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Norwegian policy contribution to the learning effect in the electric car industry

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Any potential weaknesses or mistakes of the thesis are my full responsibility.

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Abstract

Many countries support electrification of the road transport in order to lower CO2 emissions. Norway has been a phenomenon in this area, with highest plug-in electric vehicle number per capita. This study analyses Norwegian policy contribution to the learning effect in the electric car industry for the year 2010-2015. Model 1 with internal learning and Model 2 with internal and external learning are modelled. First, learning curves for the world battery electric vehicle market are estimated. Then prices are re-calculated without Norwegian battery electric vehicle sales. Results show, that without Norway, prices for battery electric vehicles would have been higher by 1 to 23 percent, depending on the car model.

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1 Introduction

More and more evidence shows that current climate situation is the result of human activity (IPCC, 2014). Most governments and scientists across the world recognize the necessity of urgent emissions reduction worldwide. There is also an increasing recognition that the best way to internalize this damage is by switching away from dirty to clean technologies. Emission of carbon dioxide -CO2- gases is the biggest externality ever seen. In 2013 transport accounted for 23% of global CO2 emissions (IEA, 2015b). No surprise there is a big focus on how to reduce emissions from the road traffic.

Currently, big debates are going on about the electrification of the road transport and alternative, less polluting fuels. Battery electric vehicles (BEV) with their current high prices need some help from the government to kick start its popularity. Countries with little support for BEVs from the government are not doing well with the number of BEVs on the road. To get certain share of the market BEVs has to become cheaper and more functional. For both of those conditions to be satisfied, technological progress is important. Research and Development and Learning by Doing could influence BEVs production costs and design. Due to spillovers, firms under invest in research and government intervention might be necessary to encourage developments in the market. Another argument for government support for BEVs is network effects. They appear when the utility of consumers is increasing in the number of owners of the same good (Greaker and Midttømme, 2014). This means that a certain network needs to be established before reaping the benefits. For example, a good charging infrastructure for BEVs.

Several studies has been published about forecasting production costs, prices and the cost of ownership for hybrid electric vehicles (HEVs), PHEV and BEVs (i.e. Thiel et al. (2010), Delucchi et al. (2014), Weiss et al. (2012)). All studies consider electric vehicles (EV) together, although they are quite different in their technology. This might be due to the fact that considering only particular types of EVs one can run into data availability problem. Some of the previous studies have got high uncertainty in projection of production cost decline.

In this thesis the learning curve approach was used to project ex-post learning rate for BEVs. Every 5th car registered in Norway in 2015 was electric car according to ZSW (2016). Norway is a special case in the BEVs market, as no other country can yet match Norway’s proportion of all-electric cars. They also are on the top of the table when it comes to the subsidies for BEVs. Therefore, a situation “world without Norwegian BEVs sale” was modelled. Thus this thesis investigates the following research question:

How much has Norwegian policy contributed towards the learning effects in the electric car industry?

The structure of this thesis is as follows: chapter 2 provides background information about current climate situation, global and Norwegian electric vehicle market and Norwegian governmental policy towards BEVs. Chapter 3 presents theoretical framework and literature review. Chapter 4 describes data collection and method. Chapter 5 presents results and discussion. Chapter 6 concludes the thesis.

2 Background

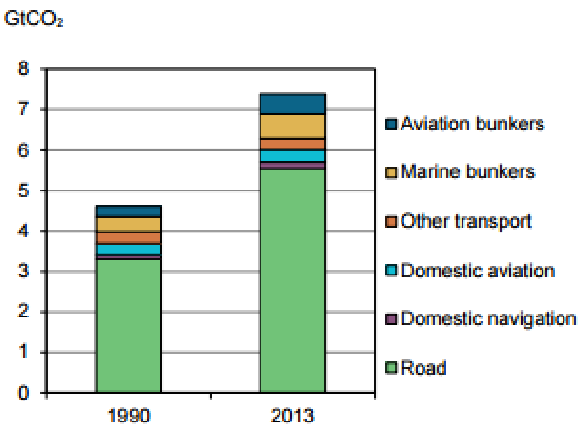
In this section the background information for this thesis will be discussed. Recent information about climate change will be presented in the first part and a more detailed presentation of the electric vehicles with terminology will be presented in the second part. The third paragraph will summarize Norwegian governmental policy and look closer into Norwegian electric vehicle (EV) market.

2.1 Recent numbers in Climate change

2.1.1 Global perspective

Despite the growing awareness of climate change in recent decades, greenhouse gas (GHG) emissions have continued to rise. Carbon dioxide (CO2) concentrations in the atmosphere have been increasing significantly over the past century. According to IEA (2015b) the 2014 concentration of carbon dioxide was about 40% higher than in the mid 1800 when it was 280 parts per million (ppm). In the last ten years an average growth of CO2 was 2 ppm/year in the last ten year. Global CO2 emissions reached 32.2 GtCO2 in 2013, an increase of 2.2% of 2012 CO2 level. Although this growth was higher than in 2012, but it was lower than the average annual growth rate since 2000. The long going debate about the cause of climate change has quiet down after The Fifth Assessment Report from the Intergovernmental Panel on Climate Change (Working Group I) stated that human influence on the climate system is clear (IPCC, 2014). According to the report, the use of energy among human activities represents by far the largest source of emissions. Two sectors produced close to two-thirds of global CO2 emissions in 2013: electricity and heat generation accounted for 42%, while transport accounted for 23% (IEA, 2015b). Figure 1 illustrates different sources for transport emissions. It is clear that emissions from road are driving the growth of transport emissions.

Figure 1: World CO2 emissions from transport



Data source: IEA (2015b).

2.1.2 Norwegian perspective

Since this thesis is looking separately into Global and Norwegian EVs market, it is important to shortly mention the climate situation in Norway. According to SSB (2015), the two main sources of greenhouse gas (GHG) in Norway are oil and gas extraction and road transport. Table 1 below provides a short summary of how shares of emissions from these two sources have changed over the years. In 2014 they made up to 45% of total GHG emissions in Norway.

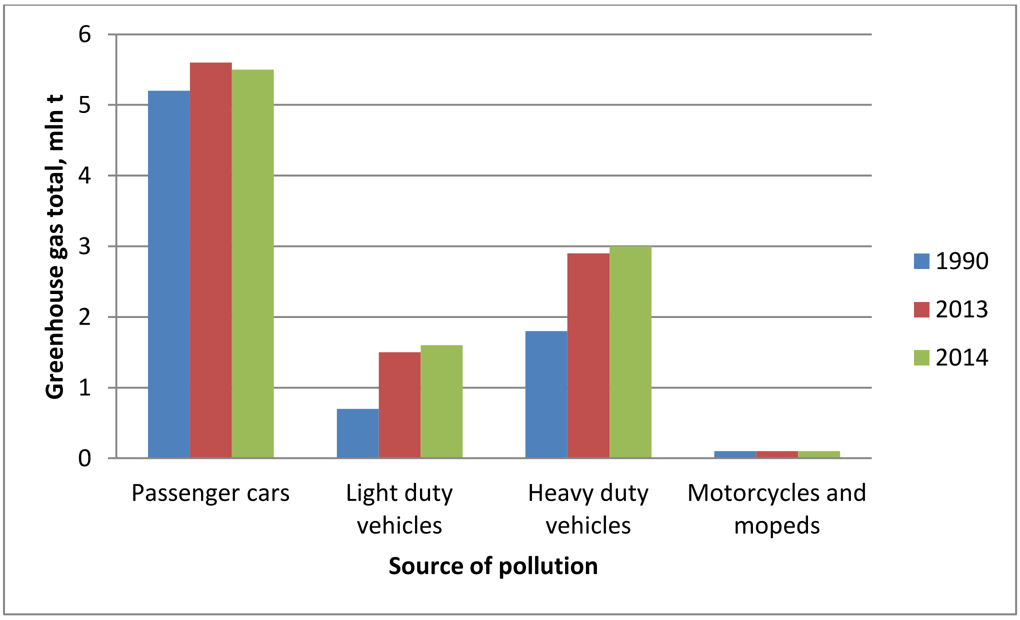
Table 1: Two main sources of GHG emissions in Norway 1990-2014

	1990	2013	2014
Oil and gas extraction - stationary combustion % of total emissions	15%	24%	26%
Road transport % of total emissions	15%	19%	19%
% of total emissions	**30%**	**43%**	**45%**

Data Source: SSB (2015).

Figure 2 shows road emissions only in Norway. In 2014 emissions from passenger cars slightly decreased, but total level of road emissions was still higher than previous years due to increase in other type of vehicle emissions. If in 1990 transport emissions was 7.8 million tonnes of GHG, in 2014 it increased to 10.2 million tonnes.

Figure 2: Road GHG emissions in Norway



Data source: SSB (2015).

2.2 Battery electric vehicles (BEVs)

2.2.1 BEVs overview

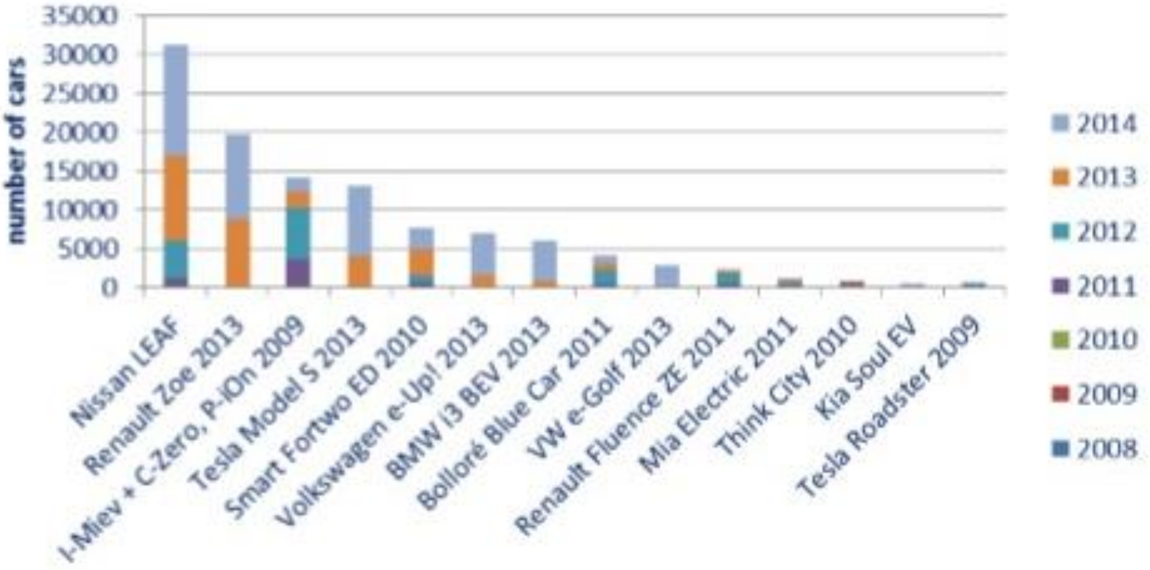
In response to increasing pollution from traffic and government EV support policies, vehicle manufactures support the gradual electrification of road transport via the introduction of innovative transport that is an alternative to the conventional polluting cars. The innovative transport includes hybrid-electric vehicles (HEVs), plug-in HEVs, fuel-cell-electric vehicles (FCEVs) and battery-electric vehicles (BEVs) (Weiss et al., 2012). This work will focus on the latter. Although many countries have introduced various incentives to increase amount of HEVs and BEVs on the road, their current prospects are darkened by high vehicle prices together with limited payload, uncertainty regarding durability and safety and short driving range just to name a few. These vehicles will have to become cheaper and more functional in order to achieve substantial market shares.

In this work BEVs are passenger cars that draw energy for mechanical propulsion from a rechargeable electric power storage device – battery (Weiss et al., 2012). BEVs history dates back to 19th century (Bellis, 2010). In the last few decades BEVs were remembered again after the concerns about the security of fossil fuel supply and transport pollution grew. Some small producers have offered BEVs for several years now, but most major manufactures have only started few years ago with their all electric commercial vehicles. For example, Tesla Roadster introduced in 2008, Mitsubishi introduced their i-MiEV in 2010, the same year as Nissan introduced their Nissan Leaf. After that every year there are numerous models of BEVs that are introduced into the market. Two figures below explain the global trends in the EV field. Figure 3 shows global sales of both BEVs and PHEVs for the last 5 years. Figure 4 presents most popular BEVs brands in Europe between 2009 and 2014.

Figure 3: Global annual sales perspective of electric cars

Data source: (IEA, 2015a)

Figure 4: BEV sales per model in Europe 2009 - 2014



Data source: Witkamp (2015).

According to Nykvist and Nilsson (2015) the single most important factor in achieving affordable mass-market BEVs is their relative cost. The key difference in cost between BEVs and conventional vehicles (CV) is the power train, or the battery. Nykvist and Nilsson (2015) in their research found that in order to become cost-competitive with conventional vehicles BEVs battery packs needs to fall below $150 per kWh. In their research lowest battery costs were found for market leaders Nissan and Tesla, at around $300 per kWh. Although the number of BEVs on the road grows every year, they still make up only a small part of road transport. Investments in research and development in batteries is needed to encourage the growth of this market. Tesla Motors has introduced first fully electric sports car, Tesla Roadster, that could travel 320km per charge (Tesla, 2009). This is so far the longest travel per charge. Tesla also announced that they will allow to use their patented battery technology in order to spurt the development of the batteries for the electric vehicles (Gallucci, 2014).

