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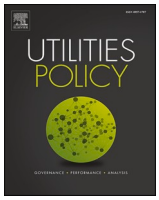

Full-length article

The relationship between electric vehicle adoption and electricity consumption: Evidence from Europe

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ABSTRACT

The relationship between electric vehicle (EV) stock and electricity consumption is complex, with many factors influencing both variables. Furthermore, higher EV adoption can have adverse and unforeseen impacts on electrical networks and generation capacity requirements, necessitating the development of proactive policies and tariff decisions. To this end, this study investigates this relationship for 20 European countries from 2000 until 2022, utilising an Error Correction Model to estimate the impact of EV sales on electricity consumption. Results indicate positive and statistically significant results for certain sub-samples, which can have far-reaching implications for policymakers and generation and network capacity planners.

1. Introduction

Electric vehicle (EV) sales have been increasing more rapidly since their introduction, with sales expected to reach 17 million in 2025, or one in every five vehicles sold would be an EV. Sales remain strong, despite concerns about countries phasing out purchase incentives, the volatility of battery mineral markets, and tighter margins. The IEA (2024) reported that the sales in 2024Q1 saw a 50 % growth over 2023Q1, with 95 % of the 14 million sold in 2023 being either in China, Europe, or the US (accounting for 60 %, 25 %, and 10 %, respectively). Sales in Africa, Eurasia, and the Middle East account for less than 1 % of total car sales (IEA, 2024).

As the number of EVs increases, the demand for charging will increase, with the IEA (2024) noting that public charging could increase sixfold by 2035. The report also notes that access to home charging is unequally distributed across countries; subsequently, public (and semi-public places with some access restrictions, such as workplace parking lots) will become more important. The sixfold increase was modelled in their "Announced Pledges Scenario" (APS), which is all policy announcements, regardless of whether they have been legislated or not. Subsequently, electricity consumption from EVs could reach as high as 15.6 % of total electricity consumption in the US by 2035 in the APS, with Europe second at 14.5 % (IEA, 2024), higher than the global prediction of 9.8 %.[1]

For a policymaker, this is quite important, as they either need to ensure that they invest in new generation capacity (in a centralised electricity market) or ensure there are sufficient incentives for the private sector to invest in new generation capacity as it is needed in a decentralised (or open) electricity market. To this end, an extensive body of literature has emerged to tackle the question of how much is needed. Most of these studies follow an ex-ante, or forward-looking, approach, where they make assumptions on various key variables to simulate the impact on the grid.

The impact of EVs on electricity consumption has been expected to be an important research topic, given the early nature of studies modelling these potential effects (ex-ante). The studies investigating this issue started with considering hybrid electric vehicles (HEVs) (see, for example, Jenkins et al., 2008; Clement-Nyns et al., 2009; Hadley and Tsvetkova, 2009; Kang and Recker, 2009) and almost instantly transitioned to EVs (see, for example, Perujo and Ciuffo, 2010; Saxena et al., 2014; Dhar et al., 2017). Saxena et al. (2014) focus on variations in driving behaviours and different types of vehicles. They do not make any assumptions about the charging behaviour, so their findings only account for the total energy required for average consumers and vehicles.

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Perujo and Ciuffo (2010), on the other hand, consider charging behaviour split into a few scenarios: a maximum incidence scenario (i.e., during peak demand) and an average incidence (i.e., vehicles are charged intelligently, spreading the load). They show the variation of electricity demand across the months and how these would change during the two scenarios mentioned. Dhar et al. (2017), similar to Saxena et al. (2014), do not make assumptions regarding consumer behaviour but mainly consider the type of transport demanded (with various EV adoption rates) to determine the impact on electricity demand and CO_2 emissions.

Furthermore, the need to quantify the impact of EVs on electricity demand is also emphasised by two recent studies already considering ways to mitigate the impact of EVs on the grid, namely Needell et al. (2023), who investigate strategies for EVs to reduce peak demand, and Kaur and Singh (2023) who proposed time-of-use tariffs as a means of demand side management. However, the EVs could also have a positive impact on the grid through vehicle-to-grid (V2G), where a vehicle is connected to the grid through the charging station. Jansen et al. (2024) provide a summary of the results from various studies, with some expecting as much as 11 GW of flexible power capacity. Ex-ante studies can (relatively) accurately quantify the impact of EVs on demand by making various assumptions; however, ex-post (backward-looking) studies can (if appropriately specified) estimate the impact *and its significance*. Against this backdrop, we set out to determine if an ex-post approach can already detect a statistically significant relationship between EV stock (the number of vehicles on the road) and electricity consumption.

We augment an elasticity of demand model to include EV stock and test it on annual data from 20 European countries over 23 years (2000–2022) to determine whether a positive (and statistically significant) relationship between EV sales and electricity consumption can already be observed at the macroeconomic level. Furthermore, we conducted a subsample analysis based on the size of the EV markets to investigate potential counteracting relationships between groups of countries. Europe was chosen as it is the second-largest EV market behind China in 2023 (IEA, 2024), but more importantly, it allows for cross-country variation to be exploited, increasing the sample size.

An ex-post approach avoids the need to make any assumptions regarding consumer behaviour and vehicle efficiencies, as with ex-ante studies. This distinction is important, as the theoretical calculations of the expected demand/consumption in ex-ante studies will need to make assumptions regarding consumers' charging and driving behaviour and the heterogeneity in vehicle types that cannot be assumed to remain constant over time. Additionally, ex-ante studies also need to consider the effect of weather conditions on battery life, as the ideal operating temperature for a battery, according to Geotab, is 21.5 °C.[2] Another reason to study these dynamics after the fact is that developing countries will benefit from developed countries' (and early adopters') hindsight and can proactively change legislation and investment decisions to avoid some of the pitfalls they observed.

The rest of this paper is structured as follows: Section 2 gives an overview of the literature; Section 3 discusses the data and methodology, and the results are presented in Section 4. We conclude the paper with Section 5.

2. Literature review

The economic literature on EVs has mainly focused on factors that influence the purchasing behaviour of consumers. At the same time, the studies on electric vehicles and electricity consumption have primarily been modelling exercises (ex-ante).

