The Electric Vehicle Transition and the Impact of Tax Policy Adjustments: Analyzing the Effect of Norway's 2023 Value-added Tax Reform

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Abstract

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This thesis examines the effects of removing tax incentives on the demand for electric vehicles using the Norwegian value-added tax reform of 2023 as a natural experiment. A theoretical discrete choice model is developed that combines horizontal and vertical product differentiation to account for heterogeneity in products and consumer preferences with respect to the willingness to pay. The model predicts that the abolition of the VAT exemption for high-priced electric vehicles will lead to a decline in overall demand for electric vehicles, particularly among high-income households. To test this, a difference-in-differences design is applied to Norwegian microdata, comparing changes in electric vehicle registrations between high- and low-income households before and after the reform. The empirical results show a statistically significant negative effect on the probability of registering an electric vehicle in high-income households after the reform, while low-income households remain largely unaffected. These results support the central hypothesis that tax incentives influence the adoption of electric vehicles and underscore the importance of targeted fiscal policy for accelerating the transition to low-emission transportation.

Keywords: *Electric Vehicles, Vehicle Market Transition, Tax Incentives, Product Differentiation, Discrete Choice Modeling, Difference-in-Difference, Policy Evaluation*

Abstrato

A transição para veículos elétricos e o impacto dos ajustes na política tributária:
Analisando o efeito da reforma do imposto sobre o valor acrescentado da Noruega em 2023

Jakob Valentin Heinig

A presente tese analisa os efeitos da remoção de incentivos fiscais na procura por veículos elétricos, utilizando a reforma do Imposto sobre o Valor Acrescentado (IVA) na Noruega, implementada em 2023, como um experimento natural. É desenvolvido um modelo teórico de escolha discreta que combina diferenciação horizontal e vertical dos produtos, de forma a captar a heterogeneidade dos bens e as preferências dos consumidores relativamente à sua disposição para pagar. O modelo prevê que a abolição da isenção de IVA para veículos elétricos de elevado valor conduzirá a uma diminuição da procura global por estes veículos, particularmente entre os agregados familiares com rendimentos mais elevados. Para testar esta previsão, aplica-se uma abordagem de diferenças-em-diferenças a microdados noruegueses, comparando as variações na compra de veículos elétricos entre agregados de rendimentos elevados e baixos, antes e depois da reforma. Os resultados empíricos revelam um efeito negativo, estatisticamente significativo, na probabilidade de comprar um veículo elétrico entre os agregados de rendimentos mais elevados após a reforma, enquanto os agregados de rendimentos mais baixos permanecem, em grande medida, inalterados. Estes resultados confirmam a hipótese central de que os incentivos fiscais influenciam a adoção de veículos elétricos e sublinham a importância de uma política fiscal direcionada para acelerar a transição para transportes com baixas emissões.

Palavras-chave: *Veículos Elétricos, Transição no Mercado Automóvel, Incentivos Fiscais, Diferenciação de Produtos, Modelação de Escolha Discreta, Diferenças-em-Diferenças, Avaliação de Políticas*

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1 Introduction

The transport sector is currently responsible for around a quarter of the EU's greenhouse gas emissions (EEA, 2024a). Decarbonizing road transport is central to the European Green Deal's goal of reducing greenhouse gas emissions by 90% in 2050 (European Commission, 2021). Among the available strategies, the acceleration of electric vehicle deployment is widely considered one of the most effective (EEA, 2024b). Norway has taken a leading role in this transition by combining tax exemptions, such as a zero percent value-added tax rate and reduced registration taxes, with substantial investments in charging infrastructure to increase electric vehicle uptake (IPAC, 2022). Previous research shows that these incentives have contributed significantly to reducing greenhouse gas emissions and promoting the adoption of electric vehicles (Bjerkan et al., 2016; Cincotta & Thomassen, 2025; Figenbaum et al., 2015; Halse et al., 2025; Isaksen & Johansen, 2025; Johansen et al., 2023; Mersky et al., 2016).

While previous studies confirm that tax incentives have had positive effects, it is uncertain to what extent these tax incentives affect electric vehicle demand or whether they persist once preferences have become established. For instance, consumers might have developed strong preferences for electric vehicles. If those preferences are anchored, consumers might not respond strongly to price changes. The effectiveness of tax incentives may also depend on complementary policy incentives such as charging infrastructure or toll exemptions. Additionally, some consumers are less sensitive to changes in prices. In this case, the impact of tax changes may vary among different groups. In January 2023, the Norwegian government reintroduced a 25% VAT on the portion of the price of electric vehicles exceeding NOK 500,000 while maintaining a weight-based registration tax. This raises a fundamental question. What impact did this reform have on consumer purchasing behavior, particularly on the share of new registered electric vehicles?

In order to address this question, this thesis is structured in two complementary sections. First, a theoretical discrete choice model of demand is developed, which captures the most relevant characteristics of the vehicle market. The model takes into account both horizontal and vertical product differentiation to describe how market shares and prices adjust in equilibrium under different VAT regimes. It is solved numerically, and the results suggest that the VAT reform reduces the price competitiveness of high-priced electric vehicles, leading to a decline in overall demand for electric vehicles. Consumers with a high willingness to pay are overrepresented in the premium segments and are therefore most exposed to the effects of the reform.

The primary prediction is that high-income consumers will adjust their purchasing behavior, reducing their purchases of electric vehicles in response to the tax. On the other hand, the model indicates that consumers with a low willingness to pay, who are more likely to purchase entry-level models, remain relatively unaffected.

The second part of the study utilizes the January 2023 VAT reform as a natural experiment, employing a linear probability specification with difference-in-differences to comprehensive Norwegian microdata. This approach involves a comparative analysis of changes in the adoption of electric vehicles between high- and low-income households before and after the reform. The design is derived from the theoretical model. The heterogeneous effects observed across groups enable the employment of low-income households as a control group, allowing for the estimation of the causal effects of the reform on high-income households. The impact of the policy cannot be directly observed due to the presence of other unobservable factors that may influence demand for electric vehicles. However, the difference-in-differences approach allows for the estimation of a counterfactual trend by exploiting differences in exposure to the tax reform. A simple before-and-after comparison between 2022 and 2023 would lead to a misinterpretation of the effects due to external factors, such as changing consumer preferences, macroeconomic fluctuations, or developments on the supply side. The difference-in-differences strategy is designed to address these issues by eliminating common shocks that impact both groups. While the control group may still be subject to influence, the theoretical model suggests that this would result in estimates that are biased toward zero. Consequently, the empirical results should be interpreted as conservative estimates of the actual impact of the reform. The analysis finds that following the VAT reform in January 2023, the probability of high-income households registering an electric vehicle fell by about six percentage points compared to low-income households. These results show that the reintroduction of VAT in the upper segment of the electric vehicle market redistributes equilibrium market shares and disproportionately affects high-income consumers, even if the general trend toward the adoption of entry-level electric vehicles continues.

The thesis is structured as follows. In Section 2, an overview of the theoretical foundations of horizontal and vertical product differentiation is provided, and the empirical literature on policy incentives for electric vehicles in Norway is summarized. In Section 3, the Norwegian market for electric vehicles is described, and the 2023 VAT reform is described in more detail. In Section 4, the theoretical discrete choice model of demand is introduced, and the results of numerical simulations are reported. In Section 5, the hypothesis derived from the theoretical framework is formalized. In Section 6, the data and the identification strategy are addressed. Section 7 presents the empirical results, and Section 8 discusses theoretical, policy implications, limitations, and future research directions.

2 Related Literature

This section first outlines the foundational theory of product differentiation, including both horizontal and vertical differentiation, in order to analyze consumer behavior. Following this, it reviews empirical studies on Norwegian electric vehicle incentives, focusing on those that use relevant frameworks to this thesis and providing broader context on the general impacts of electric vehicle policy in Norway.

2.1 Theoretical Frameworks of Product Differentiation

Theoretical literature provides essential frameworks to analyze markets characterized by heterogeneous consumer preferences and products. Key to this analysis are models distinguishing between horizontal and vertical product differentiation. Lancaster (1966) characteristic-based approach has shown that the utility of goods is not derived from them as undifferentiated objects, but rather from bundles of attributes, thus laying the foundation for formal differentiation models. In discrete choice settings, differentiation is usually divided into horizontal and vertical types (Belleflamme & Peitz, 2015, p. 112). Horizontal differentiation reflects individual consumer tastes, different buyers prefer different combinations of attributes. It was formalized by Hotelling (1929) spatial competition model, in which consumers incur “transportation costs” when product attributes deviate from their ideal point. d’Aspremont et al. (1979) refined this result by showing that, with quadratic transport costs and endogenous pricing, companies optimally position themselves at opposite ends of the product space (maximum differentiation), thus ensuring a price equilibrium. Vertical differentiation arises when products can be objectively evaluated according to their quality. Higher quality goods are preferred, but the willingness to pay for quality varies among consumers (Belleflamme & Peitz, 2015, p. 112). Jaskold Gabszewicz and Thisse (1979) formalized a duopoly model in which competing firms choose different quality levels to segment consumers by income, resulting in a high-quality product and a low-quality product, reducing price competition. Shaked and Sutton extended this insight by showing that endogenizing quality choice leads to a natural oligopoly, as only a few firms can coexist profitably when quality competition is included (Shaked & Sutton, 1982). Product differentiation reduces price competition. Firms with differentiated products that better match consumers' heterogeneous preferences have increased market power, reducing the incentives to compete on price. Differentiated markets tend to have higher prices and positive profits, even in markets with multiple competing firms (Belleflamme & Peitz, 2015, p.114-122). S. P. Anderson et al. (1992) have developed a discrete decision-making framework that jointly models horizontal and vertical product differentiation. Another model of multidimensional product differentiation, which takes quadratic transportation costs into account, is proposed by Neven and Thisse (1989).

2.2 Electric Vehicle Incentives

A large body of empirical literature applies established discrete choice modeling frameworks to evaluate the effects of policy interventions in various markets. Foundational work by S. T. Berry (1994), S. Berry et al. (2004), and Goldberg (1995) empirically demonstrated the applicability of these models in differentiated markets for the automobile industry. Recent studies have adopted structural discrete choice frameworks with random coefficients to assess electric vehicle policy incentives. For example, Johansen and Nielsen (2022) use Norwegian register data to show that electric vehicles complement rather than replace combustion vehicles and that VAT exemptions bring greater welfare gains for high-income households. Similarly, Springel (2021) highlighted the effectiveness of infrastructure incentives over purchase subsidies due to network effects. Cincotta and Thomassen (2025) demonstrated substantial declines in electric vehicle market shares upon removing tax exemptions. Further studies have adopted the random coefficients discrete choice framework to analyze differentiated product markets and policy impacts (Huse & Lucinda, 2014; Konishi & Zhao, 2017; Østli et al., 2017; Zhang et al., 2016).

Research by Halse et al. (2025) and Mersky et al. (2016) evaluates use-based incentives in comparison to infrastructure factors. Halse et al. (2025) linear probability model at the household level shows that toll exemptions and access to bus lanes in Norway have increased the adoption of electric vehicles in higher-income households, with wealthier households even purchasing additional vehicles, while poorer households have reduced their vehicle fleets, suggesting that these incentives may exacerbate inequality. Mersky et al. (2016), on the other hand, finds that the availability of charging infrastructure, income, and proximity to large cities are the strongest predictors of electric vehicle adoption, while toll and bus lane exemptions at the municipal level have no effect. Several studies highlight the reduction in purchase costs as a decisive factor. In a survey of EV owners, according to Bjerkan et al. (2016), over 80% of respondents cited reduced fixed costs, particularly tax exemptions, as the most important incentive, with lower-income households responding particularly to lower usage costs (toll and ferry exemptions). Figenbaum et al. (2015) also emphasizes that VAT and registration tax exemptions are essential for the economic competitiveness of electric vehicles, especially in urban areas where toll exemptions and bus lanes apply. In Oslo, Aasness and Odeck (2015) estimates that VAT/registration tax exemptions combined with toll-free roads, free parking, and ferries lead to annual savings of EUR 3,275 per vehicle, although congestion in bus lanes, lost toll revenue, and limited transferability outside contexts with clean electricity must be taken into account. Camara et al. (2021) shows that while high-income households achieve greater tax savings in absolute terms, lower-income households benefit more in relative terms, demonstrating that VAT and registration tax exemptions reduce regressivity and have promoted the uptake of electric vehicles across all income groups.

The quasi-experimental approach of Isaksen and Johansen (2025) is particularly relevant for this study. They estimate a threefold difference-in-difference study in Bergen that includes an increase in congestion charges with an exemption for electric vehicles. This created a strong local incentive for the adoption of electric vehicles. Their difference-in-differences analysis found that the adoption of electric vehicles increased significantly, but only in higher-income households. No response was observed in the lowest income group, raising concerns about distributional equity.

This thesis makes two significant contributions to the literature on electric vehicle policy. First, it develops a theoretical discrete choice model of demand that integrates both horizontal product differentiation with quadratic transport costs and vertical product differentiation according to S. P. Anderson et al. (1992) for four different vehicle types. This model simulates the equilibrium between prices and market shares under different VAT regimes. Second, the Norwegian VAT reform of January 2023 is treated as a natural experiment and analyzed using a difference-in-difference design based on extensive administrative microdata. Together, these approaches should provide insight into how fiscal policy affects consumer demand for electric vehicles through changes in the VAT.

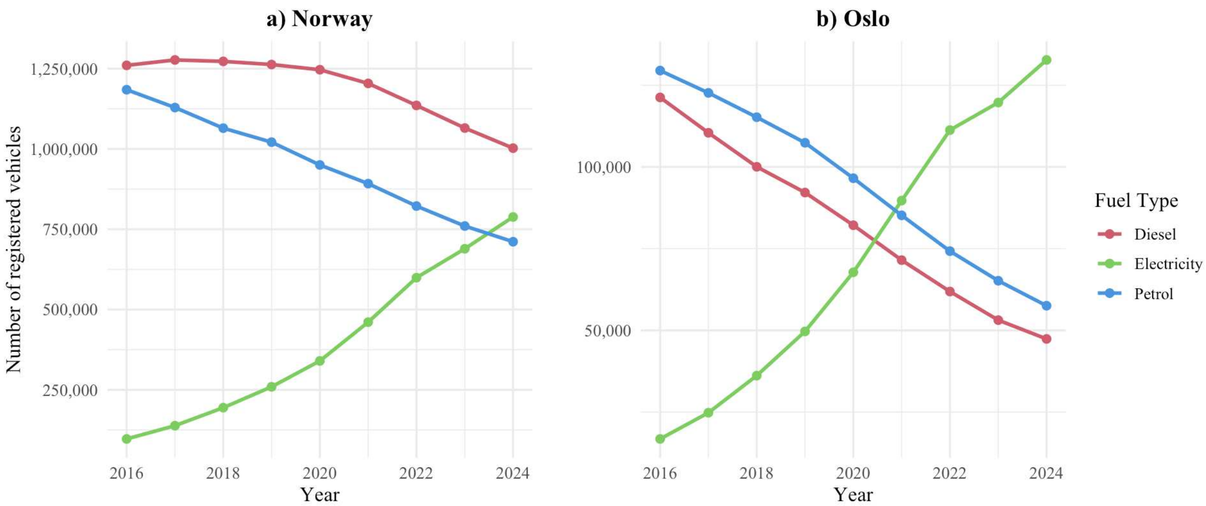
3 Background

According to the European Alternative Fuels Observatory's glossary, electric vehicles include battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs).[1] In this thesis, however, electric vehicles (EVs) refer exclusively to BEVs, vehicles powered solely by a rechargeable battery, so PHEVs and FCEVs are excluded. PHEVs do not qualify for the same VAT and purchase incentives as BEVs under current regulations. Internal combustion engine vehicles (ICEVs) are those powered by petrol or diesel combustion engines. This section offers a concise overview of the institutional background and relevant facts. Moreover, it characterizes the Norwegian EV consumer and addresses the development of EV adoption over time.

3.1 The Norwegian Electric Vehicle Trend and Incentives

Norway has established itself as the global leading nation in terms of EV adoption, with no other country having a higher number of EVs per capita (IPAC, 2022). As of 2025, 91.5% of newly registered passenger cars are zero-emission vehicles, and 29.9% of the total passenger car fleet is fully electric.[2]

Figure 1. Registered vehicles by fuel type and year in Norway and Oslo (2016-2024)



Notes: This graph uses the same fuel type definitions introduced at the beginning of this Section. This graph only considers private cars. After applying these filters to the Statistics Norway website, the obtained data is plotted in R. Data Source: Statistics Norway (SSB)

[1] Source: Glossary of the European Alternative Fuels Observatory
[2] Source: Norwegian Public Roads Administration; Updated status for zero emissions vehicles (2025)

Figure 1 illustrates this transition, showing a steady decline in diesel and petrol vehicles and a sharp rise in EV registrations, both nationally and in Oslo. In 2023, EVs exceeded petrol cars nationwide, while in Oslo, this occurred already by 2021. This development raises the question of how Norway was able to achieve such a rapid and comprehensive transition of its vehicle fleet. The following subsection provides an overview of the national incentive structures, as well as an overview of the VAT policy change.

To enable this rapid transition, national targets were set in 2017 and 2023 to ensure that all new passenger cars sold by 2025 and all new heavy duty vehicles sold by 2030 are zero emission (Norwegian Ministry of Transport and Communications, 2017). Norway introduced a comprehensive package of incentives focused on vehicle access, operating costs, infrastructure, and taxation. Since 2005, EV owners have been allowed to use bus lanes, although local restrictions have applied since 2016 (Norwegian Ministry of Finance, 2022). Free municipal parking was available until 2017. Road tolls and ferry fees were eliminated in 2009, with partial charges introduced in 2018 (capped at 50%) and increased to 70% in 2023 (Norwegian Ministry of Finance, 2022). Infrastructure related measures included the introduction of a legal right to install charging stations by households in 2017 (Norsk Elbilforening, 2024). Furthermore, Norway is committed to ensuring comprehensive coverage of fast charging infrastructure for the market development of EVs. Most areas are equipped with fast charging infrastructure, with around 9,846 charging stations available at present.[3] Fiscal incentives have also played an important role in reducing the purchase cost of electric vehicles. These included a reduced company car tax (2000-2022), VAT exemption for leasing contracts (from 2015), and full exemption from the annual road tax (1996-2021), registration tax (1990-2022), and VAT on vehicle purchases (2001-2022). As of 2023, a weight based purchase tax was introduced, and a 25% VAT is applied to the portion of the vehicle price exceeding NOK 500,000 (Norwegian Ministry of Finance, 2022).

