

## EFFICIENCY OF ELECTROMOBILITY IMPLEMENTATION INTO EUROPEAN PUBLIC PASSENGER TRANSPORT IN 2019-2023

Adam KUCHARSKI<sup>1\*</sup>, Radosław JADCZAK<sup>2</sup>

<sup>1</sup> University of Lodz; adam.kucharski@uni.lodz.pl, ORCID: 0000-0001-8699-7566

<sup>2</sup> University of Lodz; radoslaw.jadczyk@uni.lodz.pl, ORCID: 0000-0002-2393-0329

\* Correspondence author

**Purpose:** The article identifies countries that are influencing the implementation of electromobility in bus transport. The second objective is to assess the impact of macroeconomic factors contributing to the aforementioned influence.

**Design/methodology/approach:** The first objective is based on the utilisation of the DEA (Data Envelopment Analysis) method and the second one on the estimation of the parameters of a panel probit model.

**Findings:** The study identified a group of European countries that have achieved a notable level of success in electromobility implementation for bus transport. Some of them have assumed the role of influence leaders for other countries. The real GDP per capita and the difference between the income from taxes on environmental pollution for a given year and the previous year are the macroeconomic factors that were significant in becoming an influence leader.

**Research limitations:** The study considered the sole appearance of the effective DMU in the benchmarking formula. Future research should evolve to apply a procedure for determining the target share of inputs in a target technology based on the inputs “contributed” to the target technology by the benchmark DMU.

**Practical implications:** The panel model allows us to formulate scenarios in which the probability of a country's status changing from zero to one and becoming an influence leader can be affected by a predetermined change in the value of the explanatory variables. In this way, the government will be able to plan its policy for developing e-mobility in public transport.

**Social implications:** The government measures mentioned above may contribute to the development of sustainable public transport. This will enhance the quality of life in urban areas and alleviate pressure on the environment.

**Originality/value:** We present a novel approach to using benchmarking formulas from the DEA method to create binary variables and then using them in a panel probit model.

**Keywords:** DEA method, electromobility, public transport, panel data.

**Category of the paper:** Research paper.

## 1. Introduction

For more than a dozen years, electromobility has been undergoing intensive development. This transformation of transportation is expected to improve the environment and the living conditions of the population, because electric vehicles emit far fewer greenhouse gases and air pollutants than vehicles powered by traditional engines. The European Union's (EU) climate policy supports the development and large-scale implementation of electromobility using regulations and financial encouragements. Two packages of EU's initiatives are most associated in the media space: European Green Deal announced in 2019 and the Fit for 55 announced in 2021, which was supposed to incorporate the European Green Deal's climate goals into concrete law regulations. The new legislation covers virtually every area of the EU's activities and is expected to lead to climate neutrality by 2050. The planned transformation also includes public transportation. Thus, among other things, it was announced a reduction of the use of fossil fuels in transportation and a reduction of greenhouse gases emissions. Carbon dioxide emissions from passenger cars should be decreased by 37.5% by 2030 compared to 2021, while a 31% reduction was assumed for commercial vehicles.

Electromobility has become an integral part of many countries' sustainable development strategies. The comprehensive nature of the plans made obviously affects public transportation. "White Paper. Roadmap to a Single European Transport Area – Towards a competitive and resource efficient transport system", from 2011, has already drawn attention to urban transportation. Fleets of buses, taxi cars and vans have been identified as particularly suitable for the introduction of alternative powertrains and fuels. In this article, we will focus specifically on electric-powered public transportation vehicles.

Research on the electrification of public transport is clearly less prevalent than research on individual electromobility. Meanwhile, public transport, especially urban transport, is instrumental in achieving sustainable development goals. We have identified a research gap in the field of electromobility implementation in European public transport. The effectiveness of this implementation has not yet been thoroughly analysed, and there is a need for models to support policies that promote this specific aspect of electromobility.

