The adoption of electric vehicles is shifting residential electricity consumption

A.K.M Nijdam (1017205)

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Wageningen University & Research
Master Thesis Urban Environmental Management
Environmental Economics and Natural Resources Group (ENR80436)
E-mail: age.nijdam@wur.nl
Supervisor: Suphi Sen

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Abstract

To address the large climate-related challenges, a transition towards electric transport has been put in motion by policy makers all over the world. While scientific evidence highlights the substantial benefits of this widespread electric vehicle (EV) adoption, concerns about the transition persist. One of the key concerns relates to the additional electricity production required to support EVs and whether current electrical infrastructure can accommodate the growing demand. It is therefore crucial to understand the effects of EV adoption on electricity demand.

In this study on the Netherlands, a fixed effects regression was performed on panel data from Dutch municipalities to investigate and quantify the relationship between the number of electric cars and residential electricity consumption. This study found evidence of increased electricity consumption due to EV uptake, potentially offsetting the current negative trend in residential electricity consumption within the Netherlands. This research also identified varying effects among plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and small company electric vehicles. Residential electricity demand appeared to be primarily driven by PHEVs, which may be explained by differences in user behaviour. Electric company vehicles were found to decrease residential electricity demand. However, these findings are subject to certain limitations. In conclusion, this paper argues that policymakers, project planners, and electricity grid operators should take proactive measures to address the effects of rising EV adoption and consider the findings of this paper.

Keywords: Electric infrastructure; Electric vehicles; Electricity demand; Electricity grid; Energy transition; Environmental impact; Transport transition.

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1 Introduction

Climate change, driven by greenhouse gas emissions, is one of the largest challenges facing the world today. Climate change has important implications for human health, economies, biodiversity and much more (IPCC 2022). To address the challenge of climate change and deal with the limited capacity of fossil-fuels a large energy transition is needed. Although the best methods and alternative sources are debated, this transition would require a substantial change in both our energy production and consumption. Many countries have already implemented a multitude of policies to transition towards cleaner energy use (IPCC 2022). A key aspect of this transition is the effort to make the transport sector more sustainable. This sector is responsible for about 23% of worldwide C02 emissions and is currently around 95% driven by fossil fuels (EEA 2020; Jaramillo et al. 2023). Given its high share in global emissions and its heavy reliance on fossil fuels, transforming the transport sector presents a substantial opportunity to reduce overall greenhouse gas emissions.

One of the most viable and widespread changes making the transport sector more sustainable is the adoption of electric vehicles (EVs). EVs currently hold a market share of approximately 23% of new registered cars in Europe and this number is expected to continue growing (EEA 2020). Although this trend indicates some success in the transition, it is crucial to maintain a critical perspective on its consequences and effects. Notably, the surge in EV adoption is contributing to heightened electricity demand (De Tena and Pregger 2018; Rizvi et al. 2018; Shafique and Luo 2022). The increase in demand of electricity could cause the energy mix used to shift more towards non-sustainable sources, which in turn could offset the positive sustainable effects of EVs (De Tena and Pregger 2018; Rietmann, Hügler, and Lieven 2020; Shafique and Luo 2022). Simultaneously, the increased electricity demand puts pressure on the electricity grid (Rizvi et al. 2018). Especially during peak hours, electricity grids might be incapable of providing electricity to households (Kapustin and Grushevenko 2020). Consequently, it is crucial to investigate the changes in electricity demand resulting from the introduction of EVs and review the effect it has on the electricity grid. A country that would be suitable for this research is the Netherlands. Due to the strain EV adoption places on the electricity grid, discussions have already begun about restricting EV charging during peak hours in this country (NOS 2024).

The number of EVs has increased substantially in the last years (EEA 2020; Marzbnai, Osman, and Hassan 2023; Rijksoverheid 2024). It is therefore no sur-

prise that the number of publications that cover the issue has been increasing (Secinaro et al. 2022). Due to the importance of above-mentioned issues, a number of these publications focus on the interaction between adaptation of EVs, energy demand and the electricity grid. Most of these papers are published by the engineering field (Fuinhas et al. 2021). While these studies highlight critical aspects of the EV transition, there is a notable gap in economic research using econometric methods to analyse current data, particularly in the context of Europe and the Netherlands. This is problematic as the impact of EVs depends on issues such as regional energy markets, infrastructure, and consumer behaviour (Moon et al. 2018; Qiu et al. 2021). Topics that economic research often addresses and where it can provide valuable insights.

The econometric research that does exist is limited in numbers and primarily focused on household-level effects, often overlooking broader market and infrastructure dynamics. Additionally, it has yet to compare the differences between battery electric vehicles (BEVs), plug-in hybrid vehicles (PHEVs), and small company electric vehicles, with most studies addressing each type separately or combining them into one variable. Furthermore, the current literature presents conflicting findings on the topic.

The above-discussed gaps in current research are concerning as empirical evidence is essential for fully understanding the implications of the EV transition and for the guiding of effective policymaking. Decisions regarding the investment and expansion of the electricity grid should consider the adoption of EVs and their impacts, including their effect on residential electricity consumption. Without a solid empirical foundation, it becomes challenging to design policies that adequately address the evolving demands placed on energy systems.

By using a fixed effects model on panel data from Dutch municipalities on residential energy consumption and data on EV registrations within these municipalities, this research aims to extend the understanding of the effects of EV adoption on the electricity grid and explain current trends in residential electricity consumption through the adoption of EVs and/or different types of EVs, namely PHEVs, BEVs, and small company electric vehicles. Therefore, this study seeks to address the previously discussed gaps in the current literature.

Moreover, this study seeks to contextualize previous findings within the European context, emphasizing that behaviour and infrastructure in Europe, especially in the Netherlands, differ from regions like the USA, primarily due to shorter travel distances. The findings of this research will help policymakers better guide the energy transition and navigate the challenges that relate to it.

The main research question that follows is: **What effect does the increased EV adaptation have on the residential electricity consumption within the Netherlands?**

In addition, this research includes sub-questions that explore the differentiated impacts of various types of electric vehicles. These sub-questions are:

- What is the separate impact of BEVs and PHEVs on residential electricity consumption?
- How do business-owned electric vehicles influence residential electricity consumption?

The findings of this research reveal a connection between EV adoption and increased residential electricity consumption, although the found effect is only marginally significant and does not align with much previous research. In addition, this research argues that while the short-term impact of EV adoption on residential electricity consumption is small, the overall accumulation of EVs over time will still place increasing pressure on the electricity grid, highlighting the need for proactive planning and infrastructure development.