As Figure 1 shows, this comprehensive incentive system appeared to be effective in promoting the introduction of EVs, but it also imposed a significant financial burden on the government. In 2022 alone, the revenue lost from the VAT exemption for EVs was estimated at NOK 13.4 billion (Norwegian Ministry of Finance, 2022). The exemption from registration tax accounted for a further NOK 10 billion, with additional losses from insurance tax and the taxation of company vehicles (Norwegian Ministry of Finance, 2022). Overall, the annual tax

[3]Source: Norsk Elbilforening; Number of charging stations in Norway in May 2025

expenditure associated with the EV incentive program is significant. In light of these growing fiscal pressures and the maturation of the EV market, the Norwegian government introduced the adjustment to the VAT regime starting on January 1, 2023.

3.1.1 The VAT Policy Change

The reform process for the VAT regime for EVs was initiated with the ”Hurdalsplatform”, the government's program for 2021–2025. The government proposed to impose the full VAT rate of 25% on the portion of the purchase price exceeding NOK 600,000. In the revised 2022 national budget, an alternative incentive scheme was proposed to compensate for the tax burden up to NOK 500,000. Parliament rejected this solution and instead agreed on June 14, 2022, to lower the exemption limit to NOK 500,000 while maintaining the zero tax rate below that amount. The change was implemented in the 2023 budget and took effect on January 1, 2023 (Norwegian Ministry of Finance, 2022). Since then, the purchase price up to NOK 500,000 has been exempt from VAT, with the regular rate of 25% applying above that amount.[4]

The primary environmental objective of the VAT exemption was to stimulate the uptake of EVs and reduce transport emissions in line with Norway's targets under the Paris Agreement (Norwegian Ministry of Finance, 2022). The reintroduction of VAT on the portion of the purchase price exceeding NOK 500,000 serves to maintain these climate benefits by sustaining the financial incentive for EVs up to this threshold. The objective is to normalize taxation as the EVs market matures (IPAC, 2022). This measure helps to maintain the price competitiveness of EVs in all segments up to NOK 500,000, while at the same time reducing subsidies for premium models and recovering part of the lost VAT government revenue (IPAC, 2022). By limiting the VAT exemption to consumption up to a threshold of NOK 500,000, environmental policy is aligned with financial sustainability. Continuous demand below this threshold also creates favorable market conditions for manufacturers and dealers on the supply side.

3.2 Who goes green?

Understanding who adopts EVs is crucial for evaluating the impact and effectiveness of EV incentives. This subsection outlines the main socioeconomic and demographic patterns identified

[4] NOK 500,000 equals approximately EUR 42,868.78, based on an exchange rate of 1 EUR = 11.6635 NOK from Norges Bank (23 June 2025). Source: Norges Bank. The average price for passenger cars from 2016 to 2023 (including fuel types according to the definition in Section 3) is NOK 473,588.9 (EUR 40,604.36) Data Source: Opplysningsrådet for veitrafikken (OFV)

in recent research on EV adoption.

The study by Yang et al. (2023) shows that higher income significantly increases the EV adoption rate, with each increase in median household income of NOK 100,000 increasing the EV adoption rate by 38.3%. EV uptake is lower in municipalities with a high proportion of elderly people, probably due to unfamiliarity with new technologies. EV ownership is higher in urban and suburban areas, where charging infrastructure supply is higher. Bjørge et al. (2022) points out that as the market has matured, the profile of EV owners has become increasingly similar to that of ICEV users. While early adopters tended to be innovation-driven, educated, and environmentally conscious, late adopters increasingly value affordability and everyday practicality. The study by Fevang et al. (2021) reinforces these findings. It finds that EV ownership increases with wealth, income, and education. EV owners tend to be between 25 and 44 years old, and families with children are more likely to own EVs. Higher education is correlated with EV ownership. Initially, early adopters differed significantly from ICEV owners, but this difference has narrowed over time as EVs have become more established. EV ownership is more concentrated in urban and suburban areas, mainly due to commuter benefits such as toll exemptions and access to bus lanes. In terms of vehicle characteristics, EVs with longer ranges are preferred, especially by people with medium commuting distances. They also find that larger EVs are often chosen by high-income households for their range and premium features, while smaller, more affordable EVs serve as entry-level models. Bauer (2018) also points out that early adopters often purchased EVs as additional vehicles rather than replacement vehicles, especially in larger households, which raises the possibility of ecological rebound effects. Overall, earlier studies have shown similar results and specifically highlight the effectiveness of incentives (Figenbaum et al., 2015). However, Yang et al. (2023) suggests that recent reductions in Norwegian EV incentives might influence adoption, particularly given the persisting role of income.

4 Model

The introduction of a VAT exemption threshold of NOK 500,000 has two potential significant implications on the vehicle market. First, premium EVs above this threshold will lose their full tax exemption, reducing their price advantage over ICEVs. As a result, high-income consumers who previously favored premium EVs could either switch to cheaper electric alternatives or return to ICEVs entirely. Second, electric models below the threshold remain completely exempt from VAT, allowing them to retain their competitive advantage over ICEVs and remain attractive, particularly to consumers with a strong preference for electric technology. To assess the overall impact of this policy adjustment on demand for EVs rigorously, it is crucial to incorporate both substitution channels into a comprehensive analytical framework. A theoretical model is needed that takes into account vertical differentiation (consumers' willingness to pay (WTP) for high-priced (quality) models) and horizontal differentiation (fundamental preferences for EVs over combustion engines). Such a model allows precise predictions about shifts in market shares across heterogeneous consumer segments due to changes in VAT regimes.

4.1 Integrating Horizontal and Vertical Differentiation

The market consists of four producers, distinguished by both product quality and location along a Hotelling line. Two high-quality producers (H) and two low-quality producers (L) are symmetrically positioned at $x = 0$ and $x = 1$, following the maximal differentiation principle (d'Aspremont et al., 1979).

The total mass of consumers is normalized to 1. Consumers are uniformly distributed along the Hotelling line, with their exogenously determined location $x \in [0, 1]$ representing their preference for product type. The products (firms) are positioned at $j \in \{0, 1\}$, where consumers located closer to $x = 0$ exhibit a stronger preference for ICEVs and experience a disutility of τx^2 when opting for EVs. Conversely, consumers nearer to $x = 1$ prefer EVs but incur a disutility of $\tau(1 - x)^2$ if they choose an ICEV. This horizontal differentiation is formalized through the term $\tau(x - j)^2$, which quantifies the disutility associated with selecting a product that deviates from a consumer's intrinsic preference.

Vertical differentiation in this market is characterized by product quality levels s_i, where high-quality products (s_H) provide greater value than low-quality alternatives (s_L), with $s_H > s_L$. While all consumers acknowledge the superiority of higher-quality products, they differ in their WTP for quality. This heterogeneity is represented by the parameter θ, which follows a uniform distribution over the interval $[\theta_{\min}, \theta_{\max}]$. A higher value of θ corresponds to a stronger preference for quality, which is typically associated with higher income levels (Zhang et al., 2016). Consequently, vertical differentiation introduces an additional dimension of income-based heterogeneity, as consumers differ in their ability to pay for higher-quality products.

This leads to the notation $i \in \{H, L\}, j \in \{0, 1\}$, where i indexes product quality ($H =$ high, $L =$ low) and j indexes vehicle type ($0 =$ ICEV, $1 =$ EV). Consumer decision-making is modeled as a discrete choice problem under unit demand, where each consumer selects exactly one unit of a product available in the market. The utility function governing these choices is given by,

$$V_{ij}(x,\theta) = R + \theta s_i - p_{ij} - \tau(x-j)^2 \tag{1}$$

where R denotes the baseline utility derived from purchasing any product, θs_i captures the interaction between consumer preference θ and product quality s_i, p_{ij} represents the price of a product with quality i at location j, and $\tau(x-j)^2$ accounts for the disutility arising from spatial mismatch between the consumer's location and the product's position along the Hotelling line (S. P. Anderson et al., 1992; Neven & Thisse, 1989). A consumer will purchase a product only if the resulting utility is strictly positive ($V_{ij}(x,\theta) > 0$). It is assumed that the baseline utility R is sufficiently large to ensure full market participation, whereby all consumers choose to purchase a product. This framework captures the interplay between horizontal and vertical differentiation, demonstrating how both spatial and quality-based considerations influence consumer preferences.

4.2 Probabilistic Choice and the Multinominal-Logit

Following the deterministic utility framework in Equation (1), each consumer selects the product that provides the highest utility (see Appendix B). This assumption implies that two consumers with identical observable characteristics will always make the same choice. However, real-world consumer behavior deviates from this rigid assumption, as unobserved factors influence decision-making. Consumers may perceive product quality differently, even when presented with the same product attributes, due to subjective factors or personal biases. To account for these variations in consumer behavior, I introduce a probabilistic choice model, which leads to a system of multinomial logit demand equations.

4.2.1 Demand

Building on the deterministic utility function from Equation (1), I incorporate randomness through an additive error term, such that,

$$U_{ij} = V_{ij} + \varepsilon_{ij}$$

where V_{ij} represents the observable utility, while ε_{ij} captures unobserved factors influencing consumer preferences. The utility reflects the preference of a specific subgroup for a given product and is defined as:

$$U_{ij}(x, \theta) = R + \theta s_i - p_{ij} - \tau(x - j)^2 + \varepsilon_{ij} \tag{2}$$

The VAT regimes are captured as a tax charged as a fixed percentage of the transaction price. Since VAT is normally charged as a constant percentage of the sales value and therefore naturally takes the form of a simple multiplicative surcharge. Three VAT regimes are going to be considered. Under Case 1, no vehicles face VAT. In Case 2, only ICEVs incur the 25% tax, and the price including VAT is defined as follows:

$$p_{ij}^{\text{VAT}} = \begin{cases} (1+t)\, p_{ij}, & ij \in \{H0, L0\}, \\ p_{ij}, & \text{otherwise,} \end{cases}$$

In Case 3, VAT applies to all ICEVs and to high-quality EVs, while low-quality EVs remain exempt. Similarly, the price including VAT is defined as:

$$p_{ij}^{\text{VAT}} = \begin{cases} (1+t)\, p_{ij}, & ij \in \{H0, H1, L0\}, \\ p_{ij}, & \text{otherwise.} \end{cases}$$

Substituting for the specific cases into (2) gives

$$U_{ij}(x, \theta) = \underbrace{R + \theta\, s_i - \; (1+t)\, p_{ij} - \; \tau\, (x - j)^2}_{V_{ij}} + \varepsilon_{ij} \tag{3}$$

In the Norwegian reform, the 25% VAT applies only to the portion of each vehicle's price above the 500,000 NOK exemption threshold (Norwegian Ministry of Finance, 2022). Accurately modeling this would require endogenizing the VAT base. Making each firm's optimal price choice directly determine how much of its own sales lie above the tax-free cutoff. This introduces a nonlinear fixed-point in the pricing equilibrium. To keep the analysis tractable, instead the simpler assumption that VAT behaves like a uniform surcharge on the entire price is applied.

To ensure a well-defined probabilistic choice model, it is assumed that the unobserved component of utility, ε_{ij}, follows an independently and identically distributed (i.i.d.) double exponential distribution (Belleflamme & Peitz, 2015, p.128). A parameter λ captures the relative weight of observable utility differences versus unobserved taste shocks. When λ is near zero, choices are essentially random (uniform across all goods), whereas as λ grows large consumers almost certainly pick the product with the highest utility (Figure 6 Appendix B). Given the assumption about the random component in the utility function ε_{ij}, the probability that a consumer with given characteristics, denoted by the variables x and θ, selects a specific product is analytically tractable. This is expressed as follows:

$$Pr_{ij}(x,\theta) = \frac{\exp(\lambda V_{ij}(x,\theta))}{\sum \exp(\lambda V(x,\theta))} \tag{4}$$

This formulation corresponds to the multinomial logit model, where the denominator normalizes the probability distribution by summing over all available products, ensuring that the probabilities sum to one.[5] To determine the aggregate demand for a given product, I integrate the individual choice probability over the entire consumer population, characterized by the distributions of x and θ capturing both horizontal and vertical differentiation. The location parameter x is uniformly distributed over the interval $[0, 1]$, implying a density function of:

$$f(x) = 1, \quad x \in [0, 1]$$

Similarly, the WTP parameter θ follows a uniform distribution over $[\theta_{\min}, \theta_{\max}]$, with the corresponding density function:

$$g(\theta) = \frac{1}{\theta_{\max} - \theta_{\min}}, \quad \theta \in [\theta_{\min}, \theta_{\max}]$$

The total demand D_{ij} for a specific segment is then obtained by integrating this probability over the entire population:

$$D_{ij} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{ij}(x,\theta))}{\sum \exp(\lambda V(x,\theta))} f(x) g(\theta)\, d\theta\, dx \tag{5}$$

Substituting the density functions (4) and (5) into expression (6) yields:

[5] $\sum \exp(\lambda V(x,\theta)) = \exp(\lambda V_{H1}) + \exp(\lambda V_{H0}) + \exp(\lambda V_{L1}) + \exp(\lambda V_{L0})$; This notation is used throughout the thesis.

$$D_{ij} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{ij}(x,\theta))}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V(x,\theta))} \, d\theta \, dx \tag{6}$$

The factor $\frac{1}{\theta_{\max} - \theta_{\min}}$ ensures proper weighting of the integration over the whole population's WTP. The resulting expression, D_{ij}, represents the aggregated demand or market share for each segment.

4.2.2 Supply

In a horizontally and vertically differentiated market, firms set prices strategically to maximize their profits. The profit function for each firm representing a segment is given by;

$$\Pi_{ij} = (p_{ij} - c_{ij}) D_{ij} \tag{7}$$

where p_{ij} represents the price of the product and c_{ij} denotes the marginal production cost. Substituting the demand function (7) into the profit equation yields:

$$\Pi_{ij} = (p_{ij} - c_{ij}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{ij}(x,\theta))}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V(x,\theta))} d\theta \, dx \tag{8}$$

This formulation explicitly accounts for the way firms' pricing decisions influence total demand, integrating consumer heterogeneity with respect to both vehicle type preferences and willingness to pay for quality. Differentiating the profit function with respect to the product's price, firms maximize profits by selecting prices that satisfy the first-order condition (see Appendix A):

$$D_{ij} + (p_{ij} - c_{ij}) \frac{\partial D_{ij}}{\partial p_{ij}} = 0$$

Rearranging for the optimal price would lead to:

$$p_{ij}^* = c_{ij} - \frac{D_{ij}}{\frac{\partial D_{ij}}{\partial p_{ij}^*}} \tag{9}$$

This expression states that the optimal price equals marginal cost plus a markup term that depends on the price sensitivity of demand.[6] In the case of a standard multinomial logit model, where demand is simply the aggregate of probabilistic choices, a closed-form pricing formula

[6]Since $\frac{\partial D_{ij}}{\partial p_{ij}} < 0$, (see Appendix A.4), the entire fraction becomes negative and is therefore added to marginal costs.

exists. The equilibrium price follows an inverse-elasticity rule, and the markup is determined by market share and consumer price sensitivity (S. Anderson & de Palma, 1992; S. T. Berry, 1994). However, the introduction of consumer heterogeneity, as in mixed logit models, complicates the possibility of a closed-form solution. The demand function becomes an integral over a distribution of preferences, requiring numerical methods for solving the first-order conditions (S. Berry et al., 1995; Nevo, 2001; Zhang et al., 2016). Because the demand function does not simplify analytically, the optimal pricing condition must be computed numerically. In the underlying case, it is achieved through symbolic differentiation and numerical solvers, such as `vpasolve` in MATLAB, to determine the optimal prices $p^*_{H1}, p^*_{H0}, p^*_{L1}, p^*_{L0}$.

4.3 Numerical Results

Because firms compete strategically, the resulting equilibrium prices emerge from a Nash equilibrium, where each firm maximizes its profit while considering the pricing decisions of its competitors. The equilibrium condition satisfies

$$p^*_{ij} = \arg\max_{p_{ij}} \Pi_j(p_{H1}, p_{H0}, p_{L1}, p_{L0}),$$

such that no firm has an incentive to unilaterally deviate from its chosen price. The existence and uniqueness of a Nash equilibrium in pricing under logit demand is, for example, established in the models by S. P. Anderson et al. (1992). As price equilibria may not always be unique or well-behaved, requiring numerical iteration or simulation-based estimation techniques (Hanson & Martin, 1996). By integrating these dimensions, the model reflects competitive dynamics in differentiated markets, while also highlighting the computational challenges introduced by consumer heterogeneity.

To compute the optimal prices, the following parameters are specified. The quality levels are set to $s_H = 0.7$ and $s_L = 0.2$.[7] Marginal costs are set based on the estimates provided in Goldberg (1995), with $c_{H1} = c_{H0} = 0.35$ and $c_{L1} = c_{L0} = 0.1$.[8] The miss-matching parameter is set to $\tau = 1$, consistent with standard assumptions in the literature, while the baseline utility level is normalized to $R = 1$, and $\lambda = 4$ (S. P. Anderson et al., 1992; Neven & Thisse, 1989).

[7] Quality parameters are derived from OFV vehicle registration market data, corresponding to the 10th and 90th price percentiles, respectively. To normalize prices are divided by 1,000,000 NOK. Data Source: Opplysningsrådet for veitrafikken (OFV)

[8] See Table 4 in Goldberg (1995). Marginal costs are approximated for the compact and luxury vehicle categories and represent approximately 50% of the vehicle price. To reflect this, 50% of the 10th and 90th percentiles from the OFV market data are used.

