Fixed Effect of *new registered electric vehicles per 100 000 capita*

The results that are presented in Table 6.2 and 6.3 shows the estimated coefficients for each variable that was included in the regressions for the panel data in this study. For this dependent variable and panel data, the Random Effect presented a higher number of significant variables.

### 6.2.1 Elasticity Estimation - Insignificance

In order to estimate elasticity, a significance must be identified for the estimated coefficient. When estimating the results in Table 6.2 and 6.3, it is apparent that the absolute majority of the coefficients are insignificant. The tables represent all the values, inclusive the significant values and the insignificance ones, which are unable to be considered as a valuable result to estimate an elasticity with.

The moreover interesting elasticity in this study is the cross-price elasticity of demand on electric vehicles by gasoline vehicle taxes. That cross-price elasticity of demand on electric vehicles in the Random Effect and Fixed Effect regressions is shown by the amount of new registered electric vehicles per 100 000 capita and therefore it is immediately given by the coefficient for variable lognewcartax. However, there is a low significance level for that variable in our regressions. Thus, the effect can not be interpreted, due to the insignificance.

### 6.2.2 Elasticity Estimation - Significance

Table 6.2 shows that only one of the variables for each regression are statistically significant for the time period 2016 - 2020, meanwhile table 6.3 presents two significant variables.

#### 6.2.2.1 Cross-price Elasticity: Gasoline Vehicle price

Reading from table 6.2 and 6.3, it is clear that the one elasticity with significance in both models is given by the coefficient for the variable logfuelcarprice, which is given by logged data of gasoline vehicle prices. The coefficient is estimated to be 13.2 with a positive sign for the random effect regression, and therefore indicates that the cross-price elasticity of demand on EVdensity by gasoline vehicle prices has the value of 13.2 percent. This indicates that an increase in gasoline vehicle prices by one percent will increase the demand of electric vehicles by 13.2 percent, assuming all else is held constant.

The result from the fixed effect regression shows that a one percent increase in the gasoline vehicle prices leads to an increase in new registreres electric vehicles per 100 000 capita by 10.13 percent, while everything else is held constant.

#### 6.2.2.2 Income Elasticity: GDP per capita

When reading from table 6.3, it appears that the variable GDP per capita from the Fixed Effect regression has a positive relationship with the EVdensity and is significant at a 5 percent level. The value of the coefficient is estimated to be 8.15 percent. This means that the income elasticity has a value at 8.15 percent, which indicates that a one percent increase in GDP per capita will result in 8.15 percent increase in the demand of new electric vehicles per 100 000 capita.

## 6.3 Regression: Market share electric vehicles

This part of the result represents the regressions based on the panel data with the dependent variable *market share electric vehicles*. This dependent variable is labeled as *evshare* in the regression. Like for the dependent variable *EVdensity* above, the regressions in this part for

the dependent variable *market share electric vehicles,* was done using both a Random Effect and a Fixed Effect regression. The results of the regressions on dependent variable *market share electric vehicles,* labeled as evshare, is displayed in Table 6.4 and 6.5. The numbers without parentheses are the estimated coefficient values. For this variable, the Hausman test suggested the random effect regression.

| VARIABLES | Random Effect<br>evshare |
|---|---|
| logfuelprice | 0.0961 |
| | (0.167) |
| logevprice | -0.0904 |
| | (0.255) |
| logfuelcarprice | 0.894* |
| | (0.499) |
| lognewcartax | 0.0390 |
| | (0.0739) |
| loggdppercapitaconstantprices | 0.0735 |
| | (0.0852) |
| Constant | -9.277 |
| | (7.459) |
| Observations | 30 |
| Number of countryid | 6 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 6.4** Regression Random Effect of *market share electric vehicles*

| VARIABLES | Fixed Effect<br>evshare |
|---|---|
| logfuelprice | 0.0298 |
| | (0.229) |
| logevprice | -0.176 |
| | (0.275) |
| logfuelcarprice | 0.661 |
| | (0.521) |
| lognewcartax | 0.203 |
| | (0.183) |
| loggdppercapitaconstantprices | 0.867* |
| | (0.463) |
| Constant | -15.60 |
| | (9.272) |
| Observations | 30 |
| Number of countryid | 6 |
| R-squared | 0.373 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 6.5** Regression Fixed Effect of *market share electric vehicles*

Through the regression results in Table 6.4 and 6.5, the effects on the electric vehicle demand regarding the five variables can be computed.