In addition, this research suggests that while residential electricity demand is currently declining due to energy efficiency improvements, the widespread integration of EVs could potentially reverse this trend over time, or at the very least, slow the rate of decrease.

When analysing different types of vehicles, PHEVs were found to have the most notable impact, showing a significant rise in residential electricity usage. In contrast, BEVs demonstrated a negative but statistically insignificant relationship with residential electricity consumption. No clear explanation for this difference was found, although potential reasons could include the fact that BEV users may charge their vehicles less frequently at home, as these vehicles rely entirely on electricity, and users may perceive a higher risk of running out of charge when relying on public/company infrastructure compared to PHEV users. The literature suggests that PHEV users primarily rely on electricity for short trips, which could help explain their significant impact on residential electricity demand (Boston and Werthman 2016; Mandev et al. 2022; Plötz, Funke, and Jochem 2017). However, potential measurement errors and other limitations could also explain the found estimates.

For small company electric vehicles, a significant negative correlation with residential electricity consumption was observed, likely due to the fact that these

vehicles are being charged at company facilities rather than at home. This suggests that incentivizing company-owned vehicles and investing in extra grid capacity for company facilities could be more effective than expanding the residential electricity grid to accommodate EV charging. In addition, this finding provides opportunities for policy to rethink current energy structures, However, further research is needed to fully understand the implications and optimal allocation of resources.

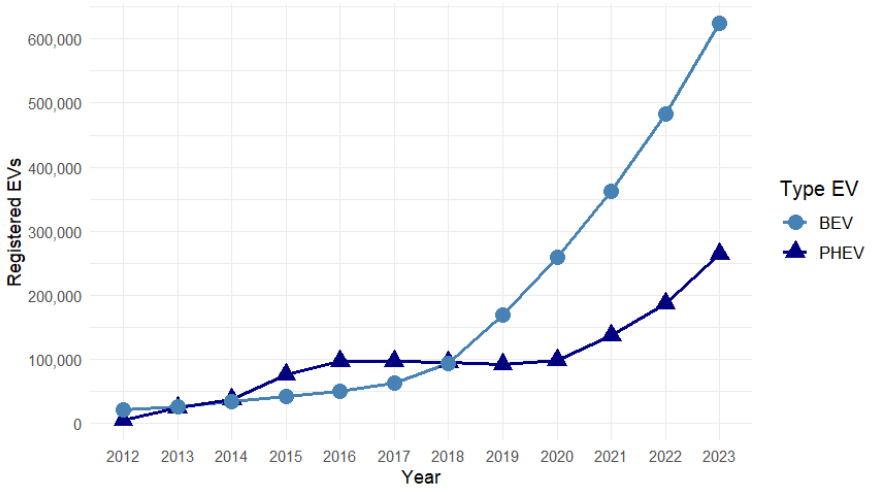
The remainder of this paper is structured as follows: Section 2 provides background information and context on the Netherlands, alongside a review of the relevant literature. Section 3 outlines the data and methodology used in the analysis. Section 4 presents the regression results which are then further discussed in Section 5. Section 6 explores the policy implications of these findings, while Section 7 addresses the study's limitations and potential future research. Finally, Section 8 contains the conclusions of this paper.

2 Background

To establish the broader context in which this study is situated, it is essential to first discuss the current situation and trends in EV adoption and residential electricity consumption in the Netherlands. First, the context of the Netherlands will be reviewed. Secondly, the current literature will be discussed.

2.1 Electric vehicles & electricity in the Netherlands

Figure 1: Number of Registered EVs 2012-2023 (Rijksoverheid 2024).



Electric vehicles: Figure 1, above, shows the total number of registered EVs in the Netherlands. The 2023 data is included in the figure for context but is not used in the regression analysis. Two types of electric vehicles are categorized: BEVs, which are fully electric. PHEVs, which are hybrid vehicles that can be charged. As can be seen, the number of EVs has grown remarkably. The number of PHEVs in the Netherlands rose from 4,685 in 2012 to 263,554 by 2023. Similarly, the number of BEVs increased from 21,990 in 2012 to 624,626 by 2023. Notable in the graph is the initial growth of PHEVs compared to BEVs until 2016, where a stagnation in PHEVs becomes apparent. However, after 2020, there was a renewed increase in the number of PHEVs, a trend that has continued to date. Additionally, the graph shows a large rise in BEVs after 2018, which has continued steadily (Rijksoverheid 2024). In 2022, about 8.827 million passenger cars were registered in total in the Netherlands. Therefore about 7.59% was hybrid or electric (CBS 2023).

Figure 2: Number of BEVs registered to a company 2012-2023 (Rijksoverheid 2024).

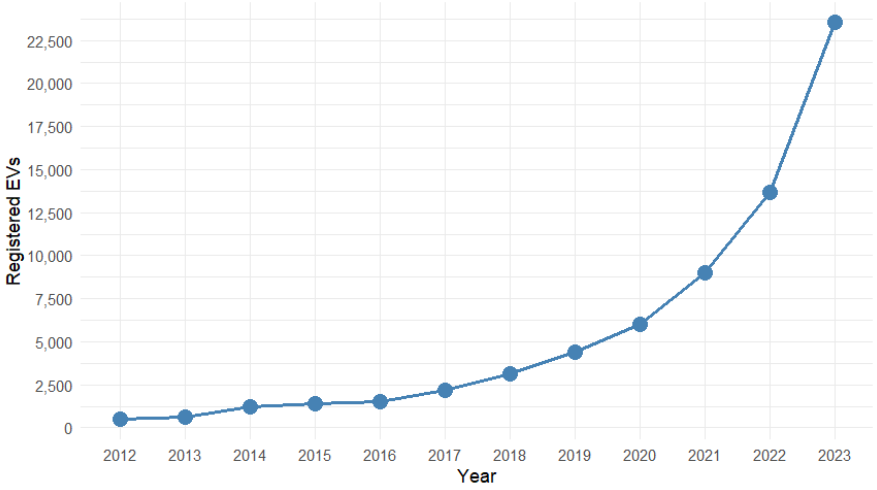
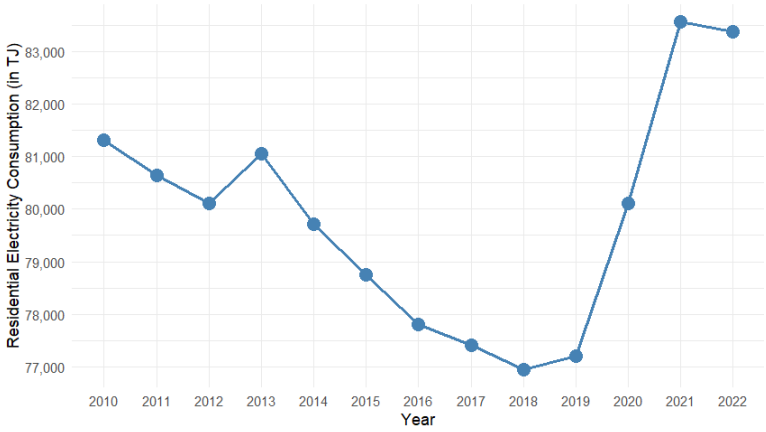