The WTP distribution is defined between $\theta_{\min} = 0.2$ and $\theta_{\max} = 2.2$.[9]

The theoretical discrete choice model provides clear predictions of how targeted VAT changes will affect market shares and firm profits in different consumer segments. Table 1 summarizes the equilibrium results under three regimes:

Table 1. Numerical results from MATLAB model for $\lambda = 4$, grouped by cases.

Product	**Price**	**Consumer Price**	**Demand**	**Top 10%**	**Bottom 10%**	**Profit**
Case 1: No VAT applied						
H1	0.7034	0.7034	0.3570	0.2379	0.0876	0.1262
H0	0.7034	0.7034	0.3570	0.2379	0.0876	0.1262
L1	0.3985	0.3985	0.1430	0.0121	0.1624	0.0427
L0	0.3985	0.3985	0.1430	0.0121	0.1624	0.0427
Case 2: VAT applied on ICEV						
H1	0.9136	0.9136	0.3360	0.2438	0.0679	0.1894
H0	0.7745	0.9682	0.2978	0.2186	0.0587	0.1264
L1	0.5050	0.5050	0.1857	0.0189	0.1905	0.0752
L0	0.4268	0.5335	0.1805	0.0188	0.1828	0.0590
Case 3: VAT applied on ICEV & high-quality EV						
H1	0.7771	0.9714	0.3078	0.2301	0.0584	0.1315
H0	0.7805	0.9756	0.3079	0.2287	0.0591	0.1326
L1	0.5188	0.5188	0.1967	0.0212	0.1951	0.0824
L0	0.4292	0.5365	0.1876	0.0200	0.1874	0.0617

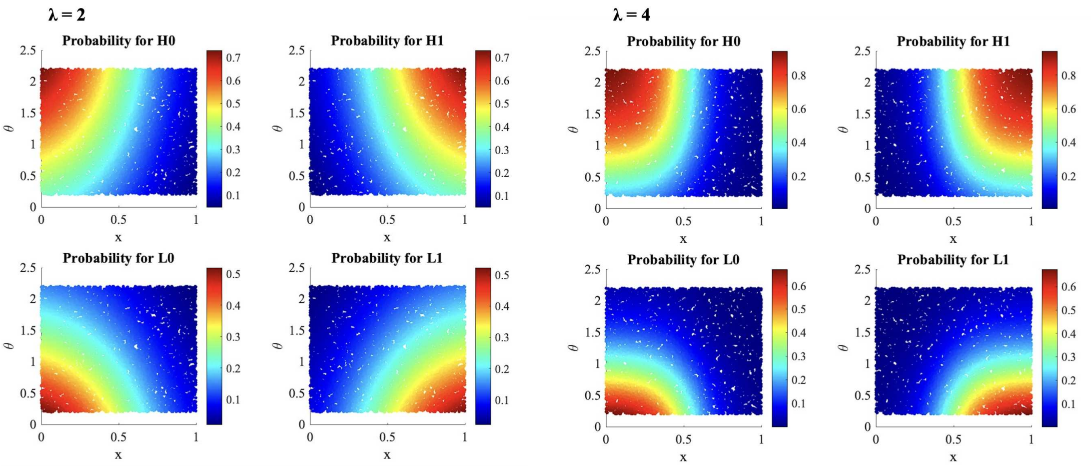
Notes: Parameter values are $R = 1$, $\lambda = 4$, $\tau = 1$, $s_H = 0.7$, $s_L = 0.2$, $\theta \sim U[0.2, 2.2]$. Marginal costs $c_{H1} = c_{H0} = 0.35$, $c_{L1} = c_{L0} = 0.1$, VAT rate $t = 0.25$. Equilibrium prices p^*_{ij} are found by numerically solving the four first order conditions with MATLAB's `fsolve`, using as initial guess the $\lambda = 2$ price equilibrium solution obtained via `vpasolve`. Top 10% and Bottom 10% refer to consumers in the 90th and 10th percentiles of the WTP distribution, respectively, computed as: $\theta_{90} = \theta_{\min} + 0.9 \cdot (\theta_{\max} - \theta_{\min})$, $\theta_{10} = \theta_{\min} + 0.1 \cdot (\theta_{\max} - \theta_{\min})$. (MATLAB Code: Appendix Section A)

In the baseline scenario without VAT, consumer prices in the respective quality segments are identical in equilibrium. Consequently, households with high WTP are distributed across

[9] These values correspond to the 10th and 90th percentiles of the household income distribution, divided by 1,000,000 NOK. It is assumed that the WTP is scaled by annual household income (Zhang et al., 2016). Household income data is sourced from Norwegian microdata. Data Source: microdata.no.

premium electric vehicles and premium combustion vehicles, each accounting for 23.79% of the top 10% segment of consumers. In contrast, households with lower incomes (bottom 10% of the WTP distribution) predominantly choose lower-quality products (L1 and L0), which each achieve a market share of 16.24% in this segment, revealing a clear income-based sorting pattern. The choice probabilities shown in Figure 2 visualize these results and indicate different patterns of consumer segmentation across two values of λ ($\lambda = 2$ and $\lambda = 4$).[10] Consumers at the upper end of the WTP distribution are significantly more likely to choose high-quality vehicles, while households with lower WTP predominantly choose low-quality segments. This segmentation illustrates clear and rational behavior that is consistent with the assumptions underlying the vertical differentiation in the model.

Figure 2. Choice probabilities for all products without VAT applied by $\lambda = 2$, $\lambda = 4$



Notes: Choice probabilities are computed for N = 10,000 simulated consumers with $x \sim U[0,1]$ and $\theta \sim U[0.2, 2.2]$. Parameter values are set to $R = 1$, $\lambda = 2$ and $\lambda = 4$, $\tau = 1$, $s_H = 0.7$, and $s_L = 0.2$, using prices from Table 1 and 7. Visualization of Equation (4).

The introduction of a targeted 25% VAT on combustion engines alone significantly changes relative pricing, increasing consumer prices for H0 from 0.7034 to 0.9682 and for L0 from 0.3985 to 0.5335. The price increase is significant enough to alter market dynamics. As a result, demand is shifting toward EVs, with high-end EVs seeing an increase in demand from 23.79% to 24.38% in the top decile and lower quality EVs a small increase from 1.21% to 1.89%. As a result, the overall share of electric vehicles in this affluent consumer segment is rising to 26.27%, reflecting a horizontal substitution effect.

[10]Increasing λ sharpens the segmentation: Consumers react more strongly to utility differences and less to random taste shocks, resulting in more distinct clusters in the choice probability patterns. For a more extreme case; see Appendix B, Figure 6.

The extension of VAT to high quality EVs in Case 3 marks the central policy change of interest in this analysis. The consumer price for premium EVs increases from 0.9136 to 0.9714, leading to an overall EV demand decline, even though demand for low-end EVs (L1) increases slightly. However, this increase is not enough to offset the decline in premium EV demand. Most notably within the highest income segment. The premium EV market share among the top decile decreases from 24.38% to 23.01%. While low quality EV share slightly increases from 1.89% to 2.12%. Overall, total EV share within this group drops by 1.14 percentage points to 25.13%, reversing the positive adoption trends established under the previous VAT regime. Lower WTP households, already concentrated in low quality segments, experience minimal shifts in purchasing behavior, reflecting their limited exposure to premium products. Nevertheless, the overall EV adoption in this segment also declines marginally by 0.49 percentage points, indicating slight spillover effects. Firms' profit also adapts to these changes. Premium EV producers experience a notable profit reduction from 0.1894 to 0.1315, underscoring the acute financial impact of the targeted VAT extension. In contrast, profits in the other segments recover, highlighting how narrowly targeted fiscal policies can substantially alter market equilibrium. Despite relatively small absolute changes in demand shares, the model shows consistent patterns of behavior across all WTP groups under different parameter specifications (Table 2):

Table 2. EV demand changes (Case 2 $\rightarrow$ Case 3) by parameter specification

	Top 10% EV			**Bottom 10% EV**			**DiD Estimator**
Specification	C2→C3	Δ abs	Δ rel	C2→C3	Δ abs	Δ rel	$\Delta^{\text{Top}} - \Delta^{\text{Bottom}}$
$\lambda = 2, \tau = 1$	0.2623→0.2510	–0.0113	–4.31%	0.2586→0.2526	–0.0060	–2.32%	–0.0053
$\lambda = 4, \tau = 1$	0.2627→0.2513	–0.0114	–4.34%	0.2584→0.2535	–0.0049	–1.90%	–0.0065
$\lambda = 6, \tau = 1$	0.2636→0.2513	–0.0123	–4.67%	0.2587→0.2539	–0.0048	–1.86%	–0.0075
$\lambda = 4, \tau = 8$	0.2519→0.2505	–0.0015	–0.60%	0.2514→0.2505	–0.0009	–0.36%	–0.0006
$\lambda = 4, \tau = 0.5$	0.2678→0.2510	–0.0168	–6.27%	0.2612→0.2551	–0.0061	–2.34%	–0.0107

Notes: For each specification, EV share = $(D_{H1} + D_{L1})$. Δ abs = EV share (Case 3) – EV share (Case 2). Δ rel = Δ abs / EV share (Case 2) × 100%. The Difference-in-Differences (DiD) estimator is calculated as: DiD $=$ (EV Share$_{\text{Top 10\%},C3}$ $-$ EV Share$_{\text{Top 10\%},C2}$) $-$ (EV Share$_{\text{Bottom 10\%},C3}$ $-$ EV Share$_{\text{Bottom 10\%},C2}$); For the formula, see Gertler et al. (2016) Results for other Specifications in 8. Consumers with high WTP (Top 10%) react more strongly to the VAT reform, as they are more exposed to taxed premium EVs. The magnitude of this response increases with more deterministic choice behavior (λ) and greater substitutability between EVs and ICEVs (lower τ). The theoretical DiD estimator is negative across all specifications, indicating a consistent reduction in EV demand among high-WTP consumers.

First, the simulations systematically show a heterogeneous tax impact. Consumers with high WTP respond with a stronger decline in demand for EVs when VAT is extended to premium EVs. Furthermore, the parameter λ, which regulates the determination of choice, drives the degree of behavioral adjustment. As λ increases, consumers place more weight on differences in utility, leading to stronger selection. In particular, households with high WTP reduce their demand more significantly as λ increases, suggesting that behavioral responses to VAT increase when choices are more deterministic. At high τ values, consumers are less willing to switch between EVs and combustion engine vehicles, thereby reducing the impact of price changes caused by VAT. Lower τ values, on the other hand, allow for greater substitution, thereby amplifying the behavioral response to taxation. Finally, households with low WTP are not completely unaffected. For all parameter combinations, a certain decline in the share for EVs can be observed in the lowest percentiles, indicating a moderate but not negligible impact.

These findings presented establish a theoretical foundation for the hypothesis developed in the following section and tested in Section 6.

5 Hypothesis

The central research question of this thesis is whether tax incentives influence the demand for EVs. Despite the fact that such incentives are generally considered an effective measure for influencing consumer behavior, their actual impact is not straightforward. The theoretical model developed in this thesis demonstrates that consumers may have strong, anchored preferences for certain types of vehicles (EVs or combustion engines) or quality. In such cases, their response to price changes resulting from tax reforms is limited (Table 2). Concurrently, the model anticipates that the reintroduction of VAT on high-priced electric vehicles will result in a decline in demand for EVs. Households with a high WTP are particularly affected, as they typically demand premium EVs that are no longer tax exempt. However, it should be noted that not all consumer groups respond in a uniform manner; the overall effect is dependent upon the distribution of preferences and price sensitivity within the population. These considerations give rise to the central hypothesis of this paper:

- The reintroduction of value-added tax on high-priced electric vehicles is expected to result in a decline in the share of newly registered EVs.

While the theoretical model provides concrete directional implications regarding the effect, these are not directly observable in the data. A variety of unobservable factors concurrently influence the development of EV demand. Consequently, a simple before and after comparison would not be empirically reliable. In order to identify the causal effect of the tax reform in a credible way, a difference-in-differences approach is employed. The heterogeneity of the response predicted in the model, stronger among households with a high WTP, makes it possible to use the reform as a natural experiment. Low-income households function as a control group. Although this group may not be completely unaffected, the theoretical framework implies that any exposure to the treatment in the control group biases the estimated effect downward. As a result, the difference-in-differences estimate is likely to understate the true causal impact of the VAT reform. The empirical strategy offers a conservative, yet theory-consistent test of the hypothesis, ensuring that any estimated effect is a credible lower bound on the true policy impact.

6 Data and Methods

This section provides an overview of the data as well as the empirical strategy and identification.

6.1 Data

This thesis utilizes microdata from version 39 (25-03-21) of the microdata.no platform, which offers extensive access to Statistics Norway's administrative registers.[11] The database contains a wide range of demographic and socioeconomic variables, as well as vehicle-related information for Norwegian individuals and households.

The analysis is constrained to vehicles owned by private households.[12] The dataset contains only passenger cars; in order to control for this, filtering was performed. The classification system is based on the coding system from the vehicle register of the Norwegian Road Administration. It allows for the exclusion of non-passenger vehicles, such as vans, lorries, and trailers. The dataset is structured as panel data across multiple years. The selection of control variables was determined by their availability and consistency over time, which defines the observation window from 2016 to 2023. At the time of analysis, vehicle-level data for the year 2024 were not available. Observations containing missing values were omitted in order to ensure data quality and comparability. The dataset incorporates technical vehicle attributes that

[11] Data Source: microdata.no. The analysis is performed using the analysis tool from microdata.no.

[12] It should be noted that leased vehicles, are excluded from the sample. Only vehicles registered to private households are included, ensuring that all observations reflect household-owned cars (Johansen & Nielsen, 2022).

are relevant for environmental characteristics and vehicle usage. This dataset exclusively includes vehicles of the fuel types petrol, diesel, and electric, in line with the definition in Section 3. The variable capturing fuel consumption measures the vehicle's fuel usage in liters per 10 kilometers (l/10km). Carbon dioxide emissions are measured in grams per kilometer (g/km). Further technical specifications comprise the vehicle length (cm) and weight (kg). This refers to the vehicle's fully operational weight in kilograms (kg).

In order to establish the link between vehicle and household, individual personal data is aggregated at household level and then merged with vehicle panel data. This is possible due to a unique identifier, combining the vehicle's licence plate number and the owner's date of birth. Each vehicle is thus associated with household characteristics. Household key variables are: Income, major city, maximum education level, number of persons in the household as well as the household's average age. The income variable captures a broad definition of annual income, including salary income, cash wages, and taxable benefits for the entire calendar year. The goal is to sort households into low-income and high-income groups based on their ability to pay for a vehicle. Therefore, the variable captures the total household income. The variable major city reflects the official residence in one of the biggest cities: Oslo, Bergen, Stavanger, and Trondheim. Educational level is defined as not completed secondary, secondary education, lower academic education, higher academic education, and research education. After merging the datasets, a dataset with a total amount of 2,072,221 observations is obtained.

6.2 Descriptives

Table 3 provides a clear overview of how the demographic profile of households that registered EVs differs from those that registered combustion engine vehicles between 2016 and 2023.[13] In 2016, households that registered EVs were slightly younger (average age 42.0 compared to 51.8), better educated (maximum level of education 3.18 compared to 2.75), more concentrated in large cities (31% compared to 19%), and wealthier (average income NOK 1.5 million compared to NOK 1.04 million) than households that registered ICEVs. By 2023, these differences had decreased. Households registering EVs were still younger than those registering ICEVs (40.6 vs. 44.5 years), but the age gap had narrowed notably. Educational level and urban residence continued to be factors associated with EV registration, but to a smaller extent. Average

[13] Each vehicle observation is linked to the household that registered it. An EV-registered (or ICEV-registered) vehicle refers to a vehicle of this type, along with demographic information that reflects the household that owns it. A household can register both EVs and ICEVs and therefore appear in both groups.

incomes had converged slightly. In terms of vehicle characteristics, ICEVs still emitted around 131 g/km of CO2 and consumed around 0.5 l/km. EVs became larger and heavier over time, which might indicate the introduction of premium models (Fevang et al., 2021).

Table 3. Household and vehicle characteristics by EV and ICEV registration (2016–2023)

	EV-registered				ICEV-registered			
Variable	**2016**		**2023**		**2016**		**2023**	
Demographics	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
Number of persons	3.25	1.22	2.98	1.25	2.64	1.23	2.73	1.28
Max. education level	3.18	0.89	3.01	0.90	2.75	0.98	2.68	0.93
City dummy (major city = 1)	0.31	0.46	0.27	0.44	0.19	0.39	0.14	0.35
Mean age household	42.0	15.11	40.65	15.89	51.83	17.09	44.54	17.40
Household income (NOK)	1,500,020.85	855,305.24	1,310 898.17	770,302.94	1,036,221.65	770,800.01	1,017,208.64	666,596.99
Vehicle characteristics	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
Fuel consumption (l/km)	0.00	0.00	0.00	0.00	0.54	0.08	0.49	0.16
CO_2 emissions (g/km)	0.00	0.00	0.00	0.00	132.62	19.12	131.20	20.22
Vehicle length (cm)	428.09	34.97	451.87	30.43	451.34	29.33	452.24	29.52
Vehicle weight (kg)	1,992.33	337.01	2,363.14	405.51	2,068.18	341.68	2,077.97	322.75

Notes: Maximum education level is defined as the highest recorded education level among household members. Education levels are coded as follows: 1 = Not completed secondary, 2 = Secondary education, 3 = Lower academic education, 4 = Higher academic education (master level), 5 = Research education. Household income refers to the total annual income aggregated across all members of the household. Statistics refer to vehicles registered as EVs or ICEVs and the characteristics of the households to which they are registered. Code: Appendix Section C.

To quantify the patterns in Table 3, separate logit models for 2016 and 2023 are estimated. The logit model is appropriate for binary outcomes, mapping a linear index of covariates to probabilities using the logistic function. Coefficients in this model represent changes in the log-odds of the outcome associated with a one-unit increase in each covariate. When exponentiated, these coefficients yield odds ratios that describe the multiplicative change in the odds of the outcome (Cameron & Trivedi, 2005, p.470). Robust standard errors are used to ensure valid inference in the presence of potential heteroskedasticity.

