

Master in Institutions and Political Economy
Master Thesis

Master Thesis title:

Can public charging
infrastructure drive electric
vehicle demand? Evidence from
Denmark

Student:

Malte Brinck Thygesen

Advisors:

Pilar Sorribas-Navarro &
Jordi Teixidó-Figueras

Academic year:

2024-2025



UNIVERSITAT DE
BARCELONA

Màster en Institucions i Economia Política

Can public charging infrastructure drive electric vehicle demand? Evidence from Denmark

June 13, 2025

Author: Malte Brinck Thygesen

University: Universitat de Barcelona

Supervisors: Pilar Sorribas-Navarro & Jordi Teixidó-Figueras

Keywords: Environmental economics, Electric vehicles, Public charging infrastructure, Public policy, Causal inference, Denmark

Abstract

Electric vehicles (EVs) are a key tool for reducing emissions in the transportation sector, which remains the only EU sector with increasing emissions since 1990. One of the main external barriers to EV uptake is the availability of public charging infrastructure. This paper investigates how the rollout of public charging stations affects EV adoption across Danish municipalities. Using a staggered difference-in-difference design, I estimate the causal effect of introducing the first public charger in a municipality. The results show a statistically significant increase of 0.47 EVs per 1,000 capita, with a noticeable effect only emerging around two years after treatment—likely reflecting the high cost and long decision time involved in private personal vehicle purchases. I additionally explore heterogeneity and find that the effect is significantly larger for high-income and urban municipalities as well as for municipalities with a larger initial share of EV's. I also find that EV's to a large extent substitute internal combustion engine (ICE) vehicles. Finally, I also estimate a positive effect of a Danish policy from 2021 which invested in public charging infrastructure. These findings offer insights for more targeted and socially balanced policy interventions.

Acknowledgments

I would like to thank my supervisors Pilar Sorribas-Navarro and Jordi Teixidó-Figueras for their guidance and support throughout the entire thesis process. Their advice and guidance have been extremely helpful in completing the work. I additionally want to express my gratitude to Clever A/S and AURA a.m.b.a. for providing additional data of their public charging infrastructure.

1 Introduction

Climate change remains one of the biggest threats to individuals, states and economies across the world, and large efforts must be made to mitigate the consequences by reducing greenhouse gas emissions. While the European Union (EU) has managed to reduce emissions from almost all sectors in recent years, the transportation sector has seen increasing emissions since 1990 as the only EU sector (EEA, 2025). Within the transportation sector, road transport emissions account for almost three quarters of the total emissions (European Environment Agency, 2022), making road transport a key sector for climate change mitigation in the EU. Relatively new technological developments of battery-driven electric vehicles (EV) have created an opportunity to decrease emissions from road transport, given that EV's emit much less greenhouse gases if running on clean energy compared to traditional internal combustion engine (ICE) vehicles running on fossil fuels. The European Parliament has therefore banned the sale of all new ICE vehicles from 2035 as part of the 2050 objective of carbon neutrality (European Parliament, 2022). At the time of writing, member nations have less than 10 years remaining to ensure that consumers and EV markets are ready for the ban on ICE vehicles. In addition to greenhouse gas emission reductions, EV's also make less noise and do not pollute locally - one of the biggest health risks for urban citizens (EEA, 2025). A transition to an electrified transportation sector is thus beneficial for climate change mitigation, public health and noise levels.

This paper engages with a potential barrier to EV uptake: public charging infrastructure. Barriers to EV adoption can generally be characterised as internal or external (Coffman et al., 2017). While internal barriers could be the driving range, charging time or price of the EV, external barriers refer to charging infrastructure and relative fuel prices (Coffman et al., 2017). Although policymakers can intervene on both the internal and external barriers, several studies find interventions on the external side, specifically regarding public charging infrastructure, to be more inexpensive and effective than intervening on the internal side through subsidies or tax benefits for EV owners (Chandra et al., 2010; S. Li et al., 2017; Yan, 2018). A few studies estimate the effect of public charging infrastructure on EV adoption rates in the US (Narassimhan & Johnson, 2018), Sweden (Egnér & Trosvik, 2018), and Germany (Illmann & Kluge, 2020; Sommer & Vance, 2021). All studies find a positive correlation between charging infrastructure and EV adoption, and Illmann and Kluge (2020)¹ find the direction of causality to be going from charging in-

¹Illmann and Kluge (2020) investigate monthly patterns of private EV registrations in Germany from 2012-2017. They use a cross-sectional augmented autoregressive distributed lag-model to estimate the effects of public charging infrastructure. The results are rather modest compared to unobservable common factors such as vehicle models or general eco-friendly trends, but the effect is notably larger for fast chargers compared to normal chargers. Granger causality suggests that the effect runs from infrastructure to EV registrations.

frastructure to EV adoption. Although the literature has grown in recent years, the topic still remains relatively new and unexplored given the recency of the EV as a component in advanced economies.

This paper addresses the question of how public charging infrastructure affects EV adoption. The analysis focuses on municipalities in the EU member state Denmark in the period from January 2018 to February 2025. This is a particularly relevant country for EV's because of the large share (81%) of renewable energy sources in Denmark's electricity mix (IEA, 2024), and given that renewable energy is a key condition for EV's to be a more sustainable solution than ICE vehicles. With monthly data from GeoFA Danmark and Statistics Denmark, I make use of the staggered investments in public charging stations to estimate a staggered difference-in-difference analysis between municipalities treated with public charging infrastructure and those not yet treated with public charging infrastructure. This identification strategy is well-suited for the setting, given that Danish municipalities did not implement charging infrastructure at the same time. The methodological approach, developed by Callaway and Sant'Anna (2021), allows me to estimate the causal effect of public charging infrastructure on EV adoption and explore the dynamic effects across time. The results reveal that implementing the first charging station leads to a statistically significant increase of 0.47 EV's per 1000 inhabitants. Additionally, assessing the heterogeneity over time suggests that it takes around two years from the first charging station and until a positive reaction from EV consumers. This lag in effect is reasonable because buying a new vehicle is one of the major parts of household budgets. Potential EV adopters therefore need some time from seeing the new charging possibilities until deciding to buy a new or change private vehicle.

I make four contributions to the existing literature on EV's. I first contribute with the baseline estimation by exploiting the variation in charging infrastructure across Danish municipalities to find evidence from a country that is yet to be analysed in this context. Denmark is not only relevant because of its renewable energy mix, but also because the EV market has accelerated in recent years, making the findings relevant for other countries seeking to stimulate premature EV markets. I secondly contribute with results suggesting that the effect is larger in high-income municipalities than in low-income municipalities. This is done by exploring heterogeneity between high-income and low-income municipalities. While other studies have identified free-rider effects of policy interventions such as subsidies and tax benefits (Chandra et al., 2010; Muehlegger & Rapson, 2018; Trotta & Sommer, 2024), no study has as far as I know investigated the socioeconomic component of public charging infrastructure. It is of interest for policymakers to know whether the effect of charging infrastructure differs across different income segments of the population as it allows for a sober comparison of different policy instruments and

their derived effects on social dynamics. My third contribution builds on social contagion theory² as I find that the effect of public charging infrastructure is larger in municipalities with a relatively larger initial share of EV's. This is done through a heterogeneous analysis splitting the sample of municipalities depending on the initial share of EV's in each municipality. While other studies have discussed the social network component of EV adoption (Breschi et al., 2020; Encarnaç o et al., 2018; Wolf et al., 2015), no other study has empirically assessed the combined influence of new infrastructure and social contagion from other EV adopters. My final contribution is an empirical assessment of an assumption in the EV literature that no other study to the best of my knowledge has questioned; namely that more EV's must equal less ICE vehicles. By analysing patterns in ICE vehicle registrations, I provide insights on whether EV's substitute or complement ICE vehicles. The results suggest that EV's to a large extent substitute ICE vehicles, which emphasises the potential for emission reductions of an electrification of the transportation sector.

The rest of the paper is structured as follows. In section 2, the background for the investigation is presented, both in terms of the conceptual framework of EV's and the institutional context of Denmark. In section 3, I describe the sample, unit of analysis, data and empirical strategy, i.e. the causal identification strategy, its assumptions and the main equations for estimation. All results are presented in section 4, which also discusses possible mechanisms in light of related literature as well as the policy implications. Finally, section 5 sums up the main conclusions of the paper and points towards limitations and future avenues of research.

2 Background

2.1 Conceptual framework: Electric vehicles

This paper is based on a relatively new, but growing breach of literature that examines the real concern of barriers to electric vehicle uptake. Coffman et al. (2017) group the barriers to EV adoption into internal and external factors. Internal barriers consist of e.g. higher prices of EV's, the charging time of the vehicle, and the potential driving range. External barriers could be the relative fuel prices between kWh and fossil fuels, and the lack of public charging infrastructure. Political initiatives have the potential to impact both internal and external barriers. For example, the prices of EV's can be influenced through policies altering the registration taxes of EV's. Trotta and Sommer (2024)

²social contagion theory suggests that behaviours, emotions, or ideas can spread through social networks much like a virus, as people unconsciously mimic and adopt what they observe in others. It emphasises the role of peer influence and shared environments in shaping individual and group behaviour (Christakis & Fowler, 2013).

examine the implementation and subsequent removal of a registration tax exemption in Denmark.³ They find that while the exemption did have a positive effect on EV adoption, it also created substantial freerider effects; richer consumers who were going to buy an EV either way benefit from the tax exemption. Muehlegger and Rapson (2018) also find that EV subsidies have very limited effects on EV adoptions for low- and middle-income households. This questions the additionality effect of policy interventions like subsidies or tax credits and suggests that interventions in the form of tax exemptions benefit the richest people the most (Muehlegger & Rapson, 2018; Trotta & Sommer, 2024).

External barriers to EV adoption can also be influenced through taxes on fossil fuels or emissions as well as the construction of public charging infrastructure. Given that actual charging infrastructure was very limited 10-15 years ago, some of the earliest studies in the literature use stated preferences to survey potential EV consumers in Belgium (Lebeau et al., 2012), Germany (Achtnicht et al., 2012; Hackbarth & Madlener, 2013; Ziegler, 2012), and Switzerland (Patt et al., 2019). Their findings suggest that a lack of public charging infrastructure is a major barrier to EV adoption and that an increasing density of charging infrastructure would effectively increase the amount of EV's. The main mechanisms pointed at from most of the choice experiments conducted relate to availability and range anxiety. The former refers to the lack of charging stations relative to EV's ("is someone else using the charger, when I need to?") while the latter refers to a lack of geographic coverage ("do I run out of battery in an area with no charging stations?"). Axsen et al. (2013) show through a survey experiment that potential EV consumers in California refrain from adopting EV's due to a lack of public charging infrastructure near their home. As such, most studies in the literature using stated preferences suggest that there is a positive relationship between public charging infrastructure and EV adoption rates (W. Li et al., 2017).

The literature using stated preferences is useful when assessing hypothetical EV adoptions in an early, undeveloped market. The alternative to stated preferences is revealed preferences, i.e. assessing the actual behaviour of consumers. Axsen et al. (2009) and Lane and Potter (2007) argue that revealed preferences are more reliable estimates of EV adoption as there tends to be a gap between environmentally friendly attitudes coming forward in choice experiments and actual behaviour - not only concerning EV's, but on a broader scale with anything related to climate change and the environment. As EV markets and data on these have improved in recent years, more studies thus investi-

³Trotta and Sommer (2024) investigate the removal of a registration tax exemption for EV's in Denmark. With data on EV registrations in the period 2013-2019, their Bayesian additive regression trees suggest that EV adoptions had been higher if the registration tax exemption had not been removed in 2016 (see Figure 1). Additionally, their data on socioeconomic factors suggest that the tax exemption mostly benefitted richer consumers, which suggests freerider effects of the policy.

gate the nexus between public charging infrastructure and EV adoption through revealed preferences. Narassimhan and Johnson (2018) investigate the EV market in the US descriptively and find a positive correlation between public charging infrastructure density and EV adoption.⁴ S. Li et al. (2017) assess the indirect network effects between infrastructure and EV adoption from a policymaking perspective in the US.⁵ They find significant feedback loops between EV infrastructure and demand; interventions on EV infrastructure strongly affects EV adoptions. The study also assesses the federal tax credit for EV owners and find investments in public charging infrastructure more than twice as effective for EV adoption as tax benefits of equal budget size (S. Li et al., 2017). Similarly, Chandra et al. (2010) deem tax credits for EV adopters in Canada "strikingly more expensive" than other policy instruments if the policy goal is to reduce emissions.⁶ These findings depict public charging infrastructure as one of the most effective policy tools - both in terms of EV adoptions and policy budgets.

Only a few studies have established links between public charging infrastructure and EV adoption within Europe. Egnér and Trosvik (2018) investigate the case of Sweden from 2010-2016 through fixed effects models and instrumental variables and find a positive effect of public charging infrastructure on EV diffusion. Their findings indicate that the mere existence of charging stations is beneficial for EV diffusion. Similar findings are found in Norway, where the first charging station causes an increase of 1.5% point in local EV ownership rate (Schulz & Rode, 2022), illustrating the importance of signalling institutional support to reduce range anxiety. Sommer and Vance (2021) estimate the causal effect of marginal increases in public charging stations in Germany. The effect is significant and positive, and stronger for fast chargers. Illmann and Kluge (2020) also investigate the EV market in Germany with a heterogeneous focus on the quantity, capacity, and abundance of charging stations and find that fast chargers have a particularly high effect on EV adoption rates. Based on the whole body of literature on EV's, the main hypothesis referring to the research question of this paper is that public charging

⁴Narassimhan and Johnson (2018) investigate the EV market in the US from 2008-2016 through fixed effects models. They find a significant positive association between public charging infrastructure and EV adoptions in that a 1% increase in public charging stations is associated with a 6.2% increase in EV purchases. They do not research causal links as the data does not contain any natural experiments. Additionally, their lagged dependent variables contain potential endogeneity, limiting the scope to descriptive evidence.

⁵S. Li et al. (2017) consider the EV market consisting of the two components of charging infrastructure and EV demand. They establish the existence of feedback loops through a model first, and then use data from the US in the period 2011-2013 to empirically assess the efficiency of policy instruments. Measuring EV demand through instrumental variables, they conclude that investments in public charging infrastructure would be more than twice as effective as tax credits for EV owners.

⁶Chandra et al. (2010) investigate tax rebates for EV owners in Canada which vary regionally. Through fixed effects models, they find that 26% of the EV's sold from 1989-2006 can be attributed to the tax rebates. However, their data allows them to identify that most of these EV adopters likely would have adopted low-emission vehicles anyway. This substantially increases the cost effectiveness of the tax rebates in terms of emission reductions.

infrastructure has a positive effect on EV adoption rates.