2.2.2 Norwegian BEVs market overview

Norway is a special case in the BEVs market. No other country can yet match Norway's proportion of all-electric cars. According to Statens Vegvesen (2015) there were 3181130 road transport vehicles registered in Norway in 2015. Grønnbil.no (2016) reports that there were 66276 BEVs registered in Norway in 2016, which constitutes to 2% of all vehicles on the road. This percentage is not so big, but

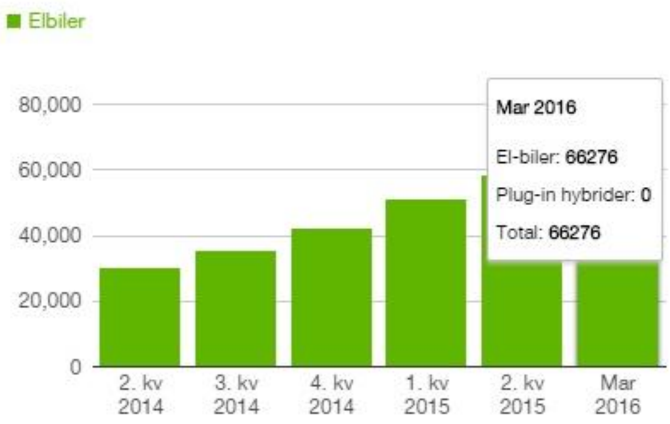
Norway is a leader among other countries. For example, Netherlands is the next big country for BEVs, but they have only 1% (Jolly, 2015).

Sometimes BEVs are called "zero emission" vehicles because driving one does not produce any direct tailpipe emissions. This is a significant difference from the conventional vehicles (CV). However, emissions might occur while generating electricity for electric vehicle charge. Norway is considered to be a place with clean energy because of its hydropower. This is why using BEVs in this country is considered to have zero emissions. If you compare it to other countries that use fossil fuels for electricity, then BEV charged with that kind of electricity has some pollution just by charging. This is important not only for global emissions, but local emissions, too. Even BEV charged with "dirty" electricity are beneficial for the city life as they have no emissions when driving.

Large parts of the electricity used in Norway come from hydropower (Statkraft, 2016). Norway is the country with largest per capita hydropower production. A significant share of the total hydroelectricity production is consumed in the country and many of the hydroelectric plants in Norway can adjust and adapt well to the variations of demand for electricity. Government also constantly invests into renewable energy market (i.e. Nordic Power Supply System) in that way making sure Norway increases its ability to produce more energy and produce even a higher surplus of electricity.

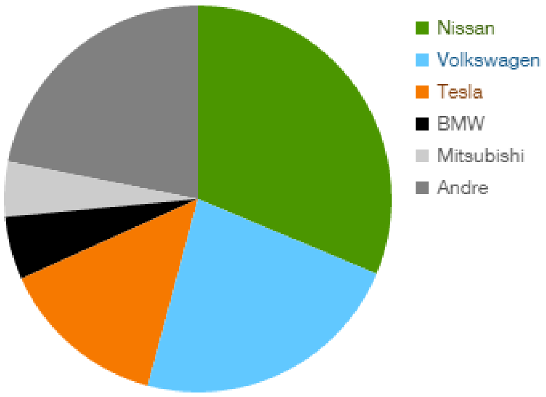
Figures below provide an overview of current BEVs situation in Norway.

Figure 5: Registered EVs in Norway 2014-2016



Data source: Grønnbil.no (2016). .

Figure 6: Market share of different stock of BEVs in Norway in 2016



Data source: Grønnbil.no (2016).

2.3 Policies for EVs

2.3.1 Norwegian policy overview

In Norway, government incentives towards electric car market makes electric car purchase price competitive with conventional cars (Holtsmark and Skonhoft, 2014). Due to this public subsidy, the number of electric cars on the Norwegian roads increased rapidly, especially in the last few years, when the better infrastructure for charging was developed.

The Norwegian subsidies to electric vehicles (BEVs) started in the 90's. The initial reason was the national companies *Energi Norge* and *Think*, who constructed small, environmentally friendly BEVs for government owned institutions, such as universities, and for local transport in urban areas. In 2011 and 2012 both companies went bankrupt and were sold to foreign investors who stopped all production.

Table 2 provides an overview of the Norwegian subsidy policy history. The subsidy policy includes non-recurring taxes. This implies a no purchase fee and a reduced percentage of Value Added Tax (VAT). There are no public parking fees, no toll or ferry payments, no annual road tax and allowed use of bus lanes and free charging. In the Oslo-region, businesses and communities are encouraged to build charge stations, as up to 50% of the cost may be covered by the government (Oslo, 2016). The mix of generous economic incentives and supply of powerful EVs, made the market grow exponentially over the next years.

Table 2: Norwegian subsidy policy for EVs

Year	Government action
1990	Abolishment of import tax
1996	Reduced annual registration tax
1997	Exemption from road toll
1999	Free parking in public spaces
2000	Reduced company car tax
2001	0% VAT
2005	Access to bus lanes nationwide
2008	Oslo launches EV charging infrastructure program
2009	Free access to road ferries

Data source: EVNORWAY (2015).

When the government announced the subsidies, they said that those will be in effect until there are 50,000 registered "zero emission vehicles" in Norway or until the year 2018 – whichever comes first (Klimaforliket, 2011-2012). However, the subsidies have been so effective that 50,000 BEVs was reached already in 2015 and for now the subsidies stay in place.

The political reasoning for the subsidies today is to reach the EUs emission reduction target for the transport sector in 2020 and make air quality better in the urban areas (EC, 2016).

Around the time the Norwegian companies went out of business, other, major car-companies started producing their own BEVs. These cars were meant to compete with conventional vehicles and are, therefore, much more powerful than their Norwegian predecessors. Especially the battery-technology used made a big difference, as the newer BEVs have a reach of over 100 km before they need charging.

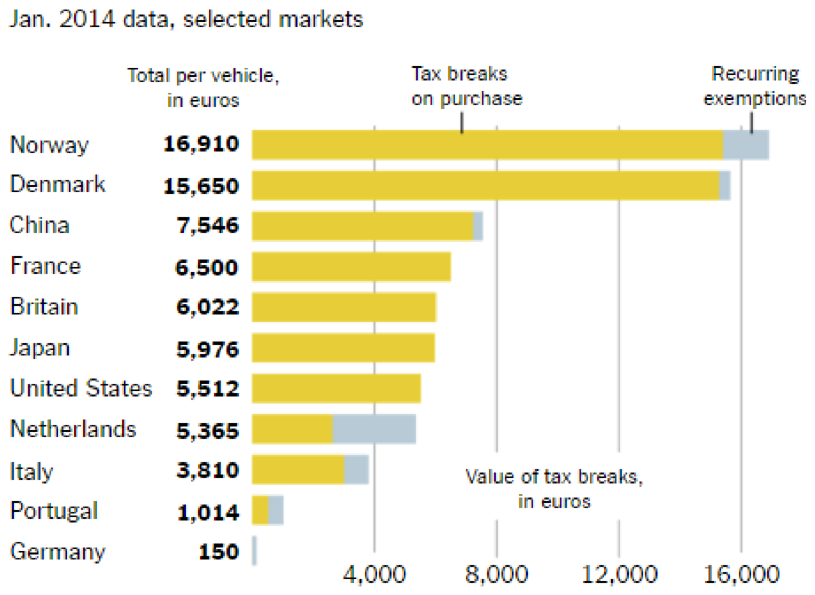
An American analysis (Hawkins et al., 2012) of the production-emissions of BEVs and CVs shows that the production-emissions of BEVs is about double that of CVs. This is mostly because of the production of lithium batteries for BEVs and that an empty fuel tank for a CV has yet to pollute much. The BEV has already polluted 13600kgCO_2 (30000 pounds) by the time it is ready for use, compared to 6350kgCO_2 (14000 pounds) for a CV – in the region they are produced.

Although Norwegian policy is often cited as an example in the media across the World, there is some criticism to it, too. For example, Holtsmark and Skonhoft (2014) argue that Norwegian policy should be eliminated as soon as possible. They conclude that BEVs subsidies are harmful to the economy and to the society for various unintended effects that it creates.

2.3.2 Global policy overview

Around the World, a few countries encourage usage and production of the BEVs. Figure 7 below shows value of tax breaks in Euros for purchasing BEVs in various countries. Norway, of course, is on the top with its generous subsidies.

Figure 7: Tax breaks on purchase and use of electric cars



Source: (Jolly, 2015).

US Federal government also has incentives in place for production of BEVs (CBO, 2012). There are a few, just to mention some: grants to companies that manufacture batteries as well as subsidised loans to expand facilities that produce BEVs.

3 Theoretical framework and literature review

Climate change is at the centre of the debate in research and in politics. Making sure that climate change is under control is a long-term issue, therefore, technological progress is at a core of both the climate change problem and the solution. The following section will cover some relevant literature review and theory of the technological progress and learning curve. It will also look closer at relevant studies within the electric vehicle field.

3.1 Technological progress in literature

Technological progress matters both for the whole economy and for a single firm. Solow (1956) in his economic growth model teaches that sustained economic growth cannot be reached without continuous technological progress, which in turn requires investment in research and development. Competitive markets, climate change policies (i.e. in energy sector) and regulations make single firms look for ways how to improve their product and offer better price for the customers. This can be done as well through technological progress: either by developing new technologies or by reducing the costs of the existing technologies. Technological progress of existing technology can be measured by the learning curve (also called technology learning, experience curve, technology change). In general there are two ways for technology to progress: either by research and development (R&D) or by Learning by Doing (LbD).

3.1.1 Research and development

Research and development (R&D) activities can be used for both developing new technologies and improving existing ones. R&D can involve:

- Research (basic or applied) by using such inputs as investments and highly skilled labour
- Pilot and demonstration plants by using such inputs as investments and highly skilled labour

The process of R&D requires investment and, therefore, is costly. Another issue with R&D is that knowledge markets are imperfect and very often new technologies has to be made available to the public for the inventor to benefit from what was created (Pizer and Popp, 2008). In certain industry areas private firms might have enough incentives to finance some R&D activities without support from the government, for example, cosmetics market. The spillover effects in this kind of market are smaller than for example in computer technology market. What is more, although incentives for R&D exist, due to spillovers companies would still invest not enough into R&D. When the new technology is released into the market, the knowledge spillover effects may lead to newer innovations. What is more, although there is patent protection, depending on the field of technology, small modification to it can count as not copying and market can also experience new versions or copies of already existing technology (Levin et al., 1987). Such problems as incomplete patent protection, knowledge spillovers to other firms and movement of skilled workers might make investment into R&D too little or unattractive to the private firms. The knowledge spillovers provide benefit to the society as a whole, but not to the innovator. Pizer and Popp (2008) in their work reports that social rates of return from innovation research come between 30% and 50%. However, private marginal rates of return range between 7% and 15%. This shows that firms do not have incentives to provide socially optimal level of R&D activity. Because society in general, rather than the individual innovators, may receive much of the benefit from basic research, government may need to support R&D activities in certain fields.

3.1.2 Learning by doing

Learning by doing (LbD) or learning by experience is used for development of already existing technologies. LbD is "free" as no high investment in knowledge is required, the only costs are current production costs. Technological learning is a concept that permits the evaluation of the decrease in unit production costs when the cumulative production increases (Kahouli-Brahmi, 2008). The technological change as a result of the accumulated experience has been used in economic theory. Manufacturing industries operating in the competitive markets use it for the projection of future costs of production (Martinsen, 2011). First time learning effects on the production costs were described by aeronautical engineer Wright (1936) where he discussed the relationship between cost and quantity. He noticed that the amount of labour needed for completing a given operation, such as constructing the airframe, declined when the operation was repeated and the workers' level of experience increased. In his work Wright (1936) suggested a mathematical model for the learning curve:

Equation 1 $$C = X^E$$

Where C is the cost of building an airplane, X is accumulated production and E is a technology specific constant.

Arrow (1962) in his work tried to formulate the effects of learning by-doing more precisely and drew a number of economic implications from those formulations. Later, a variety of mathematical formulas has been developed to estimate the cost decline that occurs as a new good is produced in greater numbers. The original learning curves were describing the costs of individual inputs and Boston Consulting Group in their research decided to extend the learning curve theory by taking total costs (BCG, 1968). In this extension they also introduced a new term “experience curves” which included total costs and cumulative quantity.

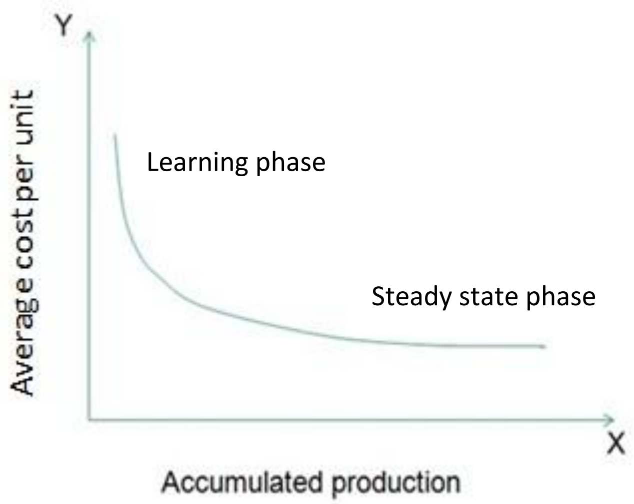
The equation that generally describes the learning curve is stated below:

Equation 2 $C(X_{cum})=C_0(X_{cum})^E$

Where C_0 is normalisation parameter,
E parameter represents learning and is negative if learning rate exists, or 0 if there is no learning
X_{cum} is the accumulated production and
$C\ (X_{cum})$ are the resulting costs

Large values of E indicate a steep curve with a high learning rate.
General graphical representation of the learning curve is presented in Figure 8. Low values on the horizontal axis (units produced) represent a process or technology that experiences significant reductions in costs. As more units are produced, the process is slowly perfected and additional decrease in costs is marginal. At this point, the process or technology is considered mature (Withum and Babiuch, 2012).