In 2016, all covariates are statistically significant at the 1% level. Holding all else constant, a one unit increase in the log of income increases the odds of registering an EV by about 22% (OR$\approx$ 1.22).[14] Each additional education level increases the odds by 23%, and residence in a major city almost doubles the odds (OR$\approx$ 1.98). By contrast, a one–year increase in mean household age lowers the odds (OR$\approx$ 0.99), while an extra household member has a

[14]Income is in log form to account for the non-linear relationship between income and EV adoption.

modest positive effect (OR≈ 1.12). By 2023, income, education, and age remain statistically significant at the 1% level, but their estimated odds ratios move closer to one (e.g., the income OR declines to 1.11), indicating weaker relative effects on EV registration. The city variable becomes insignificant, and the effect of household size is no longer statistically significant, suggesting no systematic relationship in 2023.

Table 4. Logit regression results for EV registration in 2016 and 2023

	d_electric_car	
	(1) 2016	(2) 2023
num_pers	1.1225***	0.9502
	(0.0083)	(0.0445)
mean_age	0.9882***	0.9877***
	(0.0006)	(0.0033)
max_education_level	1.2270***	1.5012***
	(0.0116)	(0.0712)
log_income	1.2175***	1.1109***
	(0.0127)	(0.0374)
city	1.9792***	1.0422
	(0.0386)	(0.0997)
Constant	0.0126***	13.7587***
	(0.0018)	(8.5432)
Observations	91,267	60,130
Prob > chi2	0.00	0.00
Pseudo R^2	0.0576	0.0255

Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Notes: This table reports odds ratios from a logistic regression model. The coefficients reflect the multiplicative change in the odds of owning an EV associated with a one unit change in each covariate. The number of observations is based on vehicles registered in the corresponding year 2016 or 2023. The dependent variable is d_electric_car = 1 for EV and 0 for ICEV. Note that Pseudo-R^2 can be artificially low or high in logistic models, so Prob $> \chi^2$ is reported to evaluate the model's fit Source: microdata.no. Code: Appendix Section C.

Because odds ratios describe relative effects only, Table 9 (Appendix B) presents average marginal effects to quantify how covariates shift the probability of EV registration. In 2016, a one-unit rise in the log of income increases the probability of registering an EV by 1.3 percentage points, and each additional education level by 3.6 percentage points. Residence in a major city adds about 12 percentage points. In 2023, the same changes raise the probability by only 0.11 percentage points for income and 0.44 percentage points for education, while the city effect is not significant. The sharp contraction of these average marginal effects might underscore that, as the EV market matured, the practical influence of traditional socioeconomic drivers, income, education, and urban residence became much weaker.

Overall, the estimates give positive links between income, education, and urban residence and EV ownership, and negative links for age and household size in accordance with the literature discussed in Section 2.2 (Fevang et al., 2021; Figenbaum et al., 2015; Yang et al., 2023).

6.3 Empirical Strategy and Identification

To quantify the causal effect of Norway's VAT reform implemented in January 2023, I employ a difference in differences (DiD) estimation design. This quasi-experimental approach allows to compare the probability of registering an EV between high- and low-income households before and after the reform.

While a simple comparison of demand for EVs before and after the reform might appear to be a suitable initial approach, it is not a reliable method of assessing the causal effect of the reform. This limitation is due to the fact that other factors may also influence EV demand. Such factors might include the general state of the economy, technological advancements, changing consumer preferences, or a broader range of government incentives. The DiD framework is particularly useful for the analysis of policy changes (Angrist & Pischke, 2009, p.169);(Cameron & Trivedi, 2005, p.768). It includes both a treatment group (affected by the policy change) and a control group (not affected by the policy change) (Angrist & Pischke, 2009, p.170). By comparing the changes in outcomes between these two groups over the same period, DiD estimator effectively controls for external factors that could affect both groups simultaneously.

Preliminary theoretical analyses and model calculations suggest that high income households are likely to be most affected by the VAT reform due to their higher probability of purchasing high quality EVs, which are subject to VAT change (Table 2). It therefore appears reasonable to focus on high income households in order to identify the specific effects of the VAT reform. In order to control for these external factors that influence demand, low income households are used as a control group.

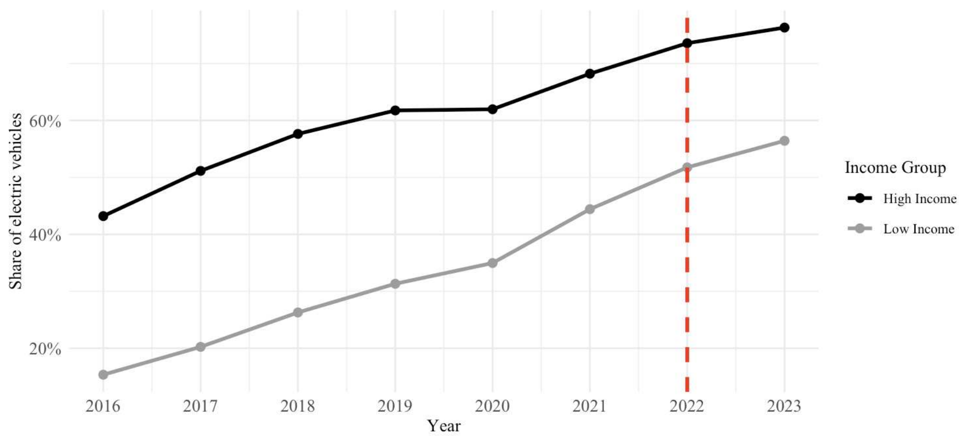
6.3.1 Assumptions

To identify a causal effect, a DiD design must satisfy a set of key identification assumptions. First, in the absence of the VAT reform, high- and low-income households would have exhibited parallel trends in EV adoption (Cameron & Trivedi, 2005; Gertler et al., 2016). For verification, I use Equation (10) to calculate the annual EV shares of both household income groups for 2016 to 2023 and visualize them in Figure 3. Some sections show almost parallel trends, but the pattern is not perfectly consistent over the entire period. I will therefore test shorter pre-reform periods in order to assess the parallel trend assumption more robustly. Violation of this assumption can lead to biased estimates of the treatment effect (Angrist & Pischke, 2009).

$$\text{EV Share}_{g,t} = \frac{\text{EV Registrations}_{g,t}}{\text{EV Registrations}_{g,t} + \text{ICEV Registrations}_{g,t}} \tag{10}$$

A carefully selected control group must replicate the counterfactual trajectory. This is only plausible if both groups are exposed to similar drivers for the EVs adoption (e.g. income growth, charging infrastructure, regional policy). If the comparison group differs in factors relevant to the outcome, its trend will deviate and the DiD estimator will distort the underlying dynamics with the policy effect. Furthermore, the study design requires no anticipation; none of the households in either the treatment or control groups should strategically adjust their purchasing behaviour before the VAT reform comes into effect (Ashenfelter, 1978). The validity of these assumptions is addressed in more detail in Section 8.2.

Figure 3. Electric vehicle share by household income group and year (2016-2023)



Notes: The trends shown were calculated using the annual numbers in Table 10 and Equation (10), which lists the number of EVs with the income dummy for each reference date on 31 December in a cross-tabulation. The income groups correspond to the low income classification of Statistics Norway. In the data, the resulting thresholds correspond approximately to the 25th and 75th percentiles of the household distribution.

6.3.2 Estimated Model

To distinguish treatment and control groups, household income data is used to create a binary indicator ($D_{income,i}$). The classification is based on the definition of low income households of Statistics Norway, and is derived from both the summary statistics and the household income distribution observed in Figure 7. Households with an income of at most 500,000 NOK are classified as low-income ($D_{income,i} = 0$). Those with an income greater than or equal to 1,500,000 NOK are categorized as high income ($D_{income,i} = 1$).[15] The cutoff roughly represents the 25th percentile and the 75th percentile of the household income of the total dataset. This should confirm that the selected thresholds effectively isolate the lower and upper bounds of the income distribution. A middle income group is excluded from the analysis. The middle income group likely contains a wide range of purchasing behaviours, from budget conscious to ambitious buyers, making it a heterogeneous and analytically ambiguous category. The dummy $D_{time,t}$ is equal to zero for all observations before 2023 and equal to one for observations from 2023 onwards. The coefficient (β_3) of the interaction term measures the average treatment effect on the treated (ATET) and is therefore a combination of these variables ($D_{income,i} \times D_{time,t}$). The outcome variable is defined as a binary indicator (EV_{it}) that estimates whether a registered vehicle is electric or a vehicle with a combustion engine. This leads to the following estimated linear probability model (LPM).

$$\Pr\big(\mathrm{EV}_{it} = 1\big) = \beta_0 + \beta_1\, D_{\text{income},i} + \beta_2\, D_{\text{time},t} + \beta_3 \left(D_{\text{income},i} \times D_{\text{time},t}\right) + X_{it}'\gamma + \varepsilon_{it}, \quad (11)$$

The model includes robust standard errors to account for heteroskedasticity. This adjustment is essential, as heteroskedasticity is inherent to the LPM. The variance of the error term depends on the predicted probability and thus violates the assumption of homoskedastic errors (Wooldridge, 2010, p.454). Robust standard errors correct for this and ensure valid inference. While probit or logit models provide more theoretically appropriate frameworks for binary outcomes, the computational constraints of the microdata analysis environment limit the feasible specification. In this context, the LPM serves as a convenient approximation to the underlying response probability. Although the LPM may predict probabilities outside a unit interval, it often provides reliable estimates (Wooldridge, 2010, p.454). The LPM is nevertheless still

[15] Statistics Norway defines low income thresholds as a percentage of median income, most often 50% or 60%. There is no official threshold. Rather, the cutoff adjusts with overall income growth and accounts for household composition. A low income household would be whose annual equivalent income falls below this threshold. Source: Statistics Norway (SSB)

suitable for estimating average treatment effects and allows for flexible application for different observation periods and household income group thresholds to validate the results.

7 Results

This section presents the estimates from the DiD model described in Equation (11). The dependent variable is a binary indicator equal to one if a registered vehicle is an EV and zero if it is an ICEV. All specifications are estimated using LPM, and robust standard errors are reported.

Table 5 reports the DiD estimates using a household income dummy as the treatment variable. Columns (1) and (2) present the results for the full sample period from 2016 to 2023. In the baseline model, the coefficient on the interaction term is –0.0596 and statistically significant at the 1% level. This implies that, after the VAT reform, the probability of registering an EV decreased by approximately 6 percentage points for high income households relative to low income households. When vehicle characteristics are included in column (2), the magnitude of the coefficient is reduced to –0.0315, which remains significant at the 1% level. The coefficient on d_income_house is 0.2583 in column (1), statistically significant at the 1% level. This captures the difference in the probability of EV registration between high income and low income households prior to the reform. Specifically, high income households were about 25.8 percentage points more likely to register EVs before the policy change. After adding covariates in column (2), this difference reduces to 13.8 percentage points, also significant at the 1% level. To mitigate possible bias from pre reform trends, the DiD estimation is repeated for a shorter period from 2020 to 2023 (Figure 3). Columns (3) and (4) represent these estimates. The coefficient on the interaction term in column (3) is –0.0209 and statistically significant at the 1% level, implying a 2.1 percentage point decline in EV registration among the treatment group relative to the control group after the reform. With covariates included in column (4), the coefficient drops to –0.0088, also statistically significant at the 1% level. In all four specifications, the coefficient on d_time is positive and significant at the 1% level. This coefficient reflects the average change in the probability of EV registration in the control group after the VAT reform.

Table 12 in Appendix B shows the results when the control group is restricted to the bottom 10% of the income distribution, while maintaining the treatment group as the top 25%. The interaction coefficient in the baseline model is –0.0259 and statistically significant at the 1% level. With covariates included, the coefficient is –0.0102, also significant at the 1% level. These results are close in magnitude to the ones reported in Table 5 for the same time period.

Table 5. DiD estimates for EV registration on household income level

	2016–2023		2020–2023	
	(1) Baseline	(2) + Covariates	(3) Baseline	(4) + Covariates
d_income_house	0.2583***	0.1377***	0.0491***	0.0149***
	(0.0023)	(0.0018)	(0.0020)	(0.0010)
d_time	0.1532***	0.0545***	0.0305***	0.0106***
	(0.0013)	(0.0010)	(0.0013)	(0.0007)
d_income_house × d_time	-0.0596***	-0.0315***	-0.0209***	-0.0088***
	(0.0015)	(0.0010)	(0.0014)	(0.0007)
Constant	0.4111***	–	0.9226***	–
	(0.0020)	–	(0.0019)	–
Observations	1,543,465	1,543,465	526,412	526,412
F statistic	29,351.4***	292,916.1***	1,647.9***	278,691.8***
R^2 (total)	0.0540	0.5705	0.0093	0.7875

Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Notes: Results based on Equation (11). Columns (1) and (2) present DiD results for 2016–2023. Columns (3) and (4) restrict the period to 2020–2023. Columns (2) and (4) include vehicle level controls: d_long, d_heavy, d_high_fuel, d_high_co2. The dependent variable d_electric_car = 1, if a registered vehicle is electric. The reported coefficient for the interaction term reflects the ATET. The constant term is suppressed in models with vehicle level controls due to the low number of unique unit combinations across categorical variables. This is a feature of the Microdata.no environment and does not affect the estimation results. Code: Appendix Section C

7.1 Robustness

To assess the robustness of the household-level DiD estimates, the model is estimated again using individual income data. This serves two purposes. First, to test the sensitivity of results to the level of income aggregation, and second, to address potential within-household heterogeneity in vehicle purchasing behavior. This will strengthen the credibility of the main results. Additionally, more clarity should be provided regarding the assumption of parallel trends. Based on visualization, the trends appear to be more parallel than those of households (Figure 8).

Table 6 shows the DiD estimates using individual income data. For the entire period from 2016 to 2023, the coefficient for the interaction term in the baseline specification is –0.0375 and in the covariate adjusted model –0.0047. Both coefficients are statistically significant at the 1% level. In the restricted sample from 2020 to 2023, the corresponding estimates are –0.0112 and –0.0021 (columns 3 and 4). The first is statistically significant at the 1% level, while the second is significant at the 5% level. The coefficient for the treatment indicator d_income is positive in all four specifications and statistically significant at the 1% level. The indicator d_time for the period after the reform is also statistically significant in each model. It is positive in the baseline regressions (0.1457 and 0.0334), significant at the 1% level, and negative in the covariate adjusted regressions (–0.0011 and –0.0012), significant at the 1% and 10% levels, respectively. However, all interaction terms indicate a negative probability of EV registration in the treatment group, which robustly supports the estimates in Tables 5 and 12 (Appendix B).

Table 6. DiD estimates for EV registrations on individual income level

	2016–2023		2020–2023	
	(1) Baseline	(2) + Covariates	(3) Baseline	(4) + Covariates
d_income	0.2389^{***}	0.0407^{***}	0.0564^{***}	0.0229^{***}
	(0.0024)	(0.0008)	(0.0019)	(0.0012)
d_time	0.1211^{***}	-0.0011^{***}	0.0152^{***}	-0.0012^{*}
	(0.0011)	(0.0004)	(0.0011)	(0.0007)
d_income × d_time	-0.0375^{***}	-0.0047^{***}	-0.0112^{***}	-0.0021^{**}
	(0.0015)	(0.0005)	(0.0013)	(0.0008)
Constant	0.4787^{***}	0.9070^{***}	0.9063^{***}	–
	(0.0017)	(0.0009)	(0.0016)	–
Observations	955,241	955,241	324,523	324,523
F statistic	$22{,}017.4^{***}$	$794{,}414.4^{***}$	$1{,}339.1^{***}$	$44{,}272.6^{***}$
R^2 (total)	0.0647	0.8534	0.0122	0.4885

Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Notes: Results based on the same DiD specification as in Table 5, but using individual level data instead of household level aggregates. The dependent variable d_electric_car = 1, if a registered vehicle is electric. Columns (2) and (4) include vehicle level controls: d_long, d_heavy, d_high_fuel, d_high_co2. The constant term is suppressed in models with vehicle level controls due to the low number of unique unit combinations across categorical variables in column (4). This is a feature of the Microdata.no environment and does not affect the estimation results. Code: Appendix Section C

8 Discussion

This section reviews the central hypothesis presented in Section 5 in light of the empirical findings from Section 7. It also reflects on how the results relate to the theoretical model and discusses their policy implications and limitations.

8.1 Hypothesis Evaluation

The overarching research question of this paper was whether tax incentives influence consumer demand for EVs. While this can be examined in a theoretical model, the empirical analysis does not allow for any direct conclusions to be drawn about the overall effect on the population. Due to the structure of the 2023 VAT reform and the available data, the design instead focuses on comparing high- and low-income households. As a result, the analysis captures the different effects between these groups but does not estimate the average treatment effect across the entire income distribution. Nevertheless, this design allows for a plausible test of whether the removal of tax incentives led to a decline in EV registrations among consumers who, according to theoretical modeling, were most affected by the reform. The empirical results consistently show that the probability of an EV registration in the treated group declined after the policy change. This is consistent with the theoretical prediction that behavioral responses to price changes depend on WTP and vehicle type preference. Furthermore, based on the choice of identification strategy, it can be seen that the coefficient d_time further supports the interpretation. In the household-level estimates, d_time is positive and significant, suggesting that the trend of registering EVs in households of the control group continued to be positive after the reform. In robustness tests at the individual level, the coefficient is slightly negative but small and statistically significant at a lower level, suggesting that the reform had only a minor impact on the demand for EVs in this group. Robustness tests with alternative definitions of the control group confirm the stability of the treatment effect. When the control group is restricted to the bottom 10% of the income distribution, the estimates remain consistent in sign and magnitude. This supports the internal validity of the design and suggests that the results are not affected by differences in the composition of the control group.

Those results are also supported by the findings of Cincotta and Thomassen (2025), who used vehicle registration data from 2000 to 2021 to simulate the long-term effects of abolishing Norway's purchase incentives for EVs. Their counterfactual analysis shows that abolishing the purchase tax exemption would reduce the market share of EVs from 66% to 25%.[16] This decline is consistent with the results of this study and confirms the conclusion that tax incentives are a decisive factor in the spread of EVs. The consistency of the results despite different methodological approaches strengthens the credibility of the observed effect.