Despite the growing literature on EV markets across the world, several questions regarding the effect of public charging infrastructure on EV adoption remain unanswered. Various studies have discussed the additional effect and potential free rider effect of policy interventions of internal barriers such as subsidies or tax benefits for EV owners (Chandra et al., 2010; S. Li et al., 2017; Trotta & Sommer, 2024). However, no study has to the best of my knowledge investigated to what extent similar patterns happen when intervening at the external barrier of charging infrastructure. I therefore contribute with a heterogeneous analysis of the effect of public charging infrastructure in high-income and low-income municipalities, respectively. Based on related literature, and given that EV's in the period of study have tended to be more expensive than comparable ICE vehicles, it is expected that high-income municipalities react more strongly to the construction of new infrastructure than low-income municipalities do. Additionally, a series of papers model EV adoptions based on game theory and network analysis (Breschi et al., 2020; Encarnação et al., 2018; Wolf et al., 2015) and suggest that social contagion and being in a network of EV adopters has the potential to increase EV adoption. I therefore empirically test these suggestions by investigating heterogeneity between municipalities that differ in the initial share of EV's. This insight is particularly relevant for governments across the world that still experience premature EV markets. To the best of my knowledge, no other study has explored heterogeneity in terms of early adopters similar to this analysis. I expect to find a larger effect in municipalities with a higher initial EV share due to social contagion and network effects.

While the majority of the literature emphasises the importance of a transition from ICE vehicles to EV's due to climate and environmental reasons, very few pay attention to two important conditions for which this transition makes the transportation sector more sustainable. All existing studies seem to assume that a larger EV uptake necessarily comes as a substitution of ICE vehicles, but no research has clearly tested this assumption. If EV's do not replace ICE vehicles, but only add to the number of private vehicles in the economy, the perceived gains of more EV's do not actually lead to lower emission levels, better resource allocation, or less pollution. Given this lack of evidence as to whether this assumed substitution actually takes place, I contribute with evidence of public charging infrastructure affecting not only EV registrations, but also ICE vehicle registrations. I expect to find a negative effect of public charging infrastructure on ICE vehicle registrations as long as the main hypothesis of higher EV adoptions hold. The sustainability of the EV transition is also conditional on the vehicles being fuelled by clean energy. Indeed, if EV's are fuelled by fossil energy sources, the net gain in terms of emissions is very limited as emissions are just transferred from ICE vehicles to energy production. As

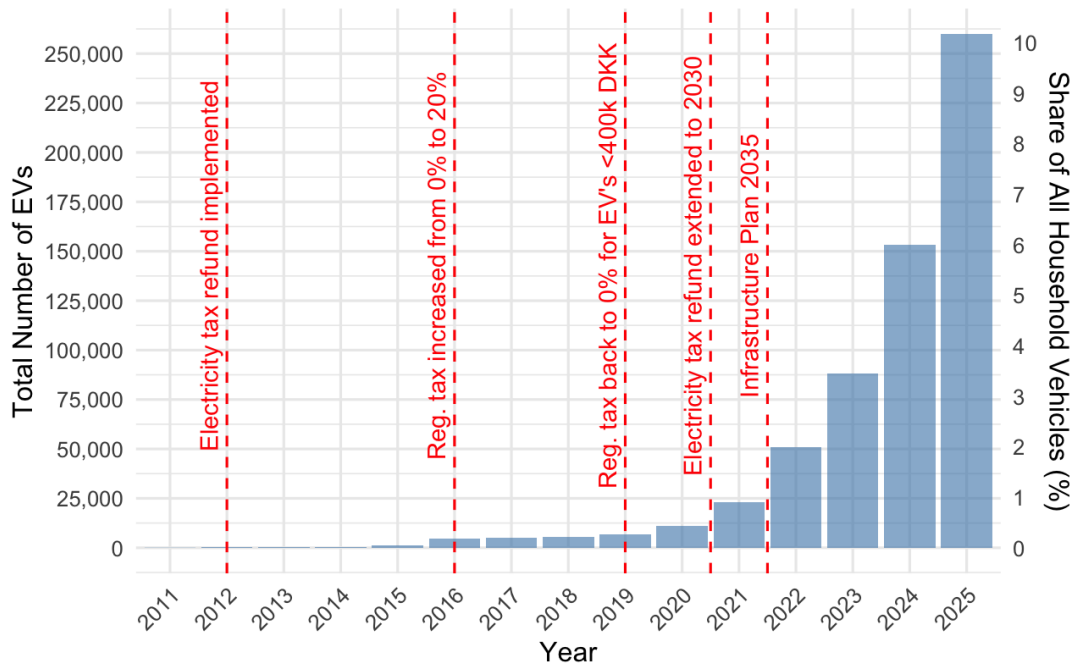
such, the EV transition is particularly relevant in countries with a higher clean energy mix such as Denmark (see [Appendix A](#)). I thereby contribute with causal evidence on a country that is not only of particular interest due to its renewable energy sources, but has also implemented policies specifically for public charging infrastructure. I conduct an analysis on municipalities specifically treated by the public investments agreed politically in 2021 and expect to find that the policy positively affected EV adoption due to the indirect network effects and reduced range anxiety.

2.2 Institutional setting: Denmark

This paper investigates EV's at the municipal level in Denmark. Arguably, EV adoptions have the potential to significantly reduce transportation emissions in Denmark given the high share of renewables in the country's energy production (IEA, [2024](#)); in 2022, the share of renewables in the total energy production amounted to 81%, as illustrated in [Appendix A](#). As a member state of the EU, Denmark is affected by EU legislation. As already mentioned, the most remarkable EU legislation with regards to EV's is the ban of the sale of new fossil fuel vehicles from 2035 - a step towards carbon neutrality in 2050 in the EU (European Parliament, [2022](#)). EU efforts towards the electrification of the transport sector are complemented by policies at the national level in Denmark. In 2020, Denmark made it legally binding for the government through the Climate Act to achieve 70% CO₂e reductions compared to the level in 1990 (Ministry of Climate, Energy and Utilities, [2020](#)). According to the latest projection from the Ministry of Climate, Energy and Utilities ([2025](#)), Denmark is expected to achieve this goal - mostly thanks to expected increases in EV demand and agricultural restructuring. This illustrates that Denmark is an ideal institutional setting for studying EV's in the broader context of climate change mitigation, given that transportation is a high-emission sector (EEA, [2025](#)).

Public investments in the EV market in Denmark have taken different forms, cf. the range of options presented in the previous section. Up until the end of 2015, EV's in Denmark had been completely exempted from registration taxes to incentivise early adoptions of the new technology. However, due to concerns over fiscal revenue, EV owners were no longer exempt from the weight-based tax and green owner tax from 2016 (Trotta & Sommer, [2024](#)). Additionally, the registration tax increased from 0% to 20% of the ICE registration tax from 2016, which resulted in a stagnation of EV adoptions (Ministry of Taxation, [2018](#)), as illustrated in [Figure 1](#). Due to the stagnation, the registration tax went back to 0% for vehicles priced below 400,000 DKK (~ 53,000 euros) in 2019. The refund for electricity taxes paid specifically for charging EV's, initially implemented in 2012, was also extended in December 2020 (Frederiksbjerg El, [2024](#)). In June 2021, as a

Figure 1: Total number and share of EV's of all household vehicles in Denmark



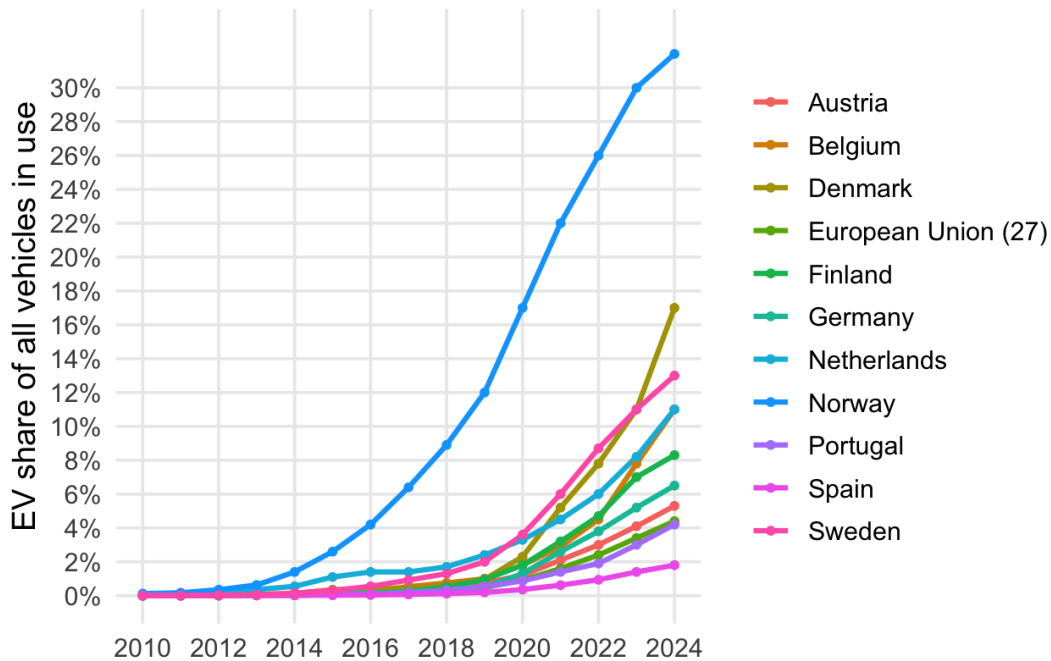
Notes: Data from Statistics Denmark (datacode BIL52). Only battery EV's registered in households are considered. Number of EV's as registered per 01/01 of each year.

part of the "Infrastructure Plan 2035", the government invested ~ 67 million euros in a rollout of public charging infrastructure from 2022 to 2028 (Ministry of Transportation, 2021). The main goal was to ensure "the geographic coverage of charging stations across the country" given that many municipalities did not have public chargers available (Ministry of Transportation, 2021).

The EV market in Denmark was rather small for many years and remained at less than 1% of total household vehicles until 2021, as illustrated in Figure 1. The market share of EV's has then increased significantly in recent years and is in the beginning of 2025 at 10.2%. Comparing to other countries in Europe, Denmark has one of the highest total shares of EV's and has consistently had higher shares than the EU average, as illustrated in Figure 2. It however still lacks significantly behind Norway, where almost one third of all vehicles were electric in 2024.

Importantly, one of the politically most relevant divides in Denmark is between urban and rural populations. Living in urban or rural areas of Denmark is one of the main characteristics in forming political opinions as preferences for healthcare, educational systems, immigration policies and transportation usually vary a lot between urban and rural voters (Nørtoft, 2019). Especially the transportation sector sees this divide because rural areas usually do not have the same high level of public transport that is found in urban

Figure 2: Share of vehicles currently in use that are electric, 2010-2024



Notes: Data from International Energy Agency via Our World in Data. Both battery EV's and plugin-hybrid EV's are considered, hence the larger number compared to [Figure 1](#)

areas. Additionally, distances are naturally larger in rural areas which makes the need for private vehicles bigger. Given these political circumstances, a relevant exploration of heterogeneity is therefore between rural and urban municipalities. As Egnér and Trosvik (2018) find a larger effect in Swedish urban municipalities, I expect to find that the effect is similarly larger in Danish urban municipalities.

3 Empirical design

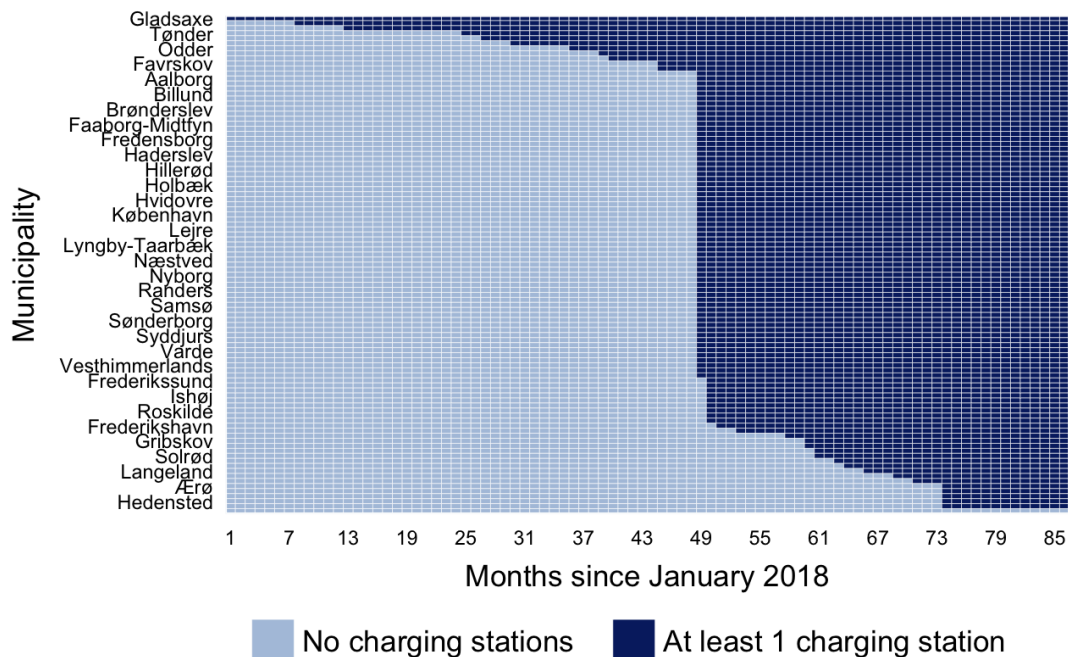
3.1 Sample and unit of analysis

The units of analysis in this study are municipalities in Denmark. There are a total of 98 municipalities as well as the island Christiansø, which technically does not belong to a municipality but is nevertheless observed in the data. As such, I analyse 99 units in total. The municipalities are observed monthly from January 2018 to February 2025, which sums up to 86 months. Given that 99 municipalities are observed 86 times, the total sample size is 8514. No municipalities or time periods have missing data, resulting in a balanced panel of data.

Treatment is defined as the initiation of operation of the first charging station in each municipality. The treatment is defined this way based on Schulz and Rode (2022) that

define treatment the same way when studying the early development of public charging infrastructure in Norway. This definition was found adequate as Schulz and Rode (2022) hint at the importance of early pushes for charging infrastructure. By studying the treatment of having the first public charging station implemented, I ensure a focus on the early development of charging infrastructure. Additionally, several studies have indicated that the mere knowledge of knowing about charging possibilities is crucial for potential EV consumers (see e.g. Coffman et al. (2017), Illmann and Kluge (2020), and Sommer and Vance (2021)), which makes this definition of the treatment relevant in the context of related literature. Figure 3 illustrates the variation in the month of which the 99 municipalities received their first public charging station. As mentioned in the previous section, a large part of the parliament agreed on significant improvements in the availability of public charging infrastructure in June 2021, with the rollout taking place from 2022 to 2028. This policy is very visible in Figure 3. The large number of municipalities treated with their first charging station in month 49, i.e. in the beginning of 2022, reflect the implementation of this policy. This policy meant that a total of 61 municipalities received new charging stations in January 2022. Additionally, the municipality Gladsaxe remained treated for the whole period of study, resulting in it being dropped from the analysis as units cannot be treated for the whole period. Also, the only municipality to never become treated is Christiansø, as seen in the bottom row of Figure 3.