A large body of research is dedicated to modelling the potential of V2G technologies to ease peak demand and aid in electricity consumption and grid stability in conjunction with renewable electricity sources. Richardson (2013) reviews the earlier studies, the earliest of which is that of Kempton and Letendre (1997), where they already note the value this technology could have for utility providers. Their main argument was that, at the time, ICEVs had ten times the mechanical power of the US power-generating plants and were idle for 95 % of the day. Yao et al. (2022) discuss the economic and environmental benefits of V2G technology when evaluating China's 2030 renewable energy plan to have 1.2 billion kW of wind and solar power. Their model finds that using V2G reduces the cost of production by around 2 % in 2030 while reducing CO_2 emissions between 2.2 % and 3.0 %. The benefits increase with a large share of EVs participating.

Saxena et al. (2014) consider the effect of EVs (2-, 3, and 4-wheelers) on electricity consumption in India. While they do not consider the macroeconomic effects, they model the electricity demand per vehicle per kilometre driven. For city driving, scooters (2-wheeler) require about 33 Wh/km, 3-wheelers require about 61 Wh/km, and 4-wheelers require between 84 Wh/km and 123 Wh/km, while the latter requires between 133 Wh/km and 165Wh/km for highway driving. These parameters allow policymakers to directly calculate the effect for various EV fleets and vehicle type combinations. Dhar et al. (2017) found that the Indian transport sector's share of electricity consumption is likely to increase to 6 % in 2050, from 1.2 % in 2010, with EVs accounting for 36 % of the transport sector's consumption in 2050 (intercity rail accounted for 82 % in 2010).

Perujo and Ciuffo (2010) modelled the demand for electricity for various EV/ICEV shares in Milan, Italy. Their results range from an increase in electricity consumption between 0.13 % and 2.5 % of total electricity consumption in 2030, with a maximum incidence (worst case scenario) of 1.69 %–34.04 %, for EV/ICEV shares ranging from 1.55 % to 30 %. They conclude that the effect would be negligible, considering the low impact they expect, excluding the worst-case scenario, which captures consumers all charging vehicles simultaneously during peak hours. However, there are a few caveats; firstly, this study was conducted before the sale of ICEVs was banned by most European countries, resulting in an increased likelihood of their extreme adoption rate (i.e., 30 %).

These studies all note, either explicitly or implicitly, the threat EVs pose to energy security, the grid's integrity, and a sufficient supply of electricity, especially in an uncontrolled environment, where users can charge as and when needed. More recent studies, such as the study by Kaur and Singh (2023), use simulated charging data to show the effect that simple price signals could have on charging, reducing peak demand by up to 7 % using EV specific time-of-use tariffs. In a prior study of EV adoption in US states from 2003 to 2011, Soltani-Sobh et al. (2017) found that electricity prices are negatively related to EV adoption. Soltani-Sobh et al. (2017) found that electricity prices were the regressors that influenced EV adoption the most. Gnann et al. (2018), who compared 40 EV market penetration models, found that for the US, the price premium over ICEVs is most often modelled, while for Germany, it is the cost of energy and charging infrastructure.

Needell et al. (2023), on the other hand, suggest that unmanaged EV usage (along with solar photovoltaic adoption) can raise electricity costs by increasing peak demand with overgeneration of energy during the middle of the day, i.e., the peak solar irradiation period. Skolthanarat et al. (2024) note the problems unmanaged charging can have for distribution equipment and suggest demand response measures. They note that some price-based measures could have unintended consequences due to their inflexibility (such as time-of-use tariffs) and propose day-ahead real-time pricing. However, there might still be a need for incentive-based measures, such as direct load control; the utility controls the load (EV charger(s)) remotely to throttle (reduce the charging rate) or temporarily pause charging.

Wang et al. (2023) take a different approach to forecasting electricity demand by utilising a machine learning model, trained on a dataset containing 76,000 EVs in Beijing (in January 2018). They can provide short-term forecasts (one to 5 h ahead) of electricity demand at the charging station level. Maity and Sarkar (2024) take a more granular view by utilising a probabilistic data-driven approach to model the

energy requirements at the trip level.

Data-driven approaches can be argued to be ex-post, where they use actual data to model or forecast the future; however, they differ from econometric methods by not considering a theoretical foundation for the models. They also require large datasets to ensure the model is sufficiently trained to produce reliable forecasts. This volume of data is not available at a macroeconomic level, especially not at an annual frequency. As such, a theory-based econometric approach is currently the only approach able to evaluate the impact of EVs at the macroeconomic/country level.

3. Methodology and data

This section will discuss the empirical framework and the data, including data sources and transformations.

3.1. Empirical framework

We base our theoretical framework on a recent study considering household electricity demand elasticities by Cialani and Mortazavi (2018), which was also used by Jin and Kim (2022). They, in turn, built on the partial adjustment model by Houthakker (1980) and Paul et al. (2009), which assumes the desired level of electricity consumed by country i at time t is a function of household income (proxied by GDP) and the price of electricity (p):

$$elec^{*}_{i,t} = \alpha_1 \left(p_{i,t}\right)^{\alpha_2} \left(gdp_{i,t}\right)^{\alpha_3} \tag{1}$$

To obtain the actual level of electricity consumed, it is assumed that it is a function of the desired level of electricity and electricity consumed in the previous period:

$$elec_{i,t} = \left(elec^{*}_{i,t}\right)^{\theta} \left(elec_{i,t-1}\right)^{1-\theta} \tag{2}$$

By substituting Eq. (1) into Eq. (2), we get:

$$elec_{i,t} = \left[\alpha_1 \left(p_{i,t}\right)^{\alpha_2} \left(gdp_{i,t}\right)^{\alpha_3}\right]^{\theta} \left(elec_{i,t-1}\right)^{1-\theta} \tag{3}$$

Taking the natural logarithms to get the demand elasticity of electricity consumption[3]

$$\ln elec_{i,t} = \theta \ln \alpha_1 + \alpha_2 \theta \ln p_{i,t} + \alpha_3 \theta \ln gdp_{i,t} + (1-\theta) \ln elec_{i,t} \tag{4}$$

Where $\theta \ln \alpha_1$ is the constant term in a traditional regression, $\alpha_2\theta$ is the price elasticity of electricity consumption, $\alpha_3\theta$ is the income elasticity of demand (proxied by GDP), and $1-\theta$ is the coefficient on the dynamic term (the previous year's electricity consumption). The latter is used to control for unobservable effects. If this coefficient is greater than or equal to 1 (or close enough to 1, say, 0.95 to 0.99), then electricity consumption is likely not stationary, and specific stationarity tests should be performed.

