Taxing Electric Vehicles: Market reaction and policy lessons from Denmark

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Abstract

This thesis studies the market reaction to the initial phase-in of electric vehicle taxation in Denmark. A unique dataset is constructed from used Tesla announcements to analyse whether the pre-announced tax change created an opportunity for speculators to buy before and sell after the registration tax is levied. We find that controlling for the available car characteristics, prices show a statistically significant negative trend on the used-car market. The number of used Tesla announcements increased by 25%, while new registrations of Tesla vehicles spiked the month before and dropped immediately after the new tax was enacted. Our results imply that upon being informed about the new legislation, the market internalized the tax increase. The results have two implications. Firstly, the data suggests that speculators did not profit on average from this artificial price increase, as it was the used-car buyers who managed to capture the implicit value difference with their purchases after the 1st of January. Secondly, the steep drop in new Tesla registrations resulted in a foregone tax revenue for the Danish government. The estimated foregone tax revenue in 2016 from the shift in Tesla Model S purchases ranges between 180 and 474 million DKK. There is a trade-off between legislative stability and fiscal effectiveness of the policy tool. This finding has policy implications for governments who intend to end the favourable tax treatment of electric vehicles in the future.

Keywords: Tesla, Registration Tax, Environmental Policy, Electric Vehicles, Denmark
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1. Introduction

By December 2015, the Tesla Model S had become the best-selling personal vehicle in Denmark. This was the first instance an electric car topped sales charts in any major market around the globe (Electrek 2016). However, this unprecedented surge in the sales of new Teslas was not without its reasons. A new legislative change, passed by the Danish government in October 2015, aimed to end the favourable tax treatment of alternative-fuel vehicles. This created a situation where prospective buyers rushed to purchase and register their Teslas before the new tax regime took effect on the 1st of January 2016, causing sales to break record. Even more surprising than the spike in sales was the near disappearance of new Teslas throughout the whole year of 2016. This overall market reaction is the focus of our study.

The motivation of market actors was twofold: while some undoubtedly moved to speculate and exploit the discrete price increase, others simply acted to avoid paying the new registration tax. Both endeavours are interesting for different reasons. The speculative action is interesting from an efficient-markets point of view. The legislation presented an arbitrage opportunity, offering substantial return at seemingly minimal risk in a short amount of time. The question remains: Does the self-correcting mechanism of markets limit speculative opportunities? This study attempts to answer this through the natural experiment provided by the discrete tax change. The second motive, that is of tax optimization, highlights the importance of modelling market behaviour when designing such policy changes as a tool to raise tax revenue and regulate market behaviour. The case of Tesla in Denmark provides a direct example of how inflationary expectations can cause accelerated short-term increases in consumption levels.

The thesis is structured under chapters and subsections. In this first chapter, a short introduction is given with a description of the background to this study, formulation of the research questions and motivation. The second chapter provides the literature review of the specific research area. The third chapter describes the methodology behind the analysis. Due to the extensive nature of the data gathering and parsing procedures, a separate chapter four details this process. The fifth chapter introduces the dataset in a descriptive nature. Chapter six analyses the dataset, presents the results and explicitly answers the research questions. A discussion of these results is included in chapter seven. Chapter eight concludes the thesis.

1.1. Background to the Regulatory Change

Disclaimer: The legislation has been altered during the writing of this thesis by a prolongation of the second step (40%) of the phase-in until 2019. This section has been kept intact and the new regulation is mentioned in the Discussion. The results in the rest of the thesis are unaffected by this change, as the legislation is only effective after 2017, which falls outside the studied period.

From 2014, there had been a demand to renew the registration tax exemption of electric cars in Denmark to support the adoption of green technology. The bill was due to expire after 2015 and the future of taxation of electric vehicles was ambiguous. The incumbent Danish government assured the public in 2014 – with a statement from Climate and Energy Minister Rasmus Helveg Petersen – that a renewal of the electric car tax exemption will be on agenda in early 2015:

> *"We would like for people to choose the most environmentally-friendly cars, and we are very aware that the exemption from registration tax for EVs expires in 2015. Therefore, we are ready to look at how we can solve this challenge, and we will do so right after New Year (…) We have a 2050 target to be independent of fossil fuels, and this demands that the transport sector makes a significant contribution. In that relation the EVs are a central component as even very gasoline-efficient cars cannot deliver the goods."* (*Politiken* 2014)

After the parliamentary election on the 28th of June 2015, a new minority government had formed with the leadership of Lars Løkke Rasmussen and a cabinet consisting of new ministers from Denmark's Liberal Party (Venstre). Immediately after the commencement of the Danish parliamentary-cycle of 2015/2016, the government and the supporting parties (The Danish People's Party, The Social Democrats and the Social Liberal Party) reached an agreement about a bill proposal that would partially and periodically phase out the tax exemption that had previously been given to all electric vehicles for sale on the Danish market (Børsen 2015). The registration tax was proposed to be phased in starting from 1st of January 2016. At the same time, the higher-bracket tax rate on all personal vehicles was lowered from 180% to 150%. The tax change was in particular expected to have an adverse effect on the competitiveness of Tesla's Model S that had become the best-selling electric car in Denmark and also became the overall best-selling car in the country in 2015 December (InsideEVs 2015). The bill was initially designed to tax luxury electric cars with immediate phase in from 2016. The bill had a proposed threshold of 800.000 DKK, above which value vehicles would be subject to an accelerated phase-in process. The more expensive Tesla Model S fell in this category and was expected to see its price soar in 2016 to nearly double the original figure. The purpose of the bill was threefold. To constantly level the playing field for gas-fuel and alternative-fuel vehicles as the new technology matures, to increase government revenues from alternative fuel vehicles that had been gaining considerable market-share and to immediately introduce the full registration-tax to electric cars in the luxury category. Table 1 shows how the accelerated phase-in of the 150% registration tax for luxury-EVs would have affected the competitiveness of the higher-end Tesla Model S.

Table 1: Overview of the originally proposed tax change (Figures in DKK)

	2015	2016	2017	2018	2019	2020
70D	589.000	739.000	844.500	1.001.100	1.129.500	1.141.500
P85D	875.000	**1.522.400**	**1.585.400**	**1.702.300**	**1.812.900**	**1.807.100**
VW e-Golf	286.500	301.300	318.100	344.300	351.200	334.300
Nissan Leaf	274.900	295.100	317.500	350.900	365.400	352.300

Source: dr.dk

The higher tax on luxury electric-vehicles, which would have almost exclusively only affected the higher-end Tesla Model S, was criticised by the European Union based on the claim that it created unfair competition in the market. Eventually complying with EU regulations, the clause on luxury-vehicles was excluded from the bill on the 27th of December (*DR.dk* 2015). The lastly implemented phase-in plan did not create a different treatment of luxury vehicles and the registration-tax on EVs was to be phased in according to a five-year plan, illustrated in Table 2.

Table 2: 5-year plan of the registration tax phase-in for electric cars

	2016	2017	2018	2010	2020
% of calculated registration tax	20%	40%	65%	90%	100%

To understand the effects of the tax change, one should first understand how the registration-tax is applied to personal vehicles in Denmark. The registration tax on cars is essentially split between two tax-brackets. The tax is based on the taxable value of the car and is calculated as 105% on the value up to 82.800 DKK and 150% of any value above that. The vehicle registration tax is then adjusted according to the car's fuel consumption. There is a 1.000 DKK increase for every kilometre that the vehicle can run under 16km/l of petrol (18km/l for diesel) and 4.000 DKK tax advantage for every kilometre over the same efficiency. The electric cars are similarly subject to the increase or deduction according to their stated energy efficiency converted to km/l of fuel. Furthermore, there is a one-off 10.000 DKK deduction from the calculated registration-tax that is only applied to all electric and plug-in hybrid cars in 2016 and 2017. (SKAT 2016)

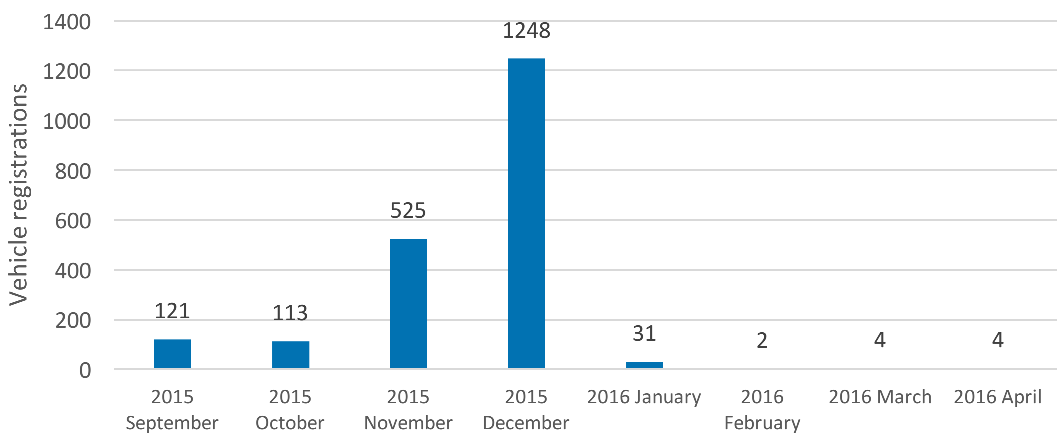
The rates in the 5-year phase-in plan depicted in Table 2 are to be applied to the above tax-scheme. For example, in 2016, if the registration tax on a traditional-fuel car was calculated to be 100.000 DKK, an electric vehicle with the same converted energy efficiency was to pay 20.000 DKK, not including the one-off rebate available to electric and hybrid vehicles. This consequently means that in 2016, an electric car would have a more than 80% tax advantage, in 2017 a more than 60% tax advantage and so on until 2020, when the same amount of tax is to be paid regardless of the car's fuel type. This is however to be viewed in the context of the previous tax-scheme, under which electric cars were fundamentally exempt from any registration tax and thus enjoyed a full 100% tax advantage over the conventional petrol or diesel fuelled vehicles. Figure 1 depicts the legislative timeline of the new tax regime. Between the parliamentary agreement and the implementation of the new tax system, the market had been given considerable time (two and a half months) to adjust its expectations and potentially alter purchasing decisions. Tesla and other EVs enjoyed a favourable policy environment in recent years before 2016. The new legislation intended to gradually end this tax advantage.

Figure 1: Timeline of the tax change

1.2. Tesla on the Danish Market

The Model S was officially introduced in Denmark in August 2013. In September 2013, the first full month of sales on the Danish market, it topped the charts for electric car sales with 42 units sold. The Tesla Model S became the best-selling car in Denmark in December 2015 with 1248 units sold only in that month (Elektrek 2016). By the end of December 2015, all together 3300 Tesla Model S have been sold in the country. After the newly introduced tax however, sales of Tesla vehicles tanked. Figure 2 illustrates the strong growth in Tesla registration numbers during the 4 months before and the immediate drop after the new bill came into power. The sharp structural break observed from the chart provided the motivation for studying the market reaction to this specific legislative change. Therefore, this chart plays a pivotal role in this study and it is referred on multiple occasions later in the text. The table in Figure 2 presents the same picture but with yearly numbers, highlighting the lasting effect of the tax change. In the entire year of 2016, new registrations fell back to the level of 2013, the first year (and indeed only 4 months, as sales only began in September) of Tesla sales in Denmark.

Figure 2: Registrations of new Tesla vehicles



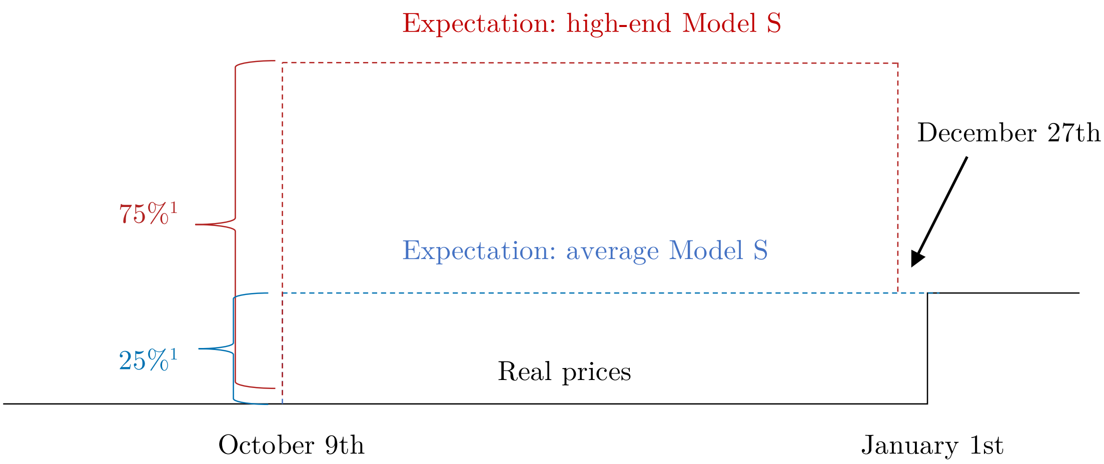
	2013	2014	2015	2016
Tesla	112	460	2738	176

Source: De Danske Bilimportører

Expectations played a major role in this development. From the day of the announcement, the market's expectations regarding prices of new Tesla vehicles as of 1st of January had shifted by an average of 25%[1], prompting buyers to bring forward their purchases to avoid paying the increased tax. The expectations for the average Tesla Model S and the high-end (luxury category) model are illustrated on Figure 3. Expectations differ due to the originally planned accelerated phase-in of the registration tax on vehicles valued above 800.000 DKK, which proposal was excluded from the final implementation of the bill on the 27th of December. On the 1st of January, expectations and real prices become aligned on the market for new Teslas.