Figure 2 displays the number of registered BEVs with a company listed as the owner. This includes both lease and purchased cars. The figure shows a comparable trend to the number of BEVs in Figure 1, indicating that company EV growth mirrored total EV growth. However, as can be seen the number of registered vehicles by company is smaller than the overall number of registered BEVs. While the total number of BEV increased from 21,990 in 2012 to 624,626 by 2023. The number of company BEVs increased from 486 to 23,555. About 2.84% of BEVs was registered to a company in 2022. Although not shown in the figure, the number of PHEVs registered to companies was even smaller. Increasing from a single vehicle in 2012 to 155 in 2023 (Rijksoverheid 2024).

Figure 3: Total residential electricity consumption in Netherlands accounting for solar energy generated behind the meter (2010-2022) (Rijksoverheid 2024).



Residential Electricity Consumption: Figure 3 illustrates the total electricity consumption of households, accounting for solar energy generated behind the meter. The graph reveals a consistent downward trend in residential electricity consumption from 2010, reaching its lowest point in 2018. This decrease in electricity consumption can be contributed to several factors, including more efficient lighting, increased appliance efficiency, better isolated housing and shifts in consumer behaviour, such as heightened awareness of energy usage and the adoption of energy-saving practices (CLO 2023; Vasseur and Marique 2019).

After a slight increase in household consumption in 2019, electricity use peaked in the following years, reversing the previous downward trend. This peak coincides with the COVID-19 period, suggesting that the increased electricity consumption can be attributed to more people staying at home (Rokicki et al. 2022). However, one should also consider other factors such as the increased usage of heating pumps, which increase annual electricity consumption of households by about 30% (Gercek et al. 2019). Moreover, while electric devices have become more energy-efficient, the number of electrical appliances in Dutch households continues to rise. The shift towards electric cooking and heating may further contribute to the increased electricity demand from households (CLO 2023). As this study will investigate, EV adoption may also be a contributing factor.

2.2 Literature review

As noted in the introduction, research on EVs remains relatively new (Secinaro et al. 2022). The high relevance of the topic has already led to a substantial number of publications. To explore potential gaps in these publications, first a short literature review was conducted. This review includes peer-reviewed articles from Scopus, Web of Science, and Google Scholar published between 2015 and 2025. The keywords used were "econometrics", "electricity demand", "residential electricity", "electric vehicle", "Plugin-hybrid vehicle", "battery electric vehicle", "panel data", "fixed effects" and "Europe" in various combinations. The references of the identified papers were also reviewed to discover additional relevant studies. Below, the gaps identified through this review will be discussed.

Most of the research examining the relationship between EVs and electricity consumption has been published within the field of engineering (Koengkan et al. 2022). Although engineering methods offer valuable insights into technical feasibility, efficiency, and grid requirements, these studies often overlook the influence of human behaviour, policy, and market conditions. It is therefore that researchers

from the fields of economics and/or social sciences have investigated this relationship through econometrical methods. The number of studies employing these approaches however remain limited (Koengkan et al. 2022). This while employing econometric methods could enhance our understanding of how EV adoption affects electricity consumption (Koengkan et al. 2022; Qiu et al. 2021). Not only can econometric methods provide empirical evidence to quantify cause-and-effect relationships, but unlike purely technical models, they also account for human decision-making, market dynamics, and regional variations, offering a more comprehensive understanding of EV adoption and its impact within the real world (Qiu et al. 2021; Coban et al. 2023).

Additionally, most current research, such as Burlig et al. (2021), Coban et al. (2023), and Liang, Qiu, and Xing (2022), focuses on household-level impacts. This approach may overlook broader factors, such as collective trends and regional characteristics that can be captured by municipal-level regressions. Ferdousee (2022) did make use of county-level data and used a two-way fixed-effects linear regression model with monthly county-level data in California, finding that the elasticity of residential electricity demand in response to EV adoption was statistically insignificant. An unexpected result that should be investigated further.

As noted, household-level research is more prevalent, but findings across household-level studies are inconsistent. To further elaborate, Burlig et al. (2021) found that the adoption of an EV by a household leads to an average increase in that household's residential electricity consumption of 0.121 kWh per hour. In a similar study, Coban et al. (2023) applied a panel fixed effects regression to examine the relationship between residential electricity consumption and electric vehicle usage in Turkey. This study estimated an electricity consumption of 0.15 kWh per hour. However, Liang, Qiu, and Xing (2022) found that EV owners in Arizona exhibit an average hourly electricity demand that is 0.4 kWh per hour higher than that of non-EV households, nearly twice the increase reported by Burlig et al. (2021) and Coban et al. (2023). The study also found that EV owners with solar panels reduce their average hourly grid demand by 1.1 kWh. Qiu et al. (2021) found that EV charging increases electricity consumption by 0.31 kWh per hour, a result only slightly lower than that of Liang, Qiu, and Xing (2022).

This variability can make it challenging to draw consistent conclusions and raises questions about why these findings differ. One potential explanation is that studies have been conducted in diverse geographical and regulatory contexts. Substantial evidence indicates that factors such as driving distances, temperature, and local behaviours can vary significantly across regions, thereby influencing elec-

tricity consumption patterns associated with EV usage (Al Wreikat, Serrano, and Sodré 2021; Kapustin and Grushevenko 2020; Moon et al. 2018; Qiu et al. 2021). In the literature review no research employing econometric methods in the (Western) European context was found, suggesting a potential gap in the literature. Conducting studies in different contexts, such as the Netherlands, could help assess the generalizability of previous findings.

