02/25
ARBEIDSNOTAT
WORKING PAPER

Demand for electric vehicles and chargers in Norway

Frode Skjeret

SNF
Samfunns- og næringslivsforskning AS
Centre for Applied Research at NHH

SNF
SAMFUNNS- OG NÆRINGSLIVSFORSKNING AS

- er et selskap i NHH-miljøet med oppgave å initiere, organisere og utføre eksternfinansiert forskning. Norges Handelshøyskole og Stiftelsen SNF er aksjonærer. Virksomheten drives med basis i egen stab og fagmiljøene ved NHH.

SNF er ett av Norges ledende forskningsmiljø innen anvendt økonomisk-administrativ forskning, og har gode samarbeidsrelasjoner til andre forskningsmiljøer i Norge og utlandet. SNF utfører forskning og forskningsbaserte utredninger for sentrale beslutningstakere i privat og offentlig sektor. Forskningen organiseres i programmer og prosjekter av langsiktig og mer kortsiktig karakter. Alle publikasjoner er offentlig tilgjengelig.

SNF
CENTRE FOR APPLIED RESEARCH AT NHH

- is a company within the NHH group. Its objective is to initiate, organize and conduct externally financed research. The company shareholders are the Norwegian School of Economics (NHH) and the SNF Foundation. Research is carried out by SNF´s own staff as well as faculty members at NHH.

SNF is one of Norway´s leading research environment within applied economic administrative research. It has excellent working relations with other research environments in Norway as well as abroad. SNF conducts research and prepares research-based reports for major decision-makers both in the private and the public sector. Research is organized in programmes and projects on a long-term as well as a short-term basis. All our publications are publicly available.

SNF Working Paper No. 02/25

Demand for electric vehicles and chargers in Norway

Frode Skjeret

SNF- project No. 10096:
Norwegian Centre for Hydrogen Value Chain Research - HyValue

The project is financed by Research Council of Norway

CENTRE FOR APPLIED RESEARCH AT NHH
BERGEN, DECEMBER 2025
ISSN 2704-0380 (Online)

PREFACE

We use a panel vector autoregressive (pVAR) model to estimate a possible interrelationship among the two dependent variable, the deployment of chargers for electric vehicles and the diffusion of electric vehicles in Norway. Using a detailed dataset on the municipality-level, we propose a model to analyse whether there exist simultaneous and dynamic interactions between the share of electric vehicles and the presence of chargers in a regional manner. We find that there is a weak relationship between the two variables, but also that the results are weak and the obtained results are not perfectly stable. Additional data – either over time (longer data series or e.g. monthly data) or higher geographical granularity may increase the significance of the model used herein.

INNHOLD

1 INTRODUCTION

Global temperatures are rising, and governments around the world are introducing a variety of measures to reduce gases causing climate change. IPCC (The Intergovernmental Panel on Climate Change) states that global temperatures will continue to increase, causing more damages unless greenhouse gas emissions are reduced (Mukherji, 2023). The transportation industry's share of greenhouse gas emissions is about 16% of all global emissions of greenhouse gases, and what is more, a large fraction of this is caused by the road transport sector (Agency, 2019). Furthermore, by transforming their portfolio of vehicles towards more sustainable ones, the car manufacturing industry is seen as one important candidate for reducing greenhouse gas emissions in Europe and elsewhere. The solution in the road transportation sector this far has been primarily the use of electric vehicles, battery electric vehicles (BEV) and plug in hybrid vehicles (PHV), but other solutions also exist. These offers a chance to reduce emissions significantly because it does not rely on petrol products (Kromer, 2007). Thus, the climate changes observed have introduced a range of restrictions – and opportunities – for the car manufacturing industry. While many legacy car manufacturers are experiencing hard economic times, others (like Tesla and many Chinese car manufacturers) have witnessed large growth the last couple of decades.

In recent years, several European countries have been taking measures to promote the electrification of road transport. The diffusion of electric vehicles was not regarded sufficiently fast, and many governments introduced policy measures for BEVs. For instance, the French government set a target to reduce GHG-emissions from road transport by 40 percent by 2030, compared to the levels of emissions in this sector in 1990. Furthermore, the French government aim at ending the sales of petrol and diesel vehicles (or internal combustion engine vehicles, ICEV) by 2040 (Haidar & Rojas, 2022). One of the measures for obtaining these targets was the implementation of a subsidy for purchasing low-emitting cars, called '*the bonus*', and also introducing a tax on vehicles that go above a specific level of CO2 emissions. Germany introduced substantial economic incentives with the intent increase BEV adoption, e.g. a grant on the purchase of BEVs (Alberini & Vance, 2025). In addition, to facilitate an increasing number of BEVs, Germany has set a target of 1 million charging points by the year 2030. Recently, several authors have reviewed the literature on government policies for incentives for purchasing BEVs (Qadir et al., 2024) (Anilan & Vij, 2024). The adoption of BEVs in these countries has been slow compared to e.g. Norway, as studied in this report.