The discrete gap between expectations and real prices immediately suggests an arbitrage opportunity. There is a possibility to buy at the lower price before the 1st of January and offer for sale on the used-car market after the tax change. Based on the expected price difference due to the registration tax, this opportunity offers a short-term (1-3 months) 25-75% profit at a minimal level of risk. Risk factors include legislative uncertainty and the value-loss that typically occurs after a car is brought out of the dealership. This latter phenomenon is described by Akerlof's famous Market for Lemons example (Akerlof 1970). Nevertheless, the appealing returns offer substantial compensation for taking these risks. Besides the retail market for new Teslas, the used-car market plays a pivotal role in realizing these speculative profits. Whether this arbitrage opportunity was possible to exploit is the primary concern of the thesis.

Figure 3: Market expectations and real prices of Tesla Model S on the Danish market



[1] ~25% (75%) is the expected price increase due to the new tax regime for an average (high-end) Tesla Model S in 2016, after taking into account converted fuel efficiency and rebates still available to electric vehicles.

1.3. Research Questions and Hypotheses

The unique situation on the Danish market for Tesla automobiles in 2015/2016 prompts us to study the market reaction to the policy change in detail. To provide a guiding framework to this study, there are two formal research questions that the thesis seeks to answer using the econometric analysis and the estimation detailed in the chapter on Methodology.

(1) Has there been an exploitable arbitrage opportunity on the market for Tesla automobiles in Denmark during the event of the pre-announced registration tax in 2015/2016?

(2) Did the pre-announced tax change result in a foregone tax revenue and to what extent did this affect the Danish government budget in 2016?

There are natural expectations with regards to the two research questions, which lead to the formulation of two hypotheses. The logic behind the hypotheses are meant to guide the Analysis and provide a framework to the entire thesis.

To answer *Research Question (1)*, we employ econometric analysis to the observed pre- and post-event prices on the used-car market. This is to study the motivation and behaviour of used-car sellers in the event window. The tax phase-in logically creates a discrete increase in the prices of newly registered Tesla automobiles after January 1st 2016. The question is whether this discrete price change is also reflected on the used-car market for Tesla Model S. Furthermore, the direction of the price change will indicate whether it was used-car sellers or buyers that benefited from the price increase. The fundamental hypothesis that is to be tested is if prices before the tax change equalled prices after the tax change. If the price difference is statistically different from 0, it provides evidence that the used-car prices adjusted with the tax change. The sign of the coefficient will provide implication as to who benefited from the tax change. To answer *Research Question (2)*, the foregone tax revenue is estimated. The surge in new Tesla registrations at the end of 2015 and the subsequent fall to nearly zero in the early months of 2016 indicate that the market adjusted such that the tax burden would be avoided by the buyers. The hypothesis for this research question is that the accelerated purchases created a situation where the announced policy tool becomes virtually ineffective in terms of its budgetary objectives.

The two research questions can be interpreted jointly as an attempt to explore whether there was a possibility for individuals or car dealers to internalize this tax revenue from the government and transform it into an arbitrage profit by buying before and selling after the tax change that took place on the 1st of January 2016. Since the agreement on the legislation in the Danish parliament was reached on the 9th of October, there appeared a window of opportunity to purchase a Tesla automobile before the tax change came into effect, allowing for a theoretical arbitrage profit to be earned by avoiding the upcoming tax burden. Whether this opportunity was exploited, who benefited from it and how it affected the government budget are the main areas of focus for this thesis. To explore whether individuals and car dealers took advantage of the arbitrage window and how market reactions affected the short-term tax revenue of the Danish state, this thesis considers both the new car sales and the used-car market for Tesla Model S in Denmark in the event window of 1st of October 2015 to 1st of May 2016. This allows us to capture the reactions of the market to events that shaped expectations and directly affected the final price of purchasing a Tesla Model S. With the uniquely gathered dataset, it was possible to extract detailed information of the used-car market from Denmark's main second-hand online marketplace (Bilbasen.dk), in addition to the data on new car sales figures provided by the Danish Car Importers Association (De Danske Bilimportører). This makes it possible to understand buyer reaction in the two markets jointly, identify who benefited from the policy shift and estimate the foregone tax revenue.

1.4. Motivation and Relevance

The thesis is motivated by the study of a unique policy environment and its interesting transition to accommodate a quickly developing technology. Questions have been raised regarding how the support schemes of electric vehicles can be upheld as governments rely substantially on the revenue collected from taxation of personal vehicles. In Brand et al.'s (2013) review of the field of policy support schemes in the UK, they point out that with the increase of fuel efficiency, more and more revenue is lost from the central budget of governments and it remains to be seen how policymakers react to this development. This was especially a pressing issue for Denmark in 2015, where there had been a whopping 180% registration tax on personal vehicles, whilst electric cars had been exempt of this tax burden. Denmark has long been in the focus of environmentalist groups as the eminent example of committing to and achieving important green goals. Now Denmark has also been one of the first countries to react to the increasing fuel efficiency of newly registered cars and the prospective of dropping tax revenues as a result of the considerable tax advantage provided to electric vehicles – much to the dislike of proponents of Denmark's green-strategy.

The thesis holds both practical and academic relevance. Denmark's transition creates a precedent for how market reaction can indeed shape the effectiveness of policy-change. The lessons learnt from the Danish case can help other governments in designing their similar policy-tools in the future. In its highly empirical nature, the study of a specific policy change provides grounds for policy discussion and expectations for the yearly scheduled tax shift or other similar tax policy, where markets have time to react to pre-announced changes. Furthermore, the thesis also holds academic relevance. Consumers face choice-sets which include the ability to not only shift their purchases between products and time periods but also between marketplaces. In order to fully understand, how buyers react to a policy change, such as a registration tax levy on automobiles, it is therefore imperative to study the behaviour of new car sales and the used-car marketplace in tandem. This study looks at the first experience of how such an incentive phase-out affects market behaviour with a uniquely constructed dataset from the Danish used-car market complementing the officially available new car registration data.

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2. Literature Review

This chapter reviews the academic literature related to and used in the writing of this thesis. Two broader areas are considered: the literature on discrete changes in consumption tax as a policy tool and the literature on the effects of green taxation, more specifically taxation and other tools available to steer car consumers towards more energy efficient vehicles purchases.

Already in 1941, the issue of taxation as an economic control in our society was raised with the view that besides its budgetary effect, taxes have regulatory effects through altering the general direction and relative levels of prices and consumption (Hart 1941). Since then, a significant body of literature has evolved with the viewpoint that consumption taxes regulate markets and shape expectations. Changing taxation to create inflationary expectations was studied as an unconventional policy tool. In his op-ed article in the New York Times, Shapiro (1991) proposes a sales tax as a short-term economic stimulant. In their papers, both Feldstein (2002) and Hall (2011) study the effects of budget neutral fiscal policies that can boost short-term consumption. The more recent literature has a multiplicity of relevant aspects for this thesis. In their study from 2016, D'Acunto, Hoang, and Weber discusses how pre-announced tax changes can accelerate consumption expenditure with the example of a natural experiment from Germany, where a 3-percentage-point increase in the consumption tax was announced to take effect in a year from the announcement. They observe a 34% increase in purchases of durable goods, which is evidence for accelerated consumption, akin to the specific case of Tesla vehicles in Denmark studied in this thesis. Similarly, Cashin (2013) studies household expenditure response to pre-announced tax changes in Japan and New Zealand. His findings include that expenditure is sensitive to discrete tax changes due to the change in future price levels. Consumers react by accelerated purchases of durables and stockpiling storable goods. He highlights that predictable changes in consumption tax provide ideal environments to study intertemporal substitution decisions. With another perspective, Barigozzi and Villeneuve (2006) focuses on the signalling value of tax policy. They model the interaction between the government and less informed consumers from a game-theoretical perspective, where the economic externalities are not necessarily incorporated in consumer decisions. The study considers three policy goals; raising public funds, correcting externalities and informing consumers. They particularly emphasize the trade-off between budgetary and informational objectives, which is an issue later raised by our study from an empirical perspective.

The other larger strain of literature relevant to this study considers the different tools available to incentivize consumers towards greener purchases on the market for personal vehicles. This body of academic works takes departure in the study of economic externalities and the optimal taxation of goods and services to internalize these externalities. One of the first and most prominent contributions to this literature came from the 1920 book of Arthur C. Pigou titled The Economics of Welfare, where he formally introduced the concept of externalities and that of Pigouvian taxes, which are a form of optimal mechanisms to control economic externalities (Pigou 1920). Among more recent articles, John and Pecchenino (1994) recognize the conflict between generations regarding environmental preservation and put it in an economic context by formalizing the problem in an overlapping generations model. Bringing it one step further, John et al. (1995) proposes a wage and capital income tax, while Ono (1996) studies two consumption tax schemes as optimal taxation of environmental externalities in in the overlapping generations model.

At around the same time as these studies, the Kyoto agreement of 1997 elevated the issue of environmental protection to an intergovernmental level, where state parties committed to taking steps to lower the emission of greenhouse gases (UNFCCC 1998). As a result, implicit and explicit emission taxes and support schemes were developed to help fuel efficient technological development in the automobile industry and widespread adoption by consumers. More comprehensive studies of these policies began to emerge in the late 2000s. Ryan, Ferreira, and Convery (2009) uses a panel-dataset from Europe to study the effects of different national vehicle and fuel taxes from the 10-year period between 1995 and 2004. Their finding is that different taxes influence individual purchasing decisions and the carbon efficiency of new car fleets is indeed highly policy variant. Giblin and McNabola (2009) and Hennessy and Tol (2011) examine in detail the impact of the carbon-based tax system introduced in Ireland in 2008. Both papers found a modest reduction in CO_2 emission and a drop in tax revenues as car owners shifted to lower tax brackets with their purchases. Rogan et al. (2011) provide a one year ex-post analysis of purchasing trends following this tax change and find an increase in fuel efficiency mostly due to a switch to diesel-fuelled vehicles.

Diamond (2009) and Gallagher and Muehlegger (2011) bring examples from the US, where hybrid-electric electric tax waivers, credits and other incentives are governed at the state level, providing a natural cross-sectional comparison of the effect of different policies. Both of their studies find fuel prices to be a stronger driver in the adoption of hybrid-electric vehicles than government incentives. From the different support schemes, upfront payments and sales tax waivers were found to be the most effective. Similarly to US states, Alberini and Bareit (2016) use the natural experiment with data from the different Swiss cantons to study the effect of circulation taxes on steering consumer choice towards low-emission vehicles. They find that even with a high tax penalty on highly polluting cars, the positive effect on the reduction of CO2 emission is moderate. From a different perspective, Ozaki and Sevastyanova (2011) studies directly the motivation behind a sample of hybrid vehicle purchases by surveying buyers of Toyota Prius hybrid vehicles in 2009. They find financial incentives to be an important factor, however other socioeconomic factors such as social norms also play a significant role in purchasing motivations of environmentally friendly cars. In their paper, Brand, Anable, and Tran (2013) assess the different policy tools available for accelerating the green transformation of personal vehicles in the UK. The paper scrutinizes the effects of various policies ranging from direct purchase taxes, through graduated vehicle road taxes to scrappage schemes. They consider the effectiveness of studied policy incentives on three grounds: (1) the life-cycle greenhouse gas emission, (2) treasury impact and (3) car ownership impact. Their conclusion is for policymakers to design upfront frees (e.g. registration taxes) such that it creates price signals, which in turn reward low-carbon and penalizes high-carbon purchases. More importantly, they raise the issue that increasing fuel efficiency creates short to medium term negative impact to the state budget and therefore we are yet to see how governments react to this development.