Examining the types of vehicles considered in current studies reveals that most do not distinguish between PHEVs and BEVs. Burlig et al. (2021) looked at differences between PHEVs and BEVs and found similar impacts on residential electricity consumption. The datasets used by Ferdousee (2022) and Coban et al. (2023) combine both vehicle types in their analysis. Qiu et al. (2021) and Liang, Qiu, and Xing (2022) do not explicitly specify whether they distinguish between the two. This lack of differentiation presents a research gap, as PHEVs and BEVs have distinct charging behaviours, energy consumption patterns, and environmental impacts (Boston and Werthman 2016; Mandev et al. 2022). Similarly, no econometric researches were found that explored whether company-owned EVs have distinct effects, highlighting another area for further study.

Other studies have aimed to model and/or predict future residential demand based on current data. One such model was made by Moon et al. (2018), which estimated the potential electricity demand and the EV charging behaviour in Korea. Depending on various EV market expansion scenarios. The study found that the additional daily electricity demand was projected to range from 194 to 447 MWh per day in the whole of Korea. In Kapustin and Grushevenko (2020), the researchers modelled several future scenarios of EVs. The study estimated about a 7 to 10% increase in electricity demand by 2040 globally.

Although these models possess predictive power and can offer valuable insights for policymakers and network operators to optimize resource allocation, they also have notable limitations (Oyedeji et al. 2023). Most importantly, the assumptions made in these models often vary. Some choose to highlight different vehicle types, different charging patterns, and others focus more upon empirical data (Marzbnai, Osman, and Hassan 2023; Miri, Fotouhi, and Ewin 2020; Qiu et al. 2021). Due to these various assumptions several studies have shown these models are flawed and do not align with empirical findings (Muratori 2018; Qiu et al. 2021; Shen et al. 2023). This highlights the importance of empirical research and the need to compare models with emperical data.

In conclusion, given the variability in findings across studies due to methodological and contextual differences, this research adds value to the existing body

of literature by generating additional empirical evidence on municipal level within European context. Additionally, this study makes a contribution by distinguishing between different types of vehicles.

3 Data and Methodology

3.1 Data

This research relies on annual panel data to answer the research question. All variable data was obtained from the Klimaatmonitor (Rijksoverheid 2024). This dataset includes the number of registered BEVs and PHEVs between 2012-2022 within all municipalities in the Netherlands, which were added up together to create the variable 'EV'. The dataset included information on company EVs weighing below 3500 kg. However, given the low number of company-owned PHEVs, only company-owned BEVs were included in the analysis.

In addition, the dataset contained the total electricity consumption of households accounting for solar energy generated behind the meter within all the municipalities from 2012-2022 (In TJ). Data that included solar energy generation was included to account for potential co-adoption effects (Liang, Qiu, and Xing 2022; Shen et al. 2023). All variables were merged based on municipality.

To account and control for several factors which could impact the total electricity consumption, several other variables were also included as controls. These were all merged based on municipality and year.

Firstly, the population of each municipality was included to control for differences in municipality size.

Secondly, given that income levels influence electricity consumption, the average income per municipality was included in the analysis. Higher income households tend to use more energy because of larger homes and higher use of appliances, while lower-income households may conserve energy to manage costs (Andersen et al. 2021). By including average income, this study aims to capture these differences in electricity use.

Thirdly, as highlighted in the background section, a factor contributing to energy savings is the increasing efficiency of households and appliances (CLO 2023; Vasseur and Marique 2019). Additionally, investments and behavioural changes further contribute to reduced energy use (Vasseur and Marique 2019). To account for this, the variables percentALabel and percentBLabel were selected as proxy variables for changes in household energy efficiency. These variables represent the percentage of homes with specific Dutch energy labels, which were introduced by the Dutch government to promote sustainability and energy savings. The labels are ranked from A (most energy-efficient) to F (least energy-efficient). For the analysis, only the two most efficient labels (A and B) were selected. The variable

reflects only the percentage of homes with an energy label, accounting for the fact that some homes remain unlabelled and that over the years more houses have become labelled (Rijksoverheid 2024).

A notable limitation of the dataset is that the residential electricity usage data contain several missing values for the years 2012, 2013, 2014, and 2015. That were the initial years of data collection. This issue was particularly present in 2012, where there were a high number of missing values. These missing values were prevalent in smaller municipalities. After performing robustness checks by excluding municipalities with missing data, it was found that the missing values did not substantially affect the results. Therefore, it was decided to drop missing values only by year and perform an unbalanced panel regression, allowing municipalities with partial data availability to remain in the analysis and prevent loss of data.

The number of missing values in the other variables was relatively small and often overlapped across observations. As a result, these missing values were also excluded from the analysis. After all missing values were dropped 3,698 observations remained (compared to the 3,773 observations originally).

Table 1: Descriptive summary.

Statistic	N	Mean	St. Dev.	Min	Max
elechouse (TJ)	3,698	234.779	292.256	5	3,469
inhabitants	3,698	50,416.300	71,946.770	931	903,399
EV	3,698	688.645	2,227.200	4	47,475
BEV	3,698	433.310	1,665.960	3	38,491
PHEV	3,698	255.335	728.941	0	14,783
EVCompany $<$ 3500 kg	3,698	11.792	66.807	0	1,914
incomeperinhabitant (€)	3,698	25,794.400	4,092.295	15,400	49,500
percentALabel (%)	3,698	17.928	10.858	0.200	63.200
percentBLabel (%)	3,698	17.583	5.682	2.100	65.400

Table 1 provides the descriptive statistics for the variables in the final dataset, which includes 3,698 observations from the years 2012 to 2022. On average, residential electricity usage per year in Dutch municipalities is 234.8 TJ, with a standard deviation of 292.3, indicating considerable variation across municipalities.

Similarly, the number of EVs, including PHEVs and BEVs, varies greatly. A municipality had an average of 688 EVs. Which consisted of 433 BEVs (11 of which are owned by companies) and 255 PHEVs. However, the number of EVs per municipality ranges from as low as 4 to as high as 47,475. This shows that there were outliers within the data.

The adoption of energy-efficient housing, as reflected in the percentage of A-label and B-label homes, also differs across municipalities. The average percentage of A-label homes is 17.93% with a maximum of 63.2%. For B-label homes, the average is 17.58%. The maximum of B-Label homes reaches 65.4%. Finally, both income per inhabitant and population size exhibit wide ranges, highlighting the diversity of municipalities and potential heteroscedasticity issues.