Figure 3: Timing of the first public charging station for each municipality in Denmark



Notes: Data from GeoFA Danmark. There are 99 rows, one for each municipality, but only every third row is labelled with the municipality name due to lack of space.

3.2 Empirical strategy

To estimate the effect of public charging infrastructure on EV adoption, I start out by employing two-way fixed effects (TWFE) models - one without and one with covariates. This approach is rather common in panel data settings as it allows to control for variation across municipalities and across time. For example, variation across municipalities could be the result of historical preferences or geography, whereas variation across time could be because of supply shocks, differences in fuel prices relative to kWh, or changes in subsidies for EV owners (Trotta & Sommer, 2024). By including unit and time fixed effects in the model, these differences are considered, and the coefficient of interest only reflects variation in the outcome variable as a result of treatment. As such, the equation for the TWFE model I estimate is presented in Equation 1.

$$Y_{it} = \alpha_i + \lambda_t + \beta \cdot D_{it} + \mathbf{X}'_{it}\boldsymbol{\gamma} + \varepsilon_{it} \quad (1)$$

where Y_{it} refers to the outcome variable, EV per 1000 inhabitants. This is presented in per capita terms to ensure that any effect is not driven by differences in population between municipalities. α_i captures unit fixed effects for municipality i , while λ_t captures time fixed effects for time t . The treatment, which is the initiation of operation of the first charging station, is captured in D_{it} . The main coefficient of interest is β , which captures the average treatment effect of introducing the first public charging station in a municipality on the number of EV registrations per 1000 inhabitants. The main assumption for causal identification is that of parallel trends: In the absence of treatment, the outcome of each control group evolves in parallel trends with the outcome of the corresponding treated group. This assumption ensures that any differences observed after treatment can be attributed to the effect of having a charging station implemented. Additionally, the vector X'_{it} captures two control variables at the municipal level - income and the share of highly educated people. These control variables are included because the literature indicates that richer and more educated people are more likely to adopt EV's (Axsen et al., 2013; Hackbarth & Madlener, 2013). Conditioning the assumption of parallel trends on these confounding factors makes the assumption more plausible. Standard errors are clustered at the municipal level.

Despite the widespread use of TWFE models in panel data settings, Callaway and Sant'Anna (2021) point out some important limitations to this approach when the treatment is implemented at different points in time - i.e. staggered. This is relevant for this project because municipalities were treated with their first charging station at different points in time. As Callaway and Sant'Anna (2021) specify, TWFE models estimate the β coefficient through a weighted average of underlying treatment effects parameters. However, some of these weights can be negative if treatment effects are dynamic (Goodman-

Bacon, 2021). This ultimately creates bias in the estimation as already treated units in early time periods can become control groups for units that are treated in later time periods even though their outcomes are likely already affected by the early treatment. The precision of the TWFE estimation in this setting is therefore questionable.

To obtain the causal effect of public charging infrastructure on EV adoption, I therefore make use of the estimator formulated by Callaway and Sant’Anna (2021). This estimator is specifically developed to cases where treatment is staggered as it compares treated units in a given time period to units that have not yet been treated in that time period. This is crucial for this study as all municipalities except one eventually received their first charging station during the period studied (as seen in Figure 3). This estimator is therefore more robust and can be causally interpreted as it allows for variation in treatment effects across time or groups. It thereby avoids some of the issues highlighted with TWFE models. Using the Callaway-Sant’Anna estimator relies on a number of assumptions to be able to claim causality. The first assumption is, similar to TWFE models, that of parallel trends. It also relies on the assumption of no anticipation - i.e. that no municipality anticipates the implementation of a charging station and thereby change their behaviour before treatment. This means that treatment does not affect the outcome before the time of treatment. While these two assumptions cannot be proved, I investigate pre-trends in the results section in order to defend the use of these assumptions. Additionally, I assume "irreversibility of treatment". This means that once a municipality has been treated with a charging station, it remains treated for the remainder of the period. This assumption seems fairly plausible as the removal of charging stations after construction is unlikely. Finally, the design also relies on the Stable Unit Treatment Value Assumption (SUTVA), assuming that there is no interference between units - this means that the treatment in one unit should not affect the outcome in another unit.⁷ As such, the main equation I estimate to causally answer the research question is specified in Equation 2.

$$Y_{it} = \alpha_i + \lambda_t + \sum_g \sum_{t \geq g} \text{ATT}(g, t) \cdot 1\{G_i = g\} \cdot 1\{t = T\} + \varepsilon_{it} \quad (2)$$

In Equation 2, Y_{it} refers to the outcome variable, EV per 1000 inhabitants. α_i captures unit fixed effects for municipality i , while λ_t captures time fixed effects for time t . The staggered feature of the model is introduced through G_i that defines the treatment time of unit i . As such, ATT captures the average treatment effect in time t for units treated in period g . This is the main difference from the TWFE model: in the Callaway-Sant’Anna

⁷It is possible that this assumption does not hold; new charging stations can potentially affect EV registrations in neighbouring municipalities. In that case, the obtained effects may potentially be underestimated if control groups also see increases in EV adoption numbers. This potential downward bias of the estimates mean that the real-world effect of public charging infrastructure may be even larger.

estimator, heterogeneity in treatment effects across time and groups are taken into account. As such, the coefficient of ATT can be interpreted as the causal effect of the treatment on the outcome. Control groups are defined as those municipalities that have not yet been treated with their first charging station in each time t .

It is likely that treatment effects are heterogeneous across different characteristics. To investigate heterogeneity in terms of income, urban/rural and the initial share of EV's out of all vehicles in each municipality, I split the sample in two to estimate the effects separately for each group. Doing this relies on a number of assumptions (Callaway & Sant'Anna, 2021). First of all, both groups must satisfy the parallel trends assumption independently. The SUTVA assumption also applies, stating that treatment in one group should not affect outcome in another group. The split also assumes that no omitted variables are driving the split; the heterogeneity explored between e.g. high- and low-income units is due to income and not another omitted factor. Finally, both groups must also have sufficient treated and control municipalities. As such, Equation 2 also specifies the main estimation for each group when exploring heterogeneity. While this approach for heterogeneity does not indicate whether the difference between estimates is significant, I compute the statistical difference between estimates through two-tailed tests, as explained in Appendix B.

3.3 Data

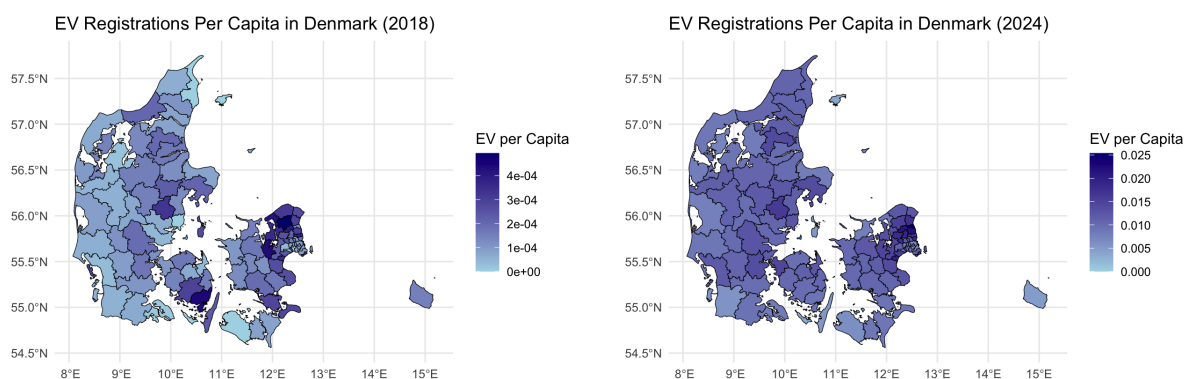
For the independent variable of the research question, public charging infrastructure, I use data from GeoFA Denmark. This database is the result of a collaboration between the Agency for Climate Data and the 99 municipalities and primarily serve to geolocate data points of interest that have not been located in public records. Their data on public charging infrastructure is publicly available and includes variables such as the initiation date of operation, the address, and the company operator. While the data specifies the company in charge of operating the station, it does not specify whether the initial investment is public or from a private company. The total number of public charging stations in the dataset amounts to 15,860, with the total number of charging points amounting to 28,448. According to news reports, the total number of charging points in Denmark on 31/12-2024 was 30,439 (Ryming, 2025). As such, the dataset accurately covers 93.5% of all public charging points. I additionally obtained data from two operators - Clever A/S and AURA Energi a.m.b.a.⁸ - which combined with the dataset from GeoFA Denmark improved the quality of the dataset in terms of missing data.

⁸Clever A/S is the largest provider of charging infrastructure for EV's in Denmark and have both private, public, and company stations. AURA Energi a.m.b.a. is an electricity provider that also administer public charging stations.

I use data from Statistics Denmark for the dependent variable of the research question, namely EV adoption. They provide monthly data on the number of new vehicle registrations in the households in each municipality from 2018-2025. This contains the number of registrations of new vehicles and includes information about the fuel type of the vehicles - whether they are electric, plugin-hybrid, use petrol, or diesel. As the market for plug-in hybrid vehicles has been very insignificant and stands at less than 4% of all household vehicles in Denmark (see [Appendix C](#)), this paper focuses on the adoption of battery EV's and not plug-in hybrids. The distinction on fuel type allows me to not only analyse the effect on EV registrations, but also analyse a potential substitution effect: do more EV's replace ICE vehicles or do they come in addition to these? When investigating this, I classify ICE vehicles as those using either petrol or diesel as fuel. Statistics Denmark also provide data on population, average income levels per municipality, and the share of highly educated citizens per municipality, which are used as control variables in the TWFE model.

The data on household EV registrations reveals a significant increase in EV adoption through the years of study. As seen in [Figure 1](#), while the total number of EV's registered in households in 2018 was 5,463, the same number in 2024 amounted to 259,791. Additionally, [Figure 4](#) illustrates how the distribution of EV's across municipalities have changed over the years. In 2018, only a few municipalities had a noteworthy number of EV registrations, while the west of Denmark, Jutland, mostly had very low EV adoption. Six years later, the picture looks much more evenly distributed across the country, although there are still larger adoption numbers in the municipalities in the east, just north of Copenhagen. These municipalities are also some of the richest in all of Denmark. These patterns could indicate that there may be heterogeneous effects given the differences in income and initial EV shares.

Figure 4: EV registrations per capita across Danish municipalities



Note: Data from Statistics Denmark (datacode BIL53).

For the heterogeneous analyses, I also use data from Statistics Denmark. I use the dataset of annual average disposable income for individuals in each municipality and split the sample at the median to explore income heterogeneity. This results in homogeneous samples, as both the high-income and low-income group contain 49 municipalities. When exploring heterogeneity based on the initial share of EV's, I use a dataset containing the total number of registered vehicles in the households per municipality. I use the data from the beginning of the period of study, namely 01/01-2018. As it contains information about the fuel types of the registered vehicles, I compute the EV share by dividing the number of EV's by the total number of vehicles registered in the households in each municipality. I then split the sample at the median, resulting in two groups: One with a higher initial share of EV's (i.e. above the median), and one with a lower initial share of EV's (i.e. below the median). This ensures homogeneous groups as 49 municipalities are assigned to each group. Finally, for the urban/rural analysis, I use Statistics Denmark's categorisation of Danish municipalities to define each municipality as either urban and rural, which takes both the population in the biggest city and the availability of jobs in each municipality into account. This results in 56 rural and 43 urban municipalities. Descriptive statistics are found in [Appendix D](#).

4 Results

In this section, I first present the baseline estimation that refers to the research question. I then explore heterogeneity across three characteristics before investigating the effect of public charging infrastructure on ICE vehicles. Finally, I investigate the policy push on charging infrastructure that was part of the "Infrastructure Plan 2035" agreed on in June 2021. For each analysis, I first report a table with the ATT estimation, before I explore the dynamic effects through an event plot.

4.1 Baseline estimation

To estimate the effect of public charging infrastructure on EV adoption, I first make use of TWFE models. [Table 1](#) presents the results of two such models: one with the baseline estimation, and one with the two control variables income and the share of highly educated people. Both models include unit and time fixed effects to account for unobserved heterogeneity across municipalities as well as common shocks through the period of study.

When controlling for the covariates income and education, the effect of implementing the first charging station is positive but insignificant. The estimate suggests that in the period after implementing the first charging station, municipalities experience an average increase of 0.05 EV's per 1000 inhabitants. Given that treatment was implemented

Table 1: Baseline effects of first station on EV registrations

	(1)	(2)	(3)
Estimator	TWFE	TWFE	C-S'A
1st Charging Station _{it}	0.037 (0.035)	0.051 (0.033)	0.47*** (0.03)
Income _{it}		<0.001* (<0.001)	
Share of Highly Educated _{it}		0.065 (0.062)	
<i>Fixed-effects</i>			
Municipality	Yes	Yes	Yes
Month	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	8,428	8,428	8,428
R ²	0.83707	0.84410	

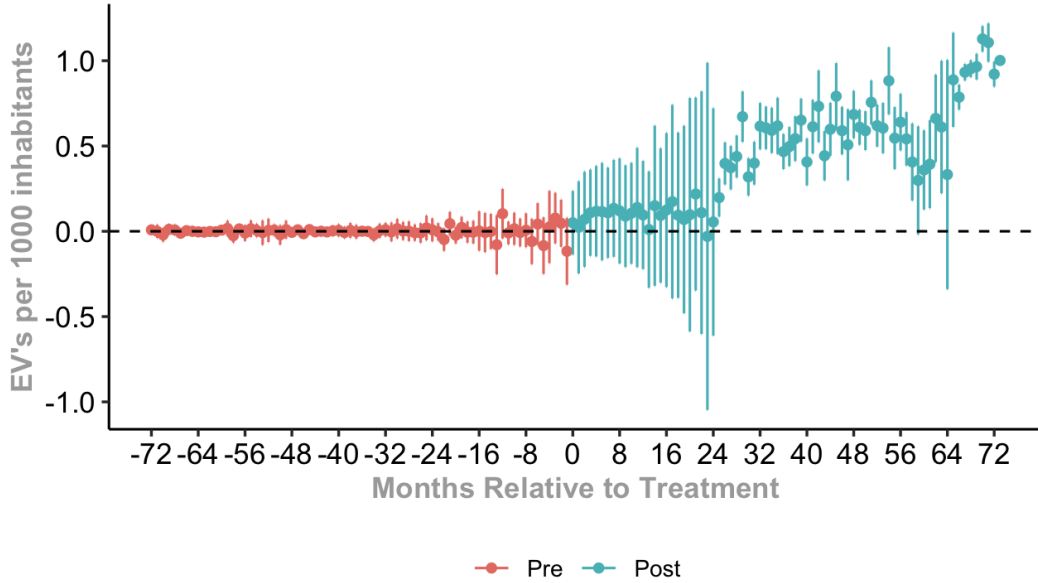
Notes: Clustered standard errors in parenthesis. *** p<0.01 ** p<0.05 * p<0.1. 1) Dependent variable: EV registrations per 1000 inhabitants. 2) Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. 3) Estimate in model 3 obtained through dynamic aggregation using Callaway and Sant'Anna (2021) staggered DiD estimator.

at different points in time for different municipalities, it is likely that the treatment effects vary over time. To explore this possibility, I visualise model 2 from [Table 1](#) in an event plot. The plot is found in [Appendix E](#) and suggests that the effect increases over time; as the time since treatment increases, the EV adoption does so too. However, the vast majority of monthly estimates are statistically insignificant (given that the standard errors overlap with 0), which is why the average weighted effect of 0.05 is also insignificant.