There are studies conducted directly on the vehicle taxation practices in Denmark. Mabit and Fosgerau (2011) specifically investigate the demand for alternative-fuel vehicles in the high registration tax environment of Denmark through stated-choice surveys. Based on their mixed-logit model, they find that hydrogen cars are widely preferred to electric and hybrid fuel cars, while the least favored alternative fuel vehicle is the bio-diesel, which is nevertheless still strongly preferred to conventional fuel vehicles. Overall, the fact that – controlling for all other factors – consumers would prefer buying alternative fuel vehicles indicates that there is an environmental concern involved in their individual decisions. In 2007, Denmark implemented a tax reform aiding demand to shift to more fuel-efficient cars. In his paper, Mabit (2014) studies the effectiveness of this policy. He finds that there had indeed been an increase in average fuel-efficiency on the Danish market. However, the main factor in this improvement is general technological development in the industry and the specific tax change was only effective to a lesser extent, along with increasing fuel prices, similar to the findings earlier presented from the United States.

This thesis contributes to the empirical literature on vehicle taxation with a new perspective on the effects of registration taxes by observing the overall market reaction to a *decrease* in support for alternative fuel vehicles. The case in this study provides important lessons with regards to policy effectiveness when vehicle purchases are allowed sufficient time to adjust to new market conditions.

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3. Methodology

This chapter describes the methodology behind the Analysis. First, the primary data used in our regressions is briefly introduced. Second, the regression methodology is explained along with the specification of the regression equations. This includes both our base regressions in *Research Question (1)* and the extensions that follow them in our Analysis. Third, we discuss the methodology employed to estimate the foregone tax revenue in *Research Question (2)*. Lastly, the limitations due to the available data and the scope of the thesis are explained.

3.1. Data

The data used in this thesis comes predominantly from two sources. One dataset contains used-car information from a large online marketplace, while the other includes statistics on the registration of newly purchased vehicles. Both datasets are limited to Denmark. The data on used-car advertisements is the primary data used to answer *Research Question (1)*. It includes a uniquely gathered set of records from used Tesla advertisements in Denmark. This dataset provides the backbone of this thesis and hence the scraping, parsing and processing of this data is explained in detail in the next chapter after Methodology. The resulting dataset includes all Tesla advertisements from Bilbasen.dk, one of Denmark's largest used-car marketplaces, in the period from the 1st of October 2015 to the 1st of May 2016. This period covers both the parliamentary agreement, the announcement (9th of October) and the first step of the phase-in (1st of January) of the studied tax change. The first observation follows the leak of news that the electric car tax exemption would be abolished. This, by construction, limits the data to observations after the first bit of information reached the public. The advertisements include the car's price, production year, driven number of kilometres and many of the most important model characteristics, such as the battery package, performance indicators and engine type (single or dual-motor). The second set of data is used in *Research Question (2)*. It is provided by the Danish Car Importers association and includes all personal vehicle registrations from 2015 through to the first quarter of 2017. The dataset includes registrations by brand and model along with their respective fuel type, however not at the individual observation, but at a monthly aggregated level.

3.2. Regressions: Research Question (1)

Research Question (1) is answered by a regression analysis of our primary data source on used Tesla advertisements. The data structure used for the regression analysis includes all Tesla Model S advertisements recorded in the 01/10/2015 – 01/05/2016 event window. Duplicates are removed, however advertisements with changing characteristics (price or km) are kept as separate observations in the dataset. The main dependent variable of interest is the advertised price, as formulated in the research hypothesis. Control variables are included in all regressions. These variables control for the seven available car characteristics; *production year, odometer value, battery package, dual-motor, dummy for performance package, dummy for extra seatrow and dummy for limited edition models*. The regressions follow standard ordinary least squares (OLS) estimation procedures. The left-hand side variables are log-transformed for easier interpretation of the results. This consequently means that the regression coefficients – multiplied by 100 –indicate the percentage change in the dependent variable, given a one unit change in the independent variable, holding all other variables constant. Regression outputs are included in standard regression tables with coefficients, significance indicators and standard errors in brackets. The Analysis has the following structure. Regressions are organized in four groups, corresponding to the numbering of the regression tables presented later. The regression equations are formally specified below with the indicated terms implicitly containing their respective coefficients.

Group (I)

First, regressions **(1)** and **(2)** are defined with a focus on the January 1st event date. These two regressions include respectively the event dummy and the week-distance variable measuring the number of weeks to and from the January 1st event.

(1) logP = α + Production Year + logKm + Battery-package + Dual-motor + Performance-package + Extra seat-row + Limited-edition + January 1st dummy

(2) logP = α + Production Year + logKm + Battery-package + Dual-motor + Performance-package + Extra seat-row + Limited-edition + January 1st + January 1st week-distance

Group (II)

In the second group, regressions are modified to include the event of the parliamentary agreement **(3)** and the time-on-market variable **(4)**, which measures the number of days an advertisement spends on the website before being taken down.

(3) logP = α + Production Year + logKm + Battery-package + Dual-motor + Performance-package + Extra seat-row + Limited-edition + October 9^{th} dummy

(4) logP = α + Production Year + logKm + Battery-package + Dual-motor + Performance-package + Extra seat-row + Limited-edition + Time-on-market

Group (III)

The third group of regressions explores how the number of kilometres driven changes with respect to the two January 1^{st} event variables. The Km values are log-transformed similarly to the price variable. Regression **(5)** includes the January 1^{st} dummy, while Regression **(6)** works with the previously described week-distance variable.

(5) logKm = α + Production Year + Battery-package + Dual-motor + Performance-package + January 1^{st} dummy

(6) logKm = α + Production Year + Battery-package + Dual-motor + Performance-package + January 1^{st} week-distance

Group (IV)

Lastly, the battery package variable is interacted with the event variable to analyse whether more valuable Teslas had a significantly different price change than less valuable models **(7)**.

(7) logP = α + Production Year + Dual-motor + Performance-package + Extra seat-row + Limited-edition + Battery Package * January 1^{st} dummy

3.3. Estimation Methodology: Research Question (2)

Research Question (2) is answered by the estimation of the foregone tax revenue directly relatable to the decline in new Tesla registrations after the tax change. The estimation is divided into two steps. First, the number of foregone registrations is defined and estimated. This number is inferred from the increased registrations in November and December 2015 (Q_{Total}), after the tax change was announced but before it took effect.

(1) Genuine purchases are defined as purchases that would have taken place regardless of the tax change. We assume no seasonality and thus the monthly average registrations from the past 6 months are taken as the estimation for genuine monthly purchases. ($\bar{Q}_{Newreg}$)

(2) Speculative purchases are inferred from the increase in used-car announcement numbers. This is made under the assumption that the increase in the average number of used-car announcements from 2015 to 2016 is driven by speculators appearing on the market. ($\Delta\bar{Q}_{Used}$)

(3) Forward-brought purchases are the purchases that took place in excess of purchase type (1) and (2). These purchases are defined as buying decisions that would have taken place in 2016, had there been no tax increase. It is this type of purchases that are of relevance in estimating the foregone tax revenue. (Q_{FB})

$$\text{Eq(1): } Q_{FB} = Q_{Total} - \bar{Q}_{Newreg} - \Delta\bar{Q}_{Used}$$

Equation (1) formalizes the relationship between type (1), (2) and (3) purchases. The second step in the estimation procedure is defining the foregone tax per vehicle. Lacking individual level registration data, this estimation must rely on the registration tax paid on an average Tesla Model S. For this reason, we define a lower and an upper bound to the foregone registration tax. The minimum (T_{Min}) and maximum (T_{Max}) amounts of registration tax are defined respectively as the tax due on a lower-end model and on a model with the strongest available battery package. The information is sourced from the official website of Tesla Denmark, where prices and the amounts of registration tax are available for the different models. Combining the estimated numbers from step one and two results in an estimation interval for the foregone tax revenue ($T_{foregone}$).

$$\text{Eq(2): } T_{foregone} = [Q_{FB} \times T_{Min} \,;\, Q_{FB} \times T_{Max}]$$

3.4. Limitations

Since this thesis only analyses the data of Tesla registrations and second-hand advertisements, it poses limitations to the generalization of its results to the entire electric car market. Firstly, the primary dataset is limited to Tesla Model S used-car listings and therefore cannot extend the analysis to models of consumption choice between different brands and technologies. This would be required to construct an economic model for estimating the market impact on tax revenues. Instead, as we described in the previous section, we limit the estimation of the foregone tax to the impact directly relatable to the decline in new Tesla registrations. Secondly, it is possible that electric car buyers have shifted their purchases within the market for EVs, for example from the luxury-category Model S to cheaper electric vehicles, such as the Volkswagen UP or the Nissan Leaf. Therefore, it would be inaccurate to argue that the near disappearance of Tesla Model S sales alone threatens the green goals that Denmark has pledged for. However, as shown later in the Discussion, there is a general decline in all electric vehicle registrations. Other environmentally friendly technologies are not considered, although there is no consensus on which fuel type has the lowest lifetime ecologic impact on the market.

A second limitation is posed by the start date of the data collection. The dataset includes observations only after the first leak of news about the proposed tax change. This limits the thesis to the analysis of a dataset only under *"non-normal"* market conditions. Having access to a longer horizon of observations from before rumours have reached the public would considerably improve the robustness of our results. This data could potentially serve as a control period in the regressions, removing this inherent bias from the dataset. Thirdly, we are limited by the availability of information that is present in the posted advertisements. Primarily, it was not possible to identify the type of sellers. This information would allow us to separate sellers according to their level of commercial activity, such as private individuals or car dealers. These groups could differ in their speculative motivations and their bargaining power on the market. Having this data could further nuance our analysis. Nevertheless, this does not change the main results of the thesis and the conclusion regarding the arbitrage opportunity, merely limits our ability to identify the actors dominating the marketplace.

*

4. Data Parsing and Preparation

Due to the extensive nature of the data gathering process that provides the backbone of the thesis, this chapter describes in detail the source and the methodology behind the unique data structure used to analyse and answer the posited research questions. The data on used-car sales was derived from a web scraper that automatically saved the publicly accessible Bilbasen.dk in xml format. The files contained the html code of the Danish used-car website's search results for Tesla automobiles posted for sale between 2015-10-01 and 2016-05-05. The scraper was programmed to run every half an hour and it was implemented after Bloomberg had published news on the abolishment of the 180% tax exemption of electric cars in their September 29 article "Teslas Hit by 180% Danish on Cars as Green Goals Ditched" (Bloomberg 2015).

4.1. HTML Parsing

The data parsing process was predominantly programmed in R. However, before the xml files were read into the R environment, a few cleaning operations were necessary to secure that the text files are correctly interpreted by the R commands. Firstly, 40 files were corrupt and contained no or erroneously coded data. These files have been removed from the dataset as they presented no usable information. Secondly, the html code in the xml files was formatted in a way that prevented the R package XML and xml2 to recognize it as an html nodeset. This was due to the appearance of double double-quote marks ("") instead of the normally used single double-quote marks ("). This issue was circumvented by running a perl code in the Mac OS X Terminal environment. The code implemented a "Find and Replace" functionality on all xml files, replacing the unwanted double double-quote marks with single double-quote marks. After the necessary file cleaning procedures, the xml's were ready to be read into the R environment to extract all relevant information for further analysis. To successfully gain out all the relevant information contained in the xml files, the XML and xml2 packages were used within R. These two packages integrate the XPath language in R that helps navigate the user through the specific parent-children node-structure of the given html codes. With the help of the XML package, it was possible to search for specific html nodes with well-defined attributes. The variable information was contained in two forms: either as the value of a node or as the assigned value of an attribute of a node. With the XPath search commands, it was possible to extract both the node's value or any of the necessary node attributes that contained the above variables. Since each element of a car sales advertisement was duplicated in the xml file, it was necessary to get rid of these duplicates before coercing the data from each individual file. To parse through the approximately 9000 files with an average of ca. 100 records each, a regular 'for loop' was constructed in R that repeated the programmed operations on each xml file in the directory. There were 7 different vectors of information extracted from the xml files, one variable available for each record of advertisement.

(1) **urls**: these served as the unique identifies (IDs) of each separate car for sale
(2) **title**: the title was essentially the model number (example: Tesla Model S P85D)
(3) **price**: the listing price of the respective car for sale
(4) **years**: the manufacturing year of the respective car for sale
(5) **kmeter**s: the odometer information available in the respective advertisement
(6) **region**: the sales region indicated in the respective advertisement
(7) **descriptions**: the description attached to the respective advertisement

In addition to the 7 variables listed, the filenames were added to each record to identify the exact datetime belonging to the advertisements. For this purpose, the filenames were conveniently formatted as 'yyyymmdd-hhmmss.xml' from the source date of the file, which allowed a direct transformation to a datetime variable in R. The resulting 8 variables were coerced into a data frame object, where each row contained one record of advertisement from the parsed xml files.

4.2. Data Cleaning

After having parsed through the xml files, the program returns a total of c.a. 950.000 observations. Since the xml files were scraped every half hour from the source site, most of these observations are duplicates of previously occurring advertisements. The unique URL IDs allow the identification of duplicate advertisements.[2] The different treatment of duplicate values results in three separate data tables that are used in different parts of the Summary of the Data and the Analysis chapters later. The three tables are constructed as follows:

[2] The uniqueness of the URLs is confirmed by Bilbasen's web support (see appendix)

(1) Leaving out all duplicate values based on the URL identifiers will result in having a data table with a list of all individual announcements. This can be taken either from the first or the last observation, providing a table with “new announcements” or “delistings” respectively.