In summary, while the analysis does not provide population-wide estimates, it provides credible evidence that the removal of tax incentives reduced demand for EVs among affected consumers. This supports the central hypothesis and highlights the role of fiscal policy in shaping consumer behavior in the vehicle market. The observed heterogeneity of treatment effects is consistent with theoretical expectations and underscores the importance of considering consumer segmentation in policy design.

8.2 Theoretical Implications

The empirical results of the DiD estimate are consistent with the core predictions of the theoretical model (Table 2). Although the DiD framework does not estimate absolute changes in market share, the observed pattern supports the theoretical interpretation that the reform selectively affected households most likely to purchase vehicles above the tax threshold.

Based on the empirical results, implications and assumptions of the model can be identified and discussed. The model parameters λ and τ are not identified in the empirical estimation, but remain theoretically plausible given the observed behavior. The presence of statistically significant treatment effects suggests that consumers responded sensibly to the changes in utility caused by the reform, which is consistent with a finite $\lambda > 0$, which determines probabilistic but systematic decision making. Although substitution between vehicle segments cannot be observed directly, the positive coefficient on the post-reform period suggests continued EV adoption in the control group. Whether this offsets the decline in the treated group remains unclear. Therefore, the data provide no direct evidence on substitution patterns. Still, the absence of a clear compensatory pattern is not inconsistent with the assumption of limited substitutability in the theoretical model, captured by a positive mismatch cost parameter $\tau > 0$. This interpretation remains speculative and cannot be empirically validated within the current framework. Furthermore, it can be argued that the simplified modeling of the tax as a proportional price surcharge proves to be useful. Although in reality only the price component above NOK 500,000 is

[16] In Cincotta and Thomassen (2025), the term "purchase taxes" is used to cover both Norwegian VAT and registration tax. The registration tax is calculated on the basis of vehicle weight, CO2 emissions, and NOx emissions and accounts for a significant portion of the purchase cost of ICEVs, from which EVs have been exempt in the past.

taxed, the model simplification is sufficient to correctly capture the aggregate behavioral trends. Additional model assumptions, such as full market participation or strategic pricing, remain empirically unanswered. The analysis is limited to observed purchases or adjustments on the supply side.

Overall, the empirical results are consistent with the core mechanisms of the theoretical model, in particular with the assumption that the tax has a disproportionately strong effect on consumers with high WTP. Although a structural identification of the model parameters is not possible in the empirical framework, the observed treatment patterns support the qualitative logic of the model. Important assumptions such as income heterogeneity, limited substitutability ($\tau > 0$) and probabilistic choice behavior ($\lambda > 0$) cannot be directly validated, but the data do not contradict them either. The structural simplifications of the model, including the stylized representation of the VAT system and market segmentation, prove sufficient to explain the most important behavioral responses. However, the results should be interpreted with caution, and further evaluation is needed to robustly assess the quantitative validity of the model. Nevertheless, these results may also have implications for the policy evaluation of the reform.

8.3 Policy Implications

The VAT reform implemented in Norway in January 2023 is a strategic policy shift designed to promote the adoption of EVs while maintaining the country's long-standing climate commitments in a financially sustainable framework. Specifically, the reform aimed to maintain price incentives for the uptake of EVs, reduce subsidies for EVs in the premium segment, and offset the lost VAT revenue by reintroducing taxation above a certain price threshold (IPAC, 2022; Norwegian Ministry of Finance, 2022, 2024). These objectives reflect the government's intention to normalize the market for EVs as it matures and to target fiscal support more efficiently. The empirical results of this study suggest that these policy objectives were partially achieved. The reform led to a statistically significant decline in EV registrations in high-income households, while lower-income households did not show a comparable change in behavior. The tax incentives were thus effectively shifted away from the top income groups while maintaining support for lower-income households. In this sense, the VAT reform served both fiscal and environmental objectives by targeting support at the bottom of the income distribution while limiting regressive subsidies for premium models. Importantly, the positive probability of EV registrations in the control group suggests that the reform has not affected the general acceptance of EVs in the subsidized segment. This is in line with the environmental objective of maintaining a high share of electric vehicles in the national vehicle fleet, particularly for vehicles below NOK 500,000. The reform can therefore be seen as a successful example of using fiscal policy to refine rather than reverse the incentive structure.

In addition, government spending on tax breaks has fallen significantly. According to estimates by the Norwegian Ministry of Finance, the fiscal value of zero taxation in 2023 and 2024 was significantly lower than in 2022 (Norwegian Ministry of Finance, 2024).[17] However, the results show a negative probability of new registrations of EVs in high-income households after the reform. The identification strategy used does not allow conclusions to be drawn as to whether this decline is due to a decline in purchases, substitution by cheaper EVs, or a switch to combustion engines. The observed change in behavior suggests that the reform has had an effect, but the specific adjustment mechanisms remain empirically unclear. From a policy perspective, the key question is therefore whether the decline in the premium segment has been offset by environmentally harmful substitution behavior. A question that cannot be answered with the available data. In general, the study shows that price-based instruments can also have an effect in mature EV markets. For policymakers in other countries, reducing financial incentives requires careful timing and targeting, particularly in markets with underdeveloped EV infrastructure, consumer preferences, and product diversity (Bjørge et al., 2022). In these contexts, the behavioral effects of fiscal changes can be more substantial, and ineffective design can undermine policy objectives.

Overall, the Norwegian VAT reform shows how fiscal measures can be used to improve the distributional and environmental efficiency of subsidies for EVs. Empirical evidence suggests that a price threshold can be an effective policy instrument to limit public spending on luxury goods without distorting incentives for the general population to switch. However, when designing such measures, market structures, substitution possibilities, and behavioral asymmetries between different consumer groups must be taken into account to ensure that climate goals are not compromised in the course of fiscal consolidation.

8.4 Limitations

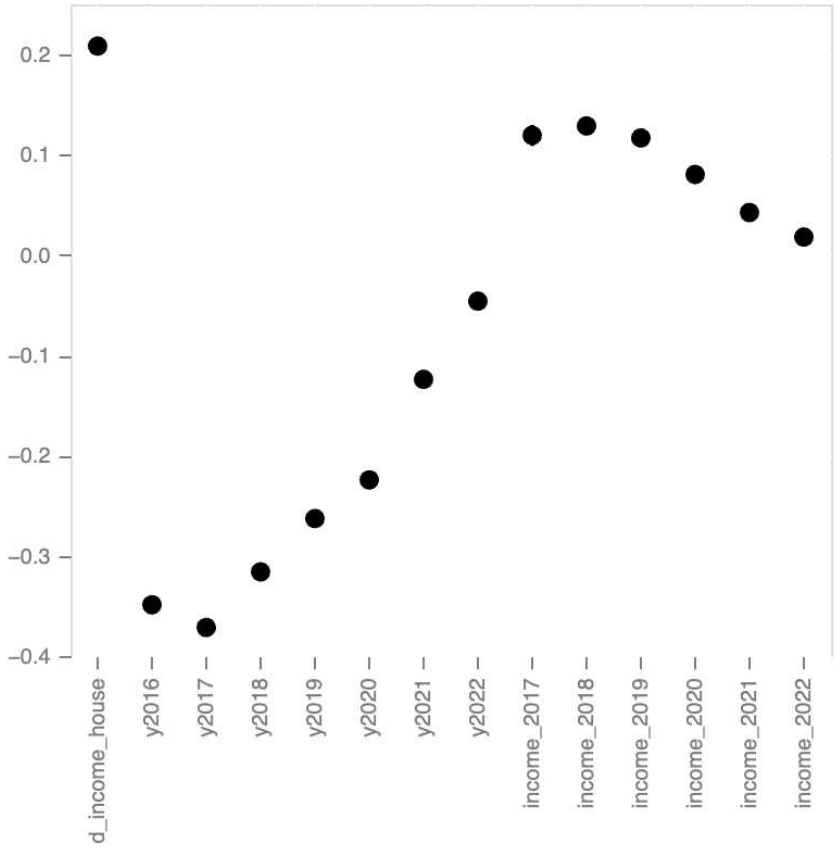
Although the results provide consistent evidence for the proposed hypothesis, they must be interpreted with caution due to the limitations of the chosen estimation strategy. While a LPM is

[17] Figure 4 of the report shows the estimated yearly tax expenditure from the zero VAT rating on sales of EVs from 2005 to 2024. Billion NOK in 2024 prices (Norwegian Ministry of Finance, 2024)

practical and easy to interpret, it has several documented limitations. First, an LPM can generate predicted probabilities that fall outside the logical range of 0 to 1, which is problematic in the context of a binary dependent variable (Wooldridge, 2010). Second, the model is inherently biased due to heteroscedasticity, as the variance of the error term depends on the predicted probability. This can lead to inefficient estimates and potentially biased standard errors, despite the use of heteroscedasticity robust standard errors to mitigate this problem (Angrist & Pischke, 2009; Wooldridge, 2010). Third, the LPM assumes that the marginal effects of the explanatory variables on the probability of an outcome are constant, which may not be realistic (Wooldridge, 2016). For instance, very low-income households might have low EV adoption regardless of tax incentives while high-income households may not respond to price incentives as strongly. This pattern would be missed in an LPM, which could flatten or misrepresent the effects. Alternative binary outcome models, such as logit or probit, offer clear advantages in this regard. They restrict predicted probabilities to the range of 0 to 1, account for nonlinearities in marginal effects, and provide more efficient maximum likelihood estimates. However, due to limitations in the Microdata.no system, this thesis could not implement these models with a panel data structure.

Beyond the model specification, there are identification issues regarding the validity of the parallel trends assumption, which is essential to the DiD design. A visual review of group specific trends in the treatment and control groups was not strictly parallel prior to the reform (Figure 3 and 8). This weakens the causal interpretation of the interaction term and may lead to biases in the treatment effect estimates. Figure 4 shows the estimated year specific coefficients from a pooled OLS model with interaction terms between income group and year indicators, omitting 2023 (the reform year) as the base. The coefficients capture the annual differences in the probability of EV registration between high- and low-income households compared to 2023 (Gertler et al., 2016).

Figure 4. Coefficient plot of pooled OLS pre-refrom

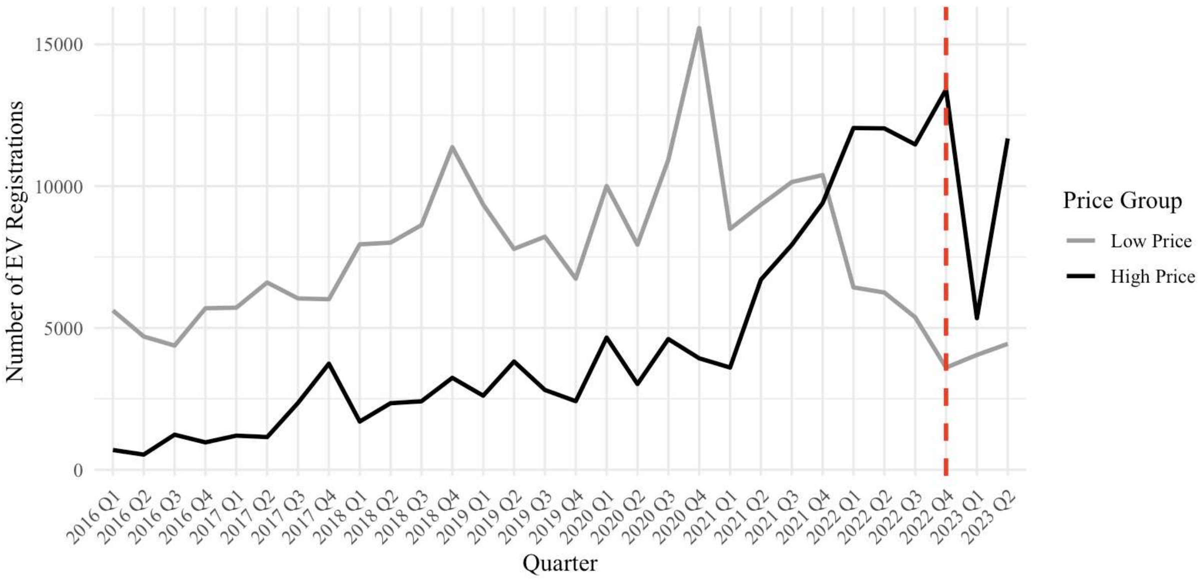


Notes: All coefficients are statistically significant at the 5% level. The variable d_income_house is defined like the dummy variable for household income in Equation (11). The variable income_2016 is ommited to account for perfect multicollinearity. All standard errors are robust to heteroskedasticity. Identification Strategy can be found in Appendix Section B

The pattern shows notable and statistically significant differences in the pre-treatment years, suggesting divergent trends between the treatment and control groups prior to the implementation of the reform. This violation of the parallel trends assumption weakens the internal validity of the DiD estimates. It suggests that the observed treatment effects may be confounded by pre-existing differences in group-specific trends and are not exclusively attributable to the policy measure. Consequently, the estimated coefficients must be interpreted with caution. To address these limitations, future work should consider alternative identification strategies that relax the assumption of parallel trends.

In addition, anticipation effects, in which consumers adjust their behavior prior to a policy change, may further distort the estimated treatment effects after the reform. Figure 5 shows quarterly EV registrations by price group from 2016 to 2023.

Figure 5. Quarterly EV registrations by price group (2016-2023)



Notes: This figure breaks down quarterly EV registrations in Norway (2016 Q1–2023 Q2) into two cohorts based on vehicle price: “Low price” includes models priced below the median transaction price, and “High price” includes models priced at or above the 75th percentile. The vertical red dotted line marks the VAT reform of January 2023. To avoid distorting price fluctuations around the reform threshold, vehicles with a price between the median and the 75th percentile are excluded. Data Source: Opplysningsrådet for veitrafikken (OFV)

This pattern is consistent with anticipatory behavior, where consumers accelerate purchases to avoid future costs. The spike and subsequent drop in high priced EV registrations resemble the ”Ashenfelter dip”, indicating that behavioral responses occurred before the treatment effect (Ashenfelter, 1978). Such intertemporal substitution violates the parallel trends assumption of the DiD framework and complicates the causal interpretation of post reform treatment effects. It is important to note that this price based classification does not map directly onto the income based treatment and control groups used in the main analysis. While it is plausible that high income households are overrepresented in the high price segment, the available data do not allow us to verify this relationship explicitly.

Finally, defining the control group can also pose challenges. For example, if some households in the lower income group were indirectly affected by the reform through adjustments in the used car market or price spillovers, for instance, the assumption of an unbiased control group could be violated. This would lead to distortions in the DiD estimates and likely weaken the estimated treatment effect. The direction of this distortion depends on the type of bias. If low income households are partially treated, for example, the estimated difference would be biased toward zero, thereby underestimating the actual effect.

In summary, it can be said that although the empirical results consistently support the hypotheses put forward, several limitations affect the reliability of the causal interpretation. The LPM introduces functional form restrictions and statistical inefficiencies that can distort marginal effects. Even more critical are violations of the assumption of parallel trends and potential anticipation effects, which weaken the internal validity of the DiD estimates. These problems underscore the need for cautious interpretation of the results and suggest that future research should use alternative identification strategies and modeling approaches to improve causal inference.

9 Conclusion

This study examined the effects of Norway's 2023 VAT reform on the adoption of EVs, with a particular focus on income related heterogeneity in consumer responses. Using a DiD model estimated with an LPM, the analysis found that the removal of tax exemptions for high-priced EVs led to a statistically significant decline in the probability of EV registrations in high-income households, while the probability of EV adoption in low-income households remained positive or declined only by a very small percentage in robustness. These results are consistent across multiple model specifications, robustness tests, and control group definitions. The empirical results support the theoretical model predictions that tax incentives affect EV purchase behavior differently depending on WTP. However, the causal interpretation of these results is subject to important limitations. The assumption of parallel trends underlying the DiD methodology appears to be violated due to pre-treatment trend differences and evidence of anticipatory behavior that could distort the estimated treatment effects. The use of an LPM further constrains the analysis, as it cannot fully capture nonlinearities in consumer response and cannot constrain predictions within valid probability bounds. Despite these limitations, the thesis provides evidence that the VAT reform had a regressive effect on the adoption of EVs, underscoring the importance of targeted policy design in the context of the green transition. Future research should explore alternative empirical strategies to better isolate causal effects and attempt to link vehicle model prices more directly to the consumption behavior of individuals or households. Overall, this work contributes to the understanding of how tax policy influences the adoption of low-emission technologies and highlights the trade-offs that need to be considered when designing fair and effective climate policy instruments.

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A Appendix: Structural Derivations and Numerical Implementation

This appendix section provides the mathematical derivations underlying the model presented in Section 4, together with a description of the computational shortcuts and MATLAB functions used to obtain the equilibrium results.