As mentioned in the methodology section, one must be cautious with the potential bias of TWFE models in settings where the treatment is staggered across time. This is certainly the case in this setting given that municipalities had their first charging station implemented at different points in time (see [Figure 3](#)). The main concern for TWFE models in staggered cases is that early treated units become control units for later treated units which biases the results. Because of this, I instead estimate the effect using the staggered estimator developed by Callaway and Sant'Anna ([2021](#)), which is found in model 3 of [Table 1](#). This is the main result that directly refers to the research question, as estimated in [Equation 2](#). Here, the effect of implementing the first charging station on EV registrations per 1000 inhabitants is positive and statistically significant at the 1% level. The coefficient of 0.47 is obtained through dynamic aggregation and indicates that installing the first charging station causes an average increase of roughly half an electric vehicle per 1000 inhabitants. Additionally, given that the estimator is specifically built for staggered settings, I further investigate heterogeneity in this treatment effect over time. [Figure 5](#) plots the dynamic effects of installing the first charging station on EV's per 1000 inhabitants.

[Figure 5](#) indicates that Danish municipalities on average do not see an effect in the first 24 months after implementing their first charging station, given that all estimates are not significantly different from 0. From month 25 after treatment and on, the effect not only increases but also becomes statistically significant. The effect remains positive and significant for the rest of the period of study with the exception of two months. Importantly, there is no significant difference between treatment and control groups in pre-treatment months. While the assumption of parallel trends in difference-in-difference designs cannot be proved per se, the insignificance of pre-treatment periods indicates that the assumption likely holds. This suggests that the effect can be interpreted causally. The patterns observed after treatment seem rather intuitive: Initially after having implemented the first charging station, there is no effect because changing private vehicles is one of the biggest parts of household budgets, and because EV's have tended to be more expensive than ICE vehicles. Even though potential EV consumers may notice the new charging station and experience less "range anxiety" of adoption an EV, it takes a while before their personal finances can allow a switch of vehicle. It is also likely that any "range

Figure 5: Dynamic effects on EV registrations per 1000 inhabitants



Notes: Data from Statistics Denmark (datacode BIL53). Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. Estimates obtained through methodology developed by Callaway and Sant’Anna (2021).

anxiety” reduction does not happen immediately, but instead takes some time to manifest itself in the conscience of potential EV adopters. From a sustainability point of view, it would also not be ideal if all ICE vehicles were replaced immediately as a lot of well-functioning vehicles, which have required a lot of resources, would go to waste. The delay in response is therefore not only intuitive, but arguably also beneficial for sustainable resource management.

Interestingly, the effect sees a slight reduction happening in month 57 after treatment. The first thing to notice is that only four municipalities were treated for 57 or more months; given that the period of study stretches for 86 months, the estimate of this and subsequent months only consists of municipalities treated in month 29 or earlier (i.e. row 2-5 in Figure 3). This is possibly why we see larger noise in the estimates here. When examining the ATT per treatment group, i.e. grouping the estimates from municipalities treated at the same times, it gets clear that the earlier treated municipalities in general tend to have a much smaller effect than the later treated groups (see Appendix F for ATT’s for each treatment group). This also helps explain the decrease happening in month 57 after treatment. Finally, these four municipalities on average have a rather low initial EV share, and three of them are rural municipalities. Exploring heterogeneity

indicates that municipalities with a low initial share as well as rural municipalities on average experience smaller effects. Thus, it is likely that the earlier treated municipalities have smaller effects due to these characteristics of the only four municipalities that were treated for 57 months or more.

To put the aggregate treatment effect of 0.47 EV's per 1000 inhabitants into perspective, it can be relevant to compare the magnitude of the estimate to other studies that causally identify the effect of charging infrastructure. Illmann and Kluge (2020) estimate that a 1% increase in charging points leads to a 0.8% increase in EV registrations in Germany. Back-of-the-envelope calculations suggest that the estimate in Illmann and Kluge (2020) translates into an increase of around 0.007 EV's per 1000 inhabitants per year (see Appendix G). Sommer and Vance (2021) estimate that the marginal effect of a new charger increases the EV registrations by 0.74 EV's per county per year in Germany. This translates into an estimate of around 0.0036 EV's per 1000 inhabitants per year (Appendix G). The result in Table 1 is notably much larger, but also captures the implementation of the first charging station and not the marginal effect of an additional station. Schulz and Rode (2022) also investigate the implementation of the first charging station, and their results suggest an average increase of 3 EV's per 1000 inhabitants (Appendix G) - a coefficient six times larger than the coefficient in Table 1. However, their measure also captures internal shifts in the EV market through the second hand vehicle market and not only new EV registrations as mine does. The difference can also be explained by the size of the EV markets in the two countries as the Norwegian EV market share of 32% is almost twice as large as in Denmark (Finnerty, 2025), as seen in Figure 2. Regardless, this comparison suggests that there is a potentially transformative effect of implementing stations in municipalities previously underserved by charging possibilities. The first station alone is potentially powerful in reducing range anxiety, signalling market maturity, and indicating institutional support (Schulz & Rode, 2022). Estimates from Germany then suggest diminishing marginal returns of adding more charging stations, but nevertheless significant effects.

4.2 Heterogeneous effects

Table 1 establishes a positive, significant, causal effect of implementing the first charger on EV registrations per 1000 inhabitants. The coefficient of 0.47 EV registrations per 1000 inhabitants is an average effect across all municipalities. In the following three subsections, I present the results of three analyses of heterogeneity; 1) high-income and low-income, 2) high and low initial share of EV's, and 3) urban and rural municipalities.

4.2.1 Income heterogeneity

[Table 2](#) presents the results of the heterogeneous analysis of income.

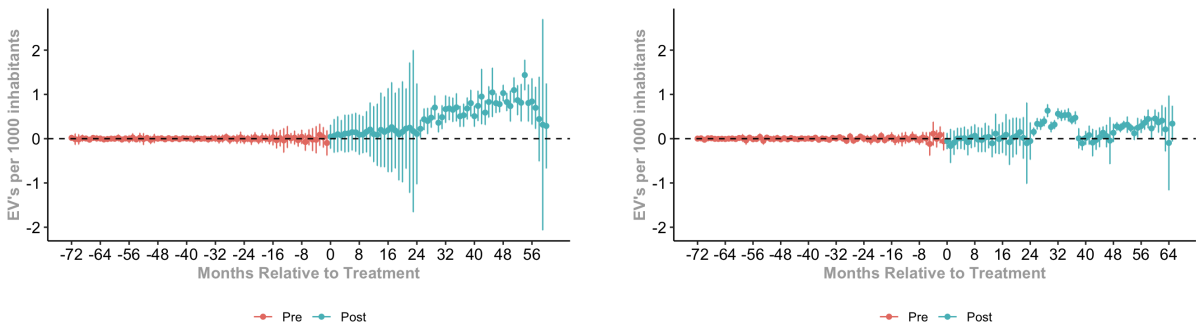
Table 2: Aggregate Treatment Effects on Electric Vehicle Registrations

Group	ATT	Std. Error	Observations
High-income	0.60***	(0.05)	4214
Low-income	0.26***	(0.03)	4214

Notes: Clustered standard errors in parenthesis. *** $p < 0.01$. 1) Dependent variable: EV registrations per 1000 inhabitants. 2) Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. 3) Estimate obtained through dynamic aggregation using Callaway and Sant’Anna (2021) staggered DiD estimator.

[Table 2](#) illustrates that implementing the first charging station in high-income municipalities causes an increase of 0.60 EV registrations per 1000 inhabitants, while the effect in low-income municipalities is 0.26. Both estimates are significant at the 1% level. The effect of implementing the first charging station therefore has an effect that is more than twice as large in high-income municipalities compared to low-income municipalities. Moreover, while the implementation of the Callaway and Sant’Anna (2021) estimator does not allow for interaction terms, the statistical difference has been computed through a two-tailed test (see [Appendix B](#)), which reveals a significant difference between these two estimates at the 1% level. Both estimates are obtained through dynamic aggregation. As such, I explore the dynamic changes of both estimates in [Figure 6](#).

Figure 6: Dynamic estimates for high-income (left) and low-income (right) municipalities



Notes: Data from Statistics Denmark (datacode BIL53). Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. Estimates obtained through methodology developed by Callaway and Sant’Anna (2021).

[Figure 6](#) indicates similar patterns as seen in the main plot in [Figure 5](#). In both cases, there is no significant effect in the first 24 months after treatment, after which the effect turns larger and significant. For high-income municipalities the effect is both larger and remains significant for a longer time compared to low-income municipalities. It only turns insignificant in month 57 for high-income municipalities, which is likely for the same reasons of sample size discussed previously, while it does so in month 38 for low-income municipalities. Importantly, the assumption of parallel trends seems valid in both groups given the insignificance of differences in pre-treatment periods. A possible explanation of the post-treatment differences is that high-income consumers have more ability to act upon their wishes to adopt EV's compared to low-income consumers. Even if low-income and high-income consumers had the same preferences to adopt EV's, there are likely larger room in private finances of high-income consumers to do so than in those of low-income consumers. Additionally, low-income consumers may not have the same wishes to prioritise a switch of their private vehicle for the sake of sustainability. After all, spending more on a private vehicle due to sustainability is likely to be further down the priority list for low-income consumers compared to high-income consumers. Thus, the larger estimate for high-income municipalities is generally in accordance with expected findings.

While the effect in high-income municipalities is much larger than in low-income ones, it is still worth to note the significant effect in low-income municipalities. This is especially relevant for policymaking. A common debate among EV market interventions is that of the additionality effect, i.e. how much a certain policy adds to e.g. the EV uptake. For example, one critique of subsidising EV's or making tax allowances for EV owners is that they are regressive; these policies only benefit richer segments of the population that arguably would have adopted EV's either way. As such, the additionality effect of such policies is potentially low as it does not lead to much higher numbers of EV's (Chandra et al., [2010](#); Muehlegger & Rapson, [2018](#); Trotta & Sommer, [2024](#)). However, in the case of public charging infrastructure, the positive and significant effect in low-income municipalities indicates that the infrastructure also makes consumers in low-income municipalities adopt more EV's. This result could indicate that policies of establishing public charging infrastructure are beneficial in leading the transition to electric transportation not only for high-income but also low-income segments of the population. However, it is important to have in mind that this estimation only divides municipalities into high- and low-income groups, and not households; the effect in low-income municipalities may still be driven by high-income individuals that live in low-income municipalities. To disentangle these possible mechanisms from each other and definitely verify the additionality effect of public charging infrastructure between income segments, detailed household-level data would be needed to identify the reaction of EV-adopting households conditional on income.

4.2.2 Initial EV share

This section investigates whether consumers react differently to the implementation of new charging stations depending on the relative number of EV’s in their municipality, i.e. the share of EV’s in the municipalities in January 2018. The results are presented in [Table 3](#).

Table 3: Aggregate Treatment Effects on Electric Vehicle Registrations

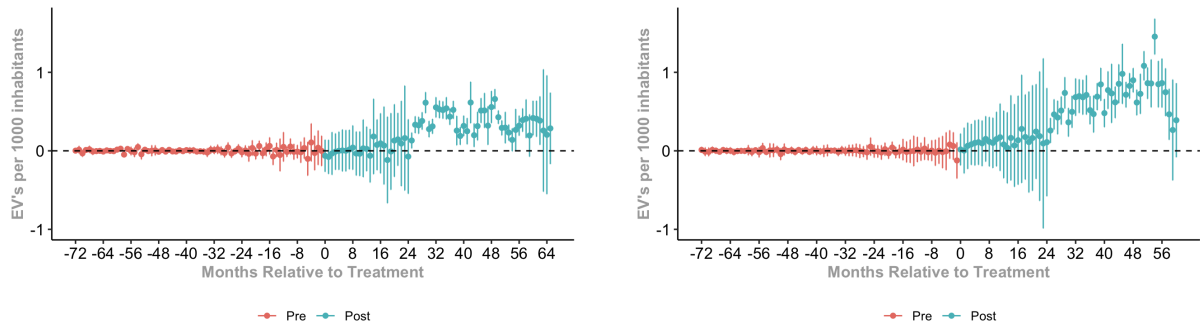
Group	ATT	Std. Error	Observations
High share	0.59***	(0.04)	4214
Low share	0.33***	(0.03)	4214

Notes: Clustered standard errors in parenthesis. *** $p < 0.01$.
 1) Dependent variable: EV registrations per 1000 inhabitants.
 2) Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. 3) Estimate obtained through dynamic aggregation using Callaway and Sant’Anna (2021) staggered DiD estimator.

[Table 3](#) illustrates that the average effect of implementing the first charging station has a positive and significant effect on EV registrations in both municipalities with a high and low initial share of EV’s. The effect is larger in municipalities with a high initial share of EV’s at 0.59 compared to the estimate of 0.33 in municipalities with a low initial share. Additionally, the difference between these two estimates is statistically significant (see [Appendix B](#)), which could indicate that implementing public charging stations in municipalities with a high initial share re-enforces existing trends and creates network effects. Potential EV consumers in these municipalities may not only see new charging options, but also the acceptance of this switch from other consumers. This suggests that the convenience of charging stations and the visibility of more EV’s have complementary effects on EV adoption. While early adopters of EV’s likely have private charging, other potential EV consumers may not have adopted EV’s yet due to range anxiety or lack of private charging options. As such, while both groups get the same convenience of new public charging options, the reaction is stronger in places where more people own EV’s. This finding is in accordance with social contagion theory (Christakis & Fowler, 2013).