(2) A second way to deal with duplicates is similar to the first method, however it sets slightly looser conditions for filtering out duplicate values by allowing those advertisements that experienced a change in their price to remain in the sample as duplicates. This will allow us to retain more data points with useful information, that is the changing price over time of the same individual car.

(3) Similarly to the previous methodologies, we filter out duplicate values, however this time the data is first tabulated based on dates. The resulting data table will essentially contain each day’s list of advertisements, giving the opportunity to analyze daily statistics.

The next step in the data cleaning process was to detect and filter out the observations that cannot be interpreted in the analysis. Notably, prices with the “Ring” value and amounts under 100.000 DKK are discarded since these advertisements often indicate leasing offers, whereas we are interested solely in the direct sales data of Tesla automobiles. Finally, a filter is imposed on the title field (model number) to provide clarity in later interpretation of the analysis; the two Model X’s and three Tesla Roadsters are excluded, hence only Tesla Model S vehicles are kept in the final dataset.

The title of the observations provides useful information that are grouped into factor and binary variables. It was possible to identify the battery package (e.g. 60 kWh), whether the advertised car has front and rear motors (dual-motor) and whether the car is equipped with the performance package that is available for the high-end models and improves the car’s acceleration and top speed. Furthermore, it was also possible to retain information on whether the car was equipped with an extra row of seats (sevenprs) and whether the car is one of the firstly released, signature edition models (signaturemodel). Even though there are other internal and external design and functionality upgrades, these five features represent the most significant factors of variation in the price of a Tesla Model S. Since it is possible to identify the first day and the last day of individual advertisements from the data. From this information, it is also possible to determine the number of days a car spent on the used-car market. For this purpose, a “time-on-market” variable is assigned to each record in the dataset.

As a last step in the data preparation procedures, the event variables were to be defined and assigned to each record in the dataset. Two event dates were selected for further analysis: the date of announcement (9th of October) and the date when the new legislation came into force (1st of January). Two approaches are used to create the event variables. First, the dates of the announcements are dummy coded; 0 for pre-event occurrences and 1 for post-event occurrences. Second, a week distance (weekdist) variable is constructed by taking the difference in weeks from the event date; negative for the weeks before the event and positive for the weeks after. Constructing the weekdist variable for the October 9th event is omitted due to availability of the data only after the 1st of October.

The final list of variables: dates; urls (unique id); title (char); price (num); year (factor); kmeters (num); region (factor); description (char); model_number (char); battery (factor); dualmotor (binary); sevenprs (binary); performancepackage (binary); timeonmarket (num); jan1_dummy (binary); oct9_dummy (binary), weekdist (numeric).

4.3. Additional Data Sources

As an additional data source to the used-car dataset, new car registration data was requested from the Danish Car Importers' Association (De Danske Bilimportører). This data included all newly registered personal vehicles in Denmark, including registration numbers on separate models, brands and their fuel type. The dataset spanned from 2015 to the early months of 2017, including all relevant periods of the analyzed legislative change. The available granularity was at a monthly level and the data did not include the prices of the registered vehicles. For prices and registration tax amounts on different Tesla models, we have relied on the quoted prices from the official website of Tesla Denmark (Teslamotors.com 2017).

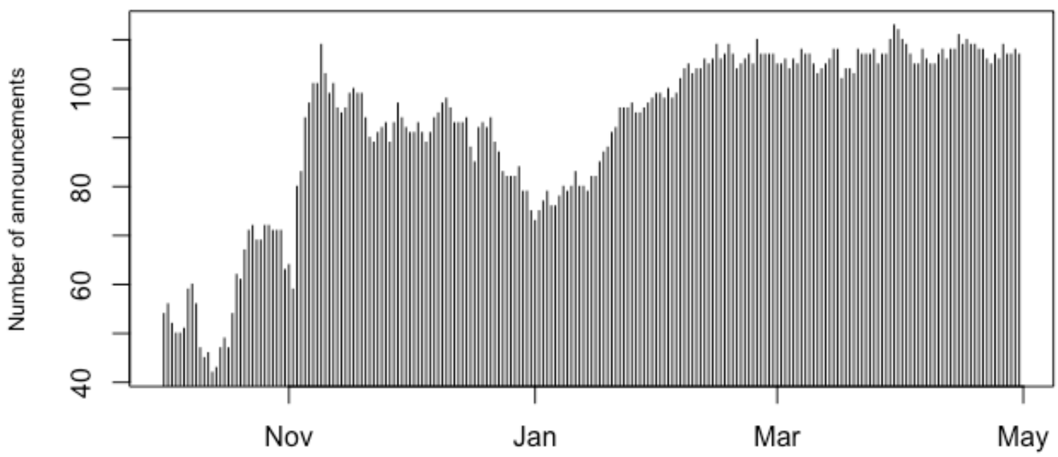
*

5. Summary of the Data

This chapter is to provide a general summary of the used-car announcements in the analysed period with the purpose of introducing the reader to the properties of the dataset at the level of individual variables and their general developments over time. The numbers will be further dissected in the Analysis section of this thesis and therefore this section is merely a representation of the most relevant trends in the data with only limited comments on their analytical significance in answering the two research questions.

From October 1st 2015 to May 1st 2016 there were 532 individual Tesla Model S announcements on Bilbasen.dk. In general terms, the change in the number of announcements between any given two dates can be calculated as the difference between the number of new announcements and the number of de-listings that occurred between those two dates. The dynamics of the number of announcements becomes relevant in relation to the end-of-year spike followed by a sharp decline in new car registrations that were shown in Figure 2 in the Introduction. As seen on Figure 4, there is considerable variation in announcement numbers around the announcement date of the tax change as well as before and after the law comes into power on the 1st of January. Announcement numbers remain relatively stable at the level of 110/day after mid-February.

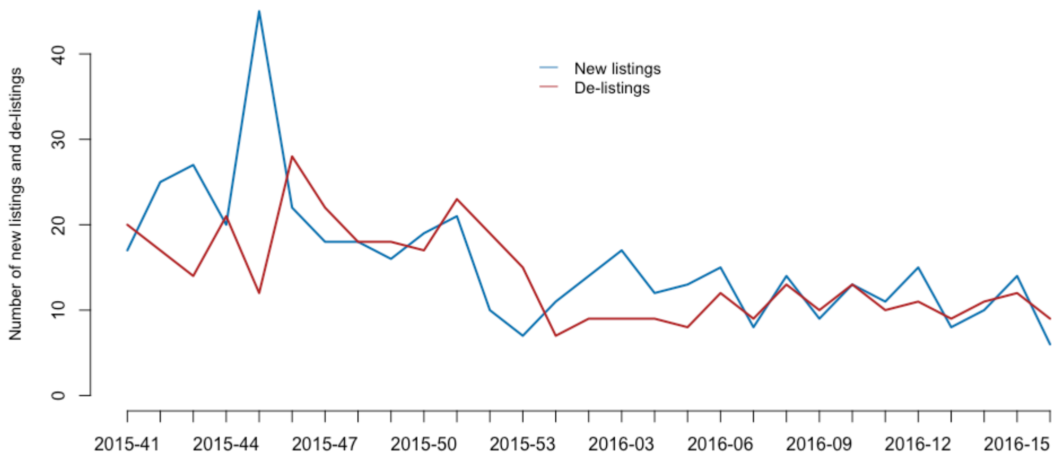
Figure 4: The evolution of announcement numbers in the event window



Looking at the change in announcement numbers in more detail involves relating new announcements to de-listings. New announcements are identified when a new URL id appears in the date-sorted dataset. Similarly, de-listings are identified as the last occurrence of the announcement in the data. While looking at daily levels of these figures would provide direct comparability with the above graph of daily announcement numbers, the weekly figures are easier to interpret visually without the loss of capturing much of the variation in the daily announcement numbers seen on Figure 4. Figure 5 shows the weekly aggregated number of new listings and de-listings. The variation in the beginning of the period is clearly depicted by the spikes and declines that move nearly identical against each other in the first 5 weeks of our data. The significant shifts in announcement numbers before and after the 1st of January are shown by the widening gap between the two lines before settling at a stable level with relatively low levels of turnover in individual announcements.

The initial weekly new listing and de-listing numbers move between the bounds of 20 to 30 on average and constitute a significant portion of the number of advertised cars in those weeks, which points to a highly active market where relatively many cars change owners over the course of a few weeks. After mid-February, however, the stable announcement numbers with a low level of turnover point at the logical interpretation that after the initial volatility, a larger portion of the advertised cars are remaining on the market for longer periods.

Figure 5: The evolution of weekly aggregated new listings and de-listings



5.1. Shift in Model S Characteristics

It is also interesting to observe the development in characteristics of a typical Model S over the analysed period. There is a considerable change in the share of new cars with 0 or low values on the odometer among the advertised cars. Furthermore, there is a shift in offerings from lower-end models to cars with more high-end features such as higher capacity battery packages or cars with the dual-motor performance feature. Both features appear to be relevant in understanding how car buyers and dealers have reacted to the changing tax rules in Denmark.

Figure 6 shows the average number of kilometres on the odometer of available offerings for each day in the event window. The shift towards cars with lower average kilometres on the odometer is quite visible, suggesting that many of the cars on offer in 2016 are new models either freshly taken out from the saloon after 1st of January or preserved in "new" condition from 2015.

Figure 7 plots the different production year categories among the advertised cars for each day in the dataset. It is visible how the expansion in the number of offerings after the 1st of January is largely driven by an influx of cars registered in 2015, in addition to the newly appearing 2016 registered vehicles.

Figure 6: The evolution of daily average kilometres on the odometer

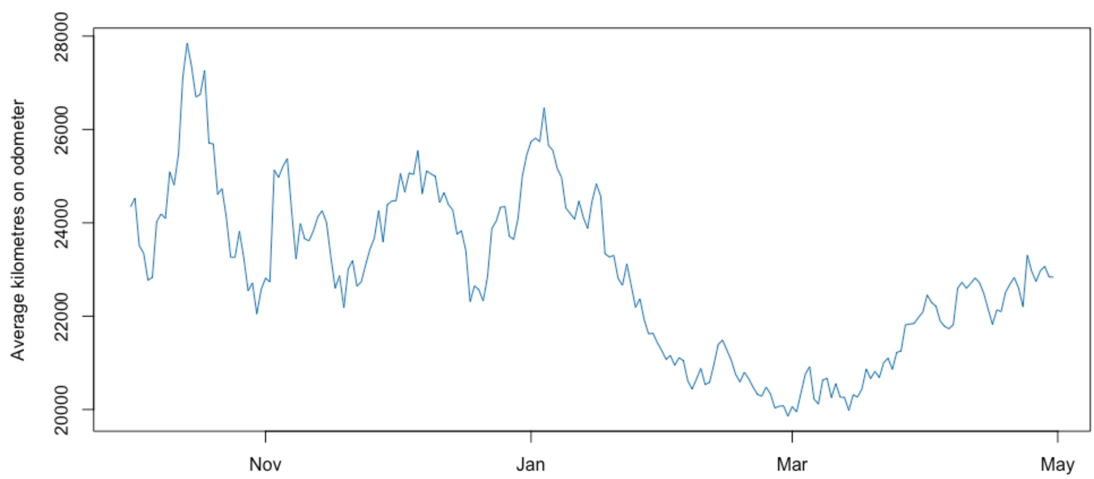
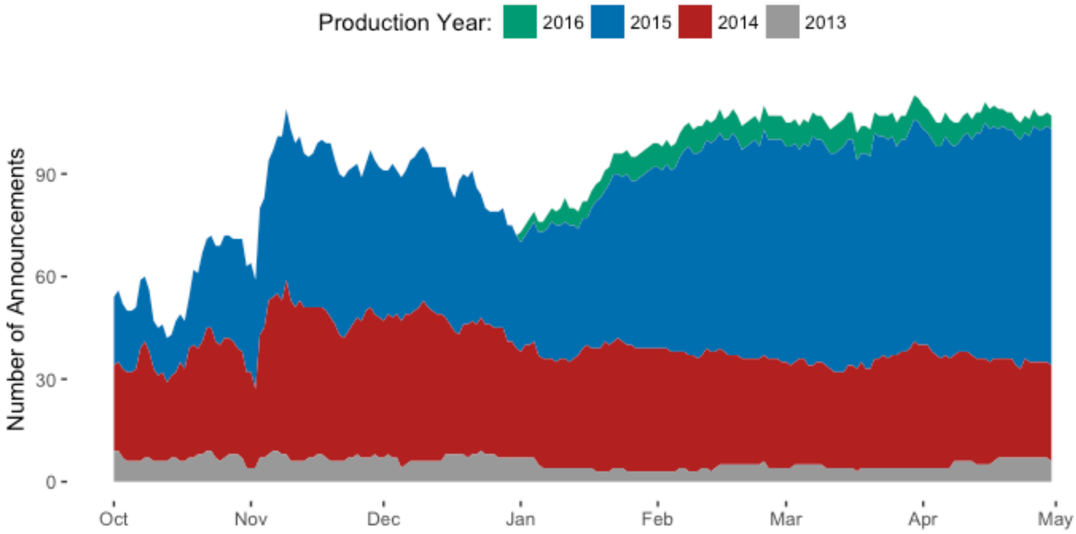