Following Cialani and Mortazavi (2018) and Jin and Kim (2022), we include the number of heating and cooling degree days and population in the model (i.e., add these three variables to Eq. (1)). The former two variables are proxies for the energy consumption as driven by the weather. The expectation is that if there is a significantly hotter (colder) day, the energy consumption would be higher due to the increased need for cooling (heating) by homes, businesses, and, potentially, industrial processes. Furthermore, we augment the model by adding EV sales to Eq. (1), indicating that the desired level of electricity can then be written as follows:

$$elec^{*}_{i,t} = \alpha_1 \left(p_{i,t}\right)^{\alpha_2} \left(gdp_{i,t}\right)^{\alpha_3} \left(pop_{i,t}\right)^{\alpha_4} \left(cdd_{i,t}\right)^{\alpha_5} \left(hdd_{i,t}\right)^{\alpha_6} \left(EV_{i,t}\right)^{\alpha_7} \tag{5}$$

Following the same steps, by first substituting Eq. (5) into Eq. (2), and then taking the natural logarithms, we get:

$$\ln elec_{i,t} = \theta \ln \alpha_1 + \alpha_2 \theta \ln p_{i,t} + \alpha_3 \theta \ln gdp_{i,t} + \alpha_4 \theta \ln pop_{i,t} + \alpha_5 \theta \ln cdd_{i,t} + \alpha_6 \theta \ln hdd_{i,t} + \alpha_7 \theta \ln EV_{i,t} + (1-\theta) \ln elec_{i,t-1} \tag{6}$$

The estimation version of Eq. (6) is given by:

$$\ln elec_{i,t} = C + \gamma \ln elec_{i,t-1} + \beta_1 \ln EV_{i,t} + \beta_2 \ln p_{i,t} + \beta_3 \ln gdp_{i,t} + \beta_4 \ln pop_{i,t} + \beta_5 \ln cdd_{i,t} + \beta_6 \ln hdd_{i,t} + \mu_t + \mu_i + \mu_r + \mu_t \times \mu_r + \epsilon_{i,t}, \tag{7}$$

where C is the sample estimate of the true (population) value for $\theta \ln \alpha_1$, γ that of $(1-\theta)$, and β that of the corresponding $\theta \ln \alpha_j$, where $j > 1$. Notably, the β's represent the elasticities of demand of electricity consumption, with our focus on β_1. The cross-sectional fixed effects and time fixed effects are given by μ_i and μ_t, respectively, while regional fixed effects are given by μ_r. $\epsilon_{i,t}$ is the error term and is assumed to be normally distributed with a mean of 0 and a standard deviation of 1.

Fixed effects are used to control for variations that would otherwise be captured within the error term. Take country (cross-sectional) fixed effects, for example, each country is unique, which means there would be country-specific factors driving electricity consumption due to various factors (such as preferential pricing for large industrial customers, or the severity of the lockdown during the COVID-19 pandemic). Including country fixed effects removes the time-invariant, country-specific variation from the error term (i.e., it removes omitted variable bias due to the specific variable types being omitted). Similarly, time fixed effects remove variations that change with time but are homogeneous across countries from the error term. We also include regional fixed effects (and an interaction term between regional and time fixed effects) to account for various omitted variables, such as technological change and policies implemented, not accounted for in time fixed effects.

The regional fixed effects can potentially be absorbed by the country fixed effects, while they can also absorb the country fixed effects. Both of these do occur in some of our models; however, we use the *reghdfe* estimator of Correia (2017), which omits redundant fixed effects. As such, there is no potential for multicollinearity due to the inclusion of both country- and regional fixed effects. Similarly, this could occur for the year fixed effects and the interaction between regional and year fixed effects. This situation was the case for some but not all years and combinations of regions and years.

The estimation of Eq. (6) would yield elasticities, but given how recently EVs have been introduced (sales and fleet data are only available from 2008) and that EV fleets (stock) have been growing exponentially, estimating the growth rate of electricity consumption would be more appropriate. Compared to the works of Cialani and Mortazavi (2018) and Jin and Kim (2022), whose samples were tested to be stationary, whereas ours exhibit non-stationarity, specifically, most of our variables are integrated of order one. This method takes the first difference of the variables and estimates a first difference equation. The derivation of the growth model (first difference of natural logarithms) follows.

For simplicity, we first divide both sides of Eq. (2) by $elect_{i,t-1}$:

$$\frac{elec_{i,t}}{elec_{i,t-1}} = \left(\frac{elec^{*}_{i,t}}{elec_{i,t-1}}\right)^{\theta} \tag{8}$$

Given that past consumption has been realised, we set $elec_{i,t-1} = elec^{*}_{i,t-1}$. Taking the natural logarithm yields:

$$\ln elec_{i,t} - \ln elec_{i,t-1} = \theta \ln elec^{*}_{i,t} - \theta \ln elec^{*}_{i,t-1}$$

Which can be simplified to $g^{elec}_{i,t} = g^{elec^{*}}_{i,t}$. Now, substituting Eq. (5) into Eq. (8), where $g^{x}_{i,t} = \ln x_{i,t} - \ln x_{i,t-1}$ represents the growth rate of $x_{i,t}$, yields:

$$g_{i,t}^{elec} = \alpha_2\theta g_{i,t}^{p} + \alpha_3\theta g_{i,t}^{gdp} + \alpha_4\theta g_{i,t}^{pop} + \alpha_5\theta g_{i,t}^{cdd} + \alpha_6\theta g_{i,t}^{hdd} + \alpha_7\theta g_{i,t}^{EV} \quad (9)$$