A.1 CASE 1

Utility functions incorporate a horizontal and vertical product differentiation component (S. P. Anderson et al., 1992).

$$V_{H1} = R + \theta s_H - p_{H1} - \tau(1-x)^2 \tag{12}$$

$$V_{H0} = R + \theta s_H - p_{H0} - \tau x^2 \tag{13}$$

$$V_{L1} = R + \theta s_L - p_{L1} - \tau(1-x)^2 \tag{14}$$

$$V_{L0} = R + \theta s_L - p_{L0} - \tau x^2 \tag{15}$$

Given the assumptions described in Belleflamme and Peitz (2015), I would obtain the probabilistic demand. In this case, however, I have to take product characteristics into account. First, I obtain the choice probabilities. These probabilities represent the likelihood that a consumer, characterized by their location (x) and WTP (θ), will choose a specific product.

$$\Pr_{H1}(x,\theta) = \frac{\exp\big(\lambda\big[R - p_{H1} - \tau(x-1)^2 + s_H\,\theta\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{16}$$

$$\Pr_{H0}(x,\theta) = \frac{\exp\big(\lambda\big[R - p_{H0} - \tau x^2 + s_H\,\theta\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{17}$$

$$\Pr_{L1}(x,\theta) = \frac{\exp\big(\lambda\big[R - p_{L1} - \tau(x-1)^2 + s_L\,\theta\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{18}$$

$$\Pr_{L0}(x,\theta) = \frac{\exp\big(\lambda\big[R - p_{L0} - \tau x^2 + s_L\,\theta\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}. \tag{19}$$

The following distributions are assumed:

$$f(x) = 1, \quad x \in [0,1], \qquad g(\theta) = \frac{1}{\theta_{\max} - \theta_{\min}}, \quad \theta \in [\theta_{\min}, \theta_{\max}].$$

Thus, for each product ij in H1, H0, L1, L0, I compute the demand (market share) as the integrated choice probabilities over the relevant product characteristics.

$$D_{H1} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp\big(\lambda\big[R - p_{H1} - \tau(x-1)^2 + s_H\,\theta\big]\big)}{(\theta_{\max}-\theta_{\min})\sum \exp\big(\lambda V(x,\theta)\big)}\,d\theta\,dx, \tag{20}$$

$$D_{H0} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp\big(\lambda\big[R - p_{H0} - \tau x^2 + s_H\,\theta\big]\big)}{(\theta_{\max}-\theta_{\min})\sum \exp\big(\lambda V(x,\theta)\big)}\,d\theta\,dx, \tag{21}$$

$$D_{L1} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp\big(\lambda\big[R - p_{L1} - \tau(x-1)^2 + s_L\,\theta\big]\big)}{(\theta_{\max}-\theta_{\min})\sum \exp\big(\lambda V(x,\theta)\big)}\,d\theta\,dx, \tag{22}$$

$$D_{L0} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp\big(\lambda\big[R - p_{L0} - \tau x^2 + s_L\,\theta\big]\big)}{(\theta_{\max}-\theta_{\min})\sum \exp\big(\lambda V(x,\theta)\big)}\,d\theta\,dx. \tag{23}$$

Let $c_{H1}, c_{H0}, c_{L1}, c_{L0}$ denote marginal costs. Then the profit functions have the following form:

$$\Pi_{H1} = (p_{H1} - c_{H1}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp\big(\lambda\big[R - p_{H1} - \tau(x-1)^2 + s_H\,\theta\big]\big)}{(\theta_{\max}-\theta_{\min})\sum \exp\big(\lambda V(x,\theta)\big)}\,d\theta\,dx, \tag{24}$$

$$\Pi_{H0} = (p_{H0} - c_{H0}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp\big(\lambda\big[R - p_{H0} - \tau x^2 + s_H\,\theta\big]\big)}{(\theta_{\max}-\theta_{\min})\sum \exp\big(\lambda V(x,\theta)\big)}\,d\theta\,dx, \tag{25}$$

$$\Pi_{L1} = (p_{L1} - c_{L1}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp\big(\lambda\big[R - p_{L1} - \tau(x-1)^2 + s_L\,\theta\big]\big)}{(\theta_{\max}-\theta_{\min})\sum \exp\big(\lambda V(x,\theta)\big)}\,d\theta\,dx, \tag{26}$$

$$\Pi_{L0} = (p_{L0} - c_{L0}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp\big(\lambda\big[R - p_{L0} - \tau x^2 + s_L\,\theta\big]\big)}{(\theta_{\max}-\theta_{\min})\sum \exp\big(\lambda V(x,\theta)\big)}\,d\theta\,dx. \tag{27}$$

To find the profit maximizing prices, I set the derivative of each profit function with respect to its price equal to zero.

$$\begin{aligned}
\frac{\partial \Pi_{H1}}{\partial p_{H1}} = 0 \quad \Longleftrightarrow \quad 0 = {} & \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{\exp\left(\lambda V_{H1}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min})\sum \exp\left(\lambda V(x,\theta)\right)} \right] d\theta\,dx \\
& - (c_{H1} - p_{H1}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda \exp\left(\lambda V_{H1}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min})\sum \exp\left(\lambda V(x,\theta)\right)} \right. \\
& \left. - \frac{\lambda \exp\left(2\lambda V_{H1}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min})\left[\sum \exp\left(\lambda V(x,\theta)\right)\right]^2} \right] d\theta\,dx
\end{aligned} \tag{28}$$

$$\begin{aligned}\frac{\partial \Pi_{H0}}{\partial p_{H0}} = 0 \quad \Longleftrightarrow \quad 0 = & \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{\exp\left(\lambda V_{H0}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \sum \exp\left(\lambda V(x,\theta)\right)} \right] d\theta \, dx \\ & - (c_{H0} - p_{H0}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda \exp\left(\lambda V_{H0}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \sum \exp\left(\lambda V(x,\theta)\right)} \right. \\ & \left. - \frac{\lambda \exp\left(2\lambda V_{H0}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \left[\sum \exp\left(\lambda V(x,\theta)\right)\right]^2} \right] d\theta \, dx \end{aligned} \tag{29}$$

$$\begin{aligned}\frac{\partial \Pi_{L1}}{\partial p_{L1}} = 0 \quad \Longleftrightarrow \quad 0 = & \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{\exp\left(\lambda V_{L1}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \sum \exp\left(\lambda V(x,\theta)\right)} \right] d\theta \, dx \\ & - (c_{L1} - p_{L1}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda \exp\left(\lambda V_{L1}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \sum \exp\left(\lambda V(x,\theta)\right)} \right. \\ & \left. - \frac{\lambda \exp\left(2\lambda V_{L1}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \left[\sum \exp\left(\lambda V(x,\theta)\right)\right]^2} \right] d\theta \, dx \end{aligned} \tag{30}$$

$$\begin{aligned}\frac{\partial \Pi_{L0}}{\partial p_{L0}} = 0 \quad \Longleftrightarrow \quad 0 = & \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{\exp\left(\lambda V_{L0}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \sum \exp\left(\lambda V(x,\theta)\right)} \right] d\theta \, dx \\ & - (c_{L0} - p_{L0}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda \exp\left(\lambda V_{L0}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \sum \exp\left(\lambda V(x,\theta)\right)} \right. \\ & \left. - \frac{\lambda \exp\left(2\lambda V_{L0}(x,\theta)\right)}{(\theta_{\max}-\theta_{\min}) \left[\sum \exp\left(\lambda V(x,\theta)\right)\right]^2} \right] d\theta \, dx \end{aligned} \tag{31}$$

To find the profit-maximizing prices, $p^*_{H1}, p^*_{H0}, p^*_{L1}, p^*_{L0}$, I define the parameters, substitute them into the FOC's, and solve. MATLAB code is presented below for $\lambda = 2$ (Results see Table 7:

```
syms p_H1 p_H0 p_L1 p_L0 theta x


% % Define parameter values
R = 1;
lambda = 2;
tau = 1;
s_H = 0.7;
s_L = 0.2;
theta_min = 0.2;
```

```
theta_max = 2.2;
c_H1 = 0.35;
c_H0 = 0.35;
c_L1 = 0.1;
c_L0 = 0.1;

denominator = (theta_max - theta_min) * ( ...
    exp(lambda*(R - p_H1 - tau*(x - 1)^2 + s_H*theta)) + ...
    exp(lambda*(R - p_L1 - tau*(x - 1)^2 + s_L*theta)) + ...
    exp(lambda*(-tau*x^2 + R - p_H0 + s_H*theta)) + ...
    exp(lambda*(-tau*x^2 + R - p_L0 + s_L*theta)) );

% FOCs:
foc_H1 = int(int(-exp(lambda*(R - p_H1 - tau*(x - 1)^2 + s_H*theta))
   / denominator, ...
                 theta, theta_min, theta_max), x, 0, 1) ...
        - int(int((lambda * exp(lambda*(R - p_H1 - tau*(x - 1)^2 +
           s_H*theta))) / denominator ...
                  - (lambda * exp(2 * lambda * (R - p_H1 - tau*(x -
                     1)^2 + s_H*theta))) / denominator^2, ...
                  theta, theta_min, theta_max), x, 0, 1) * (c_H1 -
                     p_H1) == 0;

foc_H0 = int(int(-exp(lambda*(-tau*x^2 + R - p_H0 + s_H*theta)) /
   denominator, ...
                 theta, theta_min, theta_max), x, 0, 1) ...
        - (c_H0 - p_H0) * int(int((lambda * exp(lambda*(-tau*x^2 + R
           - p_H0 + s_H*theta))) / denominator ...
                  - (lambda * exp(2 * lambda * (-tau*x^2 + R - p_H0 +
                      s_H*theta))) / denominator^2, ...
                  theta, theta_min, theta_max), x, 0, 1) == 0;

foc_L1 = int(int(-exp(lambda*(R - p_L1 - tau*(x - 1)^2 + s_L*theta))
   / denominator, ...
```

```
                theta, theta_min, theta_max), x, 0, 1) ...
        - int(int((lambda * exp(lambda*(R - p_L1 - tau*(x - 1)^2 +
            s_L*theta))) / denominator ...
                 - (lambda * exp(2 * lambda * (R - p_L1 - tau*(x -
                    1)^2 + s_L*theta))) / denominator^2, ...
                 theta, theta_min, theta_max), x, 0, 1) * (c_L1 -
                    p_L1) == 0;

foc_L0 = int(int(-exp(lambda*(-tau*x^2 + R - p_L0 + s_L*theta)) /
   denominator, ...
                theta, theta_min, theta_max), x, 0, 1) ...
        - (c_L0 - p_L0) * int(int((lambda * exp(lambda*(-tau*x^2 + R
            - p_L0 + s_L*theta))) / denominator ...
                 - (lambda * exp(2 * lambda * (-tau*x^2 + R - p_L0 +
                     s_L*theta))) / denominator^2, ...
                 theta, theta_min, theta_max), x, 0, 1) == 0;

solution = vpasolve([foc_H1, foc_H0, foc_L1, foc_L0], [p_H1, p_H0,
   p_L1, p_L0]);

disp('Optimal Prices:');
disp(['p_H1* = ', char(solution.p_H1)]);
disp(['p_H0* = ', char(solution.p_H0)]);
disp(['p_L1* = ', char(solution.p_L1)]);
disp(['p_L0* = ', char(solution.p_L0)]);
```

Listing 1. MATLAB code to solve FOC's (Section 4.3)

For numerical computations, the optimal prices and parameter specifications are plugged back into the demand and profit equations. The approach is similar for Cases 2 and 3, but with adjusted demand and profit functions and FOCs. The full MATLAB code can be found here: https://jakobheinig.github.io/model-thesis/. However, the next sections present the general form of the equations in Cases 2 and 3 for the purposes of completeness.

A.2 CASE 2

In this case, we consider a tax t that applies to $H0$ and $L0$. Prices are adjusted as:

$$p_{H0}^{VAT} = p_{H0}(1+t), \qquad p_{L0}^{VAT} = p_{L0}(1+t).$$

Utility functions:

$$V_{H1} = R + \theta s_H - p_{H1} - \tau(1-x)^2 \tag{32}$$

$$V_{H0} = R + \theta s_H - p_{H0}(1+t) - \tau x^2 \tag{33}$$

$$V_{L1} = R + \theta s_L - p_{L1} - \tau(1-x)^2 \tag{34}$$

$$V_{L0} = R + \theta s_L - p_{L0}(1+t) - \tau x^2 \tag{35}$$

Choice probabilities:

$$\Pr_{H1}(x,\theta) = \frac{\exp\big(\lambda\big[R - p_{H1} - \tau(x-1)^2 + s_H\,\theta\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{36}$$

$$\Pr_{H0}(x,\theta) = \frac{\exp\big(\lambda\big[R + \theta s_H - p_{H0}(1+t) - \tau x^2\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{37}$$

$$\Pr_{L1}(x,\theta) = \frac{\exp\big(\lambda\big[R - p_{L1} - \tau(x-1)^2 + s_L\,\theta\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{38}$$

$$\Pr_{L0}(x,\theta) = \frac{\exp\big(\lambda\big[R + \theta s_L - p_{L0}(1+t) - \tau x^2\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}. \tag{39}$$

Demand functions:

$$D_{H1} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{H1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)}\, d\theta\, dx, \tag{40}$$

$$D_{H0} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{H0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)}\, d\theta\, dx, \tag{41}$$

$$D_{L1} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{L1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)}\, d\theta\, dx, \tag{42}$$

$$D_{L0} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{L0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)}\, d\theta\, dx. \tag{43}$$

Profit functions:

$$\Pi_{H1} = (p_{H1} - c_{H1})D_{H1}, \tag{44}$$

$$\Pi_{H0} = (p_{H0} - c_{H0})D_{H0}, \tag{45}$$

$$\Pi_{L1} = (p_{L1} - c_{L1})D_{L1}, \tag{46}$$

$$\Pi_{L0} = (p_{L0} - c_{L0})D_{L0}. \tag{47}$$

First order conditions:

$$\begin{aligned}\frac{\partial \Pi_{H1}}{\partial p_{H1}} = 0 \quad \Longleftrightarrow \quad 0 = &\int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{\exp(\lambda V_{H1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right] d\theta \, dx \\ &- (c_{H1} - p_{H1}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda \exp(\lambda V_{H1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right. \\ &\left. - \frac{\lambda \exp(2\lambda V_{H1})}{(\theta_{\max} - \theta_{\min}) \left[\sum \exp(\lambda V)\right]^2} \right] d\theta \, dx \end{aligned} \tag{48}$$

$$\begin{aligned}\frac{\partial \Pi_{H0}}{\partial p_{H0}} = 0 \quad \Longleftrightarrow \quad 0 = &\int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{(1+t)\exp(\lambda V_{H0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right] d\theta \, dx \\ &- (c_{H0} - p_{H0}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda (1+t) \exp(\lambda V_{H0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right. \\ &\left. - \frac{\lambda (1+t)^2 \exp(2\lambda V_{H0})}{(\theta_{\max} - \theta_{\min}) \left[\sum \exp(\lambda V)\right]^2} \right] d\theta \, dx \end{aligned} \tag{49}$$

$$\begin{aligned}\frac{\partial \Pi_{L1}}{\partial p_{L1}} = 0 \quad \Longleftrightarrow \quad 0 = &\int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{\exp(\lambda V_{L1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right] d\theta \, dx \\ &- (c_{L1} - p_{L1}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda \exp(\lambda V_{L1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right. \\ &\left. - \frac{\lambda \exp(2\lambda V_{L1})}{(\theta_{\max} - \theta_{\min}) \left[\sum \exp(\lambda V)\right]^2} \right] d\theta \, dx \end{aligned} \tag{50}$$

$$\frac{\partial \Pi_{L0}}{\partial p_{L0}} = 0 \iff 0 = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{(1+t)\exp(\lambda V_{L0})}{(\theta_{\max}-\theta_{\min})\sum \exp(\lambda V)} \right] d\theta\, dx$$
$$- (c_{L0} - p_{L0}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda(1+t)\exp(\lambda V_{L0})}{(\theta_{\max}-\theta_{\min})\sum \exp(\lambda V)} - \frac{\lambda(1+t)^2 \exp(2\lambda V_{L0})}{(\theta_{\max}-\theta_{\min})\left[\sum \exp(\lambda V)\right]^2} \right] d\theta\, dx \tag{51}$$

A.3 CASE 3

In this case, we consider a tax t that applies to both engine combustion segments as well as high-quality EVs. The taxed prices are similar to those in Case 2.

$$p_{H1}^{VAT} = p_{H1}(1+t), \qquad p_{H0}^{VAT} = p_{H0}(1+t), \qquad p_{L0}^{VAT} = p_{L0}(1+t)$$

Utility functions:

$$V_{H1} = R + \theta s_H - p_{H1}(1+t) - \tau(1-x)^2 \tag{52}$$
$$V_{H0} = R + \theta s_H - p_{H0}(1+t) - \tau x^2 \tag{53}$$
$$V_{L1} = R + \theta s_L - p_{L1} - \tau(1-x)^2 \tag{54}$$
$$V_{L0} = R + \theta s_L - p_{L0}(1+t) - \tau x^2 \tag{55}$$

Choice probabilities:

$$\Pr_{H1}(x,\theta) = \frac{\exp\big(\lambda\big[R + \theta s_H - p_{H1}(1+t) - \tau(1-x)^2\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{56}$$
$$\Pr_{H0}(x,\theta) = \frac{\exp\big(\lambda\big[R + \theta s_H - p_{H0}(1+t) - \tau x^2\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{57}$$
$$\Pr_{L1}(x,\theta) = \frac{\exp\big(\lambda\big[R - p_{L1} - \tau(x-1)^2 + s_L\,\theta\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}, \tag{58}$$
$$\Pr_{L0}(x,\theta) = \frac{\exp\big(\lambda\big[R + \theta s_L - p_{L0}(1+t) - \tau x^2\big]\big)}{\sum \exp\big(\lambda V(x,\theta)\big)}. \tag{59}$$

Demand functions:

$$D_{H1} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{H1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \, d\theta \, dx, \tag{60}$$

$$D_{H0} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{H0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \, d\theta \, dx, \tag{61}$$

$$D_{L1} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{L1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \, d\theta \, dx, \tag{62}$$

$$D_{L0} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \frac{\exp(\lambda V_{L0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \, d\theta \, dx. \tag{63}$$