As the estimates in [Table 3](#) are obtained through dynamic aggregation, I explore the dynamic effects in municipalities with a low and high initial share of EV’s, respectively. The plots are found in [Figure 7](#). In accordance with the main plot in [Figure 5](#), there is no significant effect in the first 24 months after treatment. There is also no significant differences in the pre-treatment periods for both groups, which indicates that the assumptions

Figure 7: Dynamic estimates for municipalities with a low (left) and high (right) initial share of EV's



Notes: Data from Statistics Denmark (datacode BIL53). Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. Estimates obtained through methodology developed by Callaway and Sant'Anna (2021).

of parallel trends and no anticipation seem to hold. The effect becomes significant in month 25 after treatment in both groups, and it steadily increases for around 30 months in municipalities with a high initial share of EV's. It then turns insignificant in the 57th month after treatment after which only a few municipalities impact the estimate. In municipalities with a low initial share of EV's, the effect remains positive and significant for around 25 months, but it is not as large nor as increasing as it is for the municipalities with a high initial share of EV's. The estimate takes on more noise in month 58 as most of the municipalities were not treated for this many months.

A relevant comparison is that of the heterogeneous analysis of income and initial EV share. The estimate for municipalities that are high-income and have a high initial share of EV's is almost identical, while there is a difference of 0.07 between the two estimates for low-income (0.26) and low initial share of EV's (0.33). The correlation between income and the initial share of EV's is 0.77, suggesting that high-income municipalities tend to also have a relatively high share of EV in January 2018. This explains the similarities in the obtained estimates. However, the estimates still differ a bit between low-income and low initial share of EV's. Appendix H specifies that 12 municipalities are high-income but have a low initial share of EV's, while 11 municipalities are low-income but have a higher initial share of EV's. The relatively low estimate for low-income municipalities suggests that income is a larger constraint for EV adoption than having a low initial share of EV's. This could for example be due to structural barriers; low-income municipalities may not have access to the same credit loan options, or be able to invest in private chargers at home, which dampens the effect of public charging infrastructure. In contrast, 12 of the municipalities with a low initial share of EV's are not low-income and thereby not

constrained by income, but possibly rather by lack of infrastructure. They therefore respond more positively once they get treated with a charging station.

4.2.3 Urban/rural heterogeneity

As mentioned earlier, the urban/rural split is one of the most relevant political divides in Denmark. I therefore estimate the effect of installing the first charging station on EV registrations per 1000 inhabitants in rural and urban municipalities separately. The results are presented in [Table 4](#).

Table 4: Aggregate Treatment Effects on Electric Vehicle Registrations

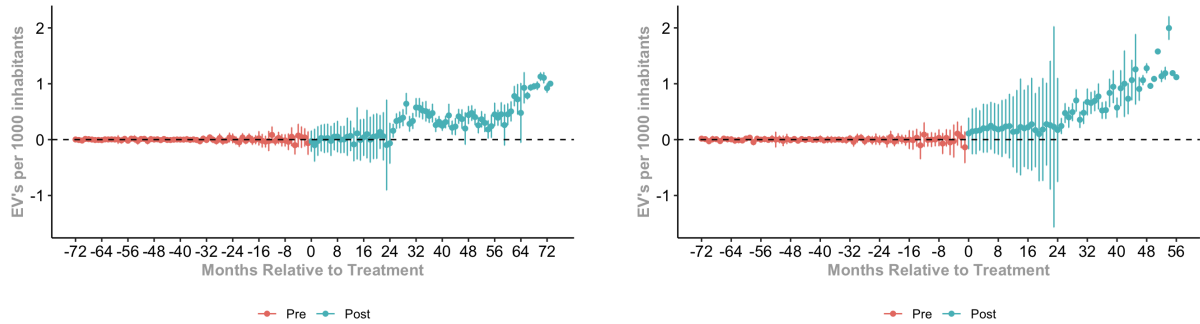
Group	ATT	Std. Error	Observations
Urban	0.59***	(0.08)	3612
Rural	0.37***	(0.03)	4816

Notes: Clustered standard errors in parenthesis. *** $p < 0.01$. 1) Dependent variable: EV registrations per 1000 inhabitants. 2) Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. 3) Estimate obtained through dynamic aggregation using Callaway and Sant’Anna (2021) staggered DiD estimator.

[Table 4](#) reveals that the average effect of implementing the first charging station in urban municipalities is 0.59 EV’s per 1000 inhabitants, while it is 0.37 EV’s per 1000 inhabitants in rural municipalities. Both estimates are significant at the 1% level. Testing the significance between these two estimates reveals that the difference is also significant at the 1% level (see [Appendix B](#)). In [Figure 8](#), I explore the dynamic treatment effects of installing the first charging station in rural and urban municipalities, respectively. Consistent with [Figure 5](#) as well as other heterogeneous analyses, there is no significant effect in the first 24 months after treatment, which is likely because it takes a while for consumers to make the decision to buy or change their private vehicle. From month 25 and on, the effect becomes significant in both plots and steadily increases in urban municipalities. The effect in urban municipalities largely keeps increasing for the rest of the period studied. Contrarily, the effect remains more moderate in rural municipalities and does not reach the size of the urban municipalities. The parallel trends assumption appears to be valid based on the pre-treatment periods in both plots.

There could be several reasons for why urban consumers react more strongly to public

Figure 8: Dynamic estimates for rural (left) and urban (right) municipalities



Notes: Data from Statistics Denmark (datacode BIL53). Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. Estimates obtained through methodology developed by Callaway and Sant’Anna (2021).

charging infrastructure than rural consumers do. First of all, urban consumers by definition live in more densely populated areas where the possibility of investing in private charging facilities is more limited than it is in rural municipalities. As they rely more on being able to charge in public stations, they thereby react more positively when seeing the new availability of such public chargers. In contrast, rural consumers need to cover larger distances. They may therefore not experience the same reduction in range anxiety as urban consumers. A secondary explanation could be related to political economy as Danish rural voters tend to be more conservative and less environmentally aware (Koszyczarek, 2022; Nørtoft, 2019). As EV’s are a relatively new and innovative product, conservative voters may not be as willing to adopt this than their urban counterparts, who are in turn more adaptive to new technological developments. Additionally, EV’s are generally viewed as a greener product that appeals more to environmentally aware consumers who wish to reduce their personal carbon footprint. As the share of environmentally aware voters is higher in urban municipalities, more consumers decide to adopt EV’s after seeing the improvements in charging infrastructure. There may be an overlap between urban and high-income consumers as well, but the moderate correlation between high-income and urban of 0.38 suggests that other factors beyond affluence contribute to the heterogeneity between urban and rural responsiveness.

4.3 Effect on ICE vehicles

Table 5 shows the causal effect of installing the first charging infrastructure on ICE vehicle registrations per 1000 inhabitants.

As indicated in Table 5, the average treatment effect of the treated municipalities is

Table 5: Aggregate Treatment Effects on ICE Vehicle Registrations

Treatment	ATT	Std. Error	Observations
1st station	-0.37***	(0.04)	8428

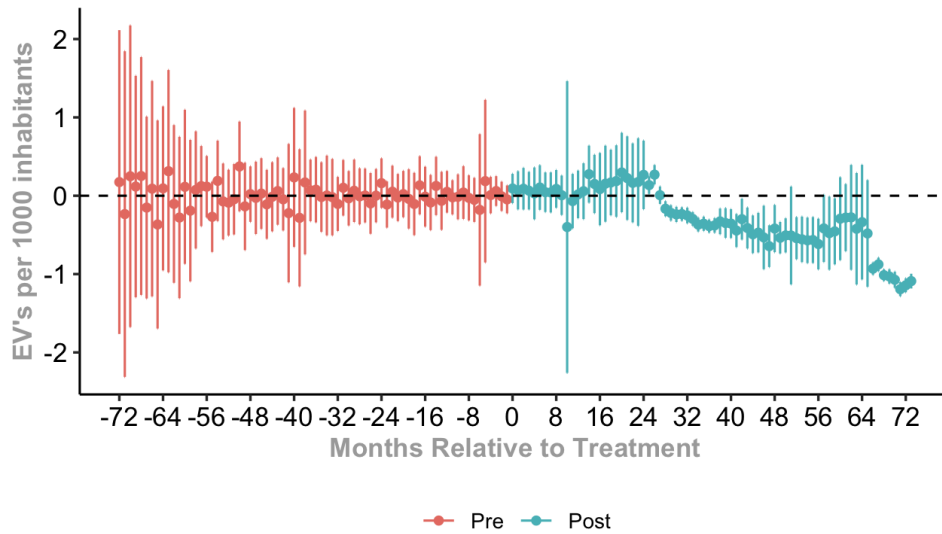
Notes: Clustered standard errors in parenthesis. *** $p < 0.01$. 1) Dependent variable: ICE vehicle registrations (petrol or diesel). Fossil registrations refer to vehicle registrations driving on either gasoline or diesel. 2) Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. 3) Estimate obtained through dynamic aggregation using Callaway and Sant’Anna (2021) staggered DiD estimator.

negative and statistically significant at the 1% level. At -0.37, the coefficient indicates that implementing the first charging station in a given municipality on average decreases the number of ICE vehicles by 0.37 per 1000 inhabitants. This result combined with the overall effect on EV’s at 0.47 per 1000 inhabitants suggests that a large amount of the EV adoptions are substitutions from high-emitting vehicles to low-emitting ones and not simply an overall growth of private vehicle ownership. I further explore the dynamic effects on ICE vehicle registrations, which are illustrated in [Figure 9](#).

[Figure 9](#) illustrates that the negative effect of the first charging station is lagged by two years, as all estimates until month 27 after treatment are insignificant. Notably, the pre-treatment estimates suggest that the assumptions of parallel trends and no anticipation are likely to hold as they are all insignificant. From month 28 after treatment, the effect turns significantly negative and generally becomes bigger. The estimate falls out of significance in month 57 after treatment, which is likely for the same reasons as those discussed concerning [Figure 5](#); only four municipalities were treated for this long, which creates noise around the estimate. Additionally, the effect is smaller for these early treated groups, possibly due to lower incomes and lower initial EV shares, which explains the small decrease observed around month 57 and on.

A number of mechanisms could explain the substitution effect observed in [Table 5](#). First of all, observing new possibilities of charging EV’s can tilt the margins of consumers towards an EV instead of an ICE vehicle, especially for those consumers that need a new private vehicle but are undecided on the fuel type. Secondly, new public charging infrastructure can indicate signs of institutional support as well as market maturity. The mere presence of new charging infrastructure can legitimise the adoption of EV’s and reduce potential uncertainty about adopting new technology. The negative effect on ICE

Figure 9: Dynamic effects on ICE vehicle registrations



Notes: Data from Statistics Denmark (datacode BIL53). ICE vehicles are defined as being fuelled by either petrol or diesel. Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. Estimates obtained through methodology developed by Callaway and Sant’Anna (2021).

vehicles could therefore both reflect a technological substitution and a broader shift in consumer confidence. Given the variety in perceived barriers to EV adoption highlighted in related literature (Coffman et al., 2017), it is likely that both of these mechanisms are at play and each influence different segments of consumers. However, we still see a difference in the magnitude of EV registrations (0.47) and ICE vehicle registrations (0.37). The fact that there is a net increase of household vehicles is in accordance with the overall pattern in Denmark as the number of private vehicle ownership is increasing (Prakash & Hall, 2024). Nevertheless, more than 3/4 of EV adoptions are offset by ICE vehicle reductions. This suggests that implementing new charging stations in places with none of these is beneficial not only to increase EV demand but also to deter ICE vehicle registrations, which is crucial for both emissions and pollution levels. As such, public investments in charging infrastructure appear to positively and efficiently impact the green transition of the transportation sector.

4.4 Policy push

A relevant subanalysis is to estimate the effect of the public push for charging stations described in section 2. While the dataset does not inform about the owner (specifically whether it was publicly or privately funded), I assume that any stations constructed in

the beginning of 2022 is due to the policy directly. Even if individual public stations were privately funded, it is likely that this private investment also happened based on the knowledge of the institutional support agreed six months earlier. I therefore remove all municipalities treated with their first charger before this policy push and run the same Callaway and Sant’Anna (2021) estimator on the remaining sample. The overall estimation is presented in Table 6.

Table 6: Aggregate Treatment Effects on Electric Vehicle Registrations

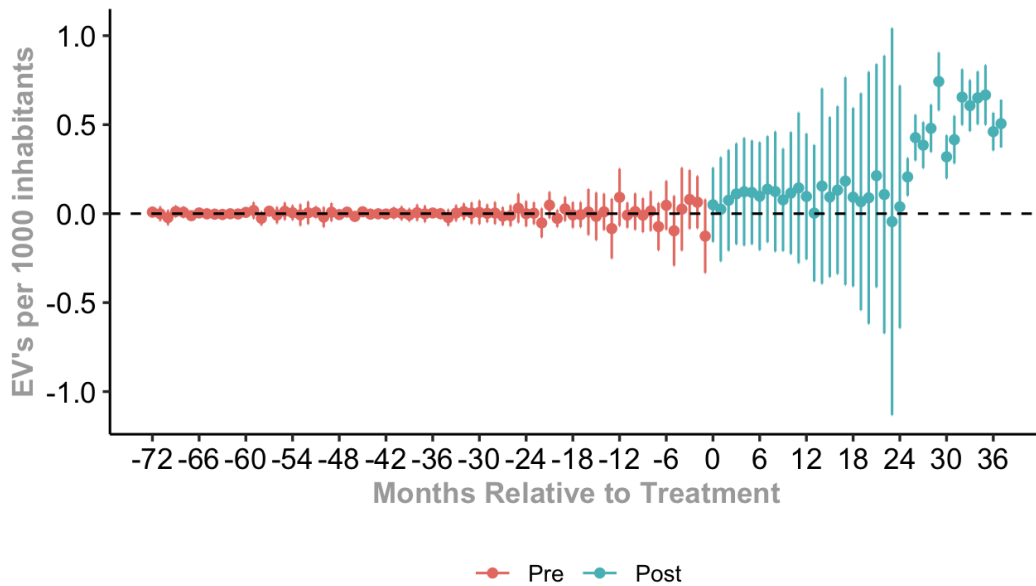
Treatment	ATT	Std. Error	Observations
1st station	0.24***	(0.07)	7568

Notes: Clustered standard errors in parenthesis. *** $p < 0.01$.
 1) Dependent variable: EV registrations per 1000 inhabitants.
 2) Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. 3) Estimate obtained through dynamic aggregation using Callaway and Sant’Anna (2021) staggered DiD estimator.

Table 6 suggests that the policy has had a positive effect on EV registrations per 1000 inhabitants, which is significant at the 1% level. Aggregating the effect dynamically suggests an increase of 0.24 EV registrations per 1000 inhabitants as a result of the policy push. Similar to the other analyses, I explore the dynamic effects to investigate heterogeneity over time, which is displayed in Figure 10.

Figure 10 shows similar patterns to the main plot, as there is no significant effect in the first two years after installing the first charging station. The assumption of parallel trends seems plausible for this analysis as well, given that the differences between pre-treatment period estimates are insignificant. The effect increases from month 25 and remains positive and statistically significant for the rest of the period. Note that the post-treatment period in this analysis runs until month 37 after treatment, given that there are 37 months from month 49 (January 2022) to the end of the period of study, month 86 (February 2025). Interestingly, there are 73 post-treatment periods in Figure 5 - almost twice as many as in Figure 10. This reason is likely why the overall estimation (0.47) is almost twice the size of the observed effect of the policy (0.24). This suggests that the difference in estimates is due to observed time. As such, the overall treatment effect of the policy is likely to continue to have an effect this year and in the coming years which would add to the effect of 0.24 EV’s per 1000 inhabitants already observed now in the data.