Notice that the constant term has cancelled out. We add a constant (K) back into the estimation equation along with time- and cross-sectional fixed effects. This approach avoids potential pitfalls in the estimation procedure stemming from not including a constant term; however, the constant in Table A2 in the Appendix is statistically insignificant for most of the models.

$$g_{i,t}^{elec} = K + \delta_1\, g_{i,t}^{EV} + \delta_2\, g_{i,t}^{p} + \delta_3\, g_{i,t}^{gdp} + \delta_4\, g_{i,t}^{pop} + \delta_5\, g_{i,t}^{cdd} + \delta_6\, g_{i,t}^{hdd} + \mu_t + \mu_i + \mu_r + \mu_t \times \mu_r + \epsilon_{i,t}, \quad (10)$$

where δ is the sample estimate of the true $\alpha_j\theta$, where $j > 1$. Again, the cross-sectional fixed effects and time fixed effects are given by μ_i and μ_t, while regional fixed effects are given by μ_r. $\epsilon_{i,t}$ is the error term and is assumed to be normally distributed with a mean of 0 and a standard deviation of 1.

An alternative approach would be to estimate an error correction model (ECM), where one would (i) test whether EV sales have a significant impact on long-run electricity consumption (an important consideration for system operators and their long-term forecasts for generation capacity planning), and (ii) address stationarity concerns with EVs (if the variables are nonstationary and cointegrated).

Rewriting Eq. (7) as an ECM is relatively straightforward, as it represents an autoregressive distributed lag model where $p = 1$ and $q_i = 0\ \forall\ i = 1,\ldots,6$, i.e., the only lag is the dependent variable, while all other explanatory variables are considered contemporaneously. Nkoro and Uko (2016) illustrate reparameterising an ARDL(p,q) model into an ECM. The resulting ECM is represented as follows:

$$g_{i,t}^{elect} = \kappa\, EC_{t-1} + C + \gamma_1\, g_{i,t}^{EV} + \gamma_2\, g_{i,t}^{p} + \gamma_3\, g_{i,t}^{gdp} + \gamma_4\, g_{i,t}^{pop} + \gamma_5\, g_{i,t}^{cdd} + \gamma_6\, g_{i,t}^{hdd} + \mu_t + \mu_i + \varepsilon_{i,t}, \quad (11)$$

Where EC_{t-1} is the error correction term from estimating Eq. (7) without the dynamic term (the lagged dependent variable), representing the long-run elasticity of demand of electricity consumption. Importantly, the residuals of the long-run equation should be stationary, i.e., form a cointegrating relationship. That is, we first estimate Eq. (7) (omitting the lagged electricity consumption term), recover the residuals from this estimation, and then include the lag of this residual in the estimation of Eq. 11 (EC_{t-1}). Eq. (11) can therefore be rewritten as follows:

$$\begin{aligned} g_{i,t}^{elect} = \kappa\, (&\ln elec_{i,t-1} - \widehat{C} - \widehat{\beta_1} \ln EV_{i,t-1} - \widehat{\beta_2} \ln p_{i,t-1} - \widehat{\beta_3} \ln gdp_{i,t-1} \\ &- \widehat{\beta_4} \ln pop_{i,t-1} - \widehat{\beta_5} \ln cdd_{i,t-1} - \widehat{\beta_6} \ln hdd_{i,t-1} - \mu_t - \mu_i - \mu_r \\ &- \mu_t \times \mu_r) + C + \gamma_1\, g_{i,t}^{EV} + \gamma_2\, g_{i,t}^{p} + \gamma_3\, g_{i,t}^{gdp} + \gamma_4\, g_{i,t}^{pop} + \gamma_5\, g_{i,t}^{cdd} \\ &+ \gamma_6\, g_{i,t}^{hdd} + \mu_t + \mu_i + \varepsilon_{i,t}, \end{aligned} \quad (12)$$

Where $\widehat{\beta_j}$ and $\widehat{C}$ are the estimates of the true population values β_j and C for all $j = 1, \ldots, j$. κ, the coefficient on the lagged residual term (error correction term), gives the speed of adjustment of any short-run deviations back to the long-run equation. It is for this reason that the coefficient should be between −1 and 0 to ensure convergence back to the long-run equation.

To test for stationarity, we utilise the HT panel unit root test developed by Harris and Tzavalis (1999) and Breitung (2000). This test is motivated by T (23) and N (20) below the minimum values of Levin et al. (2002, LLC), who recommend a T of at least 25 and an N of at least 10. Although our time dimension is close enough to the lower limit, the LLC test (and IPS of Im et al. (2003)) also suffers a dramatic loss in power once individual-specific trends are included (Baltagi, 2008). This could prove problematic, given the likelihood of macroeconomic variables only being trend-stationary (like GDP, for example).

However, Mravak (2023) tests the size and power of panel unit root tests and finds that all suffer either from a dramatic loss in power, an increase in size, or both. For our sample size, the HT panel unit root test has the highest power (between 0.248 and 0.305), while still having a modest size (between 0.132 and 0.136), whereas the commonly used LLC test has a power of between 0.765 and 0.921, but a size of 0.710 and 0.884. We are more concerned with rejecting a true null hypothesis (i.e., the size of the test), given the null hypothesis of non-stationarity and the risk of reporting results from spurious correlations. Therefore, we will put a greater emphasis on the results as reported by the HT test, but report the results for Breitung and two Fisher-type tests.

3.2. Data

We use four data types for the analysis: EV sales, macroeconomic (GDP and population), temperatures (heating and cooling degree days), and electricity (consumption and prices), outlined in Table 1. The resulting dataset consists of 20 European countries from 2000 to 2022 (i.e., T = 23 and N = 20). Other data sources required in the calculations were inflation and the average annual exchange rate for countries, both of which were sourced from the World Development Indicators.