Figure 8: General graphical representation of learning curve.



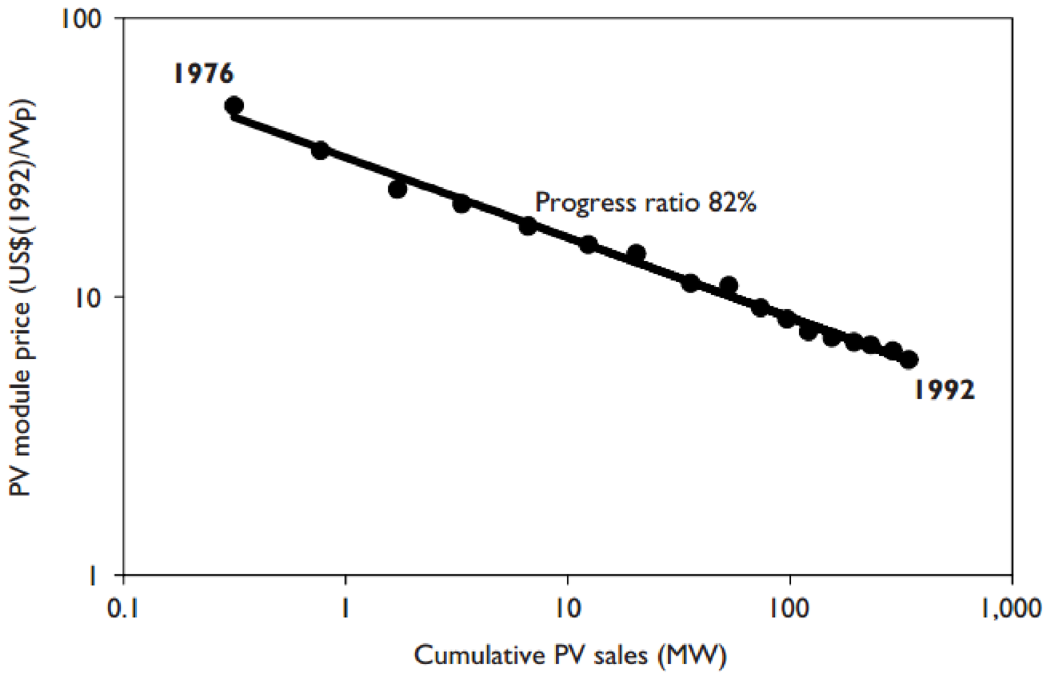
A technology learning curve is most often presented in a double-logarithmic diagram. This presentation allows easier to identify the experience effect as learning curve becomes a straight line (Figure 9). Each time cumulative output doubles, costs fall by a constant percentage equal to the learning rate (LR). The change in price is referred to as the progress ratio (PR) (IEA, 2000). The relation between the PR and E learning parameter is:

Equation 3 $PR = 2^E$

where E is negative and the LR is calculated by

Equation 4 $LR= 1-PR$

Figure 9: Technology learning curve for PV power modules 1976-1992



Data source: IEA (2000).

The learning curve in Figure 9 has PR of 82%. This means that every time cumulative production is doubled, the price is reduced to 0.82 of its previous level after doubling of cumulative sales. Then the LR from Equation 4 is 100-82=18%. This means that every doubling of cumulative sales reduces the price by 18%.

Many recent studies have used LbD method to predict the future prices. The issue with this is that originally LbD was an empirical measurement of LbD in manufacturing and not a tool to predict future costs (Jamasb and Kohler, 2008). What is more, there might be issues with the choice of learning rate that is used within the model to predict future costs. Learning rates are usually calculated using models of historical learning curves of similar projects from the past. There have been a number of researches done that shows that learning rates are different even for the same type of technology and, therefore, using specific learning rate from previous studies might give wrong predictions. This is especially important for the new energy technologies, as there has been some studies reported with very different learning rates (McDonald and Schrattenholzer, 2001). Table 3 shows how different learning rates can be even for the same type of technology. McDonald and Schrattenholzer (2001) found that most likely differences in the learning rates occur due to variability in experience depreciation, short-term pricing behaviour, varying intensities of R&D, economies of scale, differences in performance measures, definitional differences, and cost variability for factors such as land, wages, and interest payments.

Table 3: Learning rates for different technologies

Technology	Region of Study	Time Period of Study	Estimated Learning Rate	Reference
Coal Power Plants	USA	1960 – 1980	1.0 – 6.4	Joskow & Rose (1985)
Coal for Electric Utilities	USA	1948 – 1969	25	Fisher (1974)
Crude Oil at the Well	USA	1869 – 1971	5	Fisher (1974)
Solar PV Modules	World	1976 – 1992	18	IEA (2000)
Wind Power	USA	1985 - 1994	32	IEA (2000)
Wind Power	EU	1980 – 1995	18	IEA (2000)

Data source: McDonald and Schrattenholzer (2001).

3.1.3 Economic modelling of learning curves

There is a lot of discussion in the literature about R&D and LbD and whether they should be presented as an inseparable part of innovation, or they could stand alone and represent different forms of investment. When LbD is considered as an average price reduction due to learning (accumulated production), the one-factor learning curve (OFLC) model is used. Many studies have used this OFLC model to forecast cost reduction (Klaassen et al., 2005, Söderholm and Sundqvist, 2007, Ibenholt, 2002). The OFLC model advantage is relatively easily accessible data: investments and production volumes are often well recorded compared to other cost drivers (Wiesentahl et al., 2012). Thus, reliable learning curves can be found for economic modelling purposes. In practice it is difficult to distinguish technological advancement due to just learning by doing or just by research and development. Therefore, the Two-Factor-Learning Curve (TFLC) model was developed in order to separate the effects of learning-by-doing and research and development. The TFLC model takes into account cumulative R&D expenditures or knowledge stock with regard to that technology. Wiesentahl et al. (2012) describe the TFLC for a given technology t and time period y the following way:

Equation 5 $C_{t,y} = aQ_{t,y}^{\alpha} KS_{t,y}^{\beta}$

Where C - Costs of unit production,

Q - Cumulative Production,

KS - Knowledge stock (approximated through R&D investments)

α - Elasticity of learning by doing, negative sign

β - Elasticity of learning by researching, negative sign

a - normalisation parameter with respect to initial conditions

So the one-factor model analyses only LbD, whereas the two-factor model has both LbD and R&D. According to Wiesentahl et al. (2012) experience showed that supporting R&D without supporting deployment of the technology has proven to be a sub-optimal policy strategy. Equally, supporting deployment without supporting R&D will be sub-optimal, too.

It is important to mention internal and external learning here. Internal learning takes place within the boundaries of the firm whereas external learning occurs outside of the firm. For example, for this thesis, internal learning is something company achieves through making more units of that specific model and maybe by in-house R&D for that specific technology. However, BEV battery developments could be external learning, as all BEVs has it and it is a battery company that makes ones, not the car manufacture, for example. Or as mentioned in Ch 2, Tesla agreed to share their battery technology with anyone interested, to encourage the development in the market.

Few more factors are important to consider when choosing economic models for modelling technology development. One of them is whether technology learning is a global phenomenon or whether learning develops at different rates due to specific factors in different regions. Depending on the answer global, regional or a combination of those two can be chosen for simulating technology learning. In this work, a global approach will be used for few reasons. First of all, although Norway has many battery electric vehicles, they are not produced locally. So even if Norwegian contribution to the learning effect in the BEVs is evident, it is not a local or regional learning, as production is performed in other parts of the world. Second, very often technology (i.e. batteries for EVs) is the same in all countries, therefore leading to a globally defined learning rate.

Another important factor in the modelling is price or cost of the technology. As mentioned earlier, a learning curve presents a development of the production costs, as a function of accumulated production. Diffusion of technologies is however, determined by market prices (Wiesentahl et al., 2012). In real market prices can differ strongly from the actual production costs. Often in the modelling of learning curves the price data is used instead of cost data simply for the reason that the first one is more accessible. The price data will be used in this work, too. Companies are very reluctant to provide actual production costs or reveal any kind of pricing strategy from which one could determine the cost of production.

3.2 Environmental policy and Technological change

Our climate is changing and there is no doubt now that growing consumption of fossil fuels had a huge impact on that (IPCC, 2014). Scientists and policy makers look for various ways on how to make policies so they influence alternative energy advancement and would stop or at least take climate change under control.

Economic analysis of environmental policy is based on the idea that certain economic activities can create harmful consequences, which are called “negative externalities”. Externality is an economically significant effect of an activity with the consequences that affect other parties, not just the one that controls the externality-producing activity (JAFFE et al., 2004). The firms do not have economic incentives to minimize the costs of pollution. This is where environmental policy becomes important – it attempts to raise the incentive for a firm to minimize negative externalities. In the short run, efficient environmental policy requires a comparison of the marginal costs (MC) of reducing pollution with the marginal benefit (MB) of a cleaner environment. The trade-off between MC and MB is altered when technology is taken into account. Especially if considering technology innovations - cleaner equipment, cleaner methods, substitutes for environmentally harmful products, etc. It typically reduces the MC of achieving a certain unit of pollution reduction. Better results are achieved with lower costs and this can be beneficial for the environment, therefore, society and the firm that must obey the environmental policy.

Since technological advancement is one of the most important things for successful pollution control, key consideration when picking the policy instruments should be the impact of different policies on firm incentives to develop cleaner production technologies (Fischer et al., 2001). It can sometimes be a tricky choice, as short run situation may have different effects when compared to long term results. When talking about the deployment of technology there is an ongoing debate in the literature whether the government intervention would do good or bad. Some papers argue that there is a connection between climate policies and the rate of technology improvement (Bovenberg and Smulders, 1995, Goulder and Mathai, 2000). Jaffe et al. (2003) in their overview of policy and technology explains few reasons why policy and technology advancement could be related. First of all, public policies affect the prices of carbon based fuels and private firms are interested in investing in R&D in order to find cheaper ways to provide their product and win market share. What is more, higher fuel prices may induce new production methods that would require less of any kind of fuel. Also, as mentioned before, technology could improve through LbD. Therefore, firm incentives to move from usual process towards more green process could be stimulated by public policy through subsidies or indirectly through taxing and this would stimulate technological growth (Rosendahl et al., 2004).

General guideline is that if the positive externalities exist, then government support would be beneficial. As mentioned earlier, in case of positive externality the underinvestment by the firms would occur. No firm would be interested in spending its money to do research which can be used by others to claim the profits. However, one has to be careful because if private companies gets all the benefits from technology progress (as if there are no positive spill over effects) then government support could lead to over-investment in technological progress. Kneese and Schultz (1978) argued that the potential to spur technological innovation may be the single most important criteria for environmental policy in the long run. Pizer and Popp (2008) in their research found that Environmental innovation responds to environmental policies and energy prices. Polzin et al. (2015) finds that literature on previous research done in renewable energy supports an idea for renewable energy deployment.

One of the big debate questions in the environmental policy and technology area is whether environmental technology should be supported more than other type of technology. Some believe that science and technology policies should be neutral and should not be targeted to environmental concerns (OECD, 2002). The argument is based on the assumption that if externalities are properly internalised, there will be no need to point technology towards the right direction. However, this assumption is very hard to fulfil. Another reason why support for the environmental technology is often argued against is because public R&D may crowd out private research efforts. Still some research articles strongly argue in favour of directed technical change. Acemoglu et al. (2012) in their paper introduce endogenous and directed technical change in a growth model with environmental constraints and limited resources. They found out that optimal policy would include both carbon taxes and research subsidies directed towards the environmental technology. Model with endogenous technology, the one which is influenced by the policy, provided a more optimistic scenario than model with technology driven by the market.

When talking about the electric vehicle market it is important to mention Network effects. These effects are also related to government intervention for deployment of technology. Network effects appear when the utility of consumers is increasing in the number of owners of the same good (Greaker and Midttømme, 2014). This means that a certain network needs to be established before reaping the benefits. A consumer who adopts a good today will both increase the utility of the consumers already in the network, but also increase the incentive future consumers have to adopt that same good (Greaker and Midttømme, 2014). One obvious example of network externalities is electric cars market which would greatly benefit from a network of fast charging stations, for example. When it comes to government intervention and network externalities, Greaker and Heggedal (2007) shows in their research that it is important to wait for market signal before providing government support. Although the authors studied hydrogen car market, the results are important for the electric vehicle market, too. Analysis showed that public policy to encourage hydrogen technology in the personal car market would not do any good due to network externalities unless the market is ready (Greaker and Heggedal, 2007). The signal from the market could be some use of hydrogen technology in the personal transport market. Norwegian government abolished taxes for the BEV first time in 1990 (http://www.evnorway.no, 2015). And although there might be other reasons why market picked up only in 2008, one of them might as well be network externalities. Oslo municipal launched BEV charging infrastructure program in 2008. Although there was movement in the BEV market and Norway even made BEVs themselves, the infrastructure was not fully established and BEVs might have been more attractive for business than personal life. Developing charging station infrastructure, moving from two seats to family electric cars, developments in the battery charging times and driving distance all this contributed towards the rapidly growing BEV market. More and more users of the BEVs and private firms' investments into the technology could have been accepted as a signal from the market. Therefore, Norwegian policy makers announced various subsidies for electric vehicles from 2005. It seems that it has been the right time to do that, as Norway is a leading country by the number of BEVs per capita (EVNORWAY, 2015).

4 Data and methods

Now that background and most relevant theory have been covered, it is time to present some empirical analysis. This section will start with describing data used for statistical analysis. Then methods and models will be introduced.