The focus herein is on the Norwegian market for BEVs, partly because Norway is seen as one of the leaders when it comes to take on the use of BEVs, but also due to the data availability in this country. Furthermore, the Norwegian government has introduced several polices incentivising potential buyers of BEVs consumers incentives to purchase BEVs on the expense of ICEVs. Already in the 1990s were (import) taxes on BEVs removed, and later, and in the early 2000s exempt from value added taxes (VAT) was given on the purchase of BEVs. These policies contributed to making BEVs more attractive compared to purchasing ICEVs. While the above benefits were directed towards making the purchase of BEVs more attractive compared to purchasing ICEVs, other benefits were introduced for owners of BEVs, benefits related to the use of BEVs. First, in the mid-1990s, owners of BEVs were exempt from paying annual road taxes, and also, they did not have to pay charges on toll roads. In 2009, users of BEVs did not have to pay charges on ferries, for an overview of policies on incentivising BEVs in Norway, see e.g. (Figenbaum, 2017). All of these exemptions did not last all through the period covered by the data used in this paper, for instance, owners of BEVs had to pay 50% of normal from 2017.

Another set of benefits appreciated by owners of BEVs was the use of bus lanes free municipality parking from 1999 to 2017. It should be noted that the transportation (car ownership and usage of ICEVs) in Norway is subject to a very high level of taxation, the potential for providing incentives for choosing BEVs rather than ICEVs were high (Figenbaum, 2017).

Numerous studies on the incentives for BEVs adoption have had a focus on financial incentives, such as tax and toll exemptions as mentioned above. These oftentimes find that the economic benefits - tax credits, rebates and grants – reduces both the cost of purchase and the cost of usage, thereby making BEVs competitive with ICEVs (Clinton & Steinberg, 2019) (Münzel et al., 2019). Other reasons for the deployment of electric vehicles are also analysed in the literature. Social determinants of car purchase are also found to be important. For instance, some potential car buyers may choose a BEV with the intent to be regarded by others – or they regard themselves – as “green consumers”, that is, they have either pro-environmental motives for their purchase of BEVs, or other motives as e.g. being innovative (Li et al., 2022). Their main result is that pro-environmental motives are the most claimed self-image motives by the consumers studied. (Chen et al., 2020) investigates, amongst other things, socio-demographics, behavioural and economic factors related to purchasing electric vehicles. They find that young people, males, persons with relatively high income, and experience with EVs has a higher likelihood for BEV adoption. In addition, the cars’ fuel economy and environmental values were among the strongest predictors for BEV adoption. (Ingeborgrud & Ryghaug, 2019) argue that overall portfolio of incentives provided to potential car buyers: “not only provides instrumental motives to buy BEVs but represents a highly visible, national policy in support of BEVs that has been important for adoption, giving BEVs a symbolic certification as an environmentally sound mobility choice”. By analysing user experiences with different models of BEVs, they find that the symbolic dimensions of BEV-ownership and the significance of incentives promoting BEVs is of great importance.

One important factor that has been studied in the literature for promoting adoption of BEVs, is the investment of – or deployment of – a network of charging stations available for use for the users of BEVs. A range of determinants related to the charging stations have been analysed. The deployment of fast charging stations are found to be important in Denmark (Haustein et al., 2021). The distance between charging stations, between deployment of charging stations, and lessening the distance between charging points and end destination also reducing BEV owners' range anxiety, however, range anxiety – and its antecedents – are more involved (Baden, 2025). There are relatively fewer public charging stations available on the countryside, causing longer queues and more time spent on waiting for a vacant charger in these areas. They also find that the price of charging, the time spent on waiting, charging speed and the facilities at the charging stations were the most important characteristics of the charging stations, while trip features as the distance to the final destination is also significant (Hoen et al., 2023). In addition, both private and public charging possibilities close to home and work increase the propensity for buyers of private cars to choose a chargeable car, but private charging was found to have a relatively larger impact than existing densities of public charging stations (Kristoffersson et al., 2025).