Inspecting the sales and stock data, we notice that there are discrepancies, where the sales realised do not match the increases in stock, with stock increasing by more than the reported sales in some years for some countries. Although vehicle retirements can partially explain a lesser increase in EV stock than EV sales, the magnitude of the differences is too large to be solely attributed to vehicle retirements. The opposite is more difficult to reconcile. As such, we calculate cumulative sales as an alternative measure of EV stock, acknowledging the unaccounted-for retirements. A possible alternative would be to assume that the lifetime of vehicles is X years; however, this would introduce other concerns, specifically the motivation for using an ex-post approach over an ex-ante approach. The cumulative sales estimates could therefore be interpreted as an upper limit, since they would overestimate EV stock. This effect can be seen for some countries in Figure A1, which plots both these EV variables with electricity consumption.

The data is transformed into approximations of their natural logarithms by taking the inverse hyperbolic sine transformation. Bellemare and Wichman (2020) document the implications when calculating elasticities using natural logarithm approximations and find that for variables with an average greater than 10, the approximation error is less than 0.5 %. For more details on data sources and summary statistics, see Table 1.

Furthermore, we create a regional variable to control for regional variation as discussed in Section 3.1. Our sample is split into North, South, East, and West, based on the depiction of the continent in Berglee (2016), with Ireland (which Berglee (2016) lists as in the British Isles) included in Western Europe, since it is the only country from the British Isles in our sample.

4. Empirical results

We start our analysis with a simple dynamic fixed effects model, although we depart from the ultimate estimation procedure of Cialani and Mortazavi (2018) and Jin and Kim (2022) due to the nonstationary nature of our data. This approach illustrates the pitfalls of uncritically following studies and not coming to terms with the peculiarities of a particular sample of data. To this end, Table 2 shows the results for the estimation of Eq. (7). Note that all variables are in their logarithmic approximations, as discussed in Section 3.1, yielding elasticities.

Firstly, let us consider lagged electricity consumption, which has a positive and statistically significant coefficient; however, it is not close to 1. Therefore, upon first inspection, we do not see any immediate evidence to suggest the presence of non-stationarity (as mentioned in Section 3.2). EV stock is statistically insignificant in any of the model specifications; however, this could simply imply that the market is still too immature to have an observable impact on electricity consumption.

Table 1
Descriptive statistics and data sources.

Description	Mean	Std. Dev.	Min	Max	Source
Electric vehicle (EV) stock	21,899.22	86,210.93	0.00	1,013,009.00	European Alternative Fuels Observatory. Available at: EAFO [Accessed: 10 July 2025]
Electric vehicle (EV) sales	8,124.63	34,147.99	0.00	464,322.00	European Alternative Fuels Observatory. Available at: EAFO [Accessed: 10 July 2025]
Electric vehicle (EV) cumulative sales	22,144.00	89,470.24	0.00	1,175,597.00	Cumulative sum of EV sales
Electricity consumption (in TWh)	137.65	160.72	5.93	614.54	Ember (in TWh). Available at: Ember [Accessed: 04 August 2024]
GDP (in 2015 $bn)	645.97	846.02	13.91	3,618.13	World Development Indicators. Available at: World Development Indicators [Accessed: 14 November 2023]
Population (in millions)	19.65	23.76	0.44	84.08	
Inflation (where 2015 = 100)	0.94	0.13	0.52	1.36	
Exchange rates (in local currency/USD)	18.58	61.97	0.48	372.60	
Cooling degree days (**CDD**)	68.76	102.43	0.00	448.68	nrg_chdd_a dataset available at Eurostat [Accessed: 1 February 2024]
Heating degree days (**HDD**)	3,114.92	1,204.86	967.88	6,205.66	
Electricity prices (where 2015 = 100)	91.56	24.59	31.00	177.78	Average of household and non-household prices (in 2015 USD). Available at Eurostat (datasets nrg_pc_204 and nrg_pc_205). [Accessed: 14 November 2023] International Energy Association (indexed with 2015 = 100). Available at: IEAIEA [Accessed: 04 August 2024]

Note: Variable names used in results are bold in parentheses if different from the name used in the description column. The electricity price variable used was constructed by indexing the Eurostat prices with 2015 as the base year, averaging the overlapping years (2007–2017), using the IEA prices for the period before this (2000–2006), and the Eurostat prices after the overlapping portion (2018–2022). Where applicable, the data was converted from local currencies to USD. All prices are in real terms (deflated using a country-specific inflation index).

Table 2
Dynamic panel estimation of the relationship between EV stock and electricity consumption.

Electricity consumption					
Model	1	2	3	4	5
Lagged dependent	0.870*** (0.036)	0.768*** (0.034)	0.769*** (0.033)	0.773*** (0.032)	0.773*** (0.055)
EV stock	**0.001 (0.001)**	**0.001 (0.001)**	**0.001 (0.001)**	**0.001 (0.001)**	**0.001 (0.001)**
Electricity price	−0.020** (0.008)	−0.022*** (0.007)	−0.023*** (0.008)	−0.024*** (0.007)	−0.024*** (0.004)
GDP		0.098*** (0.017)	0.103*** (0.019)	0.105*** (0.018)	0.105*** (0.024)
Population			−0.028 (0.031)	−0.035 (0.030)	−0.035 (0.046)
CDD				0.005** (0.002)	0.005*** (0.001)
HDD				0.068** (0.027)	0.068*** (0.019)
C	0.745*** (0.193)	−1.409*** (0.391)	−1.071** (0.488)	−1.625*** (0.504)	−1.625* (0.797)
N	440	440	440	440	440
R_a^2	1.000	1.000	1.000	1.000	1.000

Note: *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Standard errors are given in parentheses. Country-clustered standard errors were included to account for the possible effect of cross-sectional dependence due to most countries being in the European Union. Country, year, and region fixed effects, as well as the interaction between year and region fixed effects, were included in all regressions. Robust standard errors were used in all models, aside from model 5, where we used country-clustered standard errors. The primary variable of interest is highlighted for the reader's convenience. All variables are in natural logarithm approximations, as noted in Section 3.1.