3.2 Estimation strategy

To answer the main research question and reach the goal of this research a fixed effect regression was performed. This type of regression allowed the exploration of the time-varying effect of EV adoption on residential electricity usage within Dutch municipalities, while simultaneously controlling for municipality-specific factors that remain constant over time.

$$\log(\text{elechouse}_{it}) = \beta_1 \log(\text{EV}_{it}) + \mathbf{X}_{it}\boldsymbol{\gamma} + \alpha_i + \epsilon_{it} \tag{1}$$

Equation 1, that is shown above, was estimated to reach the above-discussed goals. The equation describes the electricity usage by households per inhabitant as a function of the number of EVs per inhabitant, several control variables, the unobserved municipality-specific effect (α_i) and an error term (ϵ_{it}). The error term is assumed to be uncorrelated with the dependent variable. The dependent variable, $\log(\text{elechouse}_{it})$, is the logarithm of electricity consumption in municipality i at year t. $\log(\text{EV}_{it})$ represents the logarithm of the electric vehicle registrations, the main independent variable of interest. Which again is denoted in municipality i at year t.

The logarithm of these variables was taken to interpret the coefficients as elasticities. Additionally, this transformation was applied to reduce skewness and heteroscedasticity, ensuring more reliable estimates.

$$\begin{aligned}\log(\text{elechouse}_{it}) = \beta_1 \log(\text{EV}_{it}) + \beta_2 \log(\text{inhabitants}_{it}) + \beta_3 \log(\text{incomeperinhabitant}_{it}) \\ + \beta_4 \text{percentALabel}_{it} + \beta_5 \text{percentBLabel}_{it} + \beta_6 \text{Year}_t + \alpha_i + \epsilon_{it}\end{aligned} \tag{2}$$

Equation (2) shows the model with the control variables used. In this equation $\log(\text{incomeperinhabitant}_{it})$ controls for income variations across municipalities and

time. While percentALabel$_{it}$, percentBLabel$_{it}$ are variables for the shares of buildings with energy labels A and B in municipality i, these variables are included to account for building energy efficiency investments. The dummy variable Year$_{it}$ was added to control for unobserved factors and temporal trends such as economic conditions, regulatory changes, or other events and reduce potential omitted variable bias. This variable also allowed to control for the impact of the COVID-19 pandemic in the regression, as well as for electricity prices, which varied across years but remained constant across municipalities.

Additionally, Equation 2 was re-estimated by replacing EV_{it} with the number of PHEV, $PHEV_{it}$, BEV, BEV_{it}, and with the number of BEVs owned by companies with vehicles under 3,500 kg, $EVCompany_{it}$. As these variables contained zero values and taking the log of 0 is not possible, only the log was taken of non-zero values. This was done as zero values were considered meaningful.

Finally, the Durbin-Watson test for autocorrelation indicated positive autocorrelation. Therefore, robust standard errors (HC1) were used to address both the autocorrelation and heteroscedasticity concerns. More strict robust standard errors and clustered standard errors were also considered but these yielded similar results.

4 Results

As detailed in the Methods section, a fixed effects regression was conducted to investigate the factors influencing the elasticity of residential electricity usage per inhabitant. Table 2, below, shows the results of this regression. In appendix A, the variables are also shown while added in incremental steps to provide insight in how each set of variables affected the model.

Table 2: Regression results for EV.

	Dependent variable:
	log(elechouse)
log(EV)	0.00521*
	(0.00288)
log(inhabitants)	0.54911***
	(0.07204)
log(incomeperinhabitant)	0.43607***
	(0.06089)
Observations	3,698
Adjusted R^2	0.69357
F Statistic	581.57470*** (df = 15; 3341)

Note: regression results control for year dummies, percentALabel and percentBLabel. Robust standard errors (HC1) are reported.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

As can be seen in table 2, the estimates for the logarithm of EV are significant and positive but only on the 10% significance level. The estimates indicate that a 1% increase in EV corresponds to a 0.00521% rise in residential electricity consumption with a standard deviation of 0.00288.

The variables for the number of inhabitants and income per inhabitant are also significant at the 1% level. The estimate for the log of inhabitants is 0.54911, with a standard deviation of 0.07204. The estimate for the log of income per inhabitant is 0.43607, with a standard deviation of 0.06089.

The adjusted R^2 for the fixed effects regression is 0.69357. The F-statistic is 581.57470 with 15 and 3341 degrees of freedom and is statistically significant at the 1% level. This indicates that the variables included in the model are collectively significant in explaining residential electricity consumption.

Table 3: Regression results per vehicle type.

	Dependent variable: log(elechouse)	
	Model 1: log(BEV)	Model 2: log(PHEV)
log(BEV)	−0.00396	
	(0.00273)	
log(PHEV)		0.00870***
		(0.00239)
log(inhabitants)	0.55946***	0.56762***
	(0.07289)	(0.07200)
log(incomeperinhabitant)	0.44310***	0.43617***
	(0.06159)	(0.06086)
Observations	3,698	3,698
Adjusted R^2	0.69352	0.69657
F Statistic (df = 15; 3078)	581.46400***	606.11820***

Note: regression results control for year dummies, percentALabel and percentBLabel. Robust standard errors (HC1) are reported.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3 displays the estimates of the regression per vehicle type. As can be seen the estimate for the log of PHEV is significant at the 1% level and positive with a coefficient of 0.00870 and a standard deviation of 0.00239. This indicates that a 1% increase in PHEV corresponds to a 0.00870% rise in residential electricity consumption. The estimate for the log of BEV is not statistically significant and negative. The incremental changes in the model for the separate regressions of PHEV and BEV illustrating how the inclusion of different variables impacts the results are presented in Appendix B.

Table 4: Regression results for company electric vehicles.

	Dependent variable:
	log(elechouse)
log(nEVCompany)	-0.00197^{*}
	(0.00109)
log(inhabitants)	0.55586^{***}
	(0.07207)
log(incomeperinhabitant)	0.43957^{***}
	(0.06123)
Observations	3,698
Adjusted R^2	0.69370
F Statistic	581.92860^{***} (df = 15; 3341)
	(df = 15; 2343)

Note: regression results control for year dummies, percentALabel and percentBLabel. Robust standard errors (HC1) are reported.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 4 shows that the estimate for the log of electric vehicle companies (*log(EVCompany)*) is significant at the 10% level with a coefficient of -0.00197 and a standard deviation of 0.00109. The incremental changes in the model are shown in Appendix C.

5 Discussion

5.1 The impact of EVs on electricity demand

Our primary research question was: What effect does the increased EV adaptation have on the residential electricity consumption within the Netherlands? As shown in Table 2, the elasticity of residential electricity consumption with respect to the number of EVs was estimated to be 0.00521. Meaning a 10% increase in the number of EVs was estimated to correspond to a 0.0521% rise in residential electricity consumption.