Many studies have investigated the impact of e.g. infrastructure subsidies on the diffusion of BEVs, they find in general a positive effect (Alberini & Vance, 2025). It seems as if the literature find that subsidies for infrastructure are more cost-effective per BEV than a rebate for BEVs (the purchase of BEVs). Subsidizing the deployment of charging stations is more than twice as effective as BEV purchase in USA (Li et al., 2017). This is also found when analysing

Norwegian data, however, it is also found that this relationship disappears when government spending increases (Springel, 2021).

The relationship between charging infrastructure and EV adoption is complex, and not easily explained, and as noted in (Künle & Minke, 2022), This is mainly so because of its chicken-and-egg nature, or reverse effects between deployment of charging infrastructure and diffusion of BEVs. The reverse effects are found when the two variables show evidence of simultaneous causality, that is, causality also directs from the dependent to the explanatory variable. The main hypothesis in the thesis is that deployment of charging stations causes BEV adoption, and at the same time, a high share of BEVs affect the investment in charging infrastructure. This is also the main theme of the current report, the interplay between the deployment of charging infrastructure and diffusion of BEVs. (Schulz & Rode, 2022) study whether public charging infrastructure causes BEV adoption. While they are not able to rule out reverse effects, they conclude that public charging infrastructure contributes to the diffusion of BEVs.

The increasing range of new EVs may have a dampening effect on the demand for fast charging along the road, as shown in the forecast scenarios (Hoen et al., 2023). Long-distance trips constitute a small fraction of the overall transport needs, but the need for such trips might have a great influence on the car purchase decisions (Nicholas et al., 2017). However, many argues that BEVs will not be able to cover all transport needs (Noel et al., 2020). As the battery technology increases both when it comes to range and speed of charging, the need for charger may in fact fall.

With the current paper we hope to contribute to several strands of the recent literature on the diffusion of BEVs. First, by using a panel vector autoregressions framework, we consider the complex relationship between BEV diffusion and the charging station deployment, while allowing for a specific unobserved heterogeneity in the levels of the panels (i.e. fixed effects in municipalities). Most of the literature studying these questions use a one-equation framework, looking primarily on one direction at the time. Second, the approach used in this paper does not rely on strong assumptions about the relationships between the dependent variables. And third, by analysing orthogonalized impulse-response functions we can separate the response of the dependent variables to shocks from other fundamental factors.

The rest of the paper is organised as follows: section 2 presents the empirical specification, and describes the data used, section 3 provides the results of our work, and finally, section 4 presents our conclusions and discussion of the results.

2 METHODOLOGY

Since we are mainly interested in the interplay between the two factors, diffusion of BEVs and deployment of charging infrastructure, se use the framework of (panel) vector autoregression (pVAR). Vector autoregression is a statistical tool used to analyse the inter-relationship between the level of multiple variables as they change over time (Stock & Watson, 2001) (Holtz-Eakin et al., 1988). In a VAR-model, each variable has one equation modelling its evolution over time. The equation for each variable includes this variable's lagged values, covariates (both endogenous and exogenous), the lagged values of the other variables in the model, and an error term. Formally, the model can be described by the equation:

$$y_{it} = A_1 y_{i,t-1} + A_2 y_{i,t-2} + \cdots + A_p y_{i,t-p} + B x_{it} + u_i + \epsilon_{i,t}$$

where y_{it} is a $K \times 1$ vector of dependent variables, in our case (2×1) the share of electric vehicles in a municipality and the variable for fast chargers, herein it is an aggregated number of all fast chargers within 50 km of the municipalities' centroid. A_j are $K \times K$ matrices of parameters to be estimated. x_{it} is a vector of variables (can be endogenous, exogenous and predetermined, depending on the model specification. u_i is a vector of fixed effects, and $\epsilon_{i,t}$ is a vector of serially uncorrelated and idiosyncratic errors. i is the ith panel and t is the tth time period.

We use a panel vector autoregressive (pVAR) model to estimate a possible interrelationship among the two dependent variable. The pVAR model is particularly useful for our analysis since this framework enable the investigation of simultaneous and dynamic interactions between the share of electric vehicles and the presence of chargers in a regional manner. In addition, using the pVAR framework can be helpful a theoretical relationship between the variables is not present, and therefore does not force any a priori restrictions on the relationships among them. In particular, our focus is on orthogonalized impulse-response functions (oirf), these functions show the response of one dependent variable to an orthogonal shock in the other dependent variable. This orthogonalization enables us to identify an effect of one shock at a time, holding other shocks constant.