A similar observation is made for the results in Table B1 (cumulative EV sales), while there is a positive and statistically significant impact observed for EV sales in Table B5 (both tables are in Appendix B). Interpreting the results from Table B5: a 1 % increase in EV sales is associated with a 0.002 % increase in electricity consumption. We include the results for EV sales and cumulative EV sales in Appendix B as a robustness check, given the concern discussed in Section 3.2.

There is a concern with the results from the dynamic panel. Given the likely presence of non-stationarity, these results cannot be relied on until stationarity is formally tested to ensure that all the variables in the model are stationary.

Putting the non-stationarity concern aside for now, we find that the coefficient on electricity price is statistically significant and negative, as expected. The coefficient for GDP is positive and statistically significant. Both cooling degree days (CDD) and heating degree days (HDD) are statistically significant and positive, as also expected, as both would require more energy to heat or cool buildings to comfortable levels. The coefficient on population is negative; however, it is statistically insignificant. This finding could point to slowing population growth rates in Europe, as shown by Schiavina et al. (2022) for some regions in Europe. Our results seem to support the notion of regional heterogeneity in population growth rates, as without our regional controls, the coefficient on population growth is more negative and significant. Furthermore, this also supports the use of fixed effects to absorb unwanted variation from a model.

On first inspection, the results seem plausible, with EV sales (Table B5) positively related to electricity consumption (albeit statistically significant). However, the adjusted R^2 statistics indicate that the model perfectly predicts electricity consumption. This result is doubtful given the very real possibility of omitted variables (such as privately installed solar PV systems, which are omitted due to data availability). Liang et al. (2022) found that customers in Arizona (US) could reduce their grid consumption by co-adopting EVs and household solar PV systems.

This result highlights the possibility of non-stationarity in our model, which is tested by considering a simple autoregressive equation with only the lagged electricity consumption, i.e., no time- or cross-sectional fixed effects or any other explanatory variables. The coefficient on the lagged dependent variable is 0.998 (significant at a 1 % level), which is statistically indistinguishable from one. Therefore, in our sample, electricity consumption is not stationary. The high adjusted R^2 value is then likely a byproduct of a misspecified model, which includes nonstationary variables.

Although our approach of simply estimating an autoregressive

equation is rudimentary, it is sufficient motivation to test for the presence of unit roots. We confirm our suspicions of non-stationarity (see Table A1 in the Appendix). EV stock (as is EV sales and cumulative EV sales) and electricity consumption (our two main variables), as well as GDP and population, are integrated of order one ($I(1)$), even when accounting for drift (a time trend), i.e., these variables are not simply trending in one direction but are nonstationary.

We can therefore calculate growth rates and re-estimate our model as shown in Eq. (10) (the results of which are presented in Tables A2, B2, and B6 for EV stock, cumulative EV sales, and EV sales, respectively). The results indicate a statistically insignificant coefficient for EV stock growth (the first difference of a variable in natural logarithmic form); however, both cumulative EV sales (Table B2) and EV sales (Table B6) show positive and statistically significant coefficients on the respective EV variables. As with Table 2, the electricity price has a negative (and significant) coefficient, while population is still insignificant. The GDP, CDD, and HDD coefficients are positive and significant.

There is little economic significance in interpreting a first difference model. However, all our nonstationary variables are integrated to the same order (the first order), so we can test for cointegration. This test is conducted by estimating the long-run elasticity equation (Eq. (6), but without the dynamic term) and capturing the residuals. Unit root tests of these residuals yield cointegration of the first order ($CI(1)$) for models 2, 3, 4, and 5 (cointegration results are provided in Table A3 in the Appendix, with the results similar for cumulative EV sales and EV sales).

The results from estimating Eq. (11), the error correction model (ECM), are presented in Table 3. Firstly, we confirm that the ECM does have a long-run form, where the EC term is between −1 and 0 and is statistically significant. Therefore, there is convergence towards the long-run "steady-state" when a shock occurs. Secondly, we notice that electricity prices are negative and statistically significant. As with the results in Table 2, we find a negative (and statistically insignificant) coefficient for population on electricity consumption (again, see Schiavina et al. (2022) in this regard).

The coefficient on EV stock (and cumulative EV sales) is still insignificant; however, EV sales (Table B7) are positive in the long-run equation, which contradicts the conclusion we drew from the results of Table B5 and highlights the need to ensure the stationarity of all variables.

As for the significance of EV stock in Tables 3 and it is also important to note that while we include controls for various variables, with GDP controlling for income, it also is a measure of technological adoption, we are unable to account for private solar panel installations, as there is no data available on system sizes and installations or even the amount of electricity consumed from these systems, i.e., the grid-supplied electricity consumption reduction due to private solar panel installation. This situation could result in an omitted variable bias.

Another possible interpretation for the insignificant relationship between electricity consumption and EV stock could be significant differences in EV adoption across the countries, and despite accounting for country fixed effects, this will not account for these differences if they also change over time, as can be seen in Figure A1. Therefore, to investigate this possibility, we divide our sample into four equal groups containing five countries each according to the amount of cumulative EV sales in 2022. The results are presented in Table 4. Again, first, considering the error correction component for each group is between zero and one and is statistically significant. Therefore, there is a long-run relationship between our variables (see Table A4 for the cointegration results), and any deviations in the short run will converge to the "steady state".

Only Group 3's coefficient on EV stock is positive and statistically significant, while the others are insignificant. For cumulative EV sales (Table B4), only Group 1 is insignificant, and for EV sales (Table B8), Groups 2 and 3 are significant. The coefficients on electricity prices (Table 4) are negative and statistically significant for Groups 2, 3, and 4 in the long run and only for Group 1 in the short run. Interpreting the long-run EV stock coefficient for Group 3 (Table 4): a 1 % increase in the number of vehicles on the road leads to a 0.008 % increase in the electricity consumed, which, considering the average annual electricity consumed was 160.385 TWh for Group 3, this would equal an increase of ~12.83 GWh per annum.

Interestingly, only one of the weather variables is significant for a group in the short run, alternating between the two, except for Group 1, where both CDD (colder days) and HDD (hotter days) are significant in the short run.