European countries differ in their involvement and effectiveness in implementing both individual and mass electromobility. This is the result of several different factors. For this reason, some countries are doing better than others and it is possible to identify a leader or leaders in the process of implementing electromobility in transport. The activities of a market leader entail the emergence of followers. In public space, some countries are identified as those that are considered to be leaders in the implementation of electromobility. The suggestion that other countries should follow these leaders usually comes next. The leader-follower relationship is the starting point of our considerations. The possession of followers is not a prerequisite for success. Sometimes it is simply impossible to repeat the achievements of

a top-performing individual, which may result in a lack of subsequent followers. Therefore, we will identify a special category of “influence leader” who has followers, as opposed to a leader in the classical sense. Given the above considerations, two goals were formulated:

1. Identification of countries that are influence leaders of electromobility implementation in bus transport. This will be achieved by comparing the efficiency of the process.
2. The direction and strength of influence of macroeconomic factors contributing to the leadership in the implementation of electromobility in public transport will be then studied.

Our study is significant for two primary reasons. Firstly, it identifies benchmarks thanks to DEA method. Secondly, it demonstrates how a given country can enhance the effectiveness of its implementation of electromobility. The author's methodological contribution is a proposal for a three-stage analysis combining benchmarking with the DEA method and the estimation of probit panel models.

The rest of the article is divided into four sections. The first part provides a critical review of the literature on the implementation of electromobility in Europe. This section concludes with the formulation of research questions. The second part of the report presents the methods used. The third part of the article is devoted to the presentation of results. The fourth part of the report contains a discussion. The article concludes with conclusions.

## 2. Literature review

The primary motivations behind the planned transition to electromobility are the desire to reduce greenhouse gas emissions and the pursuit of sustainable development. These goals provide the context for our study.

Implementation of electromobility by of EU countries is due to the need to adapt to the EU's climate policy as expressed in the European Green Deal (2019) and the Fit for 55 (2021) packages of documents. They are accompanied by more detailed documents, regulating specific aspects of the process like Regulation (EU) 2023/1804 on the development of alternative fuel infrastructure.

Among Leading Initiatives of “Sustainable and Smart Mobility” strategy (EUSSSM) is the Initiative Number 3 dedicated to sustainable mobility in and between cities. One of the objectives of the EUSSSM is to ensure that regular public transport services within the EU, covering distances of up to 500 km, are carbon neutral. Therefore, the European Commission has identified the issue of public transportation in urban areas as being of importance. However, the literature on the transition of public transportation to the electric option is less numerous than that discussing individual electromobility.

Member states implement their own regulations to achieve EU-wide environmental and economic goals. An example in Poland is the Act of January 11, 2018, on electromobility and alternative fuels (Journal of Laws 2021, vol. 2269) and the related “National Policy Frameworks for the Development of Alternative Fuel Infrastructure”. Therefore, scientific papers are being written analyzing the implementation and development of electromobility in Europe and around the world. Selected aspects of EU’s climate policy are described in (Gyórfy, 2024; Motowidlak, Bukowska-Piestryńska, 2024; Nikolaidou et al., 2023), among others. The topic of reducing greenhouse gases emissions was addressed by (Tucki et al., 2019; Tucki, et al., 2020; Tsakalidis et al., 2020). Some authors have studied the current state and perspectives of the European electromobility sector (Frej et al., 2021; Marotta et al., 2023; Nanaki et al., 2022; Rokicki et al., 2022). Furthermore, the availability of transportation infrastructure is described in the papers (Klimach, Figurska, 2022; Kubás et al., 2022; Mazur et al., 2024; Tucki, Orynycz, Dudziak, 2022).

When considering whether to innovate, there are several criteria to take into account. Therefore, Nalmpantis et al. (2019) used the AHP method to create an innovation ranking for urban public road transportation. The transition to low- or zero-emission urban transportation is intended to bring environmental benefits. Pietrzak and Pietrzak (2020) identified and analyzed the environmental effects of implementing zero-emission buses in urban public transportation using the example of the city of Szczecin (Poland). Their research demonstrated that public transportation could assist in decreasing road congestion and air pollution. However, in order to achieve environmental effects in the transition to zero-emission public transport, government support is needed (Rodrigues et al., 2024).