2.1 Data

The data set used herein consists of annual data at the municipal level in Norway between 2009 and 2019. The data was originally collected for the published article ”Public charging infrastructure and electric vehicles in Norway” (Schulz & Rode, 2022). The data on public fast chargers were collected from NOBIL. The data are highly detailed, including information about charger location, entry date, and power capacity, allowing for differentiation between normal and fast charging stations. The variable for chargers that is used in the analysis in this paper is aggregated number of all fast chargers within 100 km of the respective municipality’s centroid. The Norwegian municipalities differ greatly when it comes to deployment of charging stations. When differentiating between centrality of the municipalities as high centrality municipalities and low centrality municipalities, the following pattern emerges, see figure 1 below:

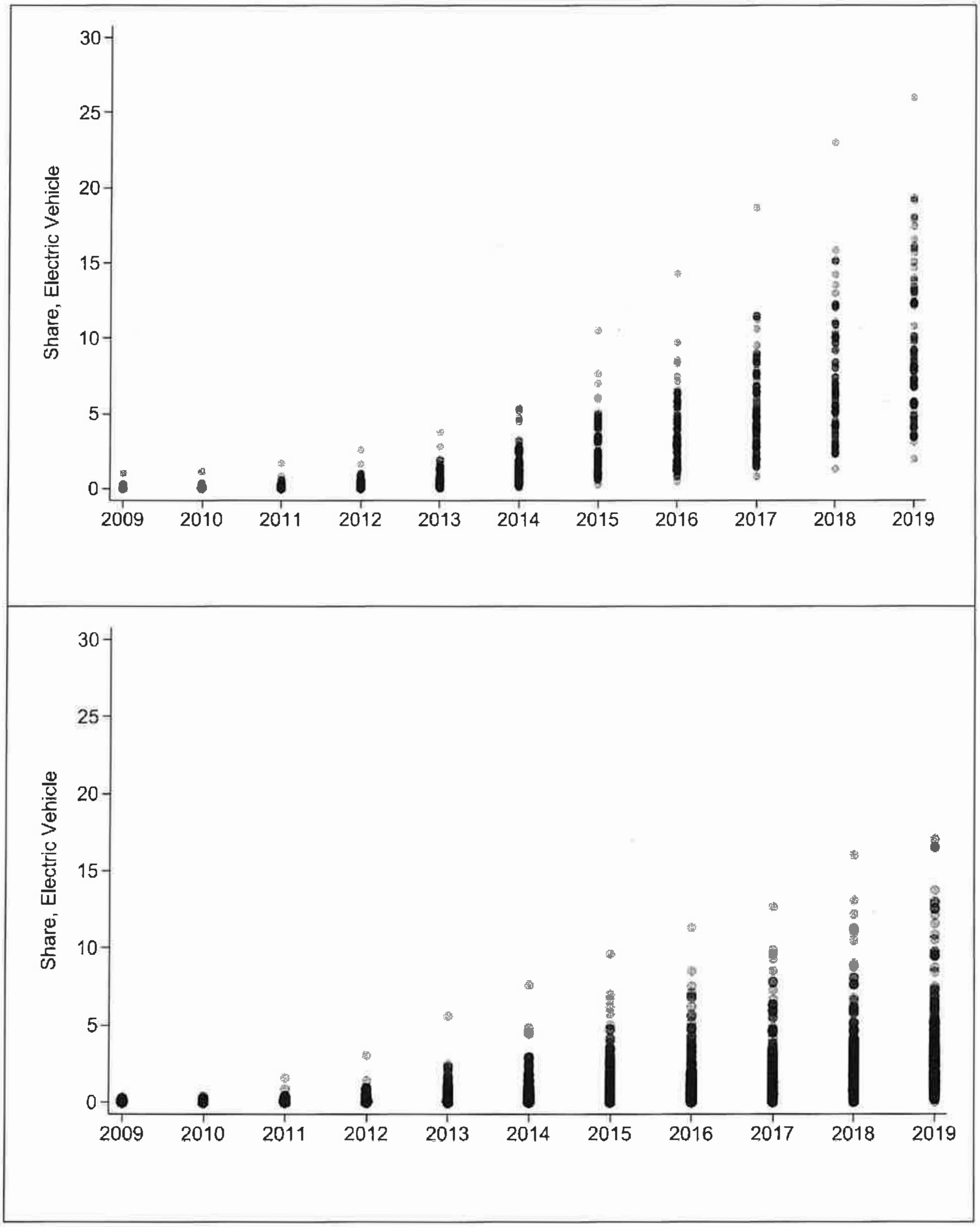

Figure 1: Share of electric vehicles in Norwegian municipalities, years along the horizontal axis and percentage on the vertical axis. Upper graph is municipalities with high centrality; lower graph is municipalities with low centrality.