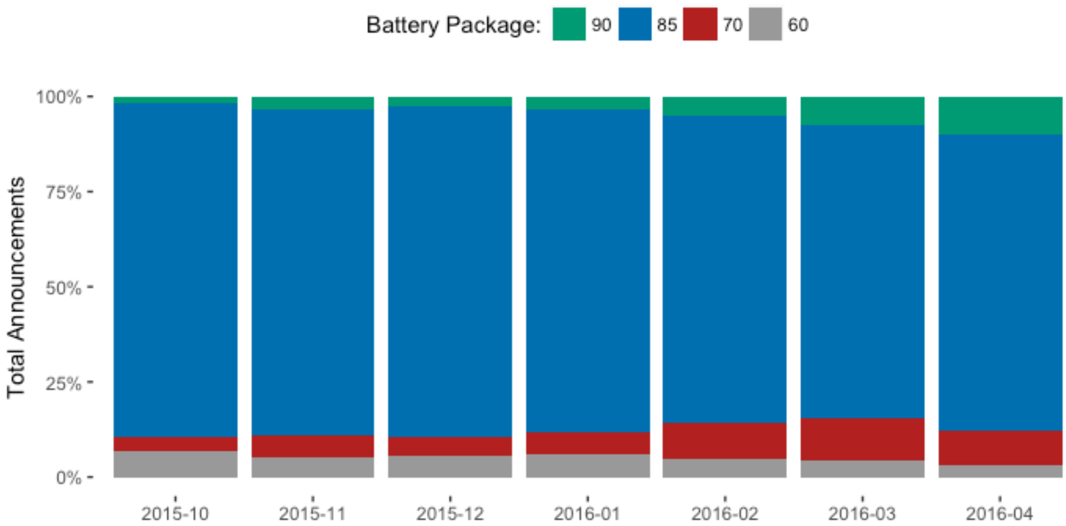
Figure 7: Development of the number of Model S offerings categorized by production year



In addition to the noted trend in the odometer data and the registration year of cars, the performance characteristics of the typical Model S provides interesting insights into a categorical shift in the used-car marketplace. To consistently group the different models in performance categories, the dimension for this categorization is selected to be the capacity of the battery. One of the main attributes determining the performance of a Tesla Model S is the battery package. Not only does the battery have a direct effect on performance but due to the availability of certain features only in higher battery packages, it also indirectly proxies the model's performance category. An example of such a feature is the performance package that is always exclusively available for the buyers of cars with the highest battery package only.

Figure 8 provides a picture of how the different performance categories evolve through the event window month by month. Notably, there is a surge in the 90 kWh high-end model, along with a slightly increasing significance of the 70 kWh mid-range category. Meanwhile, the 85 kWh battery package proved to be by a large extent the most widespread battery package being offered on the used-car market. The 60 kWh low-end model constituted only a small fringe of the market.

Figure 8: Monthly break-down of Model S offerings categorized by battery-package

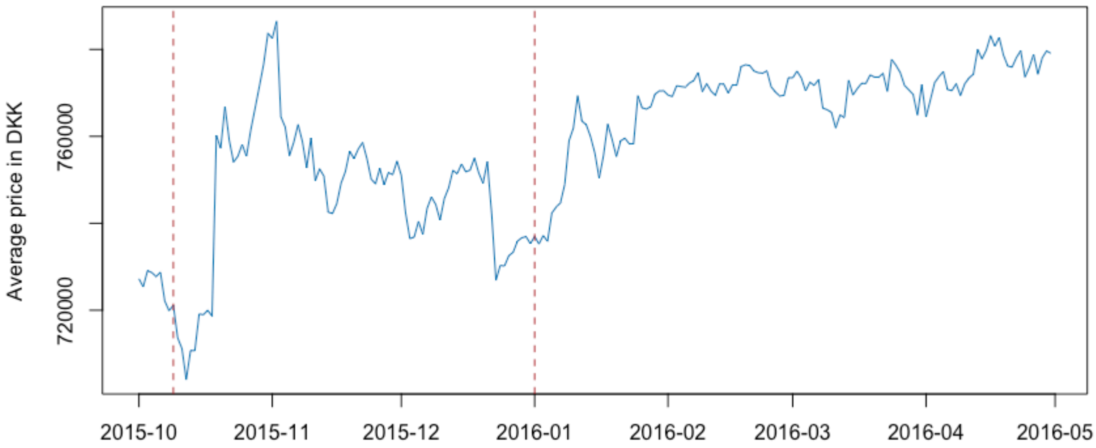


5.2. The Price of Advertised Cars

One of the most essential variables analysed in this study is the price offer included in the advertisements. This section will delve into the most important features that these average prices exhibit. Figure 9 plots the average price calculated from the observations available for each day in the event window. To highlight the events and the subsequent behaviour of prices, the plot includes two red dotted lines at the event dates of 9th of October and 1st of January.

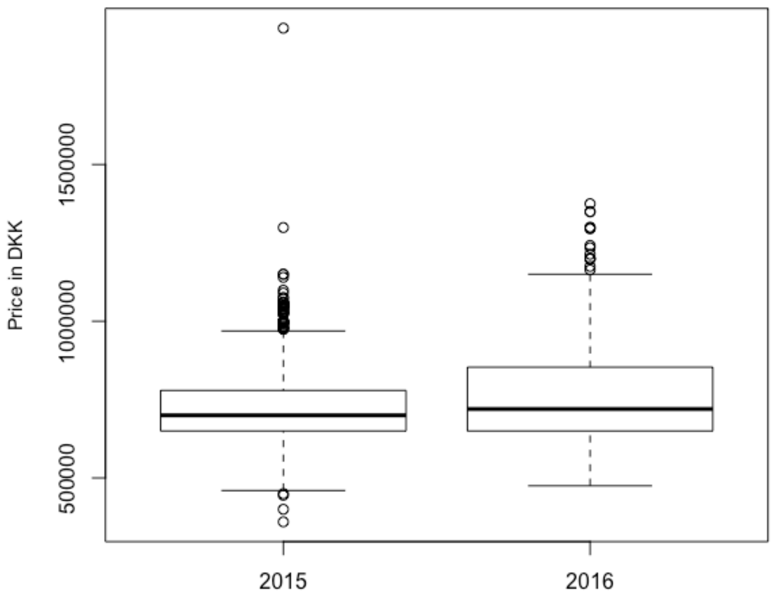
There appears to be structural shifts in the development of average prices after both events. After the parliamentary agreement is reached on the 9th of October prices reach the lowest point in our data sample with an average price of 704.017 DKK on the 12th of October. With a shortly delayed reaction there is an upward shift in prices from the pre-event level of 720.000 DKK to 760.000 DKK on average. A similar upward shift takes place on the 1st of January, when the new registration tax rules become effective. It is worth noting that up until the 27th of December, the anticipation was such that the high-end Tesla Model S will be subject to an immediate and full phase-in of the same registration tax that is applied to regular combustion engine vehicles. This ruling however was struck down by the EU labelling it anti-competitive only days before the law came into effect.

Figure 9: The evolution of daily average prices in the event window



After 1st of January, there is once again an upward shift in the average daily price, followed by what appears to be a weakly increasing trend in the price of Model S on the used-car market. The box plot in Figure 10 offers an additional view on the difference between prices in 2015 and 2016. One can observe a higher number of both positive and negative outliers in the year 2015. The plot confirms the slightly higher average prices available at the market in 2016, not controlling for the available model characteristics.

Figure 10: Box plot of Tesla Model S prices split by year of advertisement



6. Analysis

It is important to highlight that the increase in average prices can be attributed to a multiplicity of factors, including structural shifts in the market, such as the announcement and the phase-in of a new registration tax, but also to the changing characteristics of the models on offer. To explore the contribution of these different effects to the behaviour of the prices available at the used-car market, we now turn to a more detailed regression analysis. This chapter proceeds with detailed analysis using the previously described methodology with the main goal of answering the posited research questions and their accompanying hypotheses. Let us revisit these to provide an adequate starting point for the upcoming analysis.

There are two research questions that were presented in detail in the Introductory part of this thesis. *Research Question (1)* seeks an answer to whether individuals or car dealers could exploit the temporarily available tax exemption that the government announced to phase out from the 1st of January 2016, thereby achieving arbitrage profits. *Research Question (2)* asks if the markets' reaction to the announcement induced any short-term tax revenue fallout to the Danish state budget by form of a timely shift of electric car purchases from 2016 to 2015 or from new models to used cars in 2016.

To answer the first research question, the primary focus of the analysis will be on the price of used cars before and after 1st of January. Hence, the price variable of our dataset will be the designated dependent variable. The regressions work with the logarithm of these prices, as reasoned in the *Methodology section.* Additionally, to explore the trends in the data further, the base models are extended with the inclusion of other explanatory variables, as well as an alternative left-hand-side variable, the odometer value. To answer the second research question, the focus will be on discussing the tax change in two relevant unit numbers over time: (1) new car registrations and (2) the average number of used-car announcements per day.

The *Analysis* is structured as follows: First, *Research Question (1)* is answered by presenting and explaining the regression results. Second, we focus on extensions of the original regressions and results from other dependent and independent variables that can be of interest for the subsequent *Discussion* of the results. Third, robustness checks conclude the regression analysis. Lastly, *Research Question (2)* is discussed and a range for the foregone tax is estimated in the context of government policy-making.

6.1. Research Question (1)

The regression results are grouped based on the categorization presented earlier in Methodology. In the first set of regressions, we relate the price of used-car announcements directly to the model characteristics and the event of the tax change. Prices are log transformed before fitting the model. The odometer values (km) are similarly log transformed. Furthermore, there are categorical variables among the independent regressors, which are dummy coded for the regressions. These include the production year (where the reference year is 2013) and the battery package (where the reference package is the 60 kWh battery). The coefficients on the categorical variables are to be interpreted relative to these reference levels.

In Table 3 we present the results of two regressions that differ in their treatment of the event variable. In Regression (1) the *January 1st* event is represented by a single dummy variable, whose coefficient indicates the direction of price change with respect to the January 1st event. In Regression (2) the distance from the event date is measured by the *Week Distance* variable, which takes increasingly negative values for the weeks before January 1 and increasingly positive values for the weeks after. As a result, the coefficient of the *Week Distance* variable will be interpreted as the percentage change in price for each incremental week from the event date (turning signs for the period before January 1st).

As seen from Table 3, the *Event-coefficients* in both regressions posit a significant negative relation between prices before and after the tax change took place, which is surprising at first, considering the discrete increase in taxes. However, an explanation is provided by the increased number of advertisements of Teslas on the used-car market as seen previously on Figure 4. This is interpreted as a supply increase, which in turn put a downward pressure on prices on the used-car market. This result suggests that as buyers attempted to sell their previously purchased cars in hope of capturing a part of the discrete price increase after the 1st of January, prices moved in the opposite direction due to increased supply levels. As a result, prices not only stalled but in fact decreased according to both regressions' event coefficients, controlling for all available car characteristics. In turn, used Model S buyers in 2016 benefited from the adverse market conditions, as they were able to get their hands on relatively new Teslas for prices that were on par with or even below the prices in the last quarter of 2015.

Table 3: Regression results I.

	Dependent variable:	
	logPrice	
	(1)	(2)
Production year 2014	0.076***	0.076***
	(0.013)	(0.013)
Production year 2015	0.192***	0.194***
	(0.014)	(0.014)
Production year 2016	0.235***	0.238***
	(0.022)	(0.021)
Odometer: log(km)	-0.007***	-0.007***
	(0.001)	(0.001)
Battery 70 kWh	-0.060***	-0.055***
	(0.019)	(0.018)
Battery 85 kWh	0.131***	0.135***
	(0.015)	(0.015)
Battery 90 kWh	0.265***	0.274***
	(0.022)	(0.022)
Dual Motor	0.178***	0.181***
	(0.008)	(0.008)
Performance package	0.100***	0.098***
	(0.006)	(0.006)
Seven Person	0.005	0.003
	(0.009)	(0.009)
Signature Model	0.058*	0.056
	(0.034)	(0.034)
January 1st dummy	-0.029***	
	(0.006)	
Week distance from January 1st		-0.002***
		(0.0003)
Constant	13.225***	13.200***
	(0.023)	(0.023)
Observations	1,053	1,053
R^2	0.772	0.777
Adjusted R^2	0.770	0.775
Residual Std. Error (df = 1040)	0.091	0.090
F Statistic (df = 12; 1040)	293.716***	302.534***
Note:		p*p***p<0.01

* The regression outputs in this thesis are produced using the Stargazer package in R: Hlavac, Marek (2015). Stargazer: Well-Formatted Regression and Summary Statistics Tables.