This represents a modest increase compared to overall municipal electricity consumption. The additional residential electricity demand from EV adoption accounts for only a small fraction of the average municipality's total residential consumption. Given the observed growth of the EV stock in the Netherlands from 670,145 to 706,509 vehicles between 2022 and 2023 representing a growth rate of approximately 5.43%, it is expected based on our estimates that residential electricity consumption will increase by around 0.028% this year due to the uptake of electric vehicles (Rijksoverheid 2024).

However, it is important to note that the EV stock in the Netherlands has grown rapidly and is expected to continue its upward trend (ELaadNL 2025; Rijksoverheid 2024). Although growth may be limited in the short-term due to decreasing incentive policies and the currently limited availability of affordable EVs until 2030, it is expected that European policies and a greater availability of affordable EVs will cause more growth in the future. Depending on different scenarios, the growth is expected to range between 1256.5% and 1459.5% between 2025 and 2050 (ELaadNL 2025). Meaning that depending on the scenario, the growth in EVs between 2025 and 2050 would lead to an increase in residential electricity consumption of between 6.54% and 7.58% based on the estimates of this study. This indicates that, despite the modest estimates of this study, the long-term impact could still be substantial. This also implies that while residential electricity demand had been declining prior to the COVID years due to energy efficiency improvements, the widespread adoption of EVs could eventually help reverse this trend (Rijksoverheid 2024). Another issue to consider is that regional differences might arise. The growth rate of EVs is expected to be higher in urban errors, therefore the pressure on the grid will increase more in urban areas (Kester et al. 2019).

The findings of this research contrast with those of Ferdousee (2022), who, de-

spite employing a similar methodological approach, estimated a smaller and statistically insignificant impact of EV adoption on residential electricity consumption. One potential reason for this difference could be limitations in the dataset used by Ferdousee (2022), which did not account for imported electricity. Another explanation is that this study controlled for factors such as more efficient housing and included year dummies, whereas Ferdousee (2022) did not.

Kapustin and Grushevenko (2020) projected a worldwide increase in electricity consumption due to EV adoption of approximately 7–10% by 2040 from 2020. In the Netherlands, EV numbers are expected to rise from 358,178 in 2020 to 5,578,843 in the low-growth scenario and 9,156,230 in the high-growth scenario by 2040 (ELaadNL 2025). Our findings therefore suggest that residential electricity consumption will increase by approximately 7.59% in the low scenario and 12.80% in the high scenario by 2040. This aligns with the findings of Kapustin and Grushevenko (2020). However, Netherlands is a frontrunner in EV adoption and the model of Kapustin and Grushevenko (2020) represents worldwide growth.

If we convert our estimates from relative to absolute units to compare with household-level studies. At the level of an average municipality, where mean residential electricity consumption is 234.779 TJ (Table 1), our estimates suggest that a 10% increase in EV adoption would result in an additional 12.23 TJ of electricity consumption. If we look at the translated results at the average, accounting for 688 vehicles per municipality, our estimates would mean that one additional EV is associated with an annual increase of approximately 0.0177 TJ (or 49,560 kWh) in municipal residential electricity consumption, which corresponds to about 0.56 kWh per hour. However, it should be noted that converting relative effects to absolute values assumes a uniform impact across municipalities, which is not the case. An additional EV in a small municipality is a larger percentage increase in EV stock compared to an additional vehicle in a larger municipality.

When compared to household-level studies, our absolute values are higher than those found in studies such as Burlig et al. (2021), Coban et al. (2023), and Liang, Qiu, and Xing (2022). Who found that an average household electricity consumption due EVs was about 0.121 kWh per hour to 0.31 kWh per hour. The model study by Moon et al. (2018) found a increase of 0.30 kWh per hour. This difference raises questions about our findings as the effect found in this study of one additional vehicle is higher. Additionally, our findings are not very significant. Indicating problems with our estimates.

5.2 The separate impact of different types of vehicles

The first sub question was: What is the separate impact of battery electric vehicles and plug-in hybrid electric vehicles on residential electricity consumption? As shown in our estimates, the impact of BEVs on residential electricity consumption was found to be insignificant while the estimates for PHEVs showed a positive and statistically significant effect with a coefficient of 0.00880. These findings again contrast with previous literature, Burlig et al. (2021) found similar effects of PHEVs and BEVs on residential electricity consumption. Other studies found that BEVs in general demand more electricity (Boston and Werthman 2016).

The insignificant, small, and negative estimate for BEVs shows that the analysis did not capture the effect of BEVs. This means making comparisons between the impact of PHEVs and BEVs is difficult. It is expected that electricity demand for PHEVs would be lower compared to BEVs, as PHEVs rely partially on internal combustion engines. In contrast, BEVs are fully electric and are therefore more likely to be charged at home, which leads to higher electricity consumption (Boston and Werthman 2016).

The estimates of BEVs suggest that there are other factors at play that our model has not accounted for, such as differences in how these vehicles are used. For instance, BEV owners may make use of public or workplace charging options, reducing their residential charging, while PHEV owners may charge their vehicles more often at home thus explaining our found estimates. Previous research indeed indicated such behaviour (Boston and Werthman 2016). However, the limitations of this research could also explain this.

The second sub-question was: How do business-owned EVs influence residential electricity consumption? Our estimate for their impact was -0.00197, significant at the 10% level. While not highly significant, this result suggests that company-owned EVs slightly reduce residential electricity consumption. A likely explanation is that these vehicles are primarily charged at workplaces or commercial charging stations rather than at home. While the effect is small and not very significant, it suggests between private and business EVs. This finding is an important addition to the existing literature but warrants further exploration.

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6 Policy Implications

Our findings indicate that the rise in EV adoption has a modest impact on total municipal electricity usage relative to overall consumption. This suggests that in the short-term EV adoption is unlikely to be a major driver of electricity demand. Our findings do however suggest that the large-scale adoption of EVs will strain the electricity grid in the long term. Depending on the uptake scenarios, this studies findings estimated residential electricity demand to increase by approximately 6.54% to 7.58% by 2050 due EV adoption. This shows the need for policymakers to plan for the impact of EVs and provides an estimate of the expected rise in electricity demand. However, growth rates may vary significantly across regions, potentially placing greater strain on specific parts of the electricity grid.