The centrality index is obtained from Statistics Norway, 2025, high centrality is municipalities located close to large city centres, while low centrality indicates municipalities that are located far from large urban areas.

3 RESULTS

In table 1 below, we document the results of the panel vector autoregression model discussed in the previous section. Since our variables are strictly increasing in time, we have used the first-differencing of the time-series. Since the variables are increasing over time, one may obtain spurious regressions otherwise. In addition, we used the option to collapse the moment conditions for all time periods within each panel. Since the number of panels in our dataset is large the number of moment conditions is also large, the standard GMM estimators can be severely biased, a general feature in dynamic panel-data models. Collapsing the moment condition can contribute to reduce this bias, though it comes at the expense of a less efficient estimator.

Table 1: Result table. Upper panel. The effect of lagged variables on the share of electric vehicles, the lower panel documents the effect of lagged variables on chargers regionally.

	Coeff.	Wc-robust Std.err.	z	P>|z|	95% conf. interv.	
Share EV						
L1:Share EV	1,158	0,024	48,05	0,000	1,111	1,206
L1:Chargers	0,132	0,045	2,92	0,003	0,044	0,221
Chargers						
L1:Share EV	0,089	0,047	1,88	0,060	-0,003	0,180
L1:Chargers	0,899	0,162	5,56	0,000	0,583	1,217

We that both the lagged variables on the variables on themselves are both statistically significant. What is more interesting is that the number of chargers is also statistically significant on the share of electric vehicles, while the deployment of chargers is not statistically significant on the 5% level. Standard errors are WC robust, that is, based on the correction proposed in (Windmeijer, 2005), and therefore robust to arbitrary within-panel correlation. The Hansen test of overidentifying restrictions is χ^2 chi2(32) = 50.66 Prob > χ^2 = 0.019. It should be noted that the dataset is weak in the sense that a subset of the panels (municipalities) does not have sufficiently variation over time and is therefore automatically excluded from the analysis. Thus, the final analysis is only using 286 panels. The results can also be illustrated using impulse response functions, figure 2 below illustrate the impulse response functions obtained from the analysis.