More specifically about the *Event-coefficients*, both the *January 1st* and the *Week Distance* variables have coefficients that are different from 0 at the lowest significance level of 0,1%. From the regression results we can see that prices are 2,9% lower after the event date, holding other variables constant. From the *Week Distance* coefficient, we can postulate that with every passing week, prices declined by 0,2% over the observed period.

Coefficients on the additional explanatory variables behave to a large extent as expected. The signs on the *Production year* coefficients indicate that relative to the reference year of 2013, the price increases significantly for more recently produced vehicles. The percentage price increase for each category is 7%, 17% and 20% respectively for cars produced in 2014, 2015 and 2016. Intuitively, the coefficient on the *Odometer* variable is negative. This is in line with the logic that the more kilometers shown on the odometer, the lower is the announcement price, holding all other characteristics constant. The result is that for every 1% increase in kilometers run, the price decreases by 0,7%, once again holding the other model attributes constant.

The coefficients on the categorical variables for the battery package are in reference to the 60 kWh base model. It is interesting to observe the negative coefficient on the 70 kWh battery package, despite it representing a higher capacity as compared to the 60 kWh model. The rest of the *Battery* coefficients have the expected signs and significance. Switching from the 60 kWh model to the 85 kWh model represents a 13,1-13,5% price increase, while switching to the to the highest capacity 90 kWh model carries a 25,6-26,5% premium. Going further, vehicles with a *Dual motor* (front and rear wheel drive) and models with the *Performance package* increase the announcement price by a significant 18% and 10% respectively. The remaining two variables describing the advertised cars' characteristics are less significant in explaining the price variations. In particular, the limited-edition *Signature* models represent a roughly 6,5% premium over regular models, however the significance levels are unstable around the 5% level. Having the extra two seats installed in the third row (*Seven person*) is not significant at the 10% level.

It is imperative to note the high explanatory power of both regressions. The included characteristics explain 77-78% of the variation in price levels. This indicates that the non-available parameters in the dataset do not constrain our model significantly.

6.2. Base model extensions

The following pages provide extensions to the base model. We explore the effects of additional explanatory variables and experiment with the inclusion of other left-hand side variables. Firstly, we will look at how the day when the parliamentary agreement was reached on the tax change (October 9th) behaves as an event dummy. This result can be compared to the effect of the January 1st event that has been analysed in the previous section. Secondly, the regression is extended with the *Time on Market* variable to see if cars with higher advertised ask prices are typically sold slower (spend more time on market). Thirdly, we use logKm as our dependent variable and see if the events had an effect on the "age" of the vehicles offered on the used-car market.

Table 4 shows that neither the date when the parliamentary agreement was reached, nor the time-on-market variable is significant. For the first observation, it is possible that information about the agreement reached the public only gradually and that even when it did, it took additional days to materialize in a market reaction to the new information. The initial hypothesis regarding the effect of the time-on-market variable is that the more days a car spends on the market, the lower the ask price will be. This is not the case, as there is a positive but non-significant coefficient on this independent variable. With the time-on-market variable, there is the issue of endogeneity and reverse causality, as it is not clear if the number of days spent on the market is affected by an ask price that is set too high or if, as the number of days pass by, the buyer adjusts the price lower to find an interested buyer. These two effects have theoretically opposing signs and it may well be that the two effects cancel each other in our dataset such that the resulting coefficient falls close to 0.

The effect of the different regions where the car is advertised is tested and found to bear no significance. This in line with the preliminary expectation that prices should not differ across regions in a small country like Denmark. One interesting observation however is that the exclusion of region in the advertisement leads to a negative and significant coefficient (-2.568e-01). This can be interpreted as a negative signal about the seller's credibility if the region is not specified in the advertisement. The regression with the region categorical variables are dummy-coded, where the reference value is Copenhagen. The results of this regression are shown in Appendix 1.

Table 4: Regression results II.

	Dependent variable:	
	logPrice	
	(3)	(4)
Production year 2014	0.076***	0.076***
	(0.013)	(0.013)
Production year 2015	0.188***	0.186***
	(0.014)	(0.014)
Production year 2016	0.221***	0.217***
	(0.022)	(0.022)
Odometer: log(km)	-0.008***	-0.008***
	(0.001)	(0.001)
Battery 70 kWh	-0.060***	-0.057***
	(0.019)	(0.019)
Battery 85 kWh	0.132***	0.135***
	(0.016)	(0.016)
Battery 90 kWh	0.258***	0.261***
	(0.022)	(0.023)
Dual Motor	0.175***	0.175***
	(0.008)	(0.008)
Performance Package	0.100***	0.099***
	(0.006)	(0.006)
Seven Person	0.004	0.004
	(0.009)	(0.009)
Signature Model	0.068*	0.068**
	(0.035)	(0.035)
October 9^{th} dummy	-0.012	
	(0.010)	
Time on Market		0.00005
		(0.0001)
Constant	13.234***	13.220***
	(0.024)	(0.024)
Observations	1,053	1,053
R^2	0.767	0.767
Adjusted R^2	0.764	0.764
Residual Std. Error (df = 1040)	0.092	0.092
F Statistic (df = 12; 1040)	285.485***	285.237***
Note:		**p***p***p<0.01

From Figure 6 in the Chapter 5 we see a clear decline in the average odometer values of advertised vehicles after the 1st of January. In order to explore this observation further, we include the logKm as a dependent variable and regress it on the *January 1st event dummy*, as well as the *weekdistance* variable in a separate regression. Control variables are the vehicle's production year and the battery package, that determines how far the vehicle can travel on one charge. Table 5 presents the results of these two regressions with logKm as the LHS variable.

Despite the decline illustrated graphically without controlling for vehicle characteristics on Figure 6, the regression shows that in fact the event coefficients are positive and significant with values of 0.762 and 0.041 for the *January 1st event dummy* and the *week distance* variable respectively. This result is contrary to expectations, as the premise of this analysis was that the odometer values declined as newer cars came to the used-car market after the 1st of January. Nevertheless, there can be two explanations to this surprising result. Firstly, the regression controls for characteristics that are naturally correlated with the logKm value, such as the year of production and the battery package. Both of these characteristics were shown to shift after the new year as newer Teslas appear on the marketplace (Figure 8 in Chapter 5). Thus, when we control for them in the regression, the effects of the event variables are picked up by these vehicle characteristics. These effects are large, as the odometer values have large dispersion and significant variance in our dataset. Secondly, the cars that are on the used-car market are often being driven while being advertised and their odometer values are periodically updated in the advertisements. As more used cars appear on the market from 2015, the odometer values consequently increase. This means that, once we control for *production year* and the *battery package*, the driven number of kilometres increase with every passing week (hence the positive coefficient on the week distance variable) relative to the January 1st event. Nevertheless, this result also pinpoints the fact that there are more recently produced Teslas appearing on the market, as the production year appears to be the dominant effect in the initially illustrated decline in odometer values. This confirms our observation that as the tax change occurs, there is an influx of quasi-new vehicles from the year 2015, along with the appearance of vehicles produced in 2016 and these two factors play a key role in causing the shift in the average odometer values after January 1st.

Table 5: Regression results III.

	Dependent variable:	
	logKm	
	(5)	(6)
Production year 2014	-0.436	-0.449
	(0.320)	(0.320)
Production year 2015	-2.093***	-2.112***
	(0.319)	(0.318)
Production year 2016	-5.281***	-5.236***
	(0.526)	(0.524)
Battery 70 kWh	-1.056**	-1.133**
	(0.475)	(0.475)
Battery 85 kWh	-0.362	-0.426
	(0.394)	(0.394)
Battery 90 kWh	-4.503***	-4.606***
	(0.527)	(0.528)
January 1st dummy	0.762***	
	(0.152)	
Week distance from January 1st		0.041***
		(0.008)
Constant	10.695***	11.146***
	(0.490)	(0.489)
Observations	1,053	1,053
R^2	0.303	0.304
Adjusted R^2	0.298	0.300
Residual Std. Error (df = 1045)	2.370	2.367
F Statistic (df = 7; 1045)	64.867***	65.282***
Note:		**p***p***p<0.01

6.3. Robustness Checks and Model Validation

This section is to provide basic robustness checks and validate the OLS regression model used to analyse the secondary market data in this thesis. First, we look at the distribution of the residuals to validate two of the OLS assumption, namely the use of unbiased and homoscedastic estimators in the regressions. We do this with regressions (2) and (6), where the dependent variables are logPrice and logKm respectively. Thereafter, we interact the variables *battery package* and the *January 1st event dummy* to understand if this alternative functional form brings new insights to the analysis.

The OLS assumptions can be validated by looking at the residuals. From the residuals plotted against the week-distance variable measuring the time dimension of the dataset relative to the January 1st event, we see that the there are no signs of uneven distribution or change or trend in the variance of the distribution. From Figure 11 and Figure 12, we can conclude that the linear model is appropriate and the OLS assumptions regarding unbiased estimators and their homoscedasticity seem to hold in both Regression (2) with logPrice and Regression (6) with logKm as the dependent variables respectively.

Figure 11: Residuals distribution of Regression (2)

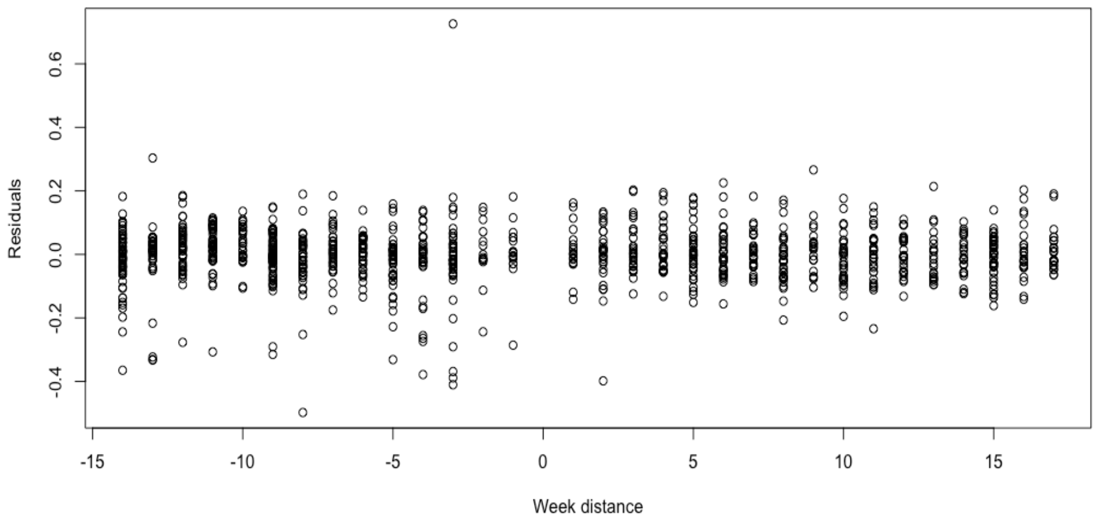
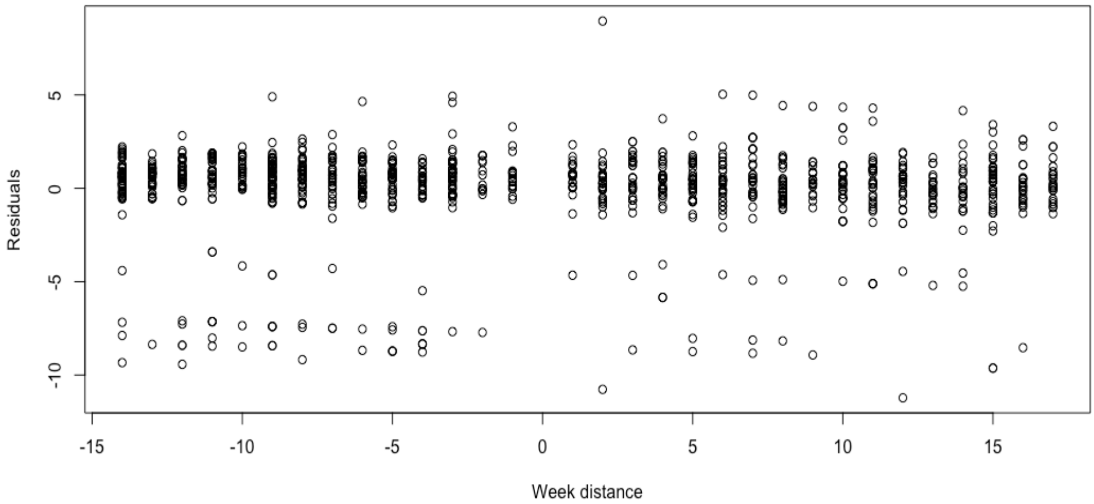


Figure 12: Residuals distribution of Regression (6)



Interacting variables allows the model to show whether the effect (coefficient) of one independent variable on the regressand is dependent on an other independent variable in the regression. In the case of our dataset, it is interesting to explore whether prices changed differently with respect to the January 1st event, when conditioning on the car's price range. Did the market have a different reaction to the tax change for high-end compared to low performance models? For this, we include a simple term that interacts the battery package (as a proxy for the car's value) with the *January 1st event dummy* in the regression. The reference value for the *battery package* variable is 60 kWh. The control variables are kept the same as in our base regression.