Profit functions:

$$\Pi_{H1} = (p_{H1} - c_{H1}) D_{H1}, \tag{64}$$

$$\Pi_{H0} = (p_{H0} - c_{H0}) D_{H0}, \tag{65}$$

$$\Pi_{L1} = (p_{L1} - c_{L1}) D_{L1}, \tag{66}$$

$$\Pi_{L0} = (p_{L0} - c_{L0}) D_{L0}. \tag{67}$$

First order conditions:

$$\begin{aligned} \frac{\partial \Pi_{H1}}{\partial p_{H1}} = 0 \quad \iff \quad 0 = & \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-(1+t) \frac{\exp(\lambda V_{H1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right] d\theta \, dx \\ & - (c_{H1} - p_{H1}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda (1+t) \exp(\lambda V_{H1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right. \\ & \left. - \frac{\lambda (1+t)^2 \exp(2 \lambda V_{H1})}{(\theta_{\max} - \theta_{\min}) \left[\sum \exp(\lambda V) \right]^2} \right] d\theta \, dx \end{aligned} \tag{68}$$

$$\begin{aligned} \frac{\partial \Pi_{H0}}{\partial p_{H0}} = 0 \quad \iff \quad 0 = & \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-(1+t) \frac{\exp(\lambda V_{H0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right] d\theta \, dx \\ & - (c_{H0} - p_{H0}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda (1+t) \exp(\lambda V_{H0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right. \\ & \left. - \frac{\lambda (1+t)^2 \exp(2 \lambda V_{H0})}{(\theta_{\max} - \theta_{\min}) \left[\sum \exp(\lambda V) \right]^2} \right] d\theta \, dx \end{aligned} \tag{69}$$

$$\frac{\partial \Pi_{L1}}{\partial p_{L1}} = 0 \iff 0 = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-\frac{\exp(\lambda V_{L1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} \right] d\theta \, dx$$
$$- (c_{L1} - p_{L1}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda \exp(\lambda V_{L1})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} - \frac{\lambda \exp(2\lambda V_{L1})}{(\theta_{\max} - \theta_{\min}) \left[\sum \exp(\lambda V)\right]^2} \right] d\theta \, dx \tag{70}$$

$$\frac{\partial \Pi_{L0}}{\partial p_{L0}} = 0 \iff 0 = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[-(1+t) \frac{\exp(\lambda V_{L0})}{(\theta_{\max} - \theta_{\min}) \sum_k \exp(\lambda V_k)} \right] d\theta \, dx$$
$$- (c_{L0} - p_{L0}) \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda (1+t) \exp(\lambda V_{L0})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} - \frac{\lambda (1+t)^2 \exp(2\lambda V_{L0})}{(\theta_{\max} - \theta_{\min}) \left[\sum \exp(\lambda V)\right]^2} \right] d\theta \, dx \tag{71}$$

A.4 Demand derivative

To verify the theoretical validity of Equation (9), I investigated whether the demand for each product decreases with respect to its own price, p_{ij}. The derivative of the demand with respect to its own price is given by the following expression (see MATLAB code in Appendix Section A.1):

$$\frac{\partial D_{ij}}{\partial p_{ij}} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \left[\frac{\lambda \frac{\partial V_{ij}}{\partial p_j} \exp(\lambda V_{ij})}{(\theta_{\max} - \theta_{\min}) \sum \exp(\lambda V)} - \frac{\lambda \frac{\partial V_{ij}}{\partial p_j} \exp(2\lambda V_{ij})}{(\theta_{\max} - \theta_{\min}) \left[\sum \exp(\lambda V)\right]^2} \right] d\theta \, dx, \tag{72}$$

common terms can be factored out, and the expression can be rewritten as follows,

$$\frac{\partial D_{ij}}{\partial p_{ij}} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \lambda \cdot \frac{\partial V_{ij}}{\partial p_{ij}} \cdot \left[\frac{\exp(\lambda V_{ij})}{Z} - \frac{\exp(2\lambda V_{ij})}{Z^2} \right] \cdot \frac{1}{\theta_{\max} - \theta_{\min}} \, d\theta \, dx \tag{73}$$

where, $Z = \sum \exp(\lambda V) > 0$. Now:

$$\frac{\exp(\lambda V_{ij})}{Z} - \frac{\exp(2\lambda V_{ij})}{Z^2} = \Pr_{ij}(x, \theta) \left[1 - \Pr_{ij}(x, \theta) \right] > 0,$$

since $\Pr_{ij}(x, \theta) \in [0, 1]$ for all ij.

Additionally:

$$\frac{\partial V_{ij}}{\partial p_{ij}} < 0 \quad \text{(for all } ij\text{, since utility decreases in price)}$$

Therefore:

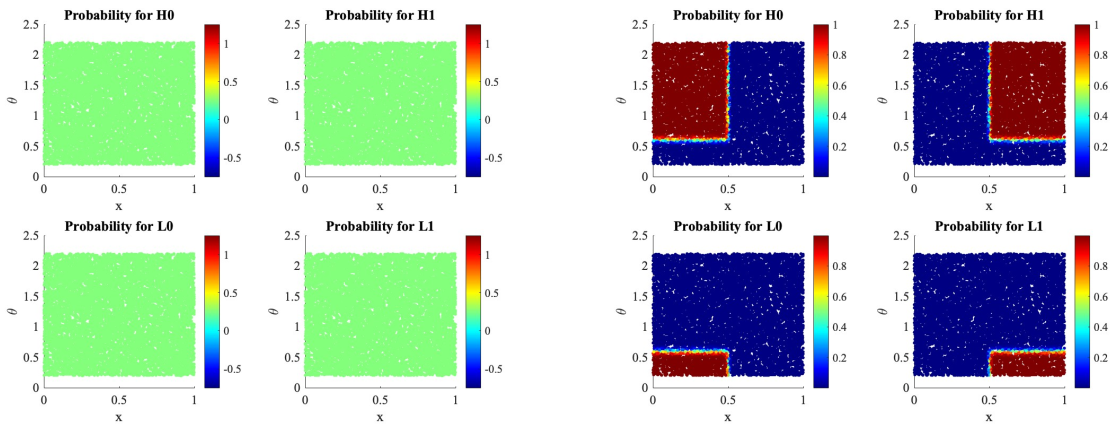
$$\frac{\partial D_{ij}}{\partial p_{ij}} = \int_0^1 \int_{\theta_{\min}}^{\theta_{\max}} \underbrace{\lambda}_{>0} \cdot \underbrace{\frac{\partial V_{ij}}{\partial p_{ij}}}_{<0} \cdot \underbrace{\Pr_{ij}(1 - \Pr_{ij})}_{>0} \cdot \underbrace{\frac{1}{\theta_{\max} - \theta_{\min}}}_{>0} \, d\theta \, dx < 0$$

Thus, the demand for each product is decreasing in its own price.

B Appendix: Additional Tables and Figures

Parameter assumption (λ)

Figure 6. Comparison of choice probabilities at different values for λ



(a) Choice probabilities for all products without VAT applied by $\lambda = 0$

(b) Choice probabilities for all products without VAT applied by $\lambda = 100$

Notes: Choice probabilities are computed for $N = 10{,}000$ simulated consumers with $x \sim U[0,1]$ and $\theta \sim U[0.2, 2.2]$. Parameter values are set to $R = 1$, $\lambda = 0$; $\lambda = 100$, $\tau = 1$, $s_H = 0.7$, and $s_L = 0.2$. Visualization of Equation (4).

In the random coefficients logit model, a finite λ yields probabilistic choice (Equation (4)):

$$Pr_{ij}(x, \theta) = \frac{\exp(\lambda V_{ij}(x, \theta))}{\sum \exp(\lambda V(x, \theta))}.$$

As $\lambda \to \infty$, the noise vanishes and consumers choose the alternative with the highest deterministic utility:

$$\lim_{\lambda\to\infty} Pr_{ij}(x,\theta) = \begin{cases} 1, & V_{ij}(x,\theta) = \max V(x,\theta), \\ 0, & \text{otherwise.} \end{cases}$$

Under the parameter assumptions for CASE 1(see Table 1),

$$p_{H1} = p_{H0} = 0.7, \quad p_{L1} = p_{L0} = 0.4, \quad s_H = 0.7,\ s_L = 0.2,\ \tau = 1,\ R = 1,$$

and the four deterministic utilities for the different segments (H1, H0, L1, L0),

$$V_{ij}(x,\theta) = R\ +\ \theta\, s_i\ -\ p_{ij}\ -\ \tau\,(x-j)^2,$$

solving $V_{H1} = V_{H0}$ and $V_{L1} = V_{L0}$ yields the horizontal indifference points (Belleflamme & Peitz, 2015, p.118):

$$x_1 = \frac{p_{H1} - p_{H0} + \tau}{2\tau} = \frac{0.7 - 0.7 + 1}{2} = 0.5, \quad x_2 = \frac{p_{L1} - p_{L0} + \tau}{2\tau} = \frac{0.4 - 0.4 + 1}{2} = 0.5.$$

Solving $V_{H1} = H_{L1}$ and $V_{H0} = V_{L0}$ yields the vertical indifference points (Belleflamme & Peitz, 2015, p.121):

$$\theta_1 = \frac{p_{H1} - p_{L1}}{s_H - s_L} = \frac{0.7 - 0.4}{0.7 - 0.2} = 0.6, \quad \theta_2 = \frac{p_{H0} - p_{L0}}{s_H - s_L} = \frac{0.7 - 0.4}{0.7 - 0.2} = 0.6.$$

These four cutoff points divide the (x,θ) space into regions where each product offers the greatest utility. When compared to the model solved in MATLAB, the results are the same as those shown in Figure 6b.

Additional numerical MATLAB results

Table 7. Numerical results from MATLAB model for $\lambda = 2$, grouped by cases.

Product	Price	Consumer Price	Demand	Top 10%	Bottom 10%	Profit
Case 1: No VAT applied						
H1	0.9781	0.9781	0.3166	0.2040	0.1058	0.1989
H0	0.9781	0.9781	0.3166	0.2040	0.1058	0.1989
L1	0.6729	0.6729	0.1834	0.0460	0.1442	0.1051
L0	0.6729	0.6729	0.1834	0.0460	0.1442	0.1051
Case 2: VAT on ICEV						
H1	0.9824	0.9824	0.3298	0.2138	0.1091	0.2086
H0	0.8451	1.0564	0.2923	0.1902	0.0962	0.1447
L1	0.6750	0.6750	0.1913	0.0485	0.1495	0.1100
L0	0.5602	0.7004	0.1866	0.0475	0.1452	0.0859
Case 3: VAT on ICEV & high-quality EV						
H1	0.8473	1.0591	0.3024	0.1989	0.0979	0.1504
H0	0.8480	1.0600	0.3030	0.1991	0.0983	0.1509
L1	0.6799	0.6799	0.2012	0.0521	0.1547	0.1167
L0	0.5616	0.7020	0.1934	0.0499	0.1490	0.0893

Note: Parameter values are $R = 1$, $\lambda = 2$, $\tau = 1$, $s_H = 0.7$, $s_L = 0.2$, $\theta \sim U[0.2, 2.2]$. Marginal costs $c_{H1} = c_{H0} = 0.35$, $c_{L1} = c_{L0} = 0.1$, VAT rate $t = 0.25$. Equilibrium prices p^*_{ij} solved via MATLAB's `vpasolve`.

Table 8. Case 2→3 Top/Bottom 10% demands by specification

Specification	Case	H1 Top 10%	L1 Top 10%	H1 Bottom 10%	L1 Bottom 10%
$\lambda = 6, \tau = 1$	Case 2	0.2577	0.0059	0.0434	0.2153
	Case 3	0.2441	0.0072	0.0346	0.2193
$\lambda = 4, \tau = 8$	Case 2	0.2289	0.0230	0.0541	0.1973
	Case 3	0.2248	0.0256	0.0489	0.2016
$\lambda = 4, \tau = 0.5$	Case 2	0.2511	0.0167	0.0766	0.1846
	Case 3	0.2321	0.0189	0.0646	0.1905

Notes: Entries are the EV demand shares D_{ij} for products H1 and L1 among the top- and bottom-10% WTP segments, reported separately for Case 2 (VAT on ICEV) and Case 3 (VAT on ICEV& high-quality EV). Optimal prices were calculated for each Specification and than demands where calculated numerically. Results are used for the calculation of Table 2

Additional descriptive statistics results and tables

Table 9. Average Marginal Effects from Logit Model on EV registration in 2016 and 2023

	d_electric_car	
	(1) 2016	(2) 2023
num_pers	0.02033***	-0.00055
	(0.0013)	(0.00051)
mean_age	-0.00201***	-0.00013***
	(0.00011)	(0.00004)
max_education_level	0.03599***	0.00441***
	(0.0017)	(0.00054)
log_income	0.01326***	0.00114***
	(0.0010)	(0.00037)
city	0.12008***	0.00045
	(0.0034)	(0.00104)
Observations	91,267	60,130
Prob > chi2	0	0
Pseudo R^2	0.0576	0.0255

Robust standard errors in parentheses. *** $p < 0.01$.

Notes: This table reports average marginal effects (dy/dx) from logit regressions. The marginal effect represents the change in the probability of owning an EV for a one-unit increase in the respective variable, holding all else constant. These results are derived from the same logit models used in Table 4. The number of observations is based on vehicles registered in the corresponding year 2016 or 2023. Code: Appendix Section C

Figure 7. Histogram on household income distribution

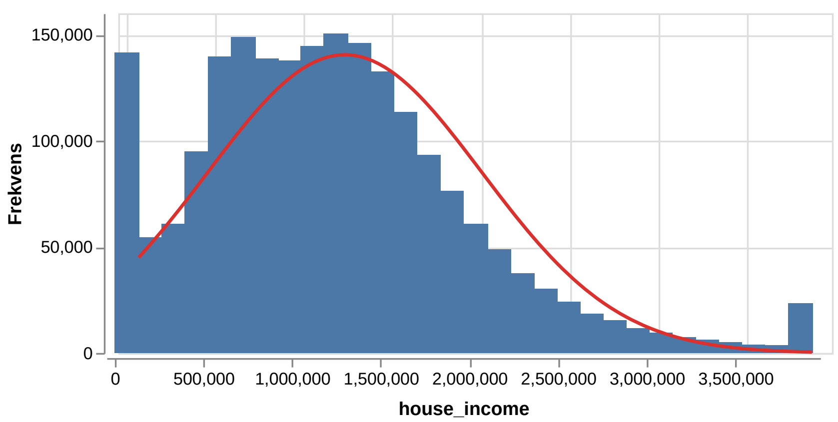


Table 10. Cross-tabulation of household income and electric car by year (2016-2023)

		2016-12-31	2017-12-31	2018-12-31	2019-12-31	2020-12-31	2021-12-31	2022-12-31	2023-12-31	Total
income = 0	electric car = 0	3598	7590	11873	16602	24817	30851	37738	43812	**176874**
	electric car = 1	653	1927	4234	7573	13345	24659	40491	56746	**149640**
income = 1	electric car = 0	6281	13418	21841	32285	51190	66142	80788	93395	**365341**
	electric car = 1	4779	14048	29718	52140	83400	141881	224817	300827	**851619**
Total		**15306**	**37002**	**67663**	**108599**	**172749**	**263537**	**383837**	**494776**	**1543465**

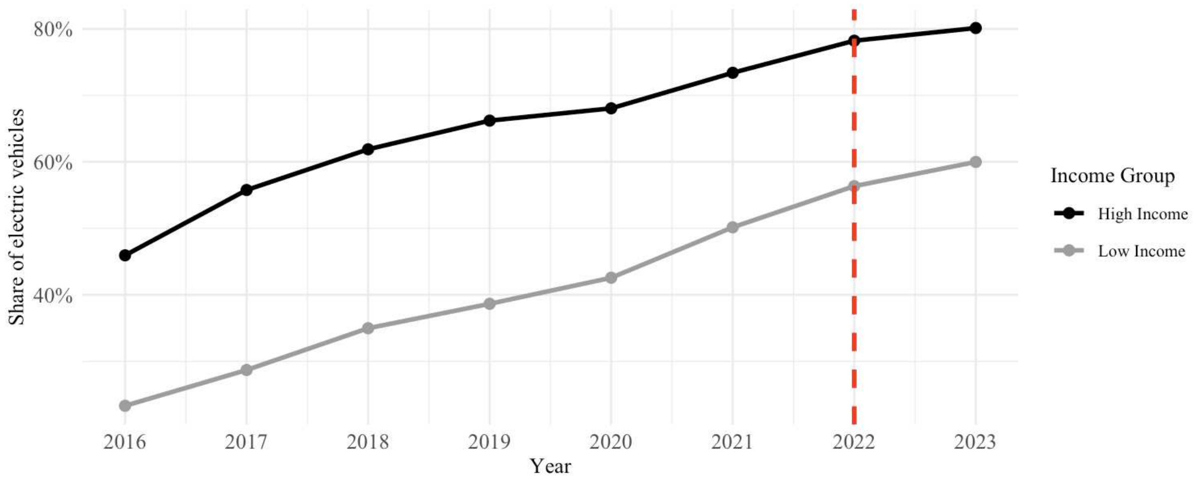
Notes: form Microdata analysis see Appendix Section C.

Table 11. Cross-tabulation of individual income and electric car by year (2016-2023)

		2016-12-31	2017-12-31	2018-12-31	2019-12-31	2020-12-31	2021-12-31	2022-12-31	2023-12-31	Total
income = 0	electric car = 0	3886	8349	13650	20844	30687	41313	52980	64722	**236414**
	electric car = 1	1181	3359	7341	13128	22740	41564	68376	97082	**254671**
income = 1	electric car = 0	2335	4880	7878	11624	16525	21035	25248	29237	**118770**
	electric car = 1	1984	6151	12789	22762	35186	58020	90641	117851	**345377**
Total		**9386**	**22740**	**41658**	**68358**	**105138**	**161932**	**237245**	**308892**	**955349**

Notes: form Microdata analysis see Appendix Section C.

Figure 8. Electric vehicle share by individual income group and year (2016-2023)



Notes: The trends shown were calculated using the annual numbers in Table 11. The resulting income thresholds correspond approximately to the 25th and 75th percentiles of the individual income distribution.

Additional results

Table 12. DiD estimates for EV registration with restricted control group (2020–2023)

	d_electric_car	
	(1) Baseline	(2) + Covariates
d_income_house	0.0552***	0.0173***
	(0.0026)	(0.0013)
d_time	0.0350***	0.0210***
	(0.0017)	(0.0009)
d_income_house × d_time	-0.0259***	-0.0102***
	(0.0017)	(0.0009)
Constant	0.9165***	–
	(0.0025)	–
Observations	494,407	494,407
F statistic	1,466.17***	269,625.13***
R^2 (total)	0.0088	0.7924

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Notes: Results based on Equation (11) using a restricted control group (bottom 10%) for the period 2020–2023. Column (2) includes vehicle controls: see Table 5. The dependent variable d_electric_car = 1, if a registered vehicle is electric. The constant term is suppressed in models with vehicle level controls due to the low number of unique unit combinations across categorical variables. This is a feature of the Microdata.no environment and does not affect the estimation results. Code: Appendix Section C

Identification strategy for Figure 4

To verify the common trends assumption, I estimate a series of placebo interactions in the pre-treatment period. I generate year indicators for 2016–2022 and interact each with the high-income dummy, omitting the 2016 interaction as the reference. I then run the following pooled OLS regression:

$$\Pr(\mathrm{EV}_{it} = 1) = \beta_0 + \beta_1 \, Income_i + \sum_{t=2016}^{2022} \gamma_t \, Year_t + \sum_{t=2017}^{2022} \delta_t \, (Income_i \times Year_t) + \varepsilon_{it},$$

Here, income_2017–income_2022 captures the differential trend of high- versus low-income households in each year relative to 2016. Plotting these coefficients (with 95% CIs) checks for any pre-treatment divergence. Insignificant estimates for 2017–2022 support the parallel trends assumption.