### 6.3.1 Elasticity Estimation - Insignificance

The aim of the regressions is to compute significance for the coefficient values for at least a ten percent level. By the estimated results in Table 6.4 and 6.5, it is clear that the coefficients are mainly insignificant. For the Fixed Effect, the table presents one significant value with " * " and for the Random Effect, the table presents one significant value with " * ".

The variable lognewcartax is the interesting cross-price elasticity here, which shows electric vehicle demand by taxes on gasoline vehicles. In both Table 6.4 and Table 6.5 it shows that this variable has not enough significance in order to be estimated. The variable logevprice, which is looking at the relation between the EV price and share of new registered cars in a country, did also come out insignificant at a ten percent significance level. These can therefore not be used as valuable results in order to estimate the cross-price elasticity.

### 6.3.2 Elasticity Estimation - Significance

Table 6.5 represents the results of Fixed Effect regression on the dependent variable *electric vehicle market share,* and shows that one variable is statistically significant at a ten percent level for the time period 2016 - 2020. On the other hand, table 6.4 represents the results of Random Effect regression, and it shows that there is one significant value in the regression, during the same time period and same significance level. The significant values are notated with " *" in the tables 6.4 and 6.5.

#### 6.3.2.1 Cross-price Elasticity: Gasoline vehicle price

One of the variables with a significant effect on the electric vehicle market share is the fuel vehicle prices. This variable is significant in the Random Effect regression as is presented in table 6.4. As shown by the data results of Random Effect, the effect of fuel vehicles is positive on demand of electric vehicles in market share, since the significant coefficient is 0,894 of the cross-price elasticity on electric vehicle market share by gasoline vehicle price. The value is positive and therefore the result indicates that a one percent increase in the gasoline vehicle prices leads to an increase in electric vehicle market share by 0,894 percent when everything else is held constant.

#### 6.3.2.2 Income Elasticity: GDP per capita

The other significant variable is the GDP per capita from the Fixed Effect regression in table 6.5, which also has a positive relationship with the market share of electric vehicles and is significant at a ten percent level. The coefficient value is estimated to be 0.87 percent which indicates that the value for the income elasticity is 0.87 percent. Therefore, a one percent increase in the GDP per capita results in a 0.87 percentage increase in the demand of electric vehicles presented in market share.

# 7. Discussion

This part will discuss, analyze and compare the regression results and datas. There will also be mentioned suggestions for further investigations based on the purpose of the thesis.

## 7.1 Regression analysis

Most of the elasticities came out as insignificant in the results for both regressions of time period 2016-2020 and for both dependent variables. There was generally higher significance in the regressions for the first dependent variable which indicates that it was easier to see a more accurate effect when using the ev sales per 100 000 capita as the dependent variable. It is difficult to compare the results achieved by the two regression models since Fixed Effect takes the specific country effect into account as an intercept, while Random Effect does not. These characteristic differences in the regression models can be explained as a reason why there were significance gaps and differences in some coefficients between the regression methods. However, most of our coefficients had the same sign (+/-) in both the random and fixed regressions.

### 7.1.1 Results analysis

Further, the one elasticity that was significant for both of the two different dependent variables when using the random effect regression, and significant for EV share when looking at the Fixed Effect regression, was the cross-price elasticity by gasoline vehicle prices. The fact that cross-price elasticity of demand on EVs by gasoline vehicle prices had this high significance is an indication that electric vehicle demand might be sensitive to gasoline vehicles price changes. The explanation can be that gasoline vehicles are a very strong substitute to electric vehicles when looking at consumers' demanding perspective. All our four regressions showed a positive effect of the gasoline vehicle prices on our dependent variables, which mean that when the gasoline vehicle prices go up, the demand for electric cars also goes up. The elasticities for the vehicle prices could however be seen as quite high, and a reason for this could be due to the limitations of the vehicle price data.