Table 6 presents the results with a focus on the interaction terms (standard errors are only reported for the variables in interaction). From the results, we can observe that the interaction term is significant and positive, despite the January 1st event dummy bearing a negative coefficient. This in turn means that the cars equipped with higher battery capacity (and consequently, the more valuable Teslas) had a 7-13% price increase when interacted with the event dummy, relative to the 60 kWh packaged vehicles. This indicates that models with a higher value were able to capture some of the tax increase, while the 60 kWh entry-models contributed mostly to the slightly negative shift in prices and thus lost from their used-car market value.

Table 6: Regression results IV.

	Dependent variable:
	logPrice
	(7)
Production year 2014	0.076^{***}
Production year 2015	0.201^{***}
Production year 2016	0.265^{***}
Dual Motor	0.187^{***}
Performance Package	0.094^{***}
Seven Person	0.005
Signature Model	0.054
Battery 70 kWh	-0.121^{***}
	(0.026)
Battery 85 kWh	0.104^{***}
	(0.020)
Battery 90 kWh	0.242^{***}
	(0.034)
January 1st	-0.114^{***}
	(0.030)
Battery 70 kWh * January 1st	0.132^{***}
	(0.037)
Battery 85 kWh * January 1st	0.076^{**}
	(0.031)
Battery 90 kWh * January 1st	0.106^{**}
	(0.044)
Constant	13.184^{***}
	(0.023)
Observations	1,053
R^2	0.768
Adjusted R^2	0.765
Residual Std. Error	0.092 (df = 1038)
F Statistic	245.203^{***} (df = 14; 1038)
Note:	**p***p***p<0.01

This concludes our regression analysis. The previous pages have been motivated by *Research Question (1)*. The main goal of this section was to find out whether there has been an arbitrage opportunity opened up by the pre-announced tax change and who benefited from the hike in prices of newly registered vehicles after the 1st of January.

Answer to Research Question (1)

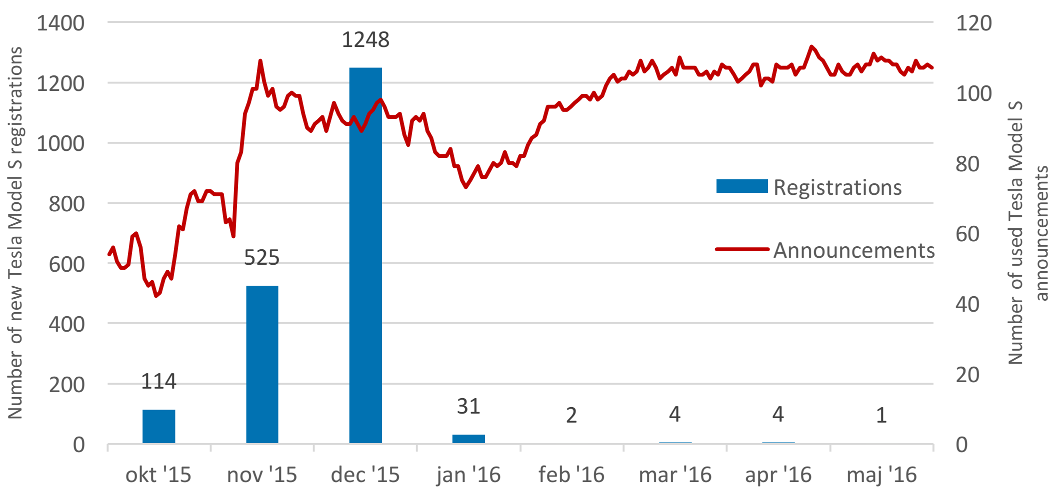
After dissecting our data on the Danish used-car market, the regression analysis showed that controlling for the available car characteristics, prices show a statistically significant, slightly declining trend with respect to both of our tested event variables. This suggests that contrary to the price increase induced by the registration tax for newly purchased cars, prices on the used-car market moved in favour of second-hand buyers of Tesla Model S vehicles. Arbitrageurs – who speculated on buying a Model S before the imposed tax took effect on the 1st of January 2016 and expecting to sell for a higher price, thereby pocketing a profit equivalent (or nearly equivalent) to the tax increase – were trapped by the self-regulating forces of the market. The higher volumes of advertisements after the new year underline the observation that the used-car market experienced a supply increase, which put a downward pressure on prices, confirmed by our regressions. The winners of this economic game were the 2016 second-hand buyers, as they managed to get their hands on recently produced Tesla models for the same or slightly lower prices as they would have been able to do so in the last months of 2015. It is this group of buyers who managed to implicitly capture the amount of the tax increase.

There has been one more actor present on this economic playground that we have so far failed to mention: the Danish government. One interpretation of the results of our previous analysis is that the tax income was partially internalized by the market, questioning the effectiveness of such pre-announced fiscal policy tools. As the example in this study shows, if the market is provided sufficient time to adjust to the new reality of the policy environment, expectations will form in such a way that nullifies the intended effect of the change. The upcoming discussion is motivated by *Research Question (2)* of this thesis and seeks to highlight the policy-making lessons, as well as providing a high-level estimation of the maximum amount of foregone tax that the government incurred due to the market's reaction to the announcement of the tax increase.

6.4. Research Question (2)

The analysis of *Research Question (2)* is less analytically driven and more discussion oriented. As a departure, it relies on two figures presented earlier that show the vastly declining number of newly registered Tesla Model S after January 1st and the moderate increase in announcement numbers on the used-car market. Based on this relationship depicted on Figure 13, we can stipulate that there has been a shift from buying newly registered Tesla Model S vehicles to activity on the used-car market, as well as a general decline in interest for Teslas after the de facto tax increase. As mentioned on the previous page in the concluding remarks of the regression analysis, it is possible that the imposed tax on electric vehicles had been partially internalized by the market, thereby limiting the realized tax revenue from the new fiscal policy.

Figure 13: Comparison of new registrations and used Tesla announcements



Estimation approaches of this foregone registration-tax can differ vastly in their complexity. In this thesis, we refrain from providing a full-scale economic model as it would fall out of the scope of this study. Although it is recognised that some intended Tesla purchases may have shifted to other luxury cars (bringing tax revenue on that account) or to other electric vehicles on the market, a detailed analysis of consumer choice is not permitted by the data at hand. Nevertheless, we note that to provide a more precise estimation regarding the fiscal consequences of the tax change, one would need to rely on a more elaborate model of consumer choice and/or an explicit model of supply and demand on both the market for new and used electric vehicles simultaneously. Instead, we merely provide a high-level estimate of the maximal foregone registration-tax to provide grounds for discussion in the context of government policy-making.

One can stipulate that the increased registrations in the months prior to the 1st of January constitute purchases that are predominantly brought forward from the new year. At the time this thesis is being written (2017 spring), registration data is available for the whole year of 2016. All in all, sales volumes have dropped significantly and as low as 176 Tesla Model S were sold in 2016. Furthermore, it is also visible after the first months of 2017 that Tesla has struggled to keep up with its sales once again in the new year. The pattern of new car registrations around the second phase-in period (2016/2017 with 40% of the calculated tax) is similar to the one studied in this thesis (2015/2016 with 20%), although at significantly reduced volumes.

Figure 14 shows a comparison of the patterns that new car registrations took for Tesla Model S vehicles at the turn of 2015/2016 and 2016/2017 respectively. The chart suggests that building on expectations that prices will increase once the tax is yet again elevated, buyers brought forward their purchases, leaving the market with no newly registered Teslas in the first quarter of 2017. This reinforces the idea that the buyers' tax optimizing behaviour nullifies the fiscal budgetary effect of the pre-announced tax change. It is also notable that the acceleration of volumes in December 2016 is only a fraction of the sales that took place in 2015.

Figure 14: New Tesla registrations at the turn of 2015/2016 and 2016/2017

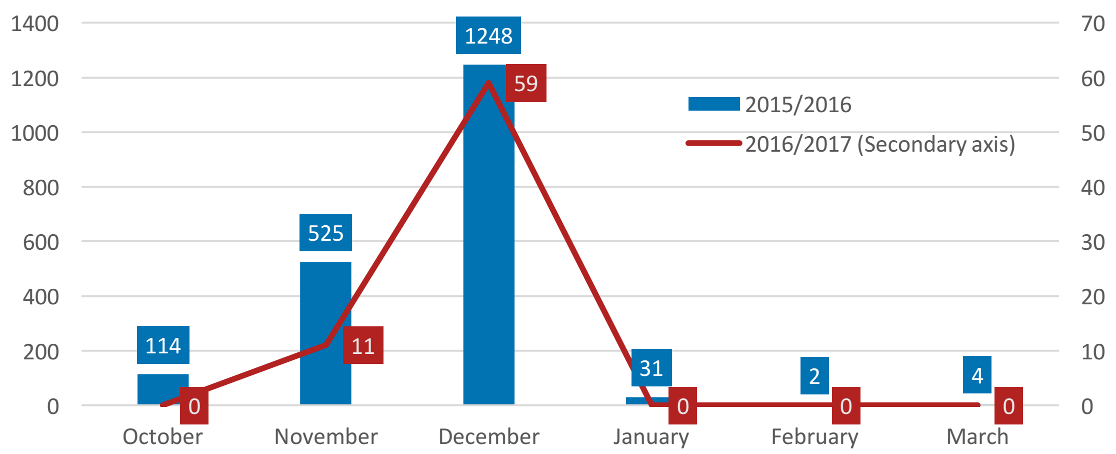
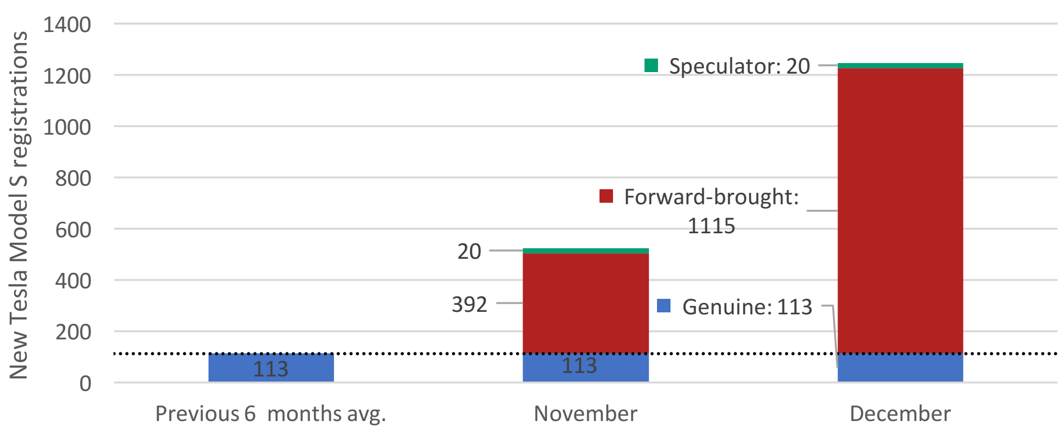


Figure 13 and Figure 14 suggest two main motivations behind the dropping volumes of new Tesla registrations after the turn of the year. Firstly, purchases had shifted to the used-car market as the tax increase prompted buyers to look for alternative buying opportunities after the new year. Secondly, decisions to buy a new Tesla were brought forward and realized before the hike in registration tax rates. These two actions prevented the realization of raising tax revenue for the Danish government on this account. The maximum amount of foregone tax can be estimated from our recently established insights about how the market for Tesla Model S has reacted. As numbers for 2017 are only available from the first quarter of the year at the time of this research, the calculations are limited to the estimation of the foregone tax amount during the year of 2016. Observing that on average 113 Tesla vehicles were registered each month in the 6 months preceding the tax change announcement (9th October 2015) and that there has been no clear trend towards higher sales volumes before the structural break in the market, it is safe to assume that the hike in registration numbers is the result of planned purchases brought forward from 2016, as well as speculators, who were looking to exploit the arbitrage provided by the market. The number of speculators is determined from the difference in average announcement numbers before and after the tax increase. Although this is a vast simplification, assuming that all additional buyers in November and December 2015 had the sole motivation to bring forward future purchases would be inaccurate and it would contradict our previously established points about the speculators' attempt at monetizing this arbitrage opportunity. For this reason, registrations are categorized in three groups: (1) genuinely planned, (2) speculative and (3) forward-brought purchases. Figure 15 illustrates this breakdown with numbers from 2015.