Figure 10: Dynamic effects on EV registrations after the 2021 infrastructure policy



Notes: Data from Statistics Denmark (datacode BIL53). Treatment is defined as the initiation of operation of the first charging station in a municipality. Control groups consist of those municipalities that have not yet been treated with their first charging station at each point in time. Once treated, a municipality remains treated for the following months. Estimates obtained through methodology developed by Callaway and Sant'Anna (2021).

Both Table 6 and Figure 10 suggest that this policy intervention has had a positive effect on EV uptake in Denmark. The budget for the whole EV part of the infrastructure plan was 500 million DKK (roughly 67 million EUR). Given that the estimated effect only reflects the responses to the first charging stations, and that the 500 million DKK are assigned for the total seven year period from 2022 to 2028, it appears to be a relatively inexpensive policy intervention, at least compared to other EV stimuli such as subsidies or tax benefits (Trotta & Sommer, 2024). This is in accordance with the policy suggestions in S. Li et al. (2017). In addition, it has the potential to legitimise the adoption of EV's and thereby also the market for both charging stations and EV's; in fact, the charging station intervention was put on hold only two years after the agreement, because the private market for charging stations had matured sufficiently for private actors to invest in infrastructure (Ministry of Transportation, 2023), thereby making the public investments redundant. This indicates that a policy intervention in the early stages of an EV market is not only an inexpensive option to directly stimulate EV adoption, but also helps early markets of new technology to mature in order to attract private investments.

5 Conclusion

Across the EU, there seems to be consensus that governmental interventions are needed for EV adoptions to play a meaningful role in reducing greenhouse gas emissions. Despite this, many countries are yet to host EV markets that match climate ambitions and targets. Assessing the available tools for governments through an ex post analysis of EV market developments is thus crucial for the design of future EV policies. In this paper, I estimate the effect of public charging infrastructure on EV adoption through an analysis of the Danish EV market. Specifically, I assess how installing the first charging station in a given municipality affects EV registrations in that municipality. Through a staggered difference-in-difference research design (Callaway & Sant’Anna, 2021), I compare municipalities treated with their first charging station with those that have not yet installed their first station. The main estimation suggests that the first charging station causes an increase of 0.47 EV’s per 1000 inhabitants - a rather large effect compared to other estimates in the literature. This large effect could indicate that early development of public charging infrastructure is important in reducing range anxiety of potential EV consumers and signals institutional support and market maturity. The dynamic effects reveal that the effect is lagged by two years, likely because potential EV consumers need to save up money before investing in a new private vehicle. I also find that the effect is larger in urban and high-income municipalities as well as municipalities with a high initial share of EV’s. Crucially for policymaking, though, the effect is also significant in rural and low-income municipalities. While related literature has found indications of free rider behaviour and labels EV policies such as tax benefits and subsidies as regressive (Chandra et al., 2010; Muehlegger & Rapson, 2018; Trotta & Sommer, 2024), this finding suggests that public charging infrastructure is positively affecting all socioeconomic groups and both urban and rural consumers. This knowledge is crucial for designing policies that do not drive further polarisation between income groups and urban/rural population. Additionally, analysing the 2021 public push for EV infrastructure suggests that the obtained effect of charging stations comes at a relatively low cost compared to other policy options, which is in accordance with the literature (S. Li et al., 2017; Trotta & Sommer, 2024). As such, if these results are to be taken seriously, governments with EV markets at the early stages could profitably focus on implementing public charging infrastructure, especially in places with a lack of charging options.

A few questions remain unanswered after this research due to limitations. First, I only estimate the effect of implementing the first charging station in this paper. The continuous effect of implementing several charging stations at once could reveal marginal effects of an additional charging station, and could potentially even suggest tipping points on when consumers stop reacting to charging stations. Also, this paper only considers new private

vehicle registrations in the households, but does not take into account the second hand vehicle market. Further research could focus on the relative shifts of private vehicles across income groups or between urban and rural municipalities. Additionally, to build on the heterogeneous findings on income in this study, further research could utilise household-level data to provide insights on the mechanisms behind the difference of high-income and low-income municipalities, specifically in terms of the household characteristics of EV adopters. This has the potential to more accurately identify the additionality effect of public charging infrastructure. Finally, I only consider public charging stations in this paper; however, private chargers are more relevant for EV owners who drive daily. Future research could investigate to what extent public charging stations complement or substitute private chargers.

References

- Achtnicht, M., Bühler, G., & Hermeling, C. (2012). The impact of fuel availability on demand for alternative-fuel vehicles. *Transportation Research Part D: Transport and Environment*, *17*(3), 262–269. <https://doi.org/10.1016/j.trd.2011.12.005>
- Axsen, J., Goldberg, S., Bailey, J., & Kurani, K. S. (2013). Hybrid, plug-in hybrid, or electric—what do car buyers want? *Energy Policy*, *61*, 532–543. <https://doi.org/10.1016/j.enpol.2013.05.122>
- Axsen, J., Goldberg, S., Bailey, J., Mountain, D. C., & Jaccard, M. (2009). Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid-electric vehicles. *Resource and Energy Economics*, *31*(3), 221–238. <https://doi.org/10.1016/j.reseneeco.2009.02.001>
- Breschi, V., Tanelli, M., Ravazzi, C., Strada, S., & Dabbene, F. (2020). *Social network analysis of electric vehicles adoption: A data-based approach*. Cornell University. Retrieved June 6, 2025, from <https://arxiv.org/abs/2001.09704>
- Callaway, B., & Sant’Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. <https://doi.org/10.1016/j.jeconom.2020.12.001>
- Chandra, A., Gulati, S., & Kandlikar, M. (2010). Green drivers or free riders? an analysis of tax rebates for hybrid vehicles. *Journal of Environmental Economics and Management*, *60*(2), 78–93. <https://doi.org/10.1016/j.jeem.2010.04.003>
- Christakis, N. A., & Fowler, J. H. (2013). Social contagion theory: Examining dynamic social networks and human behavior. *Statistics in Medicine*, *32*(4), 556–577. <https://doi.org/10.1002/sim.5408>
- Coffman, M., Bernstein, P., & Wee, S. (2017). Electric vehicles revisited: A review of factors that affect adoption. *Transport Reviews*, *37*(1), 79–93. <https://doi.org/10.1080/01441647.2016.1217282>
- EEA. (2025). *Transport and mobility*. European Environment Agency. Retrieved May 26, 2025, from <https://www.eea.europa.eu/en/topics/in-depth/transport-and-mobility>
- Egnér, F., & Trosvik, L. (2018). Electric vehicle adoption in sweden and the impact of local policy instruments. *Energy Policy*, *121*, 584–596. <https://doi.org/https://doi.org/10.1016/j.enpol.2018.06.040>
- Encarnação, S., Santos, F. P., Santos, F. C., Blass, V., Pacheco, J. M., & Portugali, J. (2018). Paths to the adoption of electric vehicles: An evolutionary game theoretical approach. *Transportation Research Part B: Methodological*, *113*, 24–33. <https://doi.org/https://doi.org/10.1016/j.trb.2018.05.002>

- European Environment Agency. (2022). Decarbonising road transport – the role of vehicles, fuels and transport demand. *Publications Office of the European Union*. <https://doi.org/10.2800/68902>
- European Parliament. (2022). *Eu ban on sale of new petrol and diesel cars from 2035 explained*. European Parliament. Retrieved May 26, 2025, from <https://www.europarl.europa.eu/topics/en/article/20221019STO44572/eu-ban-on-sale-of-new-petrol-and-diesel-cars-from-2035-explained>
- Finnerty, J. (2025). *Why norway leads the world in ev adoption*. Gridserve. Retrieved June 5, 2025, from <https://www.gridserve.com/why-norway-leads-the-world-in-ev-adoption/>
- Frederiksbjerg El. (2024). *El-refusion for elbiler*. Retrieved June 6, 2025, from <https://frederiksbjergel.dk/el-refusion-for-elbiler>
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277. <https://doi.org/10.1016/j.jeconom.2021.03.014>
- Hackbarth, A., & Madlener, R. (2013). Consumer preferences for alternative fuel vehicles: A discrete choice analysis. *Transportation Research Part D: Transport and Environment*, 25, 5–17. <https://doi.org/10.1016/j.trd.2013.07.002>
- IEA. (2024). *Energy system of denmark*. International Energy Agency. Retrieved May 26, 2025, from <https://www.iea.org/countries/denmark>
- Illmann, U., & Kluge, J. (2020). Public charging infrastructure and the market diffusion of electric vehicles. *Transportation Research Part D: Transport and Environment*, 86, 102413. <https://doi.org/https://doi.org/10.1016/j.trd.2020.102413>
- Koszyczarek, H. H. (2022). *Danskerne vil gerne spise mere klimavenligt, men kød dominerer fortsat vores aftenmåltider*. Økologisk Landsforening. Retrieved May 26, 2025, from <https://okonu.dk/mad-og-marked/danskerne-vil-gerne-spise-mere-klimavenligt-men-kod-dominerer-fortsat-vores-aftenmaltider>
- Lane, B., & Potter, S. (2007). The adoption of cleaner vehicles in the uk: Exploring the consumer attitude–action gap. *Journal of Cleaner Production*, 15(11), 1085–1092. <https://doi.org/10.1016/j.jclepro.2006.05.026>
- Lebeau, K., Van Mierlo, J., Lebeau, P., Mairesse, O., & Macharis, C. (2012). The market potential for plug-in hybrid and battery electric vehicles in flanders: A choice-based conjoint analysis. *Transportation Research Part D: Transport and Environment*, 17(8), 592–597. <https://doi.org/10.1016/j.trd.2012.07.004>
- Li, S., Tong, L., Xing, J., & Zhou, Y. (2017). The market for electric vehicles: Indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists*, 4(1), 89–133. <https://doi.org/10.1086/689702>

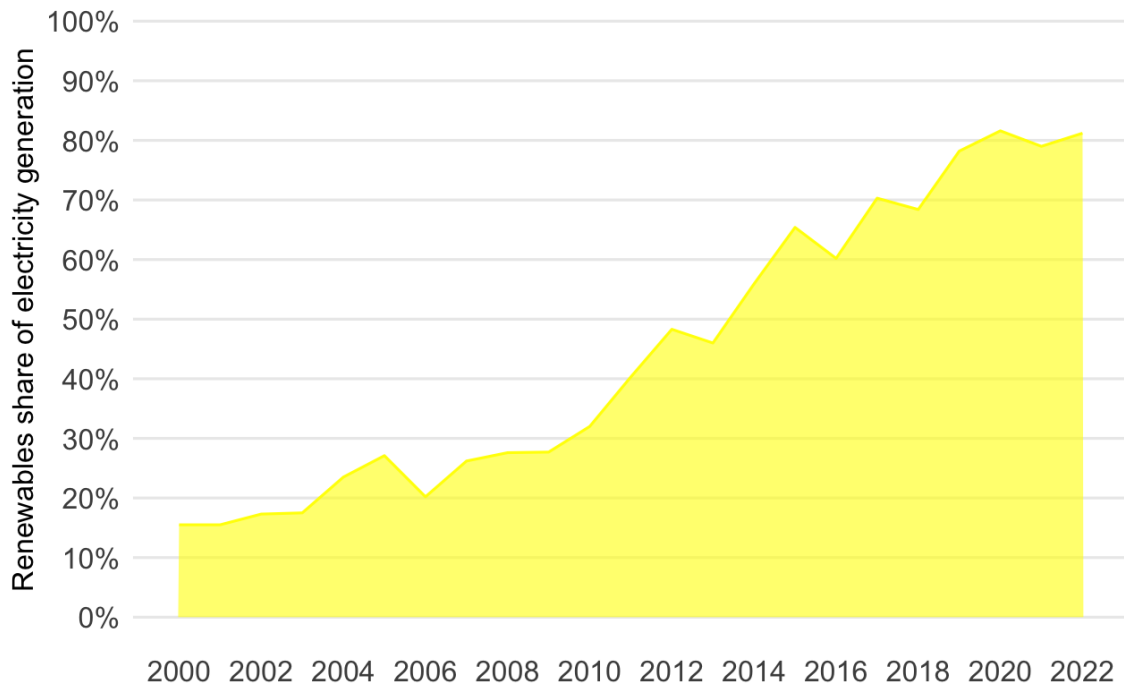
- Li, W., Long, R., Chen, H., & Geng, Y. (2017). A review of factors influencing consumer intentions to adopt battery electric vehicles. *Renewable and Sustainable Energy Reviews*, 78, 318–328. <https://doi.org/10.1016/j.rser.2017.04.076>
- Ministry of Climate, Energy and Utilities. (2020, June 26). Climate act: Act no. 965 of 26 June 2020. Retrieved May 26, 2025, from <https://www.retsinformation.dk/eli/ta/2020/965>
- Ministry of Climate, Energy and Utilities. (2025). *Kf25: Fundamentet til klimamålet for 2030 er styrket*. Ministry of Climate, Energy and Utilities. Retrieved May 26, 2025, from <https://www.kefm.dk/aktuelt/nyheder/2025/apr/kf25-fundamentet-til-klimamaalet-for-2030-er-styrket>
- Ministry of Taxation. (2018). *Skatteøkonomisk redegørelse 2018*. Ministry of Taxation. Retrieved May 26, 2025, from <https://skm.dk/aktuelt/publikationer/rapporter/skatteoekonomisk-redegoerelse-2018>
- Ministry of Transportation. (2021). *Infrastrukturplan 2025*. Ministry of Transportation. Retrieved May 26, 2025, from <https://www.trm.dk/media/rt1h51td/endelig-aftaletekst-infrastrukturplan-2035-final-a.pdf>
- Ministry of Transportation. (2023). *Ladeinfrastrukturen overhaler forventningerne*. Ministry of Transportation. Retrieved May 26, 2025, from <https://www.trm.dk/nyheder/2023/ladeinfrastrukturen-overhaler-forventningerne>
- Muehlegger, E., & Rapson, D. S. (2018). *Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California* (Working Paper No. 25359). National Bureau of Economic Research. <https://doi.org/10.1016/j.jpubeco.2022.104752>
- Narassimhan, E., & Johnson, C. (2018). The role of demand-side incentives and charging infrastructure on plug-in electric vehicle adoption: Analysis of US states. *Environmental Research Letters*, 13(7), 074032. <https://doi.org/10.1088/1748-9326/aad0f8>
- Nørtoft, M. (2019). *Landkort viser forskelle i partiernes stemmeandele*. Danmarks Statistik. Retrieved May 26, 2025, from <https://www.dst.dk/da/Statistik/nyheder-analyser-publ/bagtal/2019/2019-02-20-landkort-viser-forskelle-i-partiernes-stemmeandele>
- Patt, A., Aplyn, D., Weyrich, P., & van Vliet, O. (2019). Availability of private charging infrastructure influences readiness to buy electric cars. *Transportation Research Part A: Policy and Practice*, 125, 1–7. <https://doi.org/10.1016/j.tra.2019.05.004>
- Prakash, T., & Hall, O. (2024, May). *Vi har aldrig haft flere biler – men hver dag kører vi med 14 millioner tomme sæder*. Danmarks Radio. Retrieved May 26, 2025, from <https://www.dr.dk/nyheder/indland/vi-har-aldrig-haft-flere-biler-men-hver-dag-koerer-vi-med-14-millioner-tomme-saeder>