Considering GDP, we also see an interesting negative relationship for Group 4, which could indicate the presence of the tail-end of an inverse-U-shaped relationship between electricity consumption and GDP, given that these five countries are also high-income countries. The negative relationship between population and electricity consumption appears to be driven by some of the countries in Group 1, as it has become more negative and is now statistically significant for Group 1, insignificant for Group 2, and positive and significant for Groups 3 and 4.

In Table A5, we include the subsample results, omitting EV sales. Most of the coefficients remain similar, with no changes in the signs of the coefficients or significance. However, there is no longer a cointegrating relationship found for Group 3 (see Table A5), which points to a causal relationship between EV stock and electricity consumption for at

Table 3
Error correction estimation of the relationship between EV stock and electricity consumption.

Electricity consumption				
Model	2	3	4	5
LR				
EV stock	**0.000**	**0.000**	**0.000**	**0.000**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**
Electricity price	−0.032***	−0.034***	−0.034***	−0.035***
	(0.012)	(0.010)	(0.010)	(0.009)
GDP		0.281***	0.282***	0.283***
		(0.022)	(0.023)	(0.023)
Pop			−0.006	−0.009
			(0.049)	(0.048)
CDD				0.002 (0.003)
HDD				0.044 (0.038)
C	5.081***	−2.516***	−2.443***	−2.811***
	(0.065)	(0.601)	(0.864)	(0.909)
SR				
Lagged EC term	−0.200***	−0.200***	−0.189***	−0.189***
	(0.035)	(0.035)	(0.033)	(0.048)
D.EV stock	**−0.000**	**−0.000**	**0.000**	**0.000**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**
D.Electricity price	−0.042***	−0.042***	−0.039***	−0.039***
	(0.008)	(0.008)	(0.008)	(0.008)
D.GDP	0.215***	0.215***	0.224***	0.224***
	(0.054)	(0.054)	(0.051)	(0.034)
D.Pop		0.026 (0.260)	0.064 (0.254)	0.064 (0.318)
D.CDD			0.004***	0.004**
			(0.001)	(0.001)
D.HDD			0.059***	0.059***
			(0.017)	(0.018)
C	0.003*	0.003*	0.002 (0.001)	0.002 (0.001)
	(0.001)	(0.002)		
N	440	440	440	440
R_a^2	0.696	0.696	0.713	0.710

Note: *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Standard errors are given in parentheses. Country-clustered standard errors were included to account for the possible effect of cross-sectional dependence due to most countries being in the European Union. Country, year, and region fixed effects, as well as the interaction between year and region fixed effects, were included in all regressions. Robust standard errors were used in all models, aside from model 5, where we used country-clustered standard errors. The primary variable of interest is highlighted for the reader's convenience. All variables are in natural logarithm approximations, as noted in Section 3.1.

Table 4
Error correction estimation of the relationship between EV stock and electricity consumption with countries grouped by EV sales in 2022.

Electricity consumption				
Group	1	2	3	4
LR				
EV stock	**0.003 (0.003)**	**−0.001 (0.005)**	**0.008*** (0.003)**	**−0.002 (0.002)**
Electricity price	−0.001 (0.015)	−0.104*** (0.025)	−0.167*** (0.044)	−0.086*** (0.021)
GDP	0.242*** (0.027)	0.259*** (0.031)	0.167* (0.099)	−0.693*** (0.116)
Pop	−0.159*** (0.039)	−0.101 (0.086)	1.197*** (0.346)	0.700*** (0.142)
CDD	0.004 (0.003)	0.007 (0.005)	0.001 (0.007)	0.002 (0.007)
HDD	0.081 (0.051)	−0.074 (0.057)	−0.054 (0.081)	0.089 (0.099)
C	−1.139 (0.981)	0.707 (1.060)	−18.673*** (4.504)	13.126*** (2.960)
Cointegrated	Yes	Yes	Yes	Yes
SR				
Lagged EC term	−0.386*** (0.103)	−0.209*** (0.070)	−0.108*** (0.039)	−0.292*** (0.078)
D.EV stock	**0.001 (0.003)**	**−0.001 (0.003)**	**0.003*** (0.001)**	**−0.003* (0.002)**
D.Electricity price	−0.028** (0.012)	−0.027 (0.025)	0.000 (0.021)	−0.015 (0.022)
D.GDP	0.164 (0.105)	0.211*** (0.076)	0.593*** (0.106)	0.213 (0.158)
D.Pop	0.003 (0.707)	0.947* (0.488)	0.461 (0.293)	−0.058 (0.543)
D.CDD	0.004** (0.002)	0.007*** (0.002)	0.002 (0.001)	0.005** (0.002)
D.HDD	0.071** (0.030)	0.027 (0.022)	0.080*** (0.023)	0.034 (0.040)
C	0.004 (0.003)	0.003 (0.004)	−0.007*** (0.002)	−0.000 (0.004)
N	110	110	110	110
R_a^2	0.673	0.681	0.850	0.726
Countries	Estonia (E) Greece (S) Hungary (E) Latvia (E) Slovenia (E)	Finland (N) Ireland (W) Luxembourg (W) Poland (E) Portugal (W)	Austria (W) Belgium (W) Denmark (N) Italy (S) Spain (S)	France (W) Germany (W) Netherlands (W) Norway (N) Sweden (N)
Cumulative EV sales (2022)	2,296–16,068	25,225–76,336	85,789–172,960	215,883–1,175,597

Note: *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Standard errors are given in parentheses. Country-clustered standard errors were included to account for the possible effect of cross-sectional dependence due to most countries being in the European Union. Country and year-fixed effects were included in all regressions. Robust standard errors were used in all models. The primary variable of interest is highlighted for the reader's convenience. All variables are in natural logarithm approximations, as noted in Section 3.1. The results of the cointegration tests are presented in Table A4 in the Appendix. Groups 1 to 4 correspond to the lowest cumulative EV sales in 2022 to the highest cumulative EV sales in 2022, dividing the sample into four equal groups. Regions are given in brackets after the country names.

least this subset of countries in our sample. The coefficients can, however, not be viewed as the size of this causal effect, as there is a high likelihood of omitted variables (e.g., private solar panel installations), which would bias the coefficients.