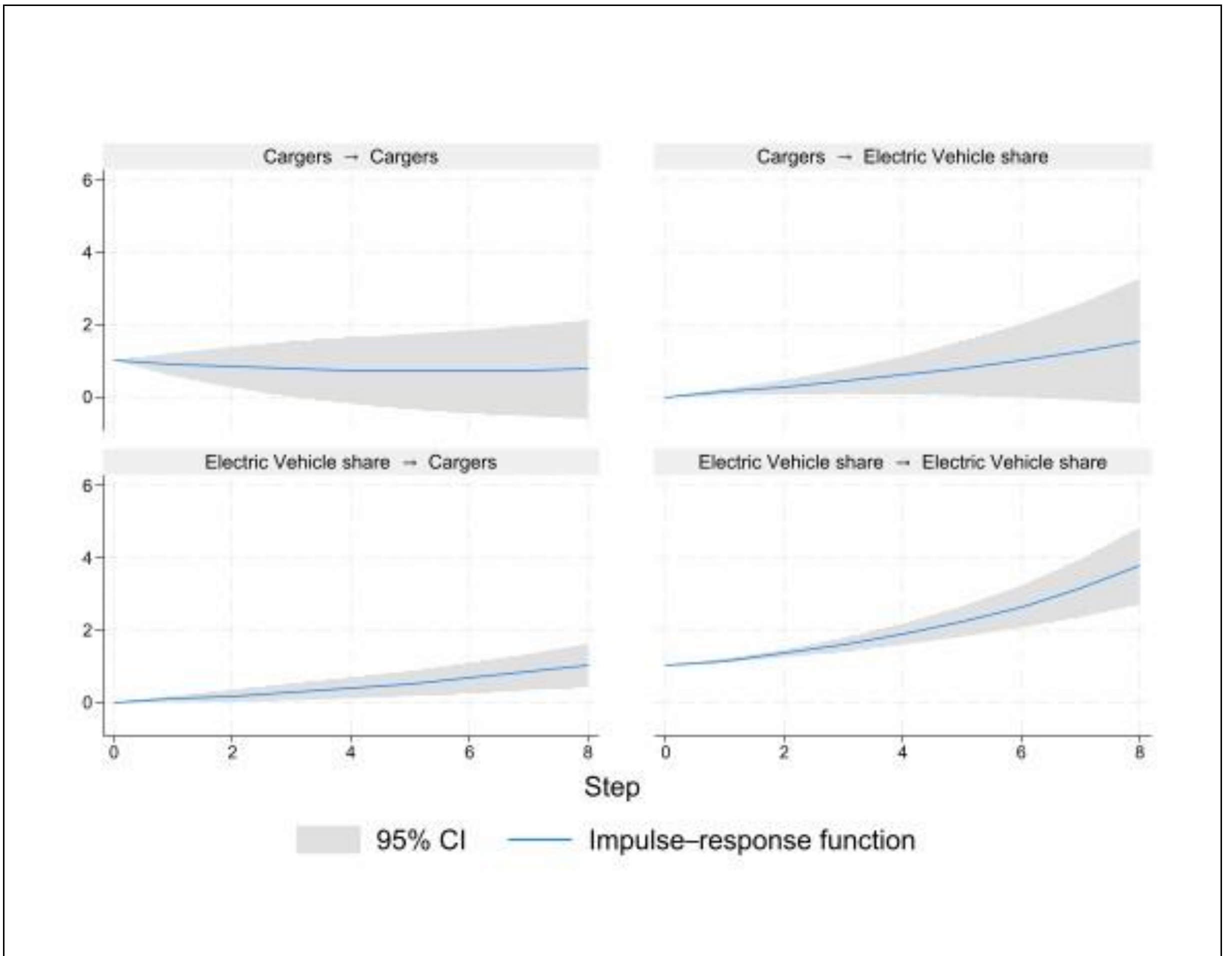

Figure 2: Impulse response functions of the documented results in table 1.

As noted above, we also analyse the impacts using orthogonalised impulse response functions, these are documented in figure 3 below. As is clear from figures 2 and 3, we are able to estimate a positive relationship between deployment of vehicle chargers and diffusion of electric vehicles. This is a purely statistical relationship, we have not included other variables into the vector autoregressions, neither have we included exogenous or endogenous variables in the regressions documented. What is more, our results are not fully stable since one of the unit roots is outside the unit circle. Thus, later research using similar methods should aim at using either a more years (that is, more years following our dataset) or increase the number of panels (use similar countries, like Sweden or Denmark), or a combination of the two.