4.1 Data collection and description

The main objective of this thesis is to find whether Norwegian government regulation for BEV subsidies anyhow influenced the technological change in the BEV market in the world. To analyse this, we need information about number of BEVs that were produced every year in the world in total as well as number for each car model. Accumulated production number will be used for each year and each car model. We also need prices for each car model for each year. For further analysis accumulated supply of each BEV brand for each year in Norway is needed. Because data involves the same type of car models observed over some years, this data is panel data.

Accumulated amount of BEVs in the world was provided by International Energy Agency (IEA). Then amount of different BEV models for each year were taken from different sources: for Nissan numbers were reported in the manufacturing reports; same with Tesla. Mitsubishi, BMW and VW were taken from auto industry blogs. KIA Soul EV numbers were provided by personal communication with the factory.

Table 4 has data for BEV world market. The results from this statistical analysis should be interpreted with caution, as data sample is very small. However, even this small sample can give an indication of what is going on in the market. It was a very big challenge to collect data. This is due to the fact that BEVs are relatively new in the market and not much data is yet available. Such challenges as different titles (*i.e. talking about the same vehicle: EVs, BEVs, all electric vehicles, Plug-in EVs*) when looking for amount of BEVs and such problems as reported price (*is it with government support? Is it including delivery fee? Is it simple model or model with leather seats?*) when collecting price of BEVs were difficult to overcome. World data needed to be coordinated with the Norwegian data (Table 5) for comparison. This means that only car models that are present in Norway with data on quantity and price could be picked for the world market, too.

Table 4: Data for the world BEV market

Model	Model index	Year	Price, USD*	Acc. Supply by model World	Acc. Supply BEV World total
Mitsubishi i-MiEV	1	2010	47087	10206	16567
Mitsubishi i-MiEV	1	2011	43569	25001	39648
Nissan Leaf	2	2011	50524	22000	42649
Mitsubishi i-MiEV	1	2012	33769	29065	92180
Nissan Leaf	2	2012	44733	48976	72269
Mitsubishi i-MiEV	1	2013	29069	31488	197582
Nissan Leaf	2	2013	37947	96692	132378
Tesla Model S	6	2013	87518	25092	203978
Mitsubishi i-MiEV	1	2014	22400	34949	366554
Nissan Leaf	2	2014	35176	158199	243304
BMW i3	3	2014	40012	16052	385451
Kia Soul EV	4	2014	31045	1437	400066
VW E-Golf	5	2014	39788	3804	397699
Tesla Model S	6	2014	78302	56747	344756
Mitsubishi i-MiEV	1	2015	18566	35935	577160**
Kia Soul EV	4	2015	25502	9887	603208**
Nissan Leaf	2	2015	23941	201850	411245**
VW E-Golf	5	2015	31509	19131	593964**
Tesla Model S	6	2015	78302	107193	505902**
BMW i3	3	2015	30952	40109	572986**

Data sources: IEA (2016); Nissan (2012); Nissan (2013); Autotrade (2014); Nissan (2015); Left-Lane (2016); AW (2016); KIA (2016a); OFV (2016); TeslaMotors (2016b).

*adjusted to 2015-prices **calculated

Total accumulated supply data was available for the years 2010-2014 and is presented in the table 5 below. The last column in table 4 was calculated by taking total world sales (table 5) and subtracting the specific car model. So, for example, for Mitsubishi i-MiEV last column a number of 2010 total world sales (26773 - from table 5) was taken and Mitsubishi i-MiEV total sales of that year were subtracted (26773 – 10206). This was important for Model 2, so total sales in the world represent external learning only.

Table 5: Total accumulated BEV number in the world

Year	TOTAL Number BEVs
2010	26773
2011	64649
2012	121245
2013	229070
2014	401503
2015	613095*

Data source: IEA (2016).
*calculated

Total number of BEVs for the year 2015 is still not available; therefore, a decision to calculate prediction was taken. 2015 total BEV number in the world was calculated by first adding “Acc. Supply by model World” (table 4) for 2014, then doing the same for 2015:

1. 34949 + 158199 + 16052 + 1437 + 3804 + 56747 = 271188
2. 35935 + 201850 + 40109 + 9887 + 19131 + 107193 = 414105

Then we check the % increase in year from 2014 to 2015:

(414105/27118)*100 = 152,7%

Then multiplying the “TOTAL number BEVs” (table 5) by 152.7%:

401503*152, 7% = 613095 - calculated TOTAL number BEVs for 2015.

To obtain data on world price of various models was very complicated. There was no one source that would provide this data, and different sources could have reported differently calculated data (for example, include subsidy). Therefore, the decision to keep Norwegian price data for the world market analysis was accepted. A detailed price data for Norwegian market was provided by the OFV (2016). However, since none of the vehicles are made in Norway, prices that originally were provided in Norwegian Kroner (NOK) were calculated into US dollars (USD) by using annual exchange rate for that year (NorgesBank, 2016). In price data with NOK some prices went up, but after converting it to USD, prices were declining every year. What is more, price data had to be adjusted to 2015-prices. Producer price index (PPI) for US was used (STATISTA, 2016). PPI measures the average price development of all goods and related services on both the domestic and the non-domestic markets, at all processing stages (Eurostat, 2014).

Table 6 presents data for Norwegian market only. This is the data by which car models were selected, as Grønnbil.no (2016) reports exact numbers of accumulated supply of cars in Norway only for those car models that represents biggest share of this market. Other type of car models just goes under the name “other”. It is important to mention Tesla Motors here. This is one of the most loved brands in Norway. However, it was difficult to obtain correct data, as Tesla makes many different car models that differ a lot in price. Amount of cars for each year is reported as a total of Teslas, not separated into different car models. Price data for Model S was in the dataset from OFV. Decision was made to take total of Teslas number and consider that they all were Model S.

Table 6: Data for Norwegian BEV market

Model	**Year**	**Price, USD***	**Acc. Supply by model Norway**
Mitsubishi i-MiEV	2011	43569	1050
Nissan Leaf	2011	50524	381
Mitsubishi i-MiEV	2012	33769	1722
Nissan Leaf	2012	44733	2868
Mitsubishi i-MiEV	2013	29069	2178
Nissan Leaf	2013	37947	9081
Tesla Model S	2013	87518	2018
Mitsubishi i-MiEV	2014	22400	4127
Nissan Leaf	2014	35176	16450
BMW i3	2014	40012	2112
Kia Soul EV	2014	31045	445
VW E-Golf	2014	39788	2018
Tesla Model S	2014	78302	6060
Mitsubishi i-MiEV	2015	18566	7314
Kia Soul EV	2015	25502	2069
Nissan Leaf	2015	23941	20924
VW E-Golf	2015	31509	10961
Tesla Model S	2015	78302	10099
BMW i3	2015	30952	3499

Data source: Grønnbil.no (2016); OFV (2016);

*adjusted to 2015-prices

Six different car manufactures and their BEVs are presented in this work. The choice of the car models was made according to data availability on the sales numbers and prices. These are the most popular BEV types in Norway and a short description of each is available below.

4.1.1 Mitsubishi i-MiEV

The i-MiEV is the first fully electrical car made by Mitsubishi Motors and was the first mass produced BEV in history (EVWORLD, 2015). It was first marketed in Japan in 2009. Performance of i-MiEV reaches 130km/h on motorways and is rechargeable at 80% within 30minutes on a quick charging station (Benders et al., 2014). On a 230V outlet it would take 6-8 hours to fully charge the battery. The car has two plugs: one on the right hand side and one on the left. Plug on the right is for usual charging, whereas the one on the left is for fast charge. The battery pack is fixed on the bottom of the vehicle, and the engine is fixed at the rear. Mitsubishi Motors i-MiEV model has been awarded with 'Ecobest 2009' award for efforts in green field by the Autobest. It has 16 kilowatt hours (KWH) battery and 100km driving range. New model is coming in 2017.

4.1.2 Nissan Leaf

Nissan is a leading corporation in the modern BEVs manufacturing, and Nissan LEAF stands for Leading Environmentally-friendly Affordable Family car (AFP, 2010). It was introduced to the European market in 2011 and to date is the world's bestselling electric car (Economist, 2015). The Nissan Leaf is a five door hatchback, and its performance reaches 150km/h. The car can have its battery's capacity recharged up to 80% in 30 minutes on fast charging stations. It takes up to 10 hours to fully recharge with a standard electrical socket. The battery is located beneath the seats, which provides stability to the car. Nissan Leaf has 4 models in the market: ACENTA and VISIA with the 24 KWH batteries and TEKNA and ACENTA with 30 KWH batteries.

Models differentiate in batteries and prices. Most models have a setting that enables you to pre-heat or pre-cool the car while it is plugged in for charging. This reduces battery energy use of the car. There are two possible options for battery: 24 KWH with driving range of 135 km and 30 KWH with driving range of 172 km (Nissan, 2016)**.**

4.1.3 KIA Soul EV

KIA Soul EV is a first fully-electric vehicle from KIA, and is a five-door hatchback. It takes 4-5 hours to charge a vehicle, or 33 minutes on a Public Rapid Charges for up to 80% battery charge (KIA, 2016b).

However, one of the downsides of KIA BEV is that it takes up to 13 hours to fully charge it on a domestic plug. KIA Soul EV can reach speed up to 145 km/h and has a 27 KWH battery with drive range of 150km (PlugInCars, 2016).

4.1.4 Volkswagen E-Golf

All electric vehicle produced by Volkswagen was introduced to the market in 2014. The design of the e-golf is based on the multi-award winning Golf hatchback and looks almost exactly the same (PlugInCars, 2016). E-Golf is named to be the most economical electric car in its class (Volkswagen, 2016), even though it is a conventional car remade to fit with electrical power, unlike its main rivals of Nissan and BMW that are BEV-only developments. E-Golf can reach up to 135 km/h speed. It takes up to 13 hours to be fully charged though the domestic plug, but takes only 30 minutes to be charged for up to 80% battery charge through a DC fast charging stations. It has 24.2 KWH battery and a driving range of 135km. New model is coming in 2017.

4.1.5 BMW i3

In 2013 a fully electrical vehicle from BMW was introduced to European market (BMWGroup, 2013a). It is the first ever vehicle from BMW released to the market for mass production to have an outer skin body made of thermoplastic – which is produced using 25% renewable or recycled materials, and the roof that is made of carbon-fibre-reinforced plastic (BMWGroup, 2013b). This lightweight and durable material allows some extra weight for the batteries and reduces overall weight of the vehicle by 10kg. The car can reach a maximum speed of 150 km/h. BMW i3 can be charged in 8 hours for up to 80% battery level; within 5 hours at a 230V; or within 3 hours at a 400V (Benders et al., 2014). Vehicle can also be charged using DC charger station which allows to charge up to 80% battery within 30 minutes. BMW i3 has 22 KWH battery and driving range of 130km. New model is coming in 2017.

4.1.6 Tesla Model S

Tesla produces fully electrical all wheel vehicles reaching maximum speed of 200km/h. Vehicles are made of an aluminium and steel which reinforces zones that strengthens the car body during the crash. Model S was introduced to the market in 2012. Vehicle can be charged in many different ways ranging from up to 29 hours for a full battery charge in a domestic plug to 40 minutes for up to 80% charge in fast charging stations (TeslaMotors, 2016a). Tesla developed a Type 2 Mennekes plugs, that matches the public plug-ins, however also enables a DC fast charging. Tesla charging stations are implemented all over Europe and their number is increasing to make it easier for BEV drivers to travel around. Tesla Model S comes in 60, 70, 85 or 90 KWH batteries and driving range from 335 to 500km.

4.2 Methods

As mentioned in the previous section, the data used in this analysis is panel data. Panel data is a type of data that includes observations from multiple cross sectional units (i.e. firms, countries, models) that are observed for at least two time periods (i.e. years, months, days) (Waldinger, 2015). Panel data are most useful when outcome variable depends on explanatory variables which are not observable but correlated with the observed explanatory variables (Schmidheiny, 2015). If such omitted variables are constant over time, panel data estimators allow to consistently estimate the effect of the observed explanatory variables. That is, it accounts for individual heterogeneity. Panel data can be studied using several techniques, three of most commonly used are pooling independent cross sections across time (pooled OLS), using fixed effects model or using random effects model.

In pooled OLS model all observations are estimated together, neglecting both, cross section and time series character of the data (Gujarati and Porter, 2009). The intercept is common for all units in this model. Since for data used in this thesis a different intercept is expected for each vehicle model, fixed effect model with dummy variables was used to analyze the data.

4.2.1 Model 1

First model was considering internal learning effect. Equation for this model:

Equation 6 $X_{i,t} = a_i * Y^{E}_{i,t}$

Where $X_{i,t}$ is price of the model i in the year t

a_i is normalisation parameter with respect to initial conditions that is common for that model across all the years of observed data

$Y_{i,t}$ is accumulated production of that model i for the year t

E is learning parameter assumed to be the same across all models due to small data sample

We estimate logarithm of the above equation:

Equation 7 $\ln X_{i,t} = \ln a_i + E*\ln Y_{i,t} + u_{i,t}$

Where $u_{i,t}$ is the error term

Expected sign of E for Model 1 is negative (E<0) if learning rate exists or zero if there is no learning. This is important, because with this analysis we are looking for the learning rate parameter. What we want to see is that the price is falling with accumulated production, therefore, downwards sloping exponential curve.

This model is considering only internal learning and no external learning. This means, that companies producing the BEVs learns from its own production over time, but no learning from the BEV market.

Since one of the ways to estimate separate intercepts for each BEV is to use dummy variables, the estimated equation then is:

Equation 8 $\ln X_{i,t} = \ln a + E*\ln Y_{i,t} + \gamma_2 D_{2,i} + \gamma_3 D_{3,i} + \ldots + \gamma_n D_{n,i} + u_{i,t}$

Where lna , $\gamma_2, \gamma_3, \gamma_n$ are coefficients to be estimated. Relationship between parameters:

$a_1 = a, a_2 = a+ \gamma_2, a_3 = a+ \gamma_3$, etc.