In summary, we find a long-run positive relationship between the number of EVs on the road (stock or cumulative sales) and electricity consumption for at least one of the groups of countries. The short-run results mimic those of the long run, where EV sales growth is positively related to electricity consumption growth for the same group of countries, significant for Group 3 for EV stock and Groups 2 to 4 for cumulative EV sales.

The size of the EV market in Groups 1 and 2 for EV stock might not be sufficiently large to have a significant relationship in our sample, which could be an important result for countries early in their journey to electrify their transport sectors. The insignificant relationship for Group 4 is more interesting, which could be because these countries have a large share of private renewable energy (like solar PV systems), especially given countries like Germany, the Netherlands, and France in the subsample. However, given the data concern discussed in Section 3.2, it could be attributed to measurement error, if cumulative EV sales (for this sample at least) is a more accurate reflection of the number of vehicles on the road.

Our results have two important implications for policy- and strategic decision-makers, especially electric utilities tasked with ensuring sufficient investments in capacity to meet expected future consumption. Firstly, there is a certain threshold, for our sample, where the relationship between EV stock and electricity consumption becomes significant. If we assume that this is between the maximum cumulative EV sales of Group 1 and the minimum cumulative EV sales of Group 2, this would be between ~16,000 and ~25,000 vehicles in our sample of countries. Secondly, it could be possible to negate the impact of EV adoption on electricity consumption (on aggregate) with a sufficiently high penetration of private solar panel installations; however, this might require the correct incentives to ensure grid stability.

5. Conclusion

This study investigates the relationship between EV adoption and electricity consumption for 20 European countries over 23 years (2000–2022). Our ex-post manner approach has important implications for strategic decision-makers. We first model a simple demand elasticity model built on the works of Cialani and Mortazavi (2018) and Jin and Kim (2022). In our sample of countries, however, we find that the data is not stationary but forms a cointegrating relationship for some of the specifications we tested. Therefore, we derive an Error Correction Model (ECM) from their empirical framework.

We conduct a complete and sub-sample analysis, with the full-sample ECM revealing a positive and statistically insignificant coefficient on EV stock (the number of EVs on the road) in the long-run equation (levels), and short-run equation (growth rates). Given the significant variation in the size of the EV markets in the respective countries, we divide the sample into four equal groups based on the cumulative EV sales (or the EV market size). In line with Cialani and Mortazavi (2018) and Jin and Kim (2022), we find a negative relationship between electricity prices and consumption, as one would expect.

In the sub-sample analysis, we find that the coefficient on EV stock is only significant for Group 3, the group of countries with the second-largest markets (of the four groups). This finding could be due to

various reasons; however, we postulate that for the smaller groups, this is simply because the size of the market is not large enough to have a significant impact on electricity consumption. For the larger group (Group 4), we postulate this could be due to an increase in the adoption of solar PV systems (which is supported by the findings of Liang et al. (2022)). These results improve substantially if we instead consider cumulative EV sales, where only the smallest group (Group 1) now has an insignificant coefficient. This analysis was done due to concerns with data quality with the EV stock and sales variables, where the differences between changes in EV stock were too large to attribute to vehicle retirements, especially in the early years of adoption, or with stock increasing by more than the reported sales in a particular year.

For the group just above the mean EV market sizes (when considering the EV stock results), we find positive and statistically significant coefficients for both the long- and short-run equations. These results showcase that despite EVs only accounting for a small portion of all vehicles on the road, we can find a relationship between EVs and electricity consumption. In general, the existence of a cointegrating relationship (when controlling for GDP, population, and temperature) indicates the presence of a causal relationship between EV sales and electricity consumption. However, our coefficients cannot be interpreted as the size of the causal relationship due to omitted variable bias, as we did not include private solar panel installations (due to data availability). Furthermore, there is also the possibility that the effects of policy changes have not fully been absorbed by country or region fixed effects, particularly those with variation across countries and time.

For policy- and strategic decision-makers, our results are important because, even while the emerging EV market is in its infancy, we find a significant relationship between the number of EVs on the road and electricity consumption for both the long- and short-run equations. In light of the recent energy crisis in Europe, partly driven by the conflict in Ukraine, it is important to ensure that the future electricity supply is sufficient and that each country is energy secure. This objective could be achieved by incentivising the adoption of private solar PV systems along with EV adoption (as showcased by Liang et al. (2022)).

Our result for the smallest groups indicates that stakeholders still have (some) time to implement the measures to limit the impact of EV adoption on electricity consumption, as suggested by, for example, Needell et al. (2023), Kaur and Singh (2023), or Skolthanarat et al. (2024). These measures would allow them to ensure their energy security, especially while decarbonising their electricity supply. For developing countries and emerging markets, our long-run results would be a sigh of relief; however, given the price difference between EVs (like with all new technologies), it is likely that the distribution grids would be the first to feel the impact of uncontrolled charging, as noted by Skolthanarat et al. (2024). This impact is due to households tending to co-locate with other households in the same income groups, i.e., more affluent neighbourhoods are likely to suffer first from overloading their local grid infrastructure in an uncontrolled charging environment, that is, unless they co-adopt with private generation.

It is important to note that even though this study does not investigate (hourly) electricity demand, and that the formal analysis is limited to annual electricity consumption (realised electricity demand over a calendar year), we comment on the former based on information contained in the literature review section. Furthermore, we also want to note that the link between hourly demand and electricity consumption is paramount when conducting grid or generation capacity expansion planning, particularly when selecting a generation source.

This study is limited by the possible omitted variable bias from not including private solar panel installations, which would have the opposite impact on electricity consumption (from the grid). Future research could investigate possible ways to estimate or proxy private solar panel installations. Our analysis could be furthered by considering EV purchase incentives to estimate the causal relationship between EVs and electricity consumption; however, this could likely still suffer from omitted variable bias if these equations do not include a measure for private generation.

CRediT authorship contribution statement

Jacobus Nel: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Roula Inglesi-Lotz:** Writing – review & editing, Supervision.

Authorship

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Appendix C. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jup.2025.102032.

Data availability

Data will be made available on request.

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