However, the cross-price elasticity by gasoline vehicle prices did achieve a lower significance level for the EV share in both regression methods. A possible conclusion for this is that the price of gasoline vehicles are more important when looking at the relative demand of electric vehicles compared to total vehicles.

Another significant elasticity was the income elasticity measured by GDP per capita, which came out significant in the Fixed Effect regression for both dependent variables EV market share and new registered EVs per 100 000 capita. However, according to the Hausman test

the Random Effect model is more accurate for the EV share, and since this variable is only significant for the fixed effect, we can not draw any conclusions regarding the EV share variable. The fixed effects were however preferred for the EVdensity variable. Therefore, GDP per capita appears to have a clearer effect on vehicle demand when looking at the demand using new registered cars per 100 000 capita. The income elasticity is also relatively high, which shows that the income of the population appears to have a relatively high effect on the EV demand. Those values might also be assumed as quite too high, which could have appeared because of data limitations. Regarding the Random Effect regressions, there were problems with significance for both dependent variables.

It is difficult to comment on why GDP per capita was only significant for the fixed effect regressions. But an explanation could be that there is higher technological progress, more efficient industry changes and better infrastructure in countries with higher GDP per capita, which leads to higher willingness to pay for electric vehicles. Since the investigated countries are generally categorized by main differences in culture and governance, it might be a strong indicator for the possible fact that these countries appear to have different infrastructure and industries within each country. Since the fixed effect takes into account the specific country effects and features, it seems like this would be a logical explanation.

Because of the high insignificance level, mainly on the elasticities for the gasoline vehicle taxes and gasoline prices, it appears difficult to understand how the governments' incentives impact the demand of electric vehicles.

## 7.2 Data analysis

The data in this study can be analyzed from different perspectives and will be commented on what parts in it that could have been improved.

### 7.2.1 Too small data

The regression in this study resulted in high insignificance levels in the majority of the variables. This can be explained mainly by too small data because of the short year interval and too small number of countries, leading to simply including too few observations. The main reason for this is because of the limitations occurring during the investigation, such as

time and data limitations. The fact that the study investigated six countries might be considered as not enough for studying the purpose of the study. For further studies it can be a good idea to focus on increasing the amount of observations in order to get a greater panel data set and to get a more significant result.

### 7.2.2 GDP estimation

Further, the data for the GDP per capita for the year 2020 could be unreliable, due to the outbreak of the coronavirus. The coronavirus makes the GDP per capita in 2020 hard to estimate, and the error term for our estimates in that year could therefore be high. However, since no data have been released yet for 2020, the current estimates available were considered the best way to solve this problem in the time frame of this thesis. We could possibly have tried to account for the pandemic and adjust the available estimates accordingly, but we came to the conclusion that the best and most time efficient approach for this thesis was to use the current estimates available.

### 7.2.3 Vehicle prices

Another important aspect when analysing the data is that the Volkswagen Golf and E-Golf did simply present the data collection of vehicle prices, which can be considered as a critical point in the study. The reason is that it might have led to an unrealistic picture of real vehicle prices that consumers face in real life when demanding electric and gasoline vehicles. There could also be a smaller or bigger gap over years in vehicle prices that might have been missed by implying only one vehicle model for each type of vehicle - Volkswagen Golf and E-Golf. That means for example that electric vehicle prices could have on average decreased rapidly over the year interval of 2016-2020, but not for the Volkswagen E-Golf, and therefore would lead to a bias in the regression results.

## 7.3 Method analysis

Because of the difficulties of finding information regarding each country's car prices, and because of the small dataset, it is arguable that a different method could have been used for the investigation. Looking at previous studies, methods like cost-benefit analysis, stated preference and before-after analysis have been used in some cases. However, it was

interesting in this study to be able to see the effect both for different countries and different years. If the data had contained more observations, the results could possibly have achieved higher significance levels.

# 8. Conclusions

By analysing the results of the study and the regressions above, it is apparent to conclude that the study has a small significance output. The variables with significance are those elasticities that can be concluded as being useful for the results. The findings from this study therefore gives mainly three conclusions.