Where a_i is normalisation parameter with respect to initial conditions that is common for that model across all the years of observed data but differs across models.

4.2.2 Model 2

Model 2 is more complicated and assumes both internal and external learning, which seems more plausible for the real world situation. Equation for model 2:

Equation 9 $X_{i,t} = a_i * Y^E_{i,t} * Z^F_t$

Where $X_{i,t}$ is price of the model i in the year t

a_i is normalisation parameter with respect to initial conditions that is common for that model across all the years of observed data

$Y_{i,t}$ is accumulated production of that model i for the year t

E is internal learning parameter that is assumed the same across all models

Z_t is accumulated production of all BEVs minus that particular model in the world for the year t (So "Total number BEVs" (Table 5) for that year - $Y_{it} = Z_t$). This is necessary as otherwise total number includes both internal and external learning.

F is external learning parameter that is the same across all models

Again, a logarithm of the above equation is needed for the estimation:

Equation 10 $\quad \ln X_{i,t} = \ln a_i + E \ln Y_{i,t} + F \ln Z_t + u_{i,t}$

Where $\quad u_{i,t}$ is the error term

Expected sign of E and F for Model 2 is negative (E<0 and F<0) if learning rate exists or zero if there is no learning. Of course, it can be that one is negative whilst the other one is zero. This would indicate that only one type of learning exists: internal (E) or external (F).

Model with dummy variables:

Equation 11 $\quad \ln X_{i,t} = \ln a + E \ln Y_{i,t} + F \ln Z_t + \gamma_2 D_{2,i} + \gamma_3 D_{3,i} + \dots + \gamma_n D_{n,i} + u_{i,t}$

4.2.3 Estimation issues

The main problems with estimation can arise due to the small data sample. In statistics, usually bigger samples make for statistically better results. Since BEVs have not been long on a market, there were certain issues with data collection (see Chapter 4). Fixed effect model statistical analysis was done for Model 1 and Model 2. Model 2 includes both internal and external learning and the data here can be highly correlated and multicollinearity phenomenon can arise. It occurs when one variable can be linearly predicted from another with a substantial degree of accuracy. In this dataset production of every model BEV increases each year and so does the total BEV number.

5 Results and discussion

In this section the results from a fixed effect model will be discussed first. Model 1 will be discussed in detail and Model 2 results will be reported. In the third part, the results from Model 1 and Model 2 will be used to construct learning curves for the world and for the world without the Norwegian BEV sales. The discussion part will provide some insights on what could be done as a further research and what other options could be considered.

5.1 Statistical analysis results

To know which effect model, fixed or random, to use with the data, the Hausman test must be performed. In this test H_0 is that random effect model should be used. If P value is higher than 0.05 then H_0 would be accepted and random effect model would be used. When ordinary Hausman test is run for this panel data, the test returns negative test statistic (chi2(2) = -13.95). According to statistics theory, negative sign can arise for two reasons: if the data sample is too small and/or if different estimates of the error variance are used in forming variance for the fixed and random coefficients. In the latter case, one needs to use the sigmamore option, which specifies that both covariance matrices are based on the (same) estimated disturbance variance from the efficient estimator (STATA, 2016). After performing Hausman with sigmamore the test statistic is positive and P-value is 0.0209 which is < 0.05. Therefore, we reject the H_0 and choose fixed effect model for estimating results.

5.2 Model 1

Table 7 shows regression results for Model 1 using fixed effect model. Learning parameter E is -0.241. This parameter appears to be statistically significant with the P value of 0.001 < 0.05. Now PR and LR can be calculated (see Equation 3 and Equation 4):

Equation 12 $PR = 2^{-E} = 2^{-0.241} = 0.846$

and the LR then is:

Equation 13 $LR= 1- PR = 1 - 0.846 = 0.154 = 15\%$

Table 7: STATA results for fixed effect Model 1

Variable	Coefficient
E	-0.2406929*** (0.056/ -4.29)
lna (Mitsubishi i-MiEV)	12.77684*** (0.566/22.56)
γ_2 (Nissan Leaf)	0.468071** (0.156/3.01)
γ_3 (BMW i3)	0.1326989 (0.134/0.99)
γ_4 (KIA Soul EV)	-0.5499719** (0.198/-2.79)
γ_5 (VW E-Golf)	-0.1235537 (0.154/-0.8)
γ_6 (Tesla Model S)	1.176901*** (0.163/7.23)

Legend: * p<.1; ** p<.05; *** p<.01; robust standard error/t-value in parenthesis.

The Mitsubishi i-MiEV coefficient is reported as constant and coefficients for other models are dummy variables. Constant values for other models are calculated by adding their constant to the Mitsubishi i-MiEV constant. Table 8 below shows constant numbers calculated and transformed from log to constant a_i for each vehicle model. The P-value for Mitsubishi shows that its constant is significantly different from 0 and the P-value for dummy variables shows its relation to the constant. The coefficients for Nissan, Kia and Tesla models are statistically significant at the 0.05 level. This indicates that their constant value is different from Mistubishi i-MiEV price, whereas BMW and VW models have constant value which is not statistically different from Mitsubishi model. Coefficients indicate the initial costs of a BEV producer when log production is zero in the learning curve. From table 8 we can see that KIA has the lowest initial costs whereas Tesla has the highest. These two cars are very different so no surprise their prices differ a lot. Tesla is a luxury car with batteries from 60 to 90 KWH and long driving range of up to 500km, whereas KIA is a family car and has only 27 KWH battery and 150km driving range. Not only technical specifications can have influence on price (costs) – labor costs and business environment in the country of origins can matter, too.

Table 8: Constants a_i for car models

Model	ln	a_i
a_1 Mitsubishi i-MiEV	12.777	353925
a_2 Nissan Leaf	13.245	565187
a_3 BMW i3	12.910	404149
a_4 KIA Soul EV	12.227	204203
a_5 VW E-Golf	12.653	312790
a_6 Tesla Model S	13.954	1148240

Results from table 8 and learning parameter E results from regression (table 7) were used to construct learning curves for each type of car model. Figures below show learning curves (predicted price) and real price (in US dollars, adjusted for inflation) for each car model.

From figures 10-15 it is clear that real prices more or less follows the predicted price path. Nissan Leaf is especially close, whereas Mitsubishi i-MiEV has more differences, as at first the real price was higher than predicted, but now it is quite a bit lower than the predicted one. Prices for all car models are declining. The observed price declines could be explained in part by declining battery costs. Substantial improvements in battery performance and technology makes BEVs more attractive for everyday life and customer number is growing (Weiss et al., 2012).