Implementing electromobility in public transport also requires technical solutions. One of the key challenges currently being faced is the limited range of electric buses, which is a result of the installed battery capacity being insufficient (Varga et al., 2019; Bi et al., 2018). Electric buses need to be charged at charging stations, and the required charging time is important for the efficiency of fleet usage (Rogge et al., 2018). The localization of charging stations is very important for the effective operation of the electric bus network (Schmidt et al., 2021; Józwiak et al., 2018).

In addition to multi-criteria methods, the efficiency of implementing and operating electromobility and public transportation is analyzed. Data Envelopment Analysis (DEA) is suitable for this purpose and is also the first stage of the procedure described in Chapter 3. Rivero Gutiérrez, De Vicente Oliva and Romero-Ania (2022) reviewed studies on bus choice in various cities around the world using the DEA method, citing eight publications published between 2001 and 2021. These studies focus on dedicated areas – primarily specific cities.

In the DEA method, the choice of inputs and outputs is crucial, which depends on the optimization goal. Almeida Neves et al. (2020) analyzed the efficiency of electromobility implementation of 20 EU countries between 2010 and 2018. Inputs included such macroeconomic variables as: labor force, gross investment expenditures per capita, electricity

consumption intensity of the economy, oil price, industrial production index. Their model included two effects: new BEV (Battery Electric Vehicle) registrations relative to total new vehicle registrations and the cumulative number of policies supporting electric mobility. Six models of environmental performance of European countries were proposed by Kucukvar et al. (2022). As inputs, they used such variables describing the state of the environment as atmospheric particulate emissions, metal depletion status, soil acidification and urban agglomeration area. The output was the environmental impact of electric vehicles measured by the distance they traveled. Xu et al. (2020) studied the environmental effectiveness of road transportation in 30 regions in China. Among the inputs they used were fuel consumption, total highways length, total trucks tonnage, number of passenger seats. Among the effects were passenger and freight traffic and adverse effects: noise, CO<sub>2</sub> emissions, and direct material losses from traffic accidents. Very often, the DEA method is used at the micro level, to evaluate the effectiveness of the decision to purchase an electric vehicle (Jahromi et al., 2013; Svoboda, Lagasse, 2013) or to plan the location of charging stations (Khalkhali et al., 2015; Wang et al., 2018; Kubás, 2022).

Efficiency analysis can be accompanied by regression models, as a second stage of research. The specifics of the phenomenon and the available data cause researchers to turn to estimation methods other than classical least squares method. Almeida Neves, et al. (2020) used a panel model in which the explanatory variable was efficiency derived from the DEA. Among the explanatory variables used, it is worth to mention: production of renewable electricity per capita, number of publicly accessible charging stations (per 100,000 people), value-added services, percentage of the population living in single-family homes and others. Rietmann and Lieven (2018) estimated the parameters of a panel model explaining the combined BEV and PHEV (Plug-in Hybrid Electric Vehicle) EV market share using the partial least squares (PLS) method. Estimation was also employed in our study. In the third stage of the procedure, the parameters of the probit panel model were estimated.

Electromobility has been implemented across the European countries, yet the extent of research comparing these countries is limited. Fanti et al. (2017) presented interactions of stakeholders in the electromobility network by nine macro-areas: industry, information technology providers, charging infrastructure, decision makers, public authorities, energy, European and international organizations, end users, and complementary services. The issue of electric vehicle exploitation was raised by Skrúcaný et al. (2019), who provided a detailed examination of the impact of such vehicles on the environmental footprint of energy efficiency when utilizing primary generation sources. The statistical study consisted of comparing a set of parameters for seven countries in the Central European region. Gruetzmacher, Vaz, and Ferreira (2021) used panel data to analyze variables that could impact the adoption rate of electric vehicles in EU countries between 2015 and 2019. Tucki et al. (2022) analyzed in detail the development of electromobility in Poland compared to other EU countries, calculating, among other things, correlation coefficients for individual variables. Kubás et al. (2022) determined

the efficiency of electric vehicle charging infrastructure implementation and, consequently, the efficiency of electromobility in all EU countries.

As outlined in the introduction, we are proposing a novel research procedure that begins with the DEA method and then employs benchmarks from this method in a panel model. This combination has not been presented in the literature to date, but we can find the methods and tools we used at each stage. The DEA method at the country level was used by Kucukvar et al. (2022), Rivero