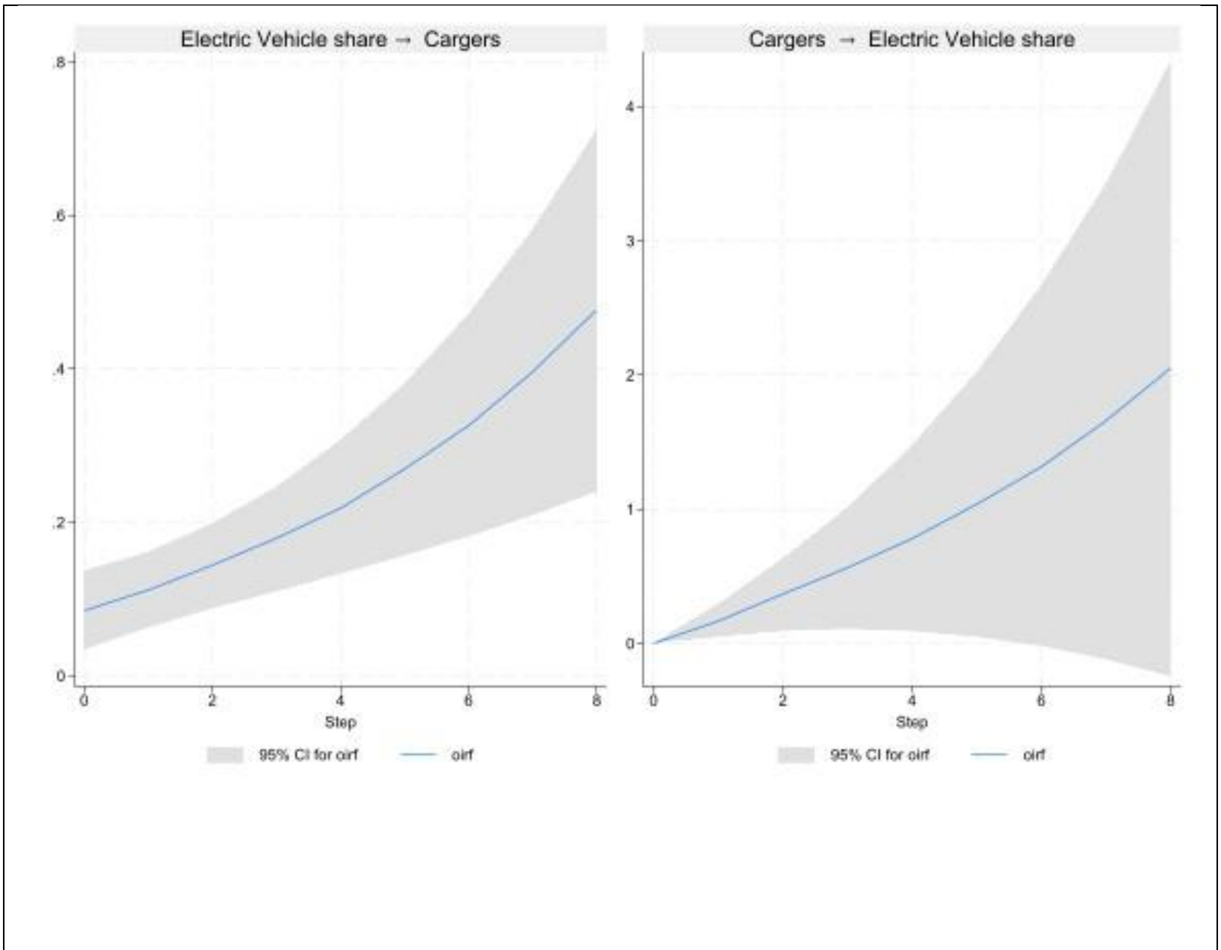

Figure 3: Orthogonalised impulse response function, isolating the effect from other covariates.

We believe that the results will be strengthened by increasing the number of observations. In particular, a subset of the panels is omitted from the analysis, and only by using more years will most likely increase the number of observations to a large extent. In addition, when we include other exogenous variables – as the variables use in (Schulz & Rode, 2022) – in the analysis, the significant relationships outlined above disappears.

4 CONCLUSION AND DISCUSSION

In the current paper, we used a panel vector autoregressive (pVAR) model to estimate the potential relationship between the deployment of chargers for electric vehicles and the diffusion of electric vehicles. We used the pVAR model because this framework enables the investigation of potential simultaneous interactions between these variables.

Our main result is that we do find a weak positive relationship between the deployment of chargers for electric vehicles and the diffusion of electric vehicles. However, the result is not stable (one Eigenvalue is higher than 1), and the analysis should be repeated when more detailed – or longer data series – is available. We also propose another research approach to the questions analysed in this paper, studying professional agents. For instance, we know that taxi drivers in Norway have a very high share of electric vehicles in larger urban areas, while hardly any are observed in less central areas. The use of monthly data could also be a productive way of analysing how deployment of chargers impacts the sales of electric vehicles.

5 REFERENCES

Agency, E. E. (2019). Greenhouse gas emissions from transport in Europe. *tech. rep., EEA*.

Alberini, A. & Vance, C. (2025). Policy forces in the German new car market: How do they affect PHEV and BEV sales? *Transportation Research Part A: Policy and Practice*, *196*, 104477.

Anilan, V. & Vij, A. (2024). Taking the wheel: Systematic review of reviews of policies driving BEV adoption. *Transportation Research Part D: Transport and Environment*, *136*, 104424.

Baden, K. B. (2025). More than just miles: range anxiety unplugged. *Transportation Research Part A: Policy and Practice*, *200*, 104661.

Chen, C.-f., de Rubens, G. Z., Noel, L., Kester, J. & Sovacool, B. K. (2020). Assessing the socio-demographic, technical, economic and behavioral factors of Nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. *Renewable and Sustainable Energy Reviews*, *121*, 109692.