Figure 10: Learning curve and real price for Mitsubishi I-MiEV, LR = 15%

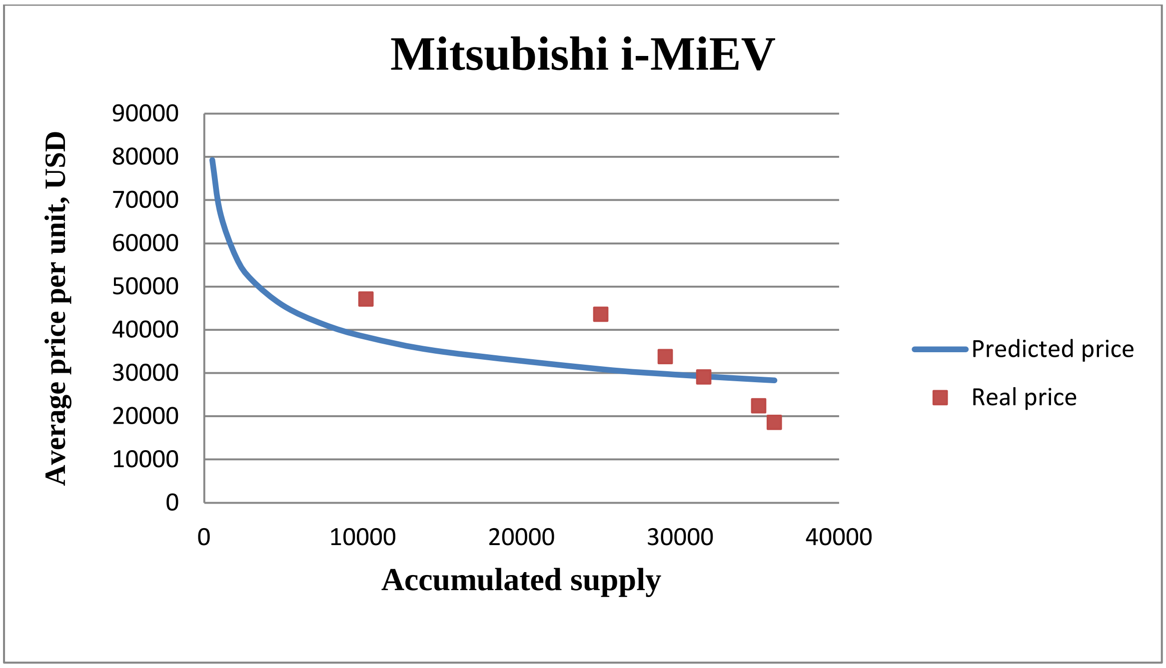


Figure 11: Learning curve and real price for Nissan Leaf, LR = 15%

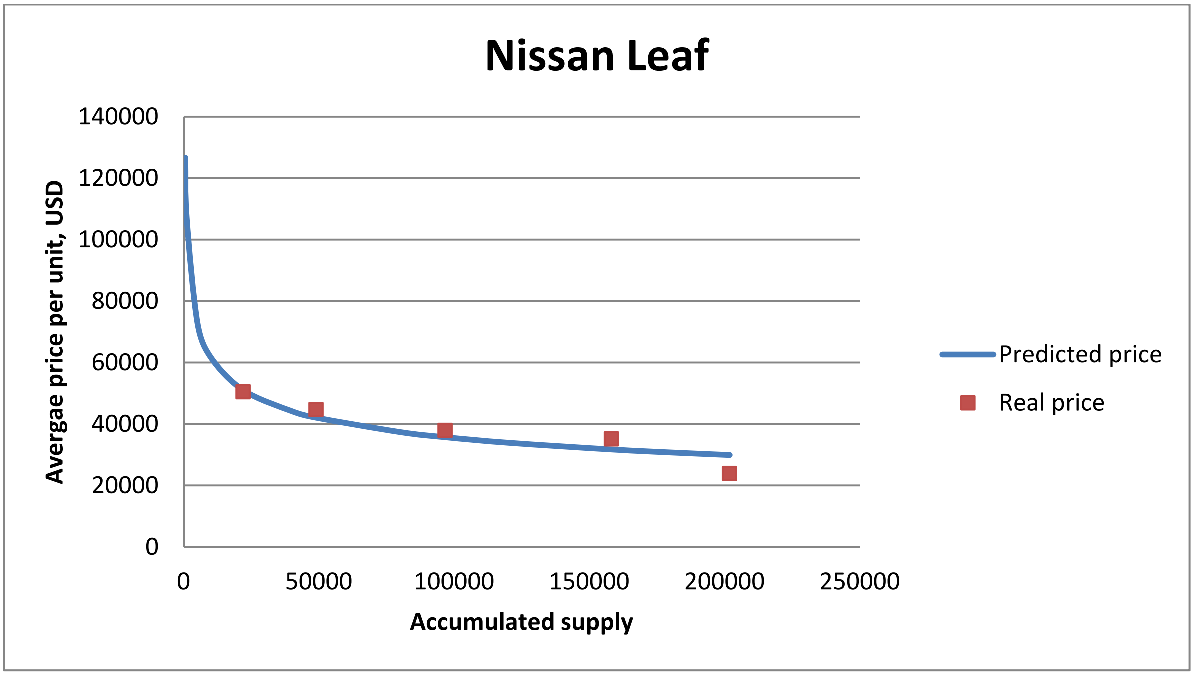


Figure 12: Learning curve and real price for BMW i3, LR = 15%

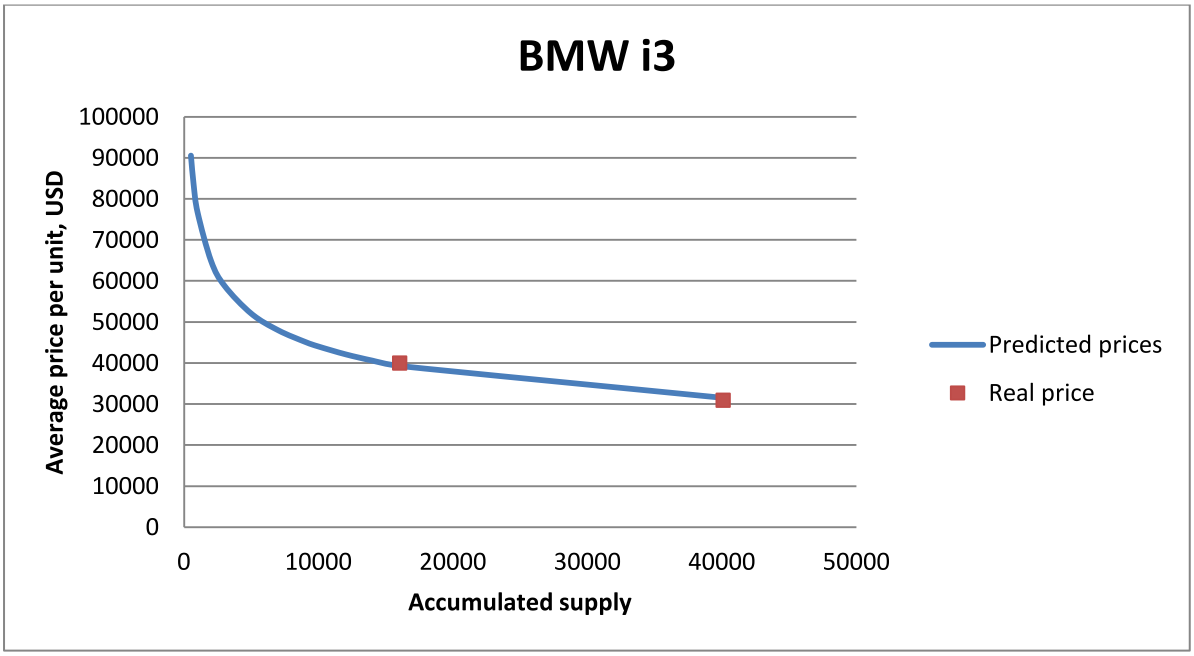


Figure 13: Learning curve and real price for KIA Soul EV, LR = 15%

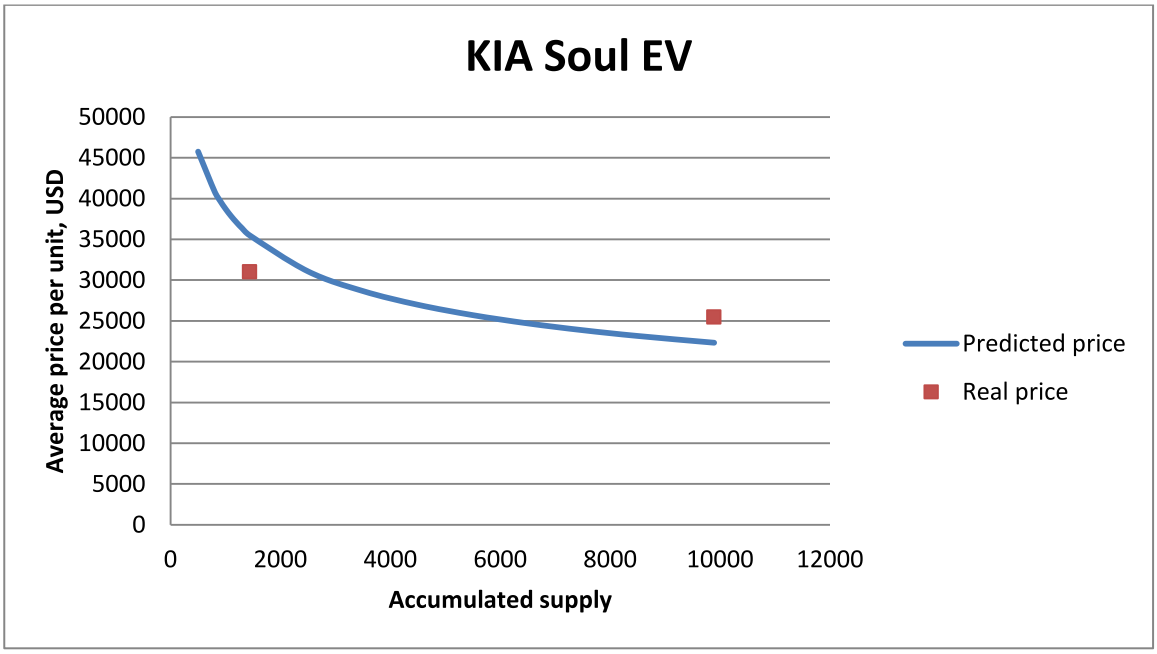


Figure 14: Learning curve and real price for VW E-Golf, LR = 15%

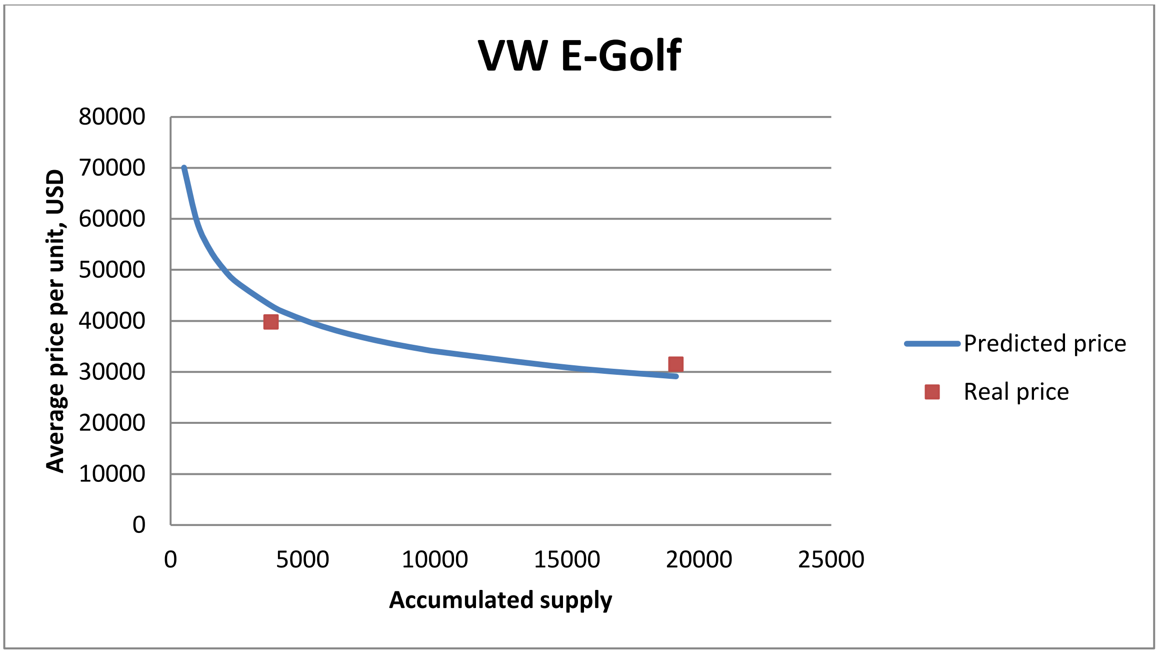
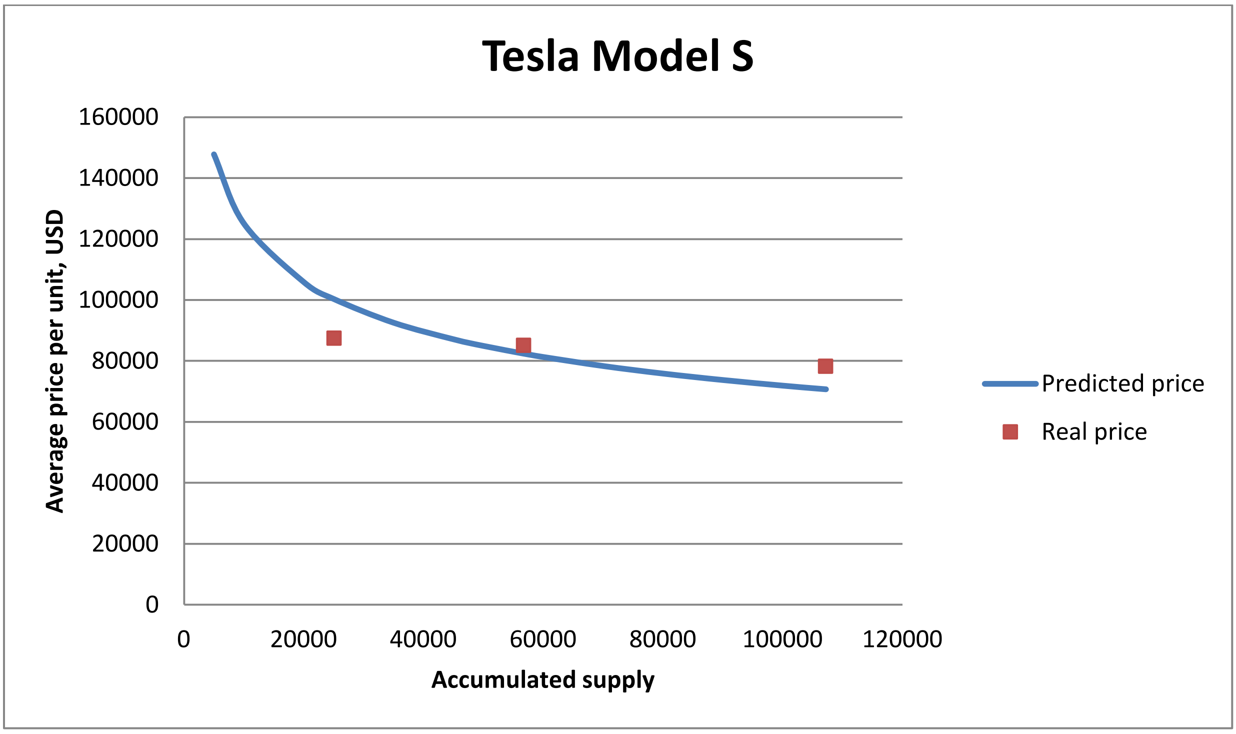


Figure 15: Learning curve and real price for Tesla Model S, LR = 15%



5.2 Model 2

Table 9 shows fixed effect analyses results for Model 2. Learning parameters, internal (E) and external (F), have negative signs, which was expected. Only the external learning rate is significant at 0.05 level. Calculations of the LR rate shows that external LR_{ex}=17% and internal LR_{in}=2%. LR_{in} is quite small and the P-value (0.571) is non-significant, which could indicate that LR_{in} might not be significantly different from 0. Nagelhout and Ros (2009) identified a learning rate of 17% for lithium-ion batteries. Looking at Model 2 results and previous research done (Nagelhout and Ros, 2009, Weiss et al., 2012, Nykvist and Nilsson, 2015), we could consider that there is a possibility that over last 5 years prices for BEVs mostly decreased due to the learning effects in battery manufacturing (external learning). Previous research on battery learning rate included only battery price, whereas research on BEVs should include price for the whole vehicle. Although, one of the main differences in design and cost between BEVs is the power train - in particular the battery, there are many other things that separates the models (interior, technology, motor, etc.) and the same learning rate could not be applied to batteries and vehicles.

Table 9: STATA results for fixed effect Model 2

Variable	Coefficient
E	-0.0191083 (0.033/-0.58)
F	-0.2635897*** (0.04/-7.37)
lna (Mitsubishi i-MiEV)	13.60165*** (0.375/36.27)
γ_2 (Nissan Leaf)	0.2498*** (0.057/4.41)
γ_3 (BMW i3)	0.5032845*** (0.083/6.09)
γ_4 (Kia Soul EV)	0.2548163** (0.11/2.43)
γ_5 (VW E-Golf)	0.4974286*** (0.091/5.46)
γ_6 (Tesla Model S)	1.288357*** (0.068/18.89)

Legend: * p<.1; ** p<.05; *** p<.01; robust standard error/t-value in parenthesis.

One of statistical reasons why E variable appears non-significant can be multicollinearity. This phenomenon appears when predictor variables are highly correlated with each other (Gujarati and Porter, 2009). This means that one variable can be linearly predicted from another with a substantial degree of accuracy. In this specific case, production of every model BEV increases each year and so does the total BEV number. Multicollinearity does not reduce the reliability of the model as a whole but affects calculations regarding individual variables.

5.3 Further data analysis

5.3.1 Calculated Learning rate

In this section results from Model 1 and Model 2 will be used to present how the world would look without Norwegian BEVs sale. The figures were modeled by taking learning parameters E and F results from statistical analysis and intercepts for each car model. The accumulated supply of each car model was changed by subtracting Norwegian accumulated supply of that model. Model 1 considers individual BEV models, therefore, the results of price change without Norwegian subsidy will be highly dependable on the amount of that particular BEV model in Norway.