- Ryming, P. (2025). *Ny rekord: Over 30,000 offentlige ladepunkter i danmark*. iNPUT magazine. Retrieved June 6, 2025, from <https://www.inputmag.dk/ny-rekord-over-30-000-offentlige-ladepunkter-i-danmark/>
- Schulz, F., & Rode, J. (2022). Public charging infrastructure and electric vehicles in norway. *Energy Policy*, 112660. <https://doi.org/10.1016/j.enpol.2021.112660>
- Sommer, S., & Vance, C. (2021). Do more chargers mean more electric cars? *Environmental Research Letters*, 16(6), 064092. <https://doi.org/10.1088/1748-9326/ac05f0>
- Trotta, G., & Sommer, S. (2024). The effect of changing registration taxes on electric vehicle adoption in denmark. *Transportation Research Part A: Policy and Practice*, 185, 104–117. <https://doi.org/10.1016/j.tra.2024.104117>
- Wolf, I., Schröder, T., Neumann, J., & de Haan, G. (2015). Changing minds about electric cars: An empirically grounded agent-based modeling approach. *Technological Forecasting and Social Change*, 94, 269–285. <https://doi.org/10.1016/j.techfore.2014.10.010>
- Yan, S. (2018). The economic and environmental impacts of tax incentives for battery electric vehicles in europe. *Energy Policy*, 123, 53–63. <https://doi.org/10.1016/j.enpol.2018.08.032>
- Ziegler, A. (2012). Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for germany. *Transportation Research Part A: Policy and Practice*, 46(8), 1372–1385. <https://doi.org/10.1016/j.tra.2012.05.016>

Appendix

A Renewable energy production in Denmark

Figure 11: Renewables share of electricity generation, Denmark



Notes: Data from IEA (2024). 85.2% of this generation comes from wind, 14.7% from solar, and 0.1% from hydro.

B Heterogeneity: Significance

The implementation of the Callaway and Sant'Anna (2021) does not currently allow for the inclusion of interaction terms. Thus, heterogeneity is explored by subsetting the samples. As a result, while I obtain two different estimates, the significance of the difference between the estimates must be calculated through a two-tailed test. This is done through the following formula:

$$\text{Test statistic: } t = \frac{\hat{\beta}_1 - \hat{\beta}_2}{\sqrt{SE_1^2 + SE_2^2}}$$

$$\text{Decision rule (two-tailed test): } \begin{cases} \text{Reject } H_0 & \text{if } |t| > t_{\alpha/2} \\ \text{Fail to reject } H_0 & \text{if } |t| \leq t_{\alpha/2} \end{cases}$$

$$\text{Approximate p-value: } p = 2 \cdot P(Z > |t|)$$

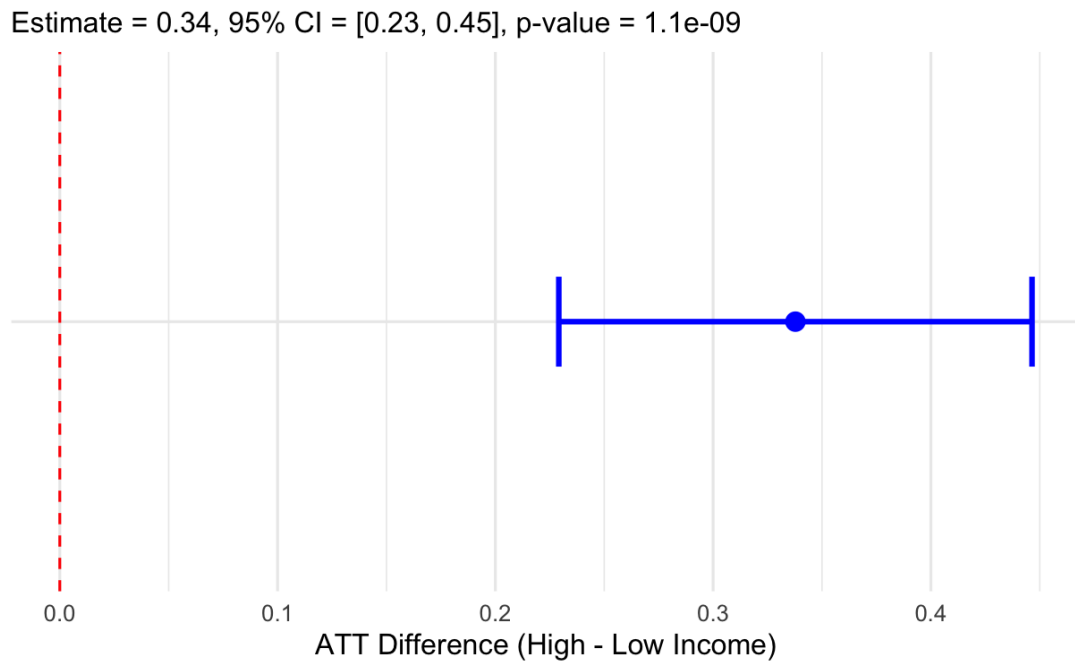
Where:

- $\hat{\beta}_1$ and $\hat{\beta}_2$ represent the two independent point estimates (e.g., treatment effects or regression coefficients).
- SE_1 and SE_2 are the corresponding standard errors of $\hat{\beta}_1$ and $\hat{\beta}_2$.
- The test statistic t compares the difference between the two estimates relative to the combined standard error.
- The denominator $\sqrt{SE_1^2 + SE_2^2}$ assumes independence between the two estimates, so their variances are additive.
- The null hypothesis H_0 is that the two estimates are equal: $H_0 : \hat{\beta}_1 - \hat{\beta}_2 = 0$.
- The critical value $t_{\alpha/2}$ corresponds to the selected significance level α for a two-tailed test (e.g., $t_{0.025} = 1.96$ for $\alpha = 0.05$ under a standard normal distribution).
- The p-value is calculated as $p = 2 \cdot P(Z > |t|)$, which gives the probability of observing a difference at least as extreme as the one observed, under the assumption of no true difference.
- For large samples, the t -distribution can be approximated by the standard normal distribution, hence the use of Z in the p-value formula.

These calculations are applied to the heterogeneous analyses in section 4.2.1, 4.2.2, and 4.2.3.

B.1 Income estimates

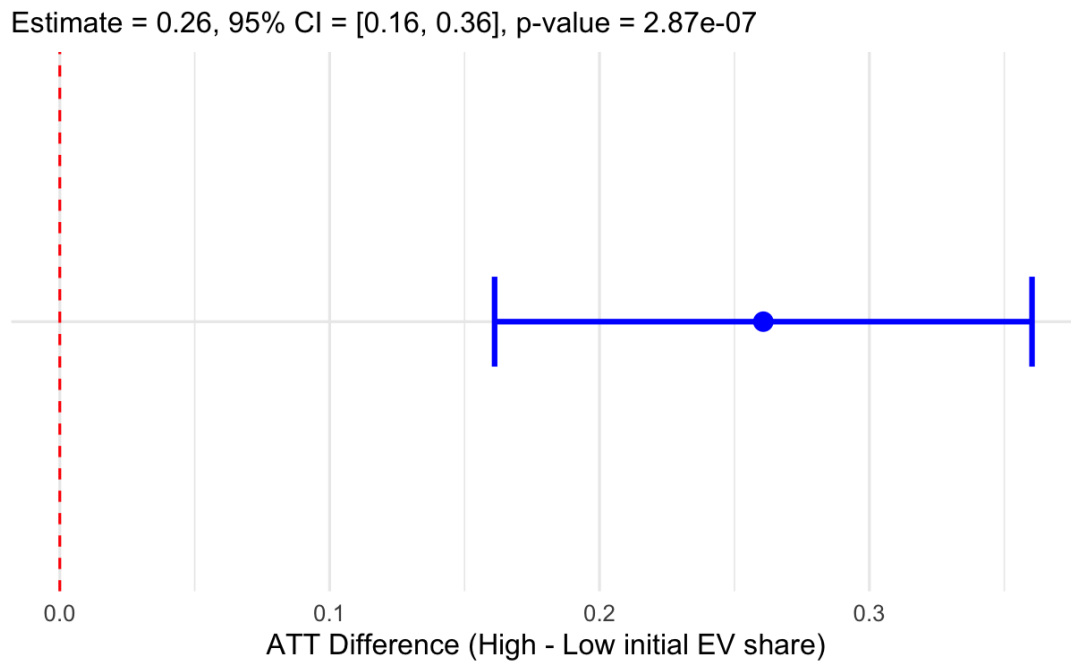
Figure 12: Significant difference between estimates for high-income and low-income municipalities



Notes: This plot shows the difference in the ATT estimates for high-income and low-income municipalities, computed through a two-tailed test described above. The difference is significantly different from 0 at the 1% level.

B.2 Initial EV share estimates

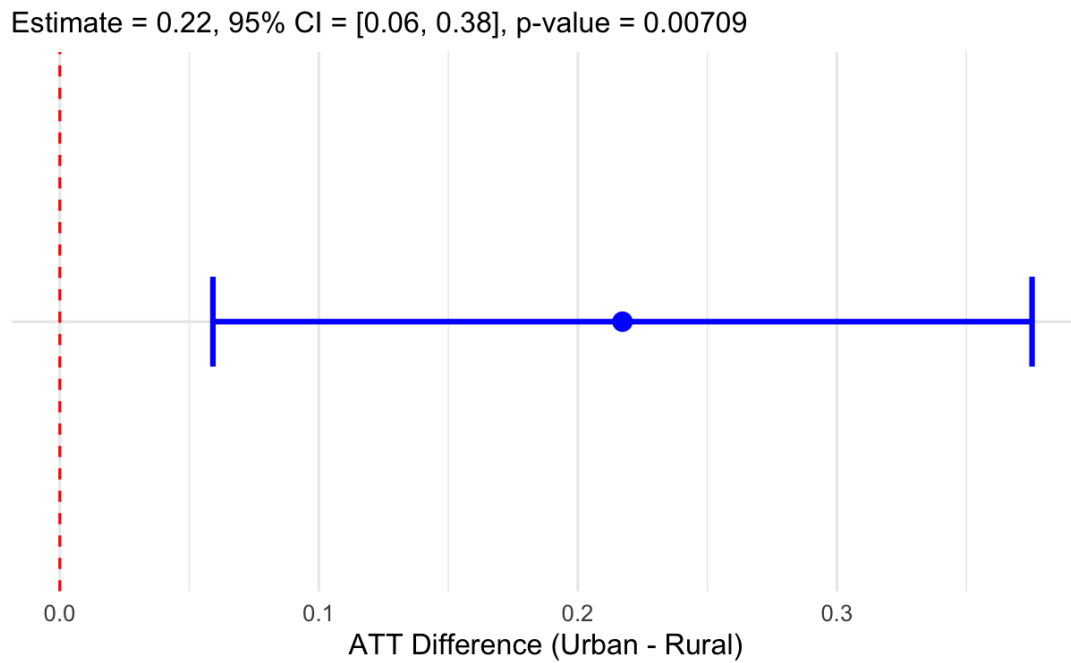
Figure 13: Significant difference between estimates for high and low initial EV share municipalities



Notes: This plot shows the difference in the ATT estimates for municipalities with a high and low initial EV share, computed through a two-tailed test described above. The difference is significantly different from 0 at the 1% level.

B.3 Urban/rural estimates

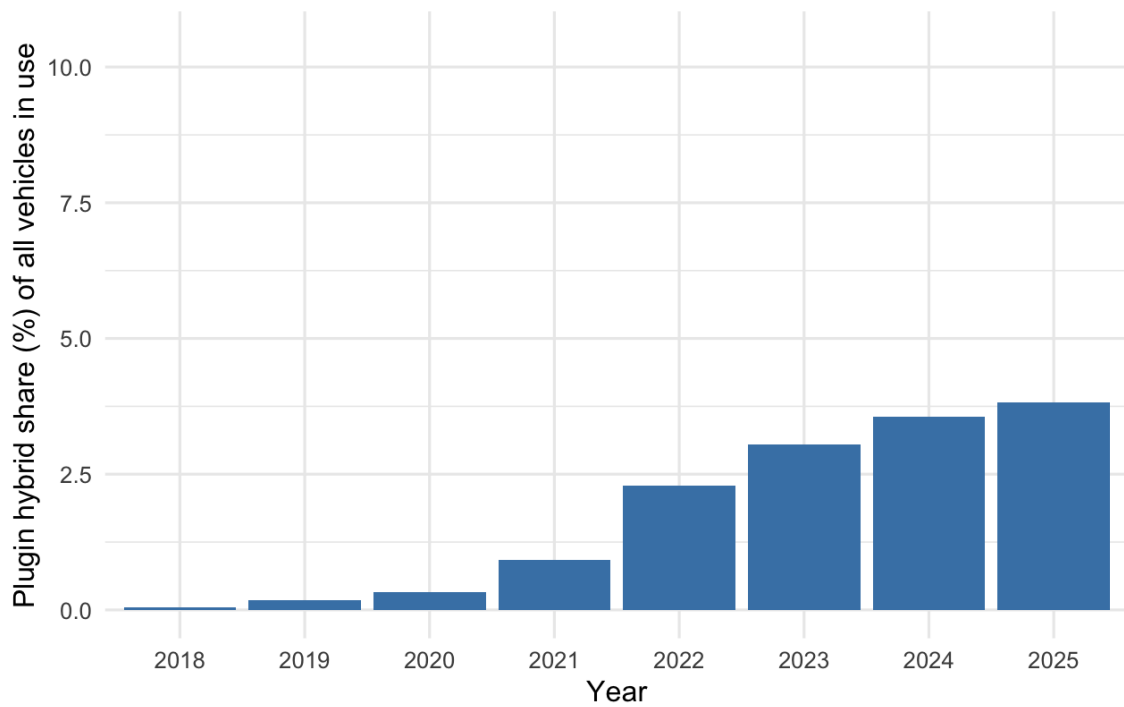
Figure 14: Significant difference between estimates for urban and rural municipalities



Notes: This plot shows the difference in the ATT estimates for urban and rural municipalities, computed through a two-tailed test described above. The difference is significantly different from 0 at the 1% level.