C Appendix: Code for the Microdata.no Analysis Tool

Logit model

```
require no.ssb.fdb:39 as db

// Creating car dataset
create-dataset cars

import db/KJORETOY_KJT_GRUP 2023-12-31 as vehicle_group
tabulate vehicle_group
keep if vehicle_group == '101'
import db/KJORETOY_KJORETOYID_FNR 2023-12-31
import db/KJORETOY_FREG_AR 2023-12-31 as year_reg
import db/KJORETOY_DRIVSTOFF_OMK 2023-12-31 as fuel_type
importdb/KJORETOY_TEKN_DRIVSTOFF_FORBRUK  2023-12-31 as
   fuel_consumption

destring fuel_type
histogram fuel_type, discrete
keep if fuel_type == 1 | fuel_type == 2  | fuel_type == 5
histogram fuel_type
tabulate fuel_type

generate d_electric_car = 0
replace d_electric_car = 1 if fuel_type == 5

tabulate d_electric_car
create-dataset id
import db/INNTEKT_HUSHNR 2023-12-31 as householdnr
merge householdnr into cars on KJORETOY_KJORETOYID_FNR
import db/BEFOLKNING_HUSHNR 2024-01-01 as householdnr2
```

```
merge householdnr2 into cars on KJORETOY_KJORETOYID_FNR

// Creating household data set
create-dataset household_income
import db/INNTEKT_HUSHNR 2023-12-31 as householdnr
import db/INNTEKT_LONN 2023-12-31 as income
collapse (sum) income, by(householdnr)
rename income house_income
merge house_income into cars on householdnr
histogram house_income, freq normal

create-dataset house_pers
import db/BEFOLKNING_HUSHNR 2024-01-01 as householdnr2
import db/BEFOLKNING_PERS_I_HUSHNR 2024-01-01 as num_pers
merge num_pers into cars on householdnr2
create-dataset house_age
import db/BEFOLKNING_HUSHNR 2024-01-01 as householdnr2
import db/BEFOLKNING_FOEDSELS_AAR_MND as birth_date
generate age = 2025 - int(birth_date/100)
collapse(mean) age -> mean_age, by(householdnr2)
merge mean_age into cars on householdnr2
create-dataset house_municipality
import db/BEFOLKNING_KOMMNR_FAKTISK 2024-01-01 as municipality
merge municipality into cars on householdnr2
create-dataset house_educ
import db/BEFOLKNING_HUSHNR 2024-01-01 as householdnr2
import db/NUDB_BU 2023-08-01 as education
tabulate education
generate education_level = substr(education,1,1)
destring education_level
recode education_level (0/3 = 1 'Not completed secondary')(4/5 = 2 '
   Secondary education')(6 = 3 'Lower academy education')(7 = 4 '
   Higher academy education (master level)')(8 = 5 'Research
   education')(9 = 6 'Not stated')
```

```
drop if education_level == 6
tabulate education_level
collapse (max) education_level -> max_education_level, by(
   householdnr2)
merge max_education_level into cars on householdnr2
use cars
histogram house_income
drop if house_income == 0
histogram house_income, freq normal
drop if sysmiss(house_income)
summarize house_income
generate log_income = ln(house_income)
generate d_income = 0
replace d_income = 1 if house_income > 1000000
generate city = 0
replace city = 1 if inlist(municipality,'0301','4601','1103','5001')
tabulate municipality if city, rowsort()
tabulate city
drop municipality
drop if sysmiss(city)
tabulate year_reg
keep if year_reg == 2023 //adjustable for years-> 2016 or 2023
summarize fuel_consumption if d_electric_car == 1
replace fuel_consumption = 0 if fuel_type == 5
summarize fuel_consumption if d_electric_car == 1
tabulate year_reg
tabulate d_electric_car city
logit d_electric_car num_pers mean_age max_education_level log_income
    city , robust level(99)
logit d_electric_car num_pers mean_age max_education_level log_income
    city , robust level(99) or
logit d_electric_car num_pers mean_age max_education_level log_income
    city , robust level(99) mfx(dydx)
```

Listing 2. Code for Logit Model Estimates (Section 6)

Household DiD

```
require no.ssb.fdb:39 as db
// Creating car dataset
create-dataset cars
import db/KJORETOY_KJT_GRUP 2023-12-31 as vehicle_group
tabulate vehicle_group
keep if vehicle_group == '101'
clone-units cars paneldata
use paneldata
import-panel db/KJORETOY_KJORETOYID_FNR db/KJORETOY_FREG_AR db/
   KJORETOY_TOT_VEKT db/KJORETOY_LENGDE db/KJORETOY_TEKN_CO2_UTSLIPP
   db/KJORETOY_DRIVSTOFF_OMK db/KJORETOY_TEKN_DRIVSTOFF_FORBRUK
   2016-12-31 2017-12-31 2018-12-31 2019-12-31 2020-12-31 2021-12-31
   2022-12-31 2023-12-31
rename KJORETOY_FREG_AR year_reg
rename KJORETOY_TOT_VEKT weight
rename KJORETOY_LENGDE length
rename KJORETOY_TEKN_CO2_UTSLIPP co2_emission
rename KJORETOY_DRIVSTOFF_OMK fuel_type
rename KJORETOY_TEKN_DRIVSTOFF_FORBRUK fuel_consumption
tabulate fuel_type
destring fuel_type
histogram fuel_type, discrete
keep if fuel_type == 1 | fuel_type == 2  | fuel_type == 5
histogram fuel_type
tabulate fuel_type
barchart(count) fuel_type if year_reg >= 2000, over(year_reg) stack
barchart(count) fuel_type if year_reg >= 2016, over(year_reg) stack
keep if year_reg >= 2016
generate d_electric_car = 0
replace d_electric_car = 1 if fuel_type == 5
tabulate d_electric_car
generate electric_car = fuel_type == 5
generate fossil_car = inlist(fuel_type,1,2)
```

```
create-dataset id
import db/INNTEKT_HUSHNR 2023-12-31 as householdnr
merge householdnr into paneldata on KJORETOY_KJORETOYID_FNR
import db/BEFOLKNING_HUSHNR 2024-01-01 as householdnr2
merge householdnr2 into paneldata on KJORETOY_KJORETOYID_FNR
// Creating household data set
create-dataset household_income
import db/INNTEKT_HUSHNR 2023-12-31 as householdnr
import db/INNTEKT_LONN 2023-12-31 as income
collapse (sum) income, by(householdnr)
rename income house_income
merge house_income into paneldata on householdnr
histogram house_income, freq normal
create-dataset house_pers
import db/BEFOLKNING_HUSHNR 2024-01-01 as householdnr2
import db/BEFOLKNING_PERS_I_HUSHNR 2024-01-01 as num_pers
collapse (max) num_pers -> max_num_pers
merge max_num_pers into paneldata on householdnr2
create-dataset house_age
import db/BEFOLKNING_HUSHNR 2024-01-01 as householdnr2
import db/BEFOLKNING_FOEDSELS_AAR_MND as birth_date
generate age = 2025 - int(birth_date/100)
collapse(mean) age -> mean_age, by(householdnr2)
merge mean_age into paneldata on householdnr2
create-dataset house_municipality
import db/BEFOLKNING_KOMMNR_FAKTISK 2024-01-01 as municipality
merge municipality into paneldata on householdnr2
create-dataset house_educ
import db/BEFOLKNING_HUSHNR 2024-01-01 as householdnr2
import db/NUDB_BU 2023-08-01 as education
tabulate education
generate education_level = substr(education,1,1)
destring education_level
```

```
recode education_level (0/3 = 1 'Not completed secondary')(4/5 = 2 '
   Secondary education')(6 = 3 'Lower academy education')(7 = 4 '
   Higher academy education (master level)')(8 = 5 'Research
   education')(9 = 6 'Not stated')
tabulate education_level
collapse (max) education_level -> max_education_level, by(
   householdnr2)
merge max_education_level into paneldata on householdnr2
use paneldata
histogram house_income, freq normal
drop if house_income == 0
histogram house_income, freq normal
drop if sysmiss(house_income)
drop if sysmiss(mean_age)
drop if sysmiss(max_num_pers)
generate city = 0
replace city = 1 if inlist(municipality,'0301','4601','1103','5001')
tabulate municipality if city, rowsort()
tabulate-panel city
drop municipality
drop if sysmiss(city)
histogram mean_age
drop if sysmiss(mean_age)
replace fuel_consumption = 0 if fuel_type == 5
replace co2_emission = 0 if fuel_type == 5
drop if sysmiss(fuel_consumption)
drop if sysmiss(co2_emission)
drop if sysmiss(weight)
drop if sysmiss(length)
summarize-panel weight length co2_emission fuel_consumption
   house_income mean_age city max_education_level max_num_pers
summarize-panel weight length co2_emission fuel_consumption
   house_income mean_age city max_education_level max_num_pers if
   d_electric_car == 1
```

```
summarize-panel weight length co2_emission fuel_consumption
   house_income mean_age city max_education_level max_num_pers if
   d_electric_car == 0
summarize
histogram house_income, freq normal
generate decentile_income_house = quantile(house_income, 10)
tabulate decentile_income_house
generate d_income_house = 0 if house_income <= 294306.0
replace d_income_house = 1 if house_income >= 1000000
drop if sysmiss(d_income_house)
tabulate-panel d_income_house electric_car
regress-panel d_electric_car d_income_house mean_age city
   max_education_level max_num_pers, pooled robust level(99)
textblock
regress-panel d_electric_car d_income_house mean_age city
   max_education_level max_num_pers, re robust
regress-panel d_electric_car d_income_house mean_age city
   max_education_level max_num_pers, fe robust
hausman d_electric_car d_income_house mean_age city
   max_education_level max_num_pers, level(95)
endblock
tabulate-panel d_income_house electric_car
generate  d_time = 0
replace d_time = 1 if year(date@panel) >= 2023
regress-panel-diff d_electric_car d_income_house d_time, robust level
   (99)
generate d_long = 0
replace d_long = 1 if length >= 449
generate d_heavy = 0
replace d_heavy = 1 if weight >= 2213.75
regress-panel-diff d_electric_car d_income_house d_time d_long
   d_heavy, robust level(99)
generate d_high_co2 = 0
replace d_high_co2 = 1 if co2_emission >= 130
```

```
generate d_high_fuel = 0
replace d_high_fuel = 1 if fuel_consumption >= 0.5
regress-panel-diff d_electric_car d_income_house d_time d_long
   d_heavy d_high_fuel d_high_co2, robust level(99)
generate t = year(date@panel) - 2016
generate trend_hi = d_income_house * t
tabulate-panel t
tabulate-panel trend_hi
textblock
generate t2 = t^2
generate trend2_hi = d_income_house * t2
endblock
regress-panel-diff d_electric_car d_income_house d_time t trend_hi,
   robust level(99)
textblock
regress-panel-diff d_electric_car d_income_house d_time t t2 trend_hi
    trend2_hi, robust
endblock
regress-panel d_electric_car d_income_house##d_time, pooled
generate y2016 = year(date@panel) == 2016
tabulate y2016
generate y2017 = year(date@panel) == 2017
generate y2018 = year(date@panel) == 2018
generate y2019 = year(date@panel) == 2019
generate y2020 = year(date@panel) == 2020
generate y2021 = year(date@panel) == 2021
generate y2022 = year(date@panel) == 2022
textblock
generate y2023 = year(date@panel) == 2023
endblock
generate income_2016 = d_income_house*y2016
tabulate income_2016
generate income_2017 = d_income_house*y2017
generate income_2018 = d_income_house*y2018
```

```
generate income_2019 = d_income_house*y2019
generate income_2020 = d_income_house*y2020
generate income_2021 = d_income_house*y2021
generate income_2022 = d_income_house*y2022
textblock
generate income_2023 = d_income_house*y2023
endblock
coefplot regress-panel d_electric_car d_income_house y2016 y2017
   y2018 y2019 y2020 y2021 y2022   income_2017 income_2018
   income_2019 income_2020 income_2021 income_2022, pooled robust
regress-panel d_electric_car d_income_house y2016 y2017 y2018 y2019
   y2020 y2021 y2022  income_2016 income_2017 income_2018 income_2019
    income_2020 income_2021 income_2022, pooled robust
// for 2020-2023
keep if year_reg >= 2020
tabulate-panel d_income_house d_electric_car
regress-panel-diff d_electric_car d_income_house d_time, robust level
   (99)
regress-panel-diff d_electric_car d_income_house d_time d_long
   d_heavy d_high_fuel d_high_co2, robust level(99)
generate d_fossil_car = 0
replace d_fossil_car = 1 if fuel_type == 1 | fuel_type == 2
regress-panel-diff d_fossil_car d_income_house d_time, robust level
   (99)
```

Listing 3. Code for DiD estimates for household level variables

Individual DiD

```
require no.ssb.fdb:39 as db
// Creating car dataset
create-dataset cars
import db/KJORETOY_KJT_GRUP 2023-12-31 as vehicle_group
tabulate vehicle_group
keep if vehicle_group == '101'
clone-units cars paneldata
use paneldata
import-panel db/KJORETOY_TEKN_SITTEPL_TOTALT db/
   KJORETOY_KJORETOYID_FNR db/KJORETOY_FREG_AR db/KJORETOY_TOT_VEKT
   db/KJORETOY_LENGDE db/KJORETOY_TEKN_CO2_UTSLIPP db/
   KJORETOY_DRIVSTOFF_OMK db/KJORETOY_TEKN_DRIVSTOFF_FORBRUK
   2016-12-31 2017-12-31 2018-12-31 2019-12-31 2020-12-31 2021-12-31
   2022-12-31 2023-12-31
rename KJORETOY_FREG_AR year_reg
rename KJORETOY_TEKN_SITTEPL_TOTALT seats
rename KJORETOY_TOT_VEKT weight
rename KJORETOY_LENGDE length
rename KJORETOY_TEKN_CO2_UTSLIPP co2_emission
rename KJORETOY_DRIVSTOFF_OMK fuel_type
rename KJORETOY_TEKN_DRIVSTOFF_FORBRUK fuel_consumption
tabulate fuel_type
destring fuel_type
histogram fuel_type, discrete
keep if fuel_type == 1 | fuel_type == 2  | fuel_type == 5
histogram fuel_type
tabulate fuel_type
barchart(count) fuel_type if year_reg >= 2000, over(year_reg) stack
barchart(count) fuel_type if year_reg >= 2016, over(year_reg) stack
keep if year_reg >= 2016
generate electric_car = 0
replace electric_car = 1 if fuel_type == 5
tabulate electric_car
```

```
// Creating person data set
create-dataset person
import db/INNTEKT_LONN 2023-12-31 as income
merge income into paneldata on KJORETOY_KJORETOYID_FNR
import db/BEFOLKNING_KOMMNR_FORMELL 2024-01-01 as municipality
generate city = 0
replace city = 1 if inlist(municipality,'0301','4601','1103','5001')
tabulate municipality if city, rowsort()
drop municipality
merge city into paneldata on KJORETOY_KJORETOYID_FNR
import db/NUDB_BU 2023-08-01 as education
import db/BEFOLKNING_FOEDSELS_AAR_MND as birth_date
generate age = 2025 - int(birth_date/100)
tabulate education
generate education_level = substr(education,1,1)
destring education_level
recode education_level (0/3 = 1 'Not completed secondary')(4/5 = 2 '
   Secondary education')(6 = 3 'Lower academy education')(7 = 4 '
   Higher academy education (master level)')(8 = 5 'Research
   education')(9 = 6 'Not stated')
tabulate education_level
import db/BEFOLKNING_KJOENN as gender
tabulate gender
destring gender
tabulate gender
recode gender (2 = 0)
rename gender male
tabulate male, nolabels
merge education_level into paneldata on KJORETOY_KJORETOYID_FNR
merge age into paneldata on KJORETOY_KJORETOYID_FNR
merge male into paneldata on KJORETOY_KJORETOYID_FNR
histogram income, freq normal
use paneldata
replace fuel_consumption = 0 if fuel_type == 5
```

```
summarize-panel seats weight length co2_emission fuel_consumption
   income education_level age city if electric_car == 1
summarize-panel seats weight length co2_emission fuel_consumption
   income education_level age city if electric_car == 0
summarize-panel seats weight length co2_emission fuel_consumption
   income education_level age city
generate decentile_income = quantile(income, 10)
tabulate decentile_income
generate d_income = 0 if income <= 500000
replace d_income = 1 if income >= 1000000
tabulate-panel d_income electric_car
generate  d_time = 0
replace d_time = 1 if year(date@panel) >= 2023
tabulate-panel d_time
tabulate-panel d_income electric_car
drop if sysmiss(d_income) | sysmiss(electric_car) | sysmiss(d_time)
regress-panel-diff electric_car d_income d_time, robust
generate d_long = 0
replace d_long = 1 if length >= 449
generate d_heavy = 0
replace d_heavy = 1 if weight >= 2140
generate d_high_co2 = 0
replace d_high_co2 = 1 if co2_emission >= 130
generate d_high_fuel = 0
replace d_high_fuel = 1 if fuel_consumption >= 0.26
regress-panel-diff electric_car d_income d_time d_long d_heavy
   d_high_fuel d_high_co2, robust
keep if year_reg >= 2020
tabulate-panel d_income electric_car
regress-panel-diff electric_car d_income d_time, robust
regress-panel-diff electric_car d_income d_time d_long d_heavy
   d_high_fuel d_high_co2, robust
```

Listing 4. Code for DiD estimates for individuel level variables