Figure 16: Mitsubishi i-MiEV total world VS world without Norwegian sales, LR=15%

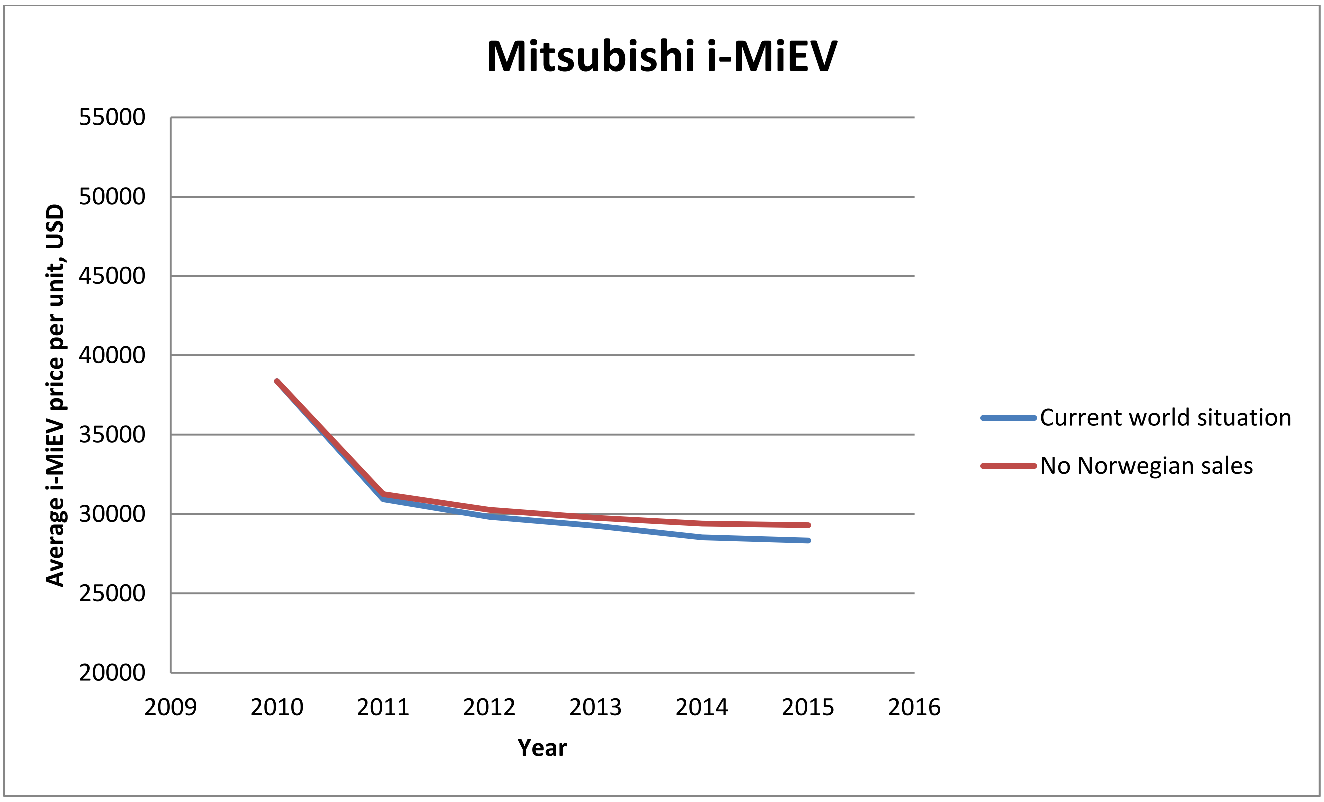


Figure 17: Nissan Leaf total world VS world without Norwegian sales, LR=15%

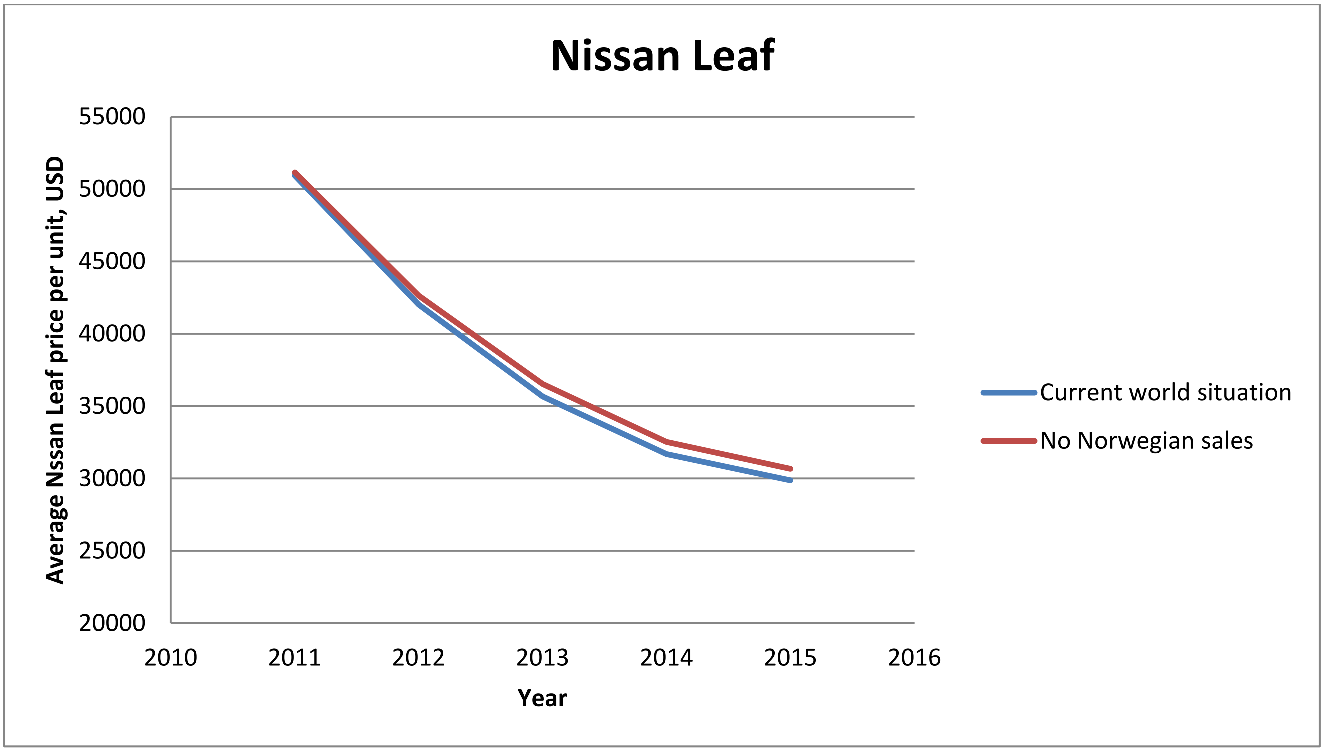


Figure 18: VW E-Golf total world VS world without Norwegian sales, LR=15%

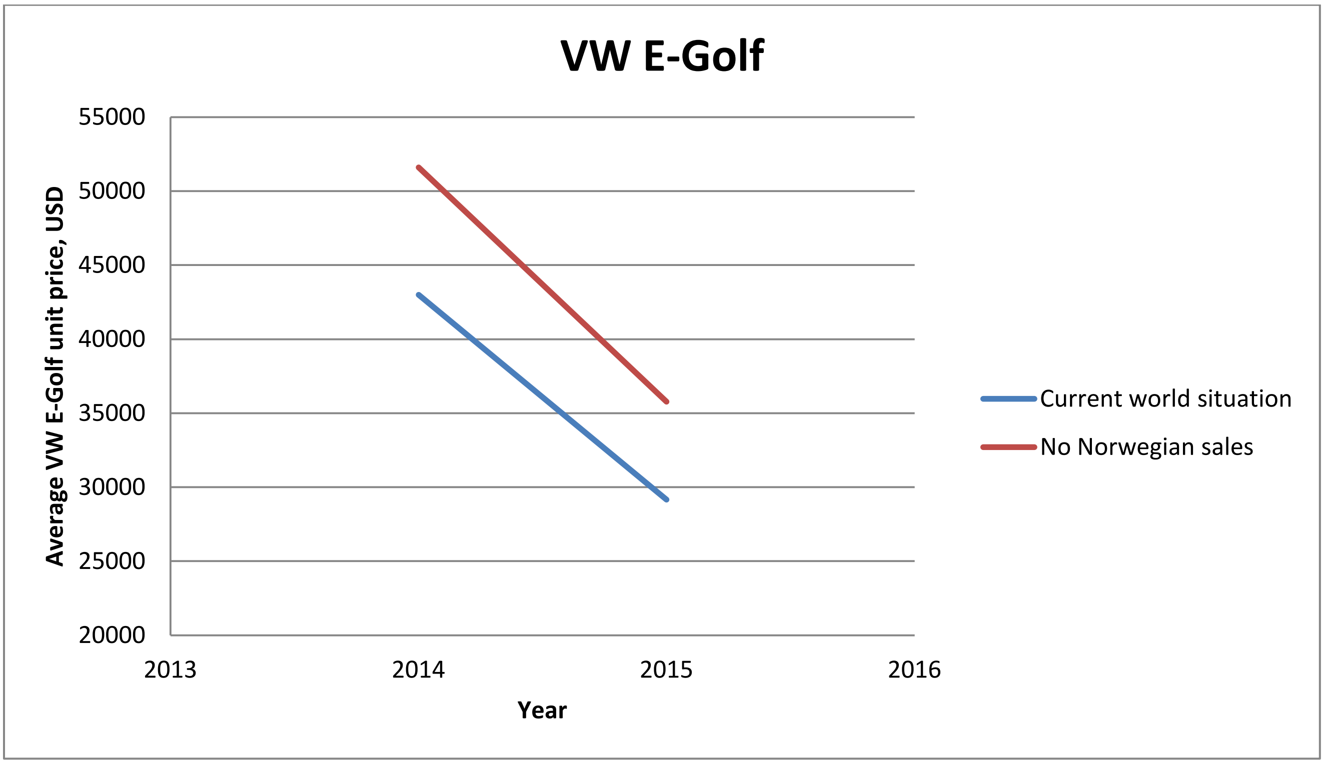


Figure 19: KIA Soul EV total world VS world without Norwegian sales, LR=15%

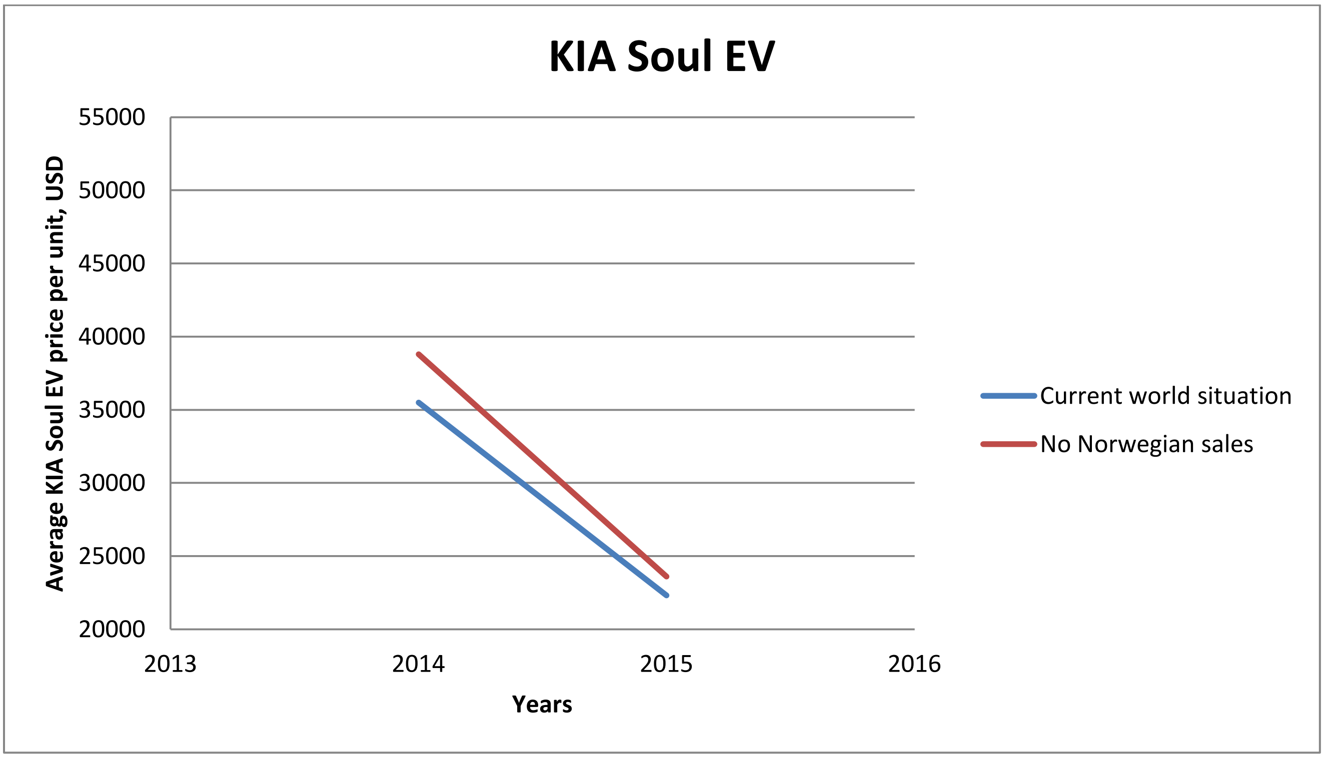


Figure 20: Tesla Model S total world VS world without Norwegian sales, LR=15%

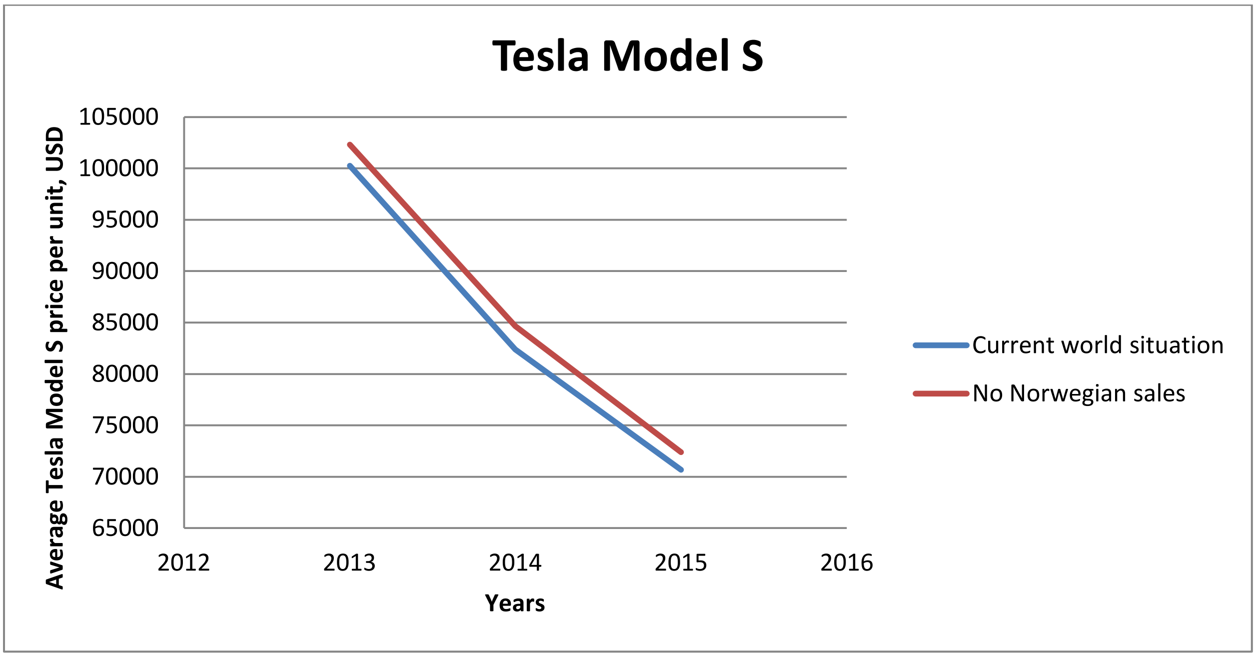
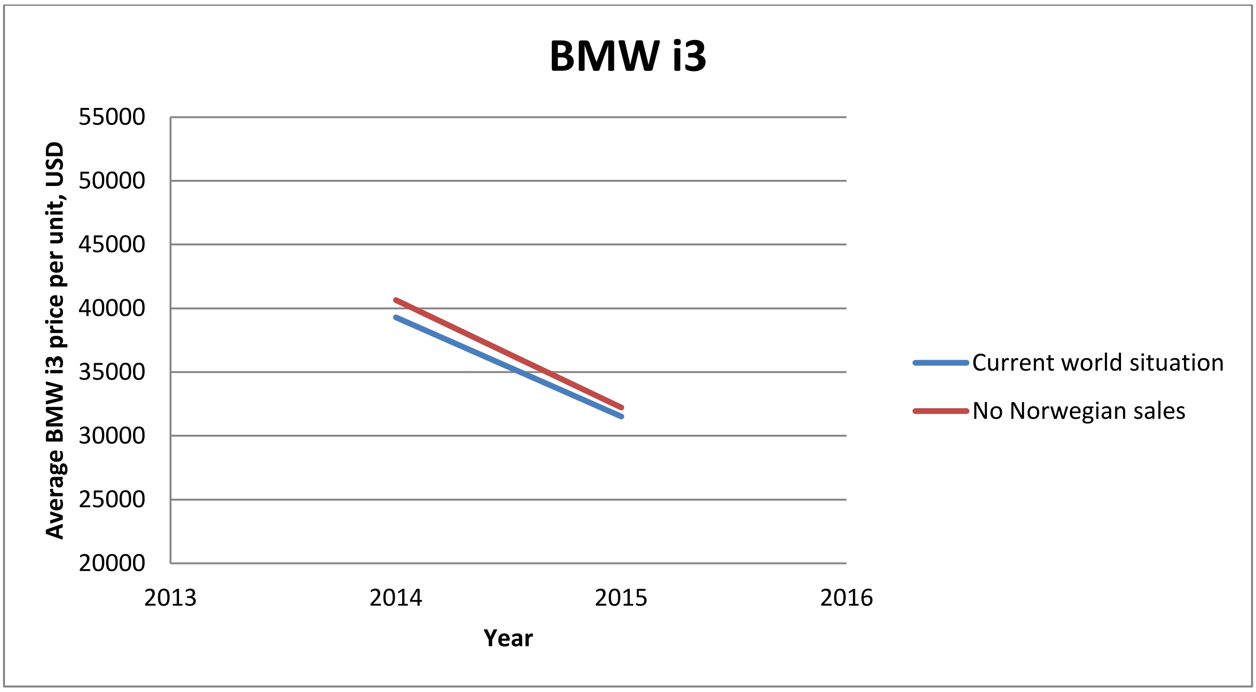


Figure 21: BMW i3 total world VS world without Norwegian sales, LR=15%



From figure 16 we can see that the Mitsubishi i-MiEVs popularity in Norway is growing. There is a bigger share of this model cars registered in Norway every year and therefore, the price would be affected more and more by the Norwegian sales.

Nissan Leaf is a popular brand in Norway but also it is the most popular electric vehicle brand in the world and we see in figure 17 that Norwegian sales has least effect on it when compared to other car models in this analysis.

Figure 18 shows the biggest price difference for the most popular BEV model in Norway, the VW E-Golf. It increased by nearly 20% in 2014 and nearly 23% in 2015. It has been extremely popular in Norway, nearly 57% of produced VW E-Golf are registered in Norway (Grønnbil.no, 2016).

From figure 19 we see that KIA Soul EV would be affected less than VW, but more than the other 4 models. The % increase in price is lower in 2015 than in 2014. This suggests that the proportion of KIA Soul EV in Norway decreased in relation to the total world production of this model.

Tesla is a popular brand in Norway. Figure 20 shows a consistent distance between the lines. This shows that Norwegian sales proportionally keep up with world production of this model.

BMW i3 % increase in price is lower in 2015 than in 2014, as can be seen in figure 21. This suggests that the proportion of BMW i3 in Norway decreased in relation to the total world production of this model.

4 BEV models, Mitsubishi, BMW, Nissan and Tesla, would have around similar effects without Norwegian sales – a price increase of 2.2% on average.

Table 10 below indicates % increase in price every year for every type of car model if there were no Norwegian sales given there has been an internal learning rate of 15%.

Table 10: **%** increase in price for each model without Norwegian sales, Model 1, LR = 15%

Model/Year	**2011**	**2012**	**2013**	**2014**	**2015**
Mitsubishi i-MiEV	1.04	1.48	1.74	3.07	3.37
Nissan Leaf	0.42	1.46	2.40	2.68	2.67
BMW i3	N/A	N/A	N/A	3.45	2.22
KIA Soul EV	N/A	N/A	N/A	9.33	5.81
VW E-Golf	N/A	N/A	N/A	19.96	22.73
Tesla Model S	N/A	N/A	2.04	2.76	2.40

Model 2 represents world situation where external learning is most important according to the data results. Parameter F (external learning) was used to calculate % change in price if there were no Norwegian sales. Results are presented in table 11.

Table 11: % increase in price without Norwegian sales, Model 2, LR=17%

	2010	2011	2012	2013	2014	2015
BEVs	0.4	1.00	1.5	1.8	2.3	2.8

This model does not consider separate BEV types. Instead it takes the whole market. Here is the overall number of BEVs that matters both in the world and in Norway. The price difference is smaller than in the Model 1.

5.3.2 30% learning rate

There are many limitations of this research that could give an underestimated or an overestimated LR, for example, too small data sample or usage of prices instead of costs for the statistical analysis. Therefore, it would be interesting to see what kind of results we would get by using LR from other studies on this data. Unfortunately, no other study for BEVs LR was done yet. Weiss et al. (2012) in their research found that the learning rate for all HEVs in USA on average is 7% for year 1999-2010. In their research they also mention previous studies that show LR for energy-demand technologies to be 18± 9%. When they calculate price prediction for BEVs, they use LR for CV which they found to be 42±27%. As mentioned in the Chapter 3, LR even for the same type of technologies can be very different. In this research calculated internal LR is 15%, but it is interesting to see how results would change if we double it. Table 12 below indicates % increase in price every year for every type of car model if there were no Norwegian sales given there has been an internal learning rate of 30%.

Table 12: % increase in price without Norwegian sales, Model 1, LR=30%

Model/Year	**2011**	**2012**	**2013**	**2014**	**2015**
Mitsubishi i-MiEV	2.27	3.30	3.82	6.80	7.46
Nissan Leaf	0.9	3.21	5.30	5.92	5.90
BMW i3	N/A	N/A	N/A	7.67	4.90
KIA Soul EV	N/A	N/A	N/A	21.41	13.10
VW E-Golf	N/A	N/A	N/A	48.56	56.12
Tesla Model S	N/A	N/A	4.49	6.09	5.32

Obviously, increased LR increased the gap between the prices with Norwegian sales and without. As was expected, models with highest % of total production ending up in Norway would be most affected. If arranged by total world production, with 1st place for highest accumulated supply in 2015 and 6th place going to lowest accumulated supply in 2015, the rating by models would look like this:

1. Nissan Leaf
2. Tesla Model S
3. BMW i3
4. Mitsubishi i-MiEV
5. VW E-Golf
6. KIA Soul EV

Table 12 results show that the first three models with highest accumulated supply in 2015 would be least affected by absence of Norwegian BEVs sales. This could mean that biggest producers of BEVs are very popular in other countries, too. There is also possibility that since Norwegian passion for BEVs is quite often discussed in the media and some companies focus on the Norwegian market to push their sales through.

5.4 Discussion

This thesis developed learning curves for BEVs for the year 2010-2015 by taking reported price and accumulated supply. Calculated statistical results were used in modeling situation “world without Norwegian BEVs sale”. This analysis provides insight into how important government support for the BEVs could be in the long term perspective.