Figure 15: Tesla purchases breakdown by motivation



As previously described, on average 113 new Tesla purchases took place each month prior to the tax change. This group of transactions is what we call genuine purchases. Regarding the number of speculators, we assume that the increase in announcement numbers on the used-car market from 2015 to 2016 is primarily due to this new player appearing on the marketplace. The forward-brought purchases are calculated as the remaining fraction of the new car registrations. Based on this estimation methodology, there were 392 and 1115 planned Tesla purchases brought forward from the next year to 2015 November and December respectively. This amounts to a total of 1507 Tesla Model S forward-brought purchases, which in effect avoided paying the increased vehicle registration tax as of 1st of January 2016. As there is no individual-level data on the exact model and value of purchases, we must rely on the average value, and consequently the average foregone tax per vehicle. In 2016, the registration tax on Tesla Model S vehicles ranged between ca. 120.000 DKK and ca. 315.000 DKK for the lower-end and higher-end models respectively (www.teslamotors.com).

Answer to Research Question (2)

This puts our foregone tax estimation in the range of <u>180 – 474 million DKK</u>. This amount is a high-level estimation of the maximum amount of foregone tax in 2016, directly relatable to the decline in sales of Tesla Model S vehicles. Announcing the tax change three months before the legislation being enacted allowed market participants to adjust their purchasing decisions and avoid paying the increased registration tax. This finding highlights that there is a trade-off in timing between providing legislative stability with longer periods to accommodate to the tax change and the effectiveness of the policy.

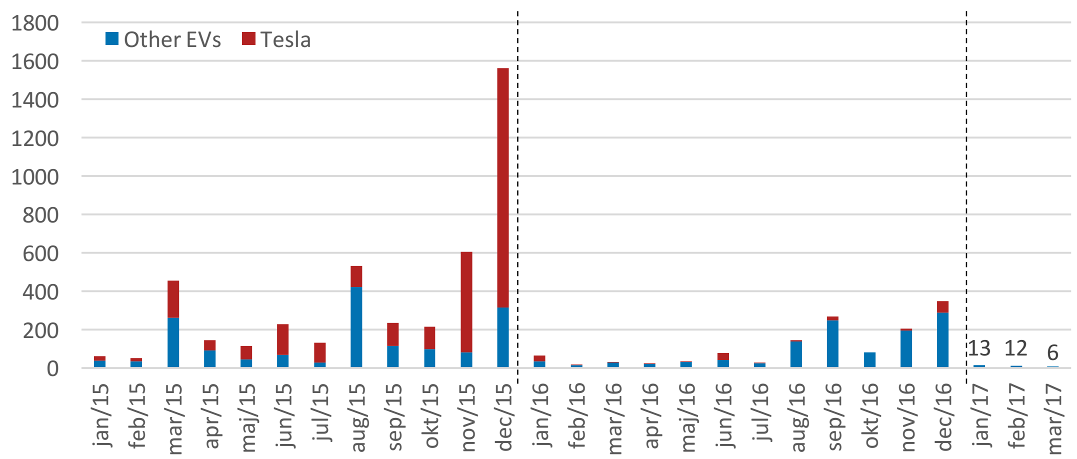
One must remember that, this number does not reflect all electric vehicles, although Tesla automobiles strongly dominated the market for Evs in Denmark before the tax change. Secondly, this calculation does not consider the substitution effect that results from Tesla's relative competitiveness decreasing compared to other luxury vehicles. As noted earlier, a more elaborate economic model would have to account for supply and demand explicitly in both the primary and used-car markets, potentially modeling intertemporal consumer choice, allowing for substitution between different brands, models and the timing of the purchase.

*

7. Discussion

Following the Analysis and the answers to the research questions, this chapter is to provide a discussion of the results in a wider context, as well as highlighting the most recent news and developments regarding the tax change in Denmark. The observed decline in new registrations is not exclusive to Tesla automobiles, which is widely considered a luxury vehicle. Other electric vehicles suffered similarly from the higher registration tax and their sales declined in similar proportions to that of Tesla's in the beginning of the year 2016. Later, as illustrated on Figure 16, the sales of other EVs climbed back to the 2015 levels, however as the second step of the phase-in process took effect, registrations virtually disappeared after January 1st, 2017 (De Danske Bilimportører). As a reaction to the disappearing Tesla (and other EV) sales, Danish media outlet Berlingske published a news article writing that "Tesla has not sold a single new car on Danish grounds in the new year" (Berlingske Business 2017). In addition to not generating tax revenue for the Danish government, this development has gone against the country's long-run transition to a greener society. Realizing the unexpected short-term effects of the policy after the first quarter of 2017, the Danish government retroactively reinstated the 20% tax from the beginning of 2017 and effective until the end of 2018, prolonging the next steps of the phase-in by at least two years relative to the originally planned schedule (Børsen 2017).

Figure 16: New Tesla and other electric vehicle registrations in Denmark



As the technology matures and the marginal cost of production approaches that of traditional technologies', many governments are looking to end or gradually lower their support mechanism for the EV industry. This is in effort to keep a balance between levelling the playing field between the competing manufacturers, while still internalizing the economic externality of higher CO2 emission of traditional fuel vehicles relative to that of EVs or other alternative fuelled cars. In Hong Kong, officials have announced the removal of their electric vehicle tax waiver (Bloomberg 2017). The tax on the purchase price of cars in Hong Kong can be as high as 115%, creating a similar market situation to the one observed in Denmark. One key difference however is the immediate enactment of the bill (Electrek 2017), which seems to be learning point from the Danish experience. From a research perspective, the market reaction in Hong Kong would allow a natural comparison to the Danish tax change.

The challenge for policy makers is to design a scheme for policy change that is both effective in the short-run and projects long-run legislative stability to the market. As the changes are announced, markets adjust expectations and attempt to swallow the amount of the tax change, as we have seen in the case of Denmark. This poses the question whether pre-announced changes in similar support schemes can have any immediate fiscal impact. On the other hand, not giving enough time for markets to adjust creates unwanted uncertainty among economic participants. The trade-off between the informational and budgetary objectives of regulatory tax policies was also raised – among others – by Barigozzi and Villeneuve (2006). A further aspect previously raised by other authors (Shapiro 1991; Feldstein 2002; Hall 2011; D'Acunto, Hoang, and Weber 2016) is that of unconventional fiscal policy effects. Pre-announced tax changes undoubtedly create inflationary expectations in the prices of goods they are levied on, which induces an increase in consumption. The natural experiment induced by the Danish tax change showed evidence of this effect in one particular segment of the economy.

The policy lessons are clear: market adjustments make it difficult for policymakers to balance between legislative stability and pursuing budgetary objectives. The behaviour of the market must be modelled in order to design effective policy changes. That being said, announcing tax changes can purposefully accelerate consumption and bring closer short-term policy goals by creating higher expectations in price levels among consumers.

*

8. Conclusion

This chapter concludes the thesis. In this study, we have set out to answer two research questions. With the first, we sought to analyse the used-car market for Tesla automobiles in Denmark around the time of a significant legislative change regarding the taxation of electric vehicles at the turn of 2015 and 2016. Through the analysis of a unique dataset constructed for this thesis, we provide an answer to whether there was an exploitable arbitrage opportunity in the registration tax change on electric vehicles that became effective on the 1^{st} of January 2016. With the second, we sought to estimate the foregone registration tax, which resulted from the sharp decline in the sales of new Tesla vehicles after the new tax was enacted. This has led to a brief discussion on the policy trade-off that arises from the results, namely that the early announcement of such tax changes creates legislative stability but reduces the effectiveness of the policy tool as markets react to these changes.

In the Chapter 5, the most important trends in the dataset were highlighted. Announcement numbers increased, while new listings and delistings from the market show less activity on the used-car market after the 1^{st} of January than earlier. Cars remain on the market for longer periods after the tax change. There are newer models on offer and consequently the average number of kilometres on the odometer declines significantly. The average price on the market shows an increasing trend, when there is no control for any of the car characteristics. In the Analysis however, we have shown that controlling for car characteristics and regressing log prices on the January 1^{st} event variables, prices decline by 2.9% after that date and the relationship is statistically significant. Other car characteristics have the expected signs and coefficients. The base model was extended in different directions. We have found that neither the day of the parliamentary agreement, nor the time a vehicle spends on the market has statistical significance in relation to the price of the vehicle. LogKm was included as an alternative LHS variable in the regression and found to be positively influenced by the January 1^{st} event variables, when the available car characteristics are included as control variables. This result highlights the significance of newer models arriving to the used-car market, since controlling for the new model characteristics, the odometer trend reverses from the decline shown in the Summary of the Data chapter. Lastly, robustness checks confirm the use of OLS in our models. Variable interaction between the value category and the January 1^{st} event dummy shows that the more valuable models in fact increased in price. The car's battery package is used as a proxy for the car's value category.

As a conclusion to *Research Question (1)*, we have established that based on the analysis, speculators were not able to exploit the arbitrage opportunity created by the tax change. Instead, it was the group of used-car buyers after the 1st of January, who indirectly internalized the tax increase by purchasing relatively new models for the same or lower price than they would have been able to do so before the turn of the year. Furthermore, due to the decline in new Tesla registrations in 2016, the market's reaction prevented the Danish government from collecting tax revenue on these models. This finding led to an estimation of the maximum amount of foregone tax, which answers *Research Question (2)*. The estimated range of the foregone tax amount directly relatable to the drop in Tesla registrations is 180 – 474 million DKK. One interpretation of this result is that, given time, markets will adjust to pre-announced changes in taxation policy and work towards swallowing the amount equivalent to the tax increase. This highlights the trade-off between providing market participants with longer time to accommodate to the new legislation and the effectiveness of the fiscal policy tool.

This thesis has revolved around analysing how the market reacts to pre-announced legislative changes using a uniquely gathered dataset of used Tesla announcements. Valuable contributions to this study could include conducting the analysis on a larger dataset including other electric vehicles and close substitutes, as well as detailed level registration data on newly purchased vehicles. An elaborate economic model would benefit the research by elevating the theoretical rigor behind the empirical analysis. Furthermore, as posited in the Discussion, looking at similar tax changes from around the globe, such as the analysis of the Hong Kong experience could provide a meaningful comparison to the case of Denmark and serve with valuable insight for other governments looking to phase out tax support schemes as the EV technology matures.

*

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Appendix

Appendix 1: Regression table with region variable

	Dependent variable:
	logPrice
Production year 2014	0.053***
	(0.013)
Production year 2015	0.161***
	(0.014)
Production year 2016	0.190***
	(0.021)
Odometer: log(km)	-0.008***
	(0.001)
Battery 70 kWh	-0.062***
	(0.018)
Battery 85 kWh	0.129***
	(0.015)
Battery 90 kWh	0.258***
	(0.021)
Dual Motor	0.175***
	(0.008)
Performance Package	0.103***
	(0.006)
Seven Person	0.001
	(0.009)
Signature Model	0.032
	(0.034)
Region: NA	-0.257***
	(0.024)
Region: Fyn	-0.016
	(0.011)

Region: Lolland-Falster	0.019
	(0.024)
Region: Nordjylland	0.0001
	(0.015)
Region: Nordsjælland	-0.002
	(0.016)
Region: Østjylland	0.010
	(0.007)
Region: Syd- og Sønderjylland	0.016*
	(0.009)
Region: Syd- og Vestsjælland	0.019
	(0.013)
Region: Vestjylland	-0.004
	(0.011)
Constant	13.247***
	(0.022)
Observations	1,053
R^2	0.793
Adjusted R^2	0.789
Residual Std. Error	0.087 (df = 1032)
F Statistic	197.923*** (df = 20; 1032)
Note:	*p**p***p<0.01

The regression outputs in this thesis are produced using the Stargazer package in R: Hlavac, Marek (2015). stargazer: Well-Formatted Regression and Summary Statistics Tables.

Appendix 2: Bilbasen.dk support correspondence about ID-uniqueness

Netop Live Guide 11/11/16 10:49

Du taler med Katrine J.
Jeg læser din besked igennem og vender straks tilbage

Katrine J.: My chat agent died! Sorry. I can see your last message.

Katrine J.: I'm reading it now :)

Du siger: Ok, perfect

Katrine J.: The URL shouldn't change even if the specifications do.

Du siger: Okay, so the URL always remains the same for the same announcement. Could there by any event where it changes over time?

Katrine J.: Not as far as I reckon, no :)

Du siger: Okay, thank you