The first conclusion is that the cross-price elasticity of demand on EV by gasoline vehicle price in this study is significant with positive sign, where the cross-price elasticity estimates the value 0.89 (Random Effect) for market share demand and 10.13 (Fixed Effect) for the quantitative demand per 100 000 capita. The data on vehicle prices are however limited, and a clear conclusion can therefore not be drawn based on this. This is close to what was shown in Penev et al's study from 2011, where they concluded that removing the gap in prices between electric vehicles and gasoline vehicles would increase the demand for electric vehicles. However, we could not see any significant effect regarding the EV price.

Second conclusion is that the income elasticity by GDP per capita does have a positive effect on the market share and quantitative demand per 100 000 capita of new registered electric vehicles in the countries, when accounting for the countries specific effects and circumstances (Fixed Effect). The income elasticity of market share demand on electric vehicles by GDP per capita estimates the value of 0.67, and the elasticity of quantitative demand per 100 000 capita of 8.15.

Third, and most important conclusion in this thesis, is that we cannot draw any further conclusions regarding the other variables. Regarding the primary variables of interest, gasoline vehicle tax and gasoline prices, there is therefore still not an answer to their actual effect on the demand for electric vehicles. The result was therefore in line with the result by Coffman et al (Coffman, Bernstein & Wee, 2017), which showed some difficulties finding conclusions on government incentives regarding EV demand. Coffman et al also found it hard to find significance regarding the effect of fuel price on EV demand, which is the same

problem faced in this study. The result of this study could also be in line with the result from Carley et al (Carley, Siddiki & Crotty, 2019), which argued a lack of influence for public policies on electric vehicle demand.

To conclude, it is still hard to say if and by how much the government incentives are influencing the EV market.

# 9. Appendix

## Exchange rates used:

| | |
|---|---|
| EURO/SEK: | 10,14 |
| EURO/NOK | 10,09 |
| EURO/RMB | 7,81 |
| EURO/YEN | 130,3 |
| EURO/DOLLAR | 1,2 |