Policymakers should also consider that a strained electricity grid could discourage EV adoption (Kester et al. 2019). Therefore resources should also strategically invest be invested in the electricity grid, as these preconditions are absolutely necessary to achieve the sustainable mobility transition. Without investments in the electricity grid, policies aimed at promoting EV adoption will be ineffective and self-contradictory. In addition, these policies will cause issues as companies need the electricity grid for other ends.

This research specifically examined the impact of EV adoption on residential electricity consumption. Interestingly, our findings suggest that company-owned electric vehicles reduce residential electricity use. While further research is needed to fully understand this dynamic, it is suggested in this paper that this reduction in residential electricity consumption may be due to company electric vehicles being charged at company facilities. This opens up potential avenues for future policy.

Encouraging the adoption of company-owned EVs could shift electricity demand from residential areas to commercial sectors, creating potential hubs for EV charging but also for the electricity grid in general. Thus creating dedicated hubs for EV charging. This would reshape current charging behaviours as EV charging predominantly takes place at home due to limited public and commercial charging options (Morrissey, Weldon, and O'Mahony 2015).

Since EV charging currently occurs mostly at home during peak hours, encouraging users to charge at commercial sites during off-peak times could be beneficial (Morrissey, Weldon, and O'Mahony 2015). Additionally, these sites could invest in energy storage systems to store clean electricity for vehicle charging thus improving grid stability and sustainability.

7 Study limitations & future research

While this study provides valuable insights into the relationship between EV adoption and residential electricity demand, and several measures were taken to address its limitations, some constraints should still be acknowledged. This is particularly relevant given the low significance of our estimates and the differences found between previous research.

First and foremost, this study measures the impact of EV adoption solely on residential electricity consumption without accounting for charging infrastructure. As a result, the estimated elasticity reflects only household charging and does not capture energy demand from public or workplace charging stations. This leads to an underestimation of total electricity demand due EVs. Therefore, the findings should be interpreted specifically in the context of residential electricity consumption rather than overall EV-related energy usage.

One should also acknowledge that the dataset used in this research was limited due to its annual and aggregate nature. This restricted the ability to capture details in the relationship between EV adoption and residential electricity consumption. More frequent and detailed data would have improved the ability of this research to explore short-term electricity fluctuations due EV adoption and improved the robustness of our findings. The aggregate nature of our estimates also does not account for the differences between larger and smaller municipalities, which could be a potential direction of future research. The aggregation of our data to annual and municipal-level data could also be a potential explanation for the insignificant estimate found for BEVs. As the municipal aggregation could mask true electricity consumption due EVs.

Another limitation related to the data is that the residence of the vehicle owner cannot always be determined through the license plate register, which was used to determine the number of EVs within a municipality. This means that the registered location is sometimes not the actual residence of the end user. This may be another potential explanation of the low robustness.

Although the fixed effects regression of this paper controls for time-invariant municipal characteristics and includes several control variables unobserved time-varying factors could still influence the results.

Lastly, the lack of similar studies on the same municipality-level within the context of the Netherlands or comparable countries limits the ability to draw direct comparisons or validate the findings. More research in this area would help situate the results within a broader context and enhance their generalizability.

Future research could build on the findings of this study in several ways. Addressing the limitations identified, such as the use of annual, aggregate data and the limitations related to EV car tracking would help deepen our understanding of the relationship between EV adoption and electricity demand. This is crucial as the true size of EV adoption's impact remains uncertain. In addition, the inconclusive findings related to the differences between PHEVs and BEVs on electricity impact should be explored further.

Some of the findings of this study also warrant further exploration. For example, the impact of company-owned EVs warrants further exploration, as our findings suggest distinct charging patterns for these vehicles. A deeper analysis of these patterns could provide valuable insights for shaping future regulations and infrastructure planning to better accommodate the growing adoption of EVs. Additionally, exploring potential regional differences could provide valuable insights into which areas will be most impacted by EV adoption. A potential avenue for further research could involve exploring the differences between urban and rural areas, which would help identify regions most likely to experience strain from EV adoption.

Overall, research in these areas will be crucial for improving our understanding of the relationship between EV adoption and electricity demand. By addressing these gaps future studies can offer valuable insights for policymakers and better inform the transition to sustainable mobility.

8 Conclusion

In this study a fixed effects model was applied to panel data from Dutch municipalities, examining residential electricity usage and EV registrations. The study aimed to deepen understanding of the relationship between EV adoption and electricity demand and to create empirical evidence. The central research question was: What effect does the increased EV adaptation have on the residential electricity consumption within the Netherlands?

The findings indicate that the overall impact of increased EV adoption on residential electricity consumption is relatively modest in the short term. A 1% increase in the number of EVs was estimated to lead to a 0.00521% rise in electricity consumption. Although this represents a small fraction of overall municipal consumption, this study highlighted accumulation effects. Policymakers should recognize that an overburdened electricity grid may hinder EV adoption and/or economic progress. Therefore investments in EV uptake must be accompanied by improvements to the electricity infrastructure.

The study also revealed differences between BEVs and PHEVs in terms of their effects on residential electricity demand. The demand from PHEVs was found to be statistically significant with a 1% increase in PHEVs leading to a 0.0088% increase in residential electricity consumption, while the impact of BEVs was found to be insignificant. This finding raised several questions. One might expect PHEVs to have a lower electricity demand due to their partial reliance on gasoline. The results suggest that other factors may be influencing the outcomes. Several explanations for this were given. One explanation could be limitations in the data, such as measurement errors regarding the residence of EV owners, which may account for these unexpected findings.

Furthermore, the study found that business-owned electric vehicles reduced residential electricity consumption, suggesting that these vehicles are predominantly charged at business locations rather than residential properties. This suggests an opportunity for policies that encourage company-owned EV adoption, shifting demand from residential areas to commercial sectors and therefore create electricity hubs. This could help to tackle energy storage challenges by optimizing electricity use during peak hours, enhance grid accessibility for commercial users.

The estimates of this study were not strongly significant and several limitations were discussed. Only residential electricity demand was used. And annual and aggregate data was used that contained measurement errors. Aside from this, only the impact of EVs on residential electricity consumption was assessed.

Future research should address the limitations of this study to validate or extend the findings of this paper. Especially, the differing electricity impacts of PHEVs and BEVs require further investigation. In addition, some findings of this paper should be explored further. For example, the charging patterns of company-owned EVs could provide valuable insights for regulatory and infrastructure planning. While also regional differences should be explored further.