Clinton, B. C. & Steinberg, D. C. (2019). Providing the Spark: Impact of financial incentives on battery electric vehicle adoption. *Journal of Environmental Economics and Management*, *98*, 102255.

Figenbaum, E. (2017). Perspectives on Norway's supercharged electric vehicle policy. *Environmental Innovation and Societal Transitions*, *25*, 14-34.

Haidar, B. & Rojas, M. T. A. (2022). The relationship between public charging infrastructure deployment and other socio-economic factors and electric vehicle adoption in France. *Research in Transportation Economics*, *95*, 101208.

Haustein, S., Jensen, A. F. & Cherchi, E. (2021). Battery electric vehicle adoption in Denmark and Sweden: Recent changes, related factors and policy implications. *Energy Policy*, *149*, 112096.

Hoen, F. S., Díez-Gutiérrez, M., Babri, S., Hess, S. & Tørset, T. (2023). Charging electric vehicles on long trips and the willingness to pay to reduce waiting for charging. Stated preference survey in Norway. *Transportation Research Part A: Policy and Practice*, *175*, 103774.

Holtz-Eakin, D., Newey, W. & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the econometric society*, 1371-1395.

Ingeborgrud, L. & Ryghaug, M. (2019). The role of practical, cognitive and symbolic factors in the successful implementation of battery electric vehicles in Norway. *Transportation Research Part A: Policy and Practice*, *130*, 507-516.

Kristoffersson, I., Pyddoke, R., Kristofersson, F. & Algers, S. (2025). Access to charging infrastructure and the propensity to buy an electric car. *Transportation Research Part D: Transport and Environment*, *139*, 104588.

Kromer, M. A. (2007). *Electric powertrains: opportunities and challenges in the US light-duty vehicle fleet* [Massachusetts Institute of Technology].

Künle, E. & Minke, C. (2022). Macro-environmental comparative analysis of e-mobility adoption pathways in France, Germany and Norway. *Transport Policy*, *124*, 160-174.

Li, L., Wang, Z., Gong, Y. & Liu, S. (2022). Self-image motives for electric vehicle adoption: Evidence from China. *Transportation Research Part D: Transport and Environment*, *109*, 103383.

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.

Mukherji, A. (2023). Climate change 2023 synthesis report.

Münzel, C., Plötz, P., Sprei, F. & Gnann, T. (2019). How large is the effect of financial incentives on electric vehicle sales?–A global review and European analysis. *Energy Economics*, *84*, 104493.

Nicholas, M. A., Tal, G. & Turrentine, T. S. (2017). Advanced plug-in electric vehicle travel and charging behavior interim report.

Noel, L., de Rubens, G. Z., Kester, J. & Sovacool, B. K. (2020). Understanding the socio-technical nexus of Nordic electric vehicle (EV) barriers: A qualitative discussion of range, price, charging and knowledge. *Energy Policy*, *138*, 111292.

Qadir, S. A., Ahmad, F., Al-Wahedi, A. M. A., Iqbal, A. & Ali, A. (2024). Navigating the complex realities of electric vehicle adoption: A comprehensive study of government strategies, policies, and incentives. *Energy Strategy Reviews*, *53*, 101379.

Schulz, F. & Rode, J. (2022). Public charging infrastructure and electric vehicles in Norway. *Energy Policy*, *160*, 112660.

Springel, K. (2021). Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy*, *13*(4), 393-432.

Stock, J. H. & Watson, M. W. (2001). Vector autoregressions. *Journal of Economic perspectives*, *15*(4), 101-115.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of econometrics*, *126*(1), 25-51.

We use a panel vector autoregressive (pVAR) model to estimate a possible interrelationship among the two dependent variable, the deployment of chargers for electric vehicles and the diffusion of electric vehicles in Norway. Using a detailed dataset on the municipality-level, we propose a model to analyse whether there exist simultaneous and dynamic interactions between the share of electric vehicles and the presence of chargers in a regional manner. We find that there is a weak relationship between the two variables, but also that the results are weak and the obtained results are not perfectly stable. Additional data – either over time (longer data series or e.g. monthly data) or higher geographical granularity may increase the significance of the model used herein.

SNF

Samfunns- og næringslivsforskning AS
Centre for Applied Research at NHH

Helleveien 30
NO-5045 Bergen
Norway

P +47 55 95 95 00
E snf@snf.no
W snf.no

Trykk: MAKE!Graphics - avd. Bergen