The accuracy of the results depends on the reliability of the collected input data and its size. The amount of data used in this study was very small and, therefore, is important more for illustrative point than actual statistical results. Another issue with the data arises when we look into the learning curve theory. The learning curve approach theoretically should be used for modeling production costs. However, since manufacturers are very careful about this sensitive data, in this analysis vehicle prices were used. Another big issue with price data is that it is different across the world. Also, some reported prices are with delivery fees and some without. The best thing is to use the same source for all data, however, this was not possible. The same source was used for each type of BEV model, but not across models. The problem with using prices and not costs arise when market situation is considered. At the point of the vehicles introduction to the market, prices can be lower than production costs because manufacturers try to open markets for innovative products (IEA, 2000). Then with increasing technological learning production costs may decline below the actual market price. Only later prices tend to parallel costs. This limitation can be leading to underestimation of LR and could be solved by using longer time series in the future when more data will be available.

Different BEV models are made in different countries. Most parts of particular BEV model are made in different countries, too. These things are important when considering what kind of currency should be used in analysis. In this case, both Euros and US dollars were considered. LR with Euros was 13% and with US dollars 15%. Model 2 with Euros gave positive sign of E due to multicollinearity problem. However, when Model 2 was run with US dollars, the results for both internal and external LR were negative, as expected. Therefore, US dollars were picked for the main analysis. This only shows how much uncertainty there is in the calculation of the learning rate. In Model 2 $LR_{external}$ is 23%. BEVs differ a lot in design and other specific things, but nearly all of them run on the lithium-ion battery. One could argue that R&D in battery field gives this quite high external LR.

Methodological issue with this research is related to constant rate of cost decline in the learning curve. Economies of scale and innovation tend to reduce costs of labor and capital in manufacturing. However, prices could increase due to change in prices of raw materials, energy and other components that are used in the production (Weiss et al., 2012). Therefore, forecasting based on experience curves can be limited by the changes in the price of production factors.

Another important point to mention is that accurate learning rates require that analyzed products remains homogenous throughout the analysis period. This requirement is not valid for BEVs as manufacturers add constant improvements to their produced models, such as better air condition systems, various safety improvements, etc. The absence of homogeneity may lead to an underestimation of actual learning rates.

Finally, it is important to mention that this analysis was done only on some chosen BEV models. Data that was provided by IEA reports total BEV number for 17 countries only (Electric Vehicle Initiative partners) but IEA considers that they represent 95%+ of the global BEV stock (IEA, 2016).

Learning curve analysis can cause a lot of uncertainty because of issues discussed above. It would be interesting to see what kind of results would be given if different theoretical approach was taken. For example, Weiss et al. (2012) in their research calculates the costs of electrification for the BEVs. First, they divide the price of BEVs into two components: electrification costs and ancillary costs. They first calculate ancillary costs for conventional vehicles (share of 82% of CV price) and then assume that the calculated ancillary costs apply to BEVs, too. Then the difference between the calculated ancillary costs and the average BEV price represents the costs of electrification. Because BEV models involve so much more than just battery, it is difficult to estimate learning parameter. Especially if Tesla is taken, a premium sports car, that offers more than just transport run by battery. It includes special interior, computerized control of the vehicle, you can even start it by using a Tesla application on your phone. This all ads extra costs to the vehicle. If electrification price would be calculated, then it could be possible to get data set which will not be model related (since it would be from average price of BEVs). From electrification costs one could calculate price/kWh that could be applied to any kind of model. However, this need more complicated calculations and could be considered for future research.

6 Conclusion

In this thesis learning curve approach was used to project ex-post learning rates for BEVs. A special focus was on the Norwegian BEV market and whether Norwegian environmental policy has had any effect on the LR in the BEV market. A small sample of BEV models with accumulated production and price was used to perform a small statistical analysis. 2 models were used for the analysis and their results were used to model "the world without Norwegian BEV sales". The same learning rate was applied but accumulated production was adjusted by the amount of registered BEVs in Norway.

The results of this analysis can provide a valuable input for:

i) Market projections for BEVs;
ii) Support the establishment of subsidy programs and tax allowances that facilitate the electrification of road transport.

From the results in this research it is clear that Norwegian environmental policy had effects on the BEV market. The size of those effects is another question. When taking into account separate models of BEVs, the effect is higher depending on the share of total production that ends up in Norway for that particular model. For example, more than 50% of VW E-Golf produced vehicles were registered in Norway. Therefore, the effect of Norwegian BEV sales for this model is very high. On the other hand, the rest of the models vary between 1-10%. Effects are even lower when calculations are done with model 2 results. Still, in the long run Norwegian policy is important for the BEV market.

Even being a phenomenon in the BEV market, Norway cannot win it alone. Good news is that there could be some indirect effects of the Norwegian environmental policy. There are quite a few media publications about Norway's success with BEVs and how other countries should take an example. One successful story makes others believe in their success, too.

There are advantages and disadvantages in the topic of electrification of the road transport. Although it seems that there is a long way to go to make BEVs attractive to every family, we need to continue looking for solutions. Road traffic is responsible for a huge amount of CO2 and we do not have all that much time to carefully consider available alternatives before going for them. It is not clear yet whether the BEVs will be a big part of emissions reductions but acting, not just talking, is important. And that is what Norway is doing.

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