In conclusion, while this study provides valuable insights into the effects of EV adoption on residential electricity consumption, it also highlights the need to better understand the dynamics of the relationship between EVs and residential electricity demand. As the adoption of EVs continues to grow, it is crucial for policymakers to consider the broader impacts on electricity infrastructure and consumption patterns.

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Appendices

A Appendix summary table EV

Table 5: Incremental regression results with robust standard errors (EV).

	Dependent variable:				
	log(elechouse)				
			panel linear		
	Model 1	Model 2	Model 3	Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)
log(EV)	0.013***	0.003**	−0.012***	−0.013***	0.005*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
log(inhabitants)		0.762***	0.703***	0.700***	0.549***
		(0.058)	(0.062)	(0.068)	(0.072)
log(incomeperinhabitant)			0.144***	0.140***	0.436***
			(0.020)	(0.023)	(0.061)
percentALabel				0.0001	0.0001
				(0.0002)	(0.0002)
percentBLabel				0.0003	−0.001***
				(0.0002)	(0.0002)
Year2013					0.004
					(0.003)
Year2014					−0.031***
					(0.004)
Year2015					−0.063***
					(0.007)
Year2016					−0.090***
					(0.008)
Year2017					−0.116***
					(0.011)
Year2018					−0.131***
					(0.011)
Year2019					−0.145***
					(0.014)
Year2020					−0.123***
					(0.016)
Year2021					−0.103***
					(0.019)
Year2022					−0.134***
					(0.022)
Observations	3,698	3,698	3,698	3,698	3,698
R^2	0.098	0.198	0.210	0.210	0.723
Adjusted R^2	0.006	0.116	0.129	0.129	0.694
F Statistic	363.359***	413.814***	296.453***	178.437***	581.575***
(df)	(1; 3355)	(2; 3354)	(3; 3353)	(5; 3351)	(15; 3341)
Note:					*p<0.1; **p<0.05; ***p<0.01

B Appendix summary tables per vehicle type

Table 6: Incremental regression results with robust standard errors (BEV).

	Dependent variable:				
	log(elechouse)				
			panel linear		
	Model 1	Model 2	Model 3	Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)
log(BEV)	0.015***	0.006***	0.013***	0.014***	−0.004
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
log(inhabitants)		0.645***	0.652***	0.669***	0.559***
		(0.062)	(0.060)	(0.066)	(0.073)
log(incomeperinhabitant)			−0.074***	−0.064**	0.443***
			(0.025)	(0.026)	(0.062)
percentALabel				−0.0002	0.0001
				(0.0002)	(0.0002)
percentBLabel				0.0001	−0.001***
				(0.0002)	(0.0002)
Year2013					0.008***
					(0.002)
Year2014					−0.025***
					(0.003)
Year2015					−0.054***
					(0.005)
Year2016					−0.079***
					(0.007)
Year2017					−0.105***
					(0.010)
Year2018					−0.118***
					(0.010)
Year2019					−0.129***
					(0.013)
Year2020					−0.104***
					(0.015)
Year2021					−0.081***
					(0.018)
Year2022					−0.109***
					(0.021)
Observations	3,698	3,698	3,698	3,698	3,698
R^2	0.143	0.208	0.211	0.212	0.723
Adjusted R^2	0.055	0.127	0.131	0.131	0.694
F Statistic	557.546***	441.467***	299.792***	180.188***	581.464***
(df)	(1; 3355)	(2; 3354)	(3; 3353)	(5; 3351)	(15; 3341)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: Incremental regression results with robust standard Errors (PHEV)

	Dependent variable:				
	log(elechouse)				
			panel linear		
	Model 1	Model 2	Model 3	Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)
log(PHEV)	0.006***	−0.002***	−0.012***	−0.012***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
log(inhabitants)		0.895***	0.640***	0.650***	0.568***
		(0.051)	(0.064)	(0.069)	(0.072)
log(incomeperinhabitant)			0.155***	0.160***	0.436***
			(0.014)	(0.021)	(0.061)
percentALabel				−0.00004	0.0001
				(0.0002)	(0.0002)
percentBLabel				0.0003	−0.001***
				(0.0002)	(0.0002)
Year2013					−0.010*
					(0.005)
Year2014					−0.047***
					(0.006)
Year2015					−0.082***
					(0.009)
Year2016					−0.109***
					(0.010)
Year2017					−0.135***
					(0.012)
Year2018					−0.150***
					(0.013)
Year2019					−0.164***
					(0.015)
Year2020					−0.143***
					(0.017)
Year2021					−0.124***
					(0.019)
Year2022					−0.156***
					(0.023)
Observations	3,698	3,698	3,698	3,698	3,698
R^2	0.025	0.199	0.240	0.241	0.726
Adjusted R^2	-0.074	0.118	0.162	0.163	0.697
F Statistic	86.816***	417.660***	353.552***	212.832***	589.530***
df	(1; 3355)	(2; 3354)	(3; 3353)	(5; 3351)	(15; 3341)
Note:					*p<0.1; **p<0.05; ***p<0.01

C Appendix summary table company vehicle

Table 8: Incremental regression results with robust standard errors (Company BEV).

	Dependent variable:				
	log(elechouse)				
			panel linear		
	Model 1	Model 2	Model 3	Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)
log(nEVCompany)	0.015***	0.007***	0.008***	0.008***	−0.002*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
log(inhabitants)		0.662***	0.677***	0.679***	0.556***
		(0.057)	(0.060)	(0.068)	(0.072)
log(incomeperinhabitant)			−0.011	−0.011	0.440***
			(0.016)	(0.021)	(0.061)
percentALabel				−0.00000	0.0001
				(0.0002)	(0.0002)
percentBLabel				0.0001	−0.001***
				(0.0002)	(0.0002)
Year2013					0.008***
					(0.002)
Year2014					−0.026***
					(0.003)
Year2015					−0.056***
					(0.005)
Year2016					−0.081***
					(0.007)
Year2017					−0.107***
					(0.009)
Year2018					−0.120***
					(0.010)
Year2019					−0.133***
					(0.012)
Year2020					−0.108***
					(0.014)
Year2021					−0.086***
					(0.017)
Year2022					−0.114***
					(0.020)
Observations	3,698	3,698	3,698	3,698	3,698
R^2	0.129	0.213	0.213	0.213	0.723
Adjusted R^2	0.040	0.133	0.133	0.132	0.694
F Statistic	496.946***	454.130***	303.113***	181.791***	581.929***
df	(1; 3355)	(2; 3354)	(3; 3353)	(5; 3351)	(15; 3341)
Note:					*p<0.1; **p<0.05; ***p<0.01