C Vehicle shares

Figure 15: Plugin Hybrid Share of Total Vehicles in use, 2018-2025



Notes: Data from Statistics Denmark (datacode BIL710). The graph shows the yearly market share of Plugin-hybrid vehicles out of all vehicles registered in households in Denmark per 1st of January of each year.

D Descriptive statistics

D.1 Statistics tables

Table 7: Descriptive Statistics by Income Group

	Low Income	High Income
Mean EV Regs. (1000 cap)	0.27	0.42
Mean EV Share (01/2018)	0.16	0.32
Mean Income (DKK)	235,874.8	287,633.4
SD Income	8,751.0	53,946.1
Min Income (DKK)	213,852.0	250,280.9
Max Income (DKK)	248,673.1	512,593.9
Mean Population	50,762	67,508
Avg. Treatment Month	50.35	47.76
SD Treatment Month	10.04	13.96
N Municipalities	49	50

Notes: This table reports mean characteristics of municipalities in the low- and high-income groups used in the heterogeneous effects analysis. Income groups are based on the median of average household income in the period 2018-2025.

Table 8: Descriptive Statistics by Initial EV Share Group

	Low Initial EV Share	High Initial EV Share
Mean EV Regs. (1000 cap)	0.28	0.42
Mean EV Share (01/2018)	0.13	0.36
SD EV Share (2018)	0.04	0.22
Min EV Share	0.00	0.19
Max EV Share	0.19	1.15
Mean Income (DKK)	241,342.3	282,647.9
Mean Population	47,110.9	71,575.1
Avg. Treatment Month	48.56	49.53
SD Treatment Month	11.80	12.67
N Municipalities	50	49

Notes: This table reports mean characteristics of municipalities in the low- and high-initial EV share groups used in the heterogeneous effects analysis. Groups are based on the median of electric vehicle share as of January 2018.

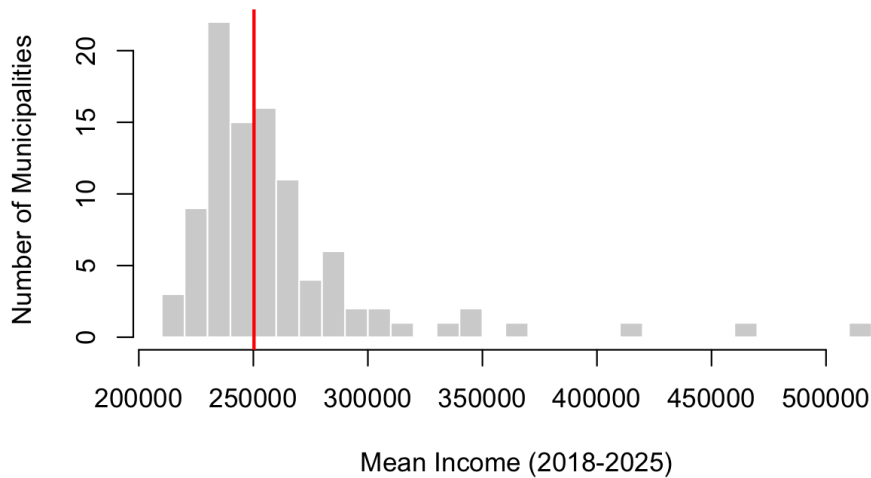
Table 9: Descriptive Statistics by Urban-Rural Group

	Rural	Urban
Mean EV Regs. (1000 cap)	0.30	0.41
Mean EV Share (01/2018)	0.18	0.33
Mean Income (DKK)	245,838.9	282,555.4
Mean Population	37,865.2	87,029.6
Avg. Treatment Month	49.04	49.05
SD Treatment Month	12.94	11.28
N Municipalities	56	43

Notes: This table reports mean characteristics of municipalities by urban-rural classification (as per Statistics Denmark) used in the heterogeneous analysis. Urban-rural groups are coded as 1 for rural and 0 for urban municipalities.

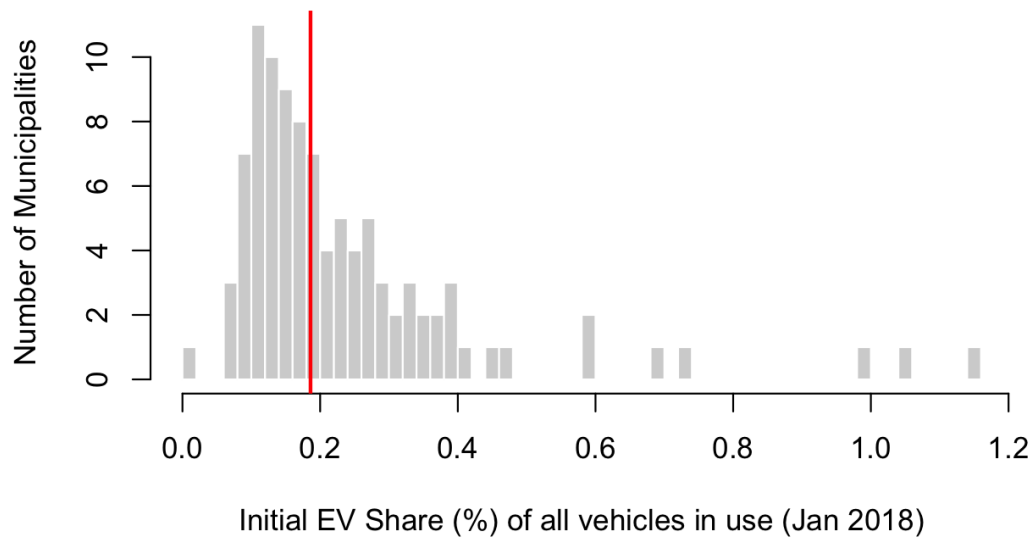
D.2 Distribution plots

Figure 16: Distribution of income



Notes: This histogram illustrates the variation in income across the 99 municipalities. The red line indicates the median splitting the sample into the two low-income and high-income groups.

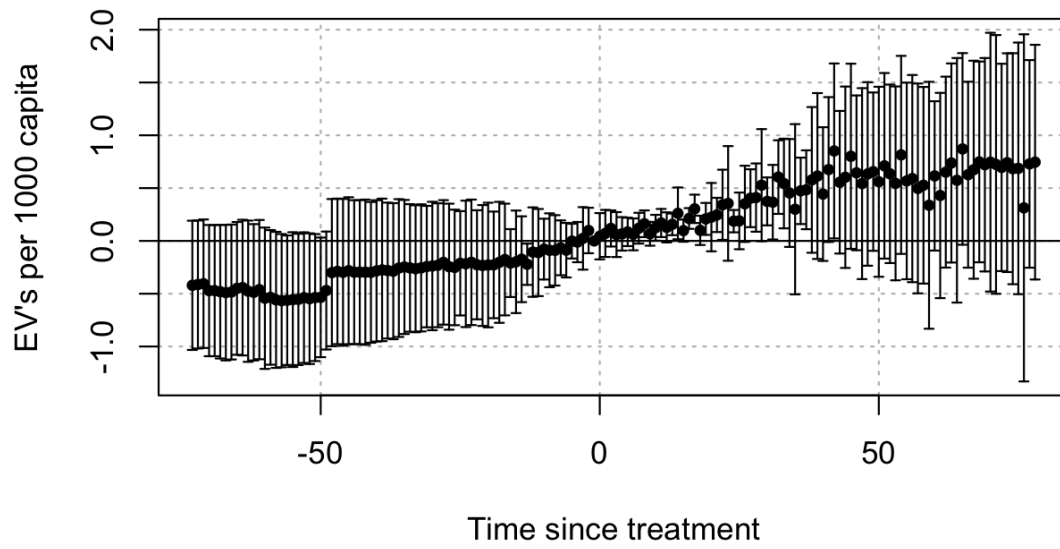
Figure 17: Distribution of initial EV share



Notes: This histogram illustrates the variation in initial EV share across the 99 municipalities. The red line indicates the median splitting the sample into the two groups of low and high initial share of EV's.

E Event plot of TWFE model

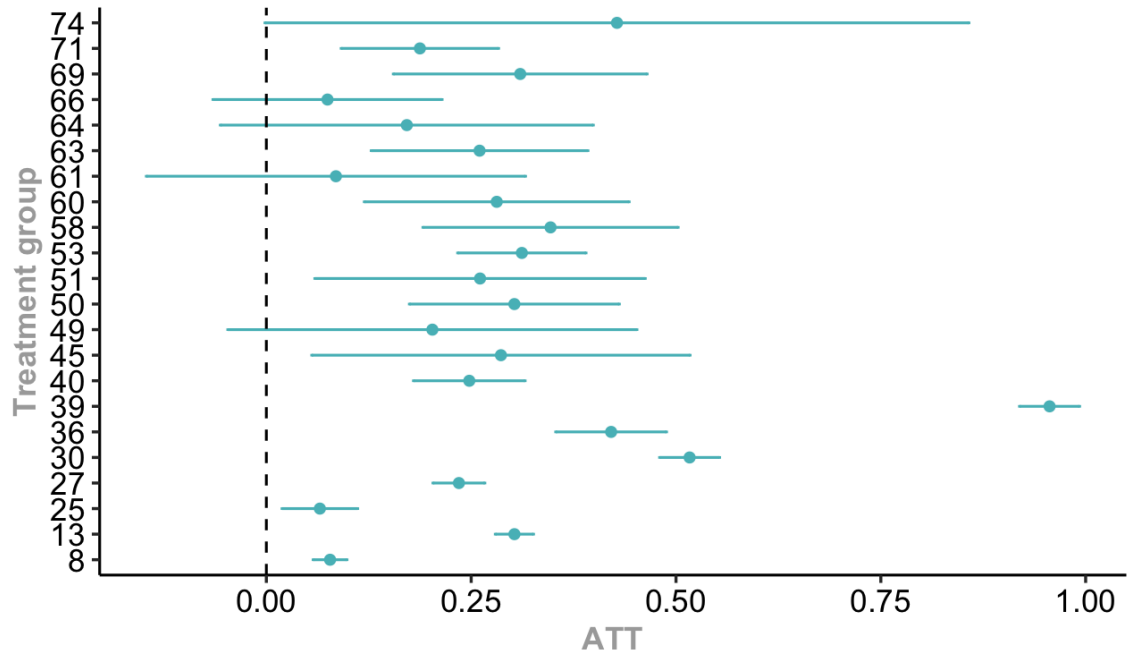
Figure 18: Dynamic effects in TWFE model



Note: This plot visualises model 2 from [Table 1](#).

F Group ATT

Figure 19: Aggregate ATT by group



Notes: The graph shows the average ATT for each treatment group. Standard errors not overlapping with 0 indicates significance at the 1% level.

G Back-of-the-Envelope Calculations

G.1 Illmann and Kluge (2020)

To compare the elasticity estimate from Illmann and Kluge (2020) to the results in this study, I conduct a back-of-the-envelope normalisation of their effect into per capita terms. Illmann and Kluge (2020) estimate that a 1% increase in public charging points leads to a 0.8% increase in monthly BEV registrations. Based on German national statistics from 2017, the total number of new EV registrations per month was approximately 6,000. Therefore, a 1% increase in chargers is associated with an increase of:

$$0.008 \times 6,000 = 48 \text{ BEV registrations per month}$$

Annualising this effect yields:

$$48 \times 12 = 576 \text{ EV registrations per year}$$

Germany's population in 2017 was approximately 83 million. To express this effect in per capita terms:

$$\frac{576}{83,000,000} \times 1,000 = 0.0069 \approx 0.007 \text{ EVs per 1,000 capita per year}$$

Conclusion: The estimate in Illmann and Kluge (2020) implies that a 1% increase in public charging infrastructure results in approximately **0.007 additional EVs per 1,000 people per year**. This magnitude is considerably smaller than the dynamic effect estimated in this paper (**0.47 EVs per 1,000 capita**), which is expected given the cumulative nature of the estimate in Illmann and Kluge (2020).

G.2 Sommer and Vance (2021)

To compare the estimate from Sommer and Vance (2021) to the present study, I convert their result into per capita terms. Sommer and Vance (2021) estimate that one additional normal public charging point is associated with an increase of:

$$0.062 \text{ new EV registrations per county per month}$$

This corresponds to:

$$0.062 \times 12 = 0.744 \approx 0.74 \text{ new BEVs per county per year}$$

Germany comprises approximately 400 NUTS-3 counties, with a total population of

around 83 million. Thus, the average county population is:

$$\frac{83,000,000}{400} = 207,500 \text{ people}$$

Expressing the annual increase in EVs per capita:

$$\frac{0.74}{207,500} \times 1,000 = 0.0036 \text{ EVs per 1,000 capita per year}$$

Conclusion: According to Sommer and Vance (2021), the addition of one public charging point is associated with an increase of approximately **0.0036 BEVs per 1,000 people per year**. Compared to the estimate of **0.47 BEVs per 1,000 capita** found in this study (based on the dynamic effect of the first station), this magnitude is substantially smaller. The difference likely reflects the marginal nature of Sommer and Vance (2021)'s estimate—capturing small additions to already-developed infrastructure—whereas my study captures the larger behavioral response associated with initial charger deployment in previously unserved municipalities.

G.3 Schulz and Rode (2022)

Focusing on Norway, Schulz and Rode (2022) estimate that five years after the implementation of a municipality's first public charging point, EV ownership rates increase by 1.5 percentage points. This increase is described as a 200% growth relative to the baseline EV share, implying that the initial BEV ownership share was approximately:

$$\frac{1.5}{2} = 0.75\%$$

Therefore, the total cumulative effect over five years is an increase from 0.75% to 2.25% of the population owning a EV, corresponding to:

$$1.5\% \times 1,000 = 15 \text{ EVs per 1,000 capita}$$

To express this as an annualised effect:

$$\frac{15}{5} = 3 \text{ EVs per 1,000 capita per year}$$

Conclusion: Schulz and Rode (2022) suggest that the first charging point results in a cumulative gain of **15 EVs per 1,000 people** over five years, or approximately **3 EVs per 1,000 people per year**. This estimate is substantially larger than the German-based elasticity estimates in other studies, and also larger than this paper's estimate of **0.47 EVs per 1,000 people**.

H Contingency tables of heterogeneous analyses

Table 10: Cross-tabulation of income level and initial EV share

	Low initial EV %	High initial EV %
Low-income	38	11
High-income	12	38

Notes: This table shows the distribution of municipalities across the splits between high and low income, and high and low initial share of EV's. The sum adds up to the 99 municipalities.

Table 11: Cross-tabulation of income level and urban/rural

	Rural %	Urban %
Low-income	37	12
High-income	19	31

Notes: This table shows the distribution of municipalities across the splits between high and low income, and urban and rural. The sum adds up to the 99 municipalities.

Table 12: Cross-tabulation of initial EV share and urban/rural

	Rural %	Urban %
Low initial EV %	38	12
High initial EV %	18	31

Notes: This table shows the distribution of municipalities across the splits between urban and rural, and high and low initial share of EV's. The sum adds up to the 99 municipalities.