*Exchange rates are all collected using the exchanges in 2021, 4th April*

## Data used in the regression:

| country | countryid | year | evshare | fuelprice | gdppercapitaconstantprices | newcartax | fuelcarprice | evprice | newev | newev per 100 000 capita | Population |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Norway | 1 | 2016 | 0.154447197 | 1.57 | 59536.66 | 13446.25 | 28914 | 36650 | 24929 | 474.75 | 5251000 |
| Norway | 1 | 2017 | 0.206971321 | 1.64 | 60429.80 | 12616.62 | 28914 | 39250 | 33761 | 637.48 | 5296000 |
| Norway | 1 | 2018 | 0.311710348 | 1.74 | 60806.36 | 13191.76 | 28280 | 39250 | 47839 | 896.20 | 5338000 |
| Norway | 1 | 2019 | 0.423546681 | 1.74 | 61094.68 | 13232.76 | 30080 | 39250 | 62213 | 1156.59 | 5379000 |
| Norway | 1 | 2020 | 0.542654079 | 1.49 | 65414.10 | 11177.5 | 30930 | 32980 | 79461 | 1465.80 | 5421000 |
| Germany | 2 | 2016 | 0.003704193 | 1.32 | 37567.87 | 5984.96 | 28914 | 36650 | 15289 | 18.60 | 82194000 |
| Germany | 2 | 2017 | 0.00748679 | 1.32 | 38401.59 | 5984.96 | 28914 | 39250 | 30385 | 36.76 | 82658000 |
| Germany | 2 | 2018 | 0.010633108 | 1.47 | 38771.80 | 5984.96 | 28280 | 39250 | 42452 | 51.07 | 83124000 |
| Germany | 2 | 2019 | 0.017063376 | 1.47 | 38880.70 | 5984.96 | 30080 | 39250 | 68172 | 81.63 | 83517000 |
| Germany | 2 | 2020 | 0.065592913 | 1.3 | 36964.31 | 5984.96 | 30930 | 32980 | 200244 | 239.00 | 83784000 |
| Sweden | 3 | 2016 | 0.008645835 | 1.42 | 43218.87 | 8081.4 | 28914 | 36650 | 3535 | 35.94 | 9836000 |
| Sweden | 3 | 2017 | 0.01160538 | 1.41 | 43735.40 | 8081.4 | 28914 | 39250 | 4796 | 48.42 | 9905000 |
| Sweden | 3 | 2018 | 0.020532668 | 1.52 | 44073.29 | 8081.4 | 28280 | 39250 | 8130 | 81.53 | 9972000 |
| Sweden | 3 | 2019 | 0.043810016 | 1.51 | 44150.72 | 8082.88 | 30080 | 39250 | 16974 | 169.13 | 10036000 |
| Sweden | 3 | 2020 | 0.095533244 | 1.35 | 46400.46 | 8082.88 | 30930 | 32980 | 29846 | 295.53 | 10099000 |
| China | 4 | 2016 | 0.010397063 | 0.88 | 6835.80 | 5653.52 | 28914 | 36650 | 285151 | 20.17 | 1414049000 |
| China | 4 | 2017 | 0.018826412 | 0.83 | 7269.94 | 5653.52 | 28914 | 39250 | 532936 | 37.50 | 1421022000 |
| China | 4 | 2018 | 0.033614379 | 0.99 | 7725.34 | 5653.52 | 28280 | 39250 | 887269 | 62.15 | 1427648000 |
| China | 4 | 2019 | 0.041249327 | 0.92 | 8155.79 | 3488.52 | 30080 | 39250 | 957621 | 66.79 | 1433784000 |
| China | 4 | 2020 | 0.048775995 | 0.76 | 8325.02 | 3488.52 | 30930 | 32980 | 1094865 | 76.07 | 1439324000 |
| Japan | 5 | 2016 | 0.003784432 | 1.07 | 32276.55 | 1245.6 | 28914 | 36650 | 16717 | 13.08 | 127763000 |
| Japan | 5 | 2017 | 0.004245872 | 0.99 | 33030.68 | 1245.6 | 28914 | 39250 | 19066 | 14.95 | 127503000 |
| Japan | 5 | 2018 | 0.00622865 | 1.16 | 33204.67 | 1245.6 | 28280 | 39250 | 27376 | 21.52 | 127202000 |
| Japan | 5 | 2019 | 0.005415622 | 1.16 | 33491.80 | 1245.6 | 30080 | 39250 | 23648 | 18.64 | 126860000 |
| Japan | 5 | 2020 | 0.00419084 | 1.05 | 32280.18 | 1245.6 | 30930 | 32980 | 16408 | 12.97 | 126476000 |
| USA | 6 | 2016 | 0.004798637 | 0.62 | 47798.15 | 2355.58 | 28914 | 36650 | 84260 | 26.09 | 323016000 |
| USA | 6 | 2017 | 0.006188902 | 0.59 | 48623.08 | 2358.08 | 28914 | 39250 | 106700 | 32.82 | 325085000 |
| USA | 6 | 2018 | 0.013637726 | 0.71 | 50279.08 | 2365.22 | 28280 | 39250 | 236407 | 72.27 | 327096000 |
| USA | 6 | 2019 | 0.013718729 | 0.7 | 50621.17 | 2367.33 | 30080 | 39250 | 233890 | 71.08 | 329065000 |
| USA | 6 | 2020 | 0.017624343 | 0.59 | 46509.36 | 2367.33 | 30930 | 32980 | 256273 | 77.42 | 331003000 |

**evshare:** Share of electric vehicles among total number of cars*

**newev**: New registered electric vehicles* (source: EV volumes)

**fuelprice** (source: Bloomberg)

**gdppercapitaconstantprices**: gdp per capita, constant prices in EURO** (source: The World Bank, IMF)

**newcartax**: Vehicle tax of a new car***(source: ACEA tax guide 2016-2020)

**fuelcarprice:** Price of a Volkswagen Golf (source: cars-data)

**evprice:** Price of a Volkswagen E-Golf (source: cars-data)

*Light vehicles **Collected in local currency and converted to EURO ***Data collected using a *Volkswagen Golf 2020 1,5 TSI 130 hp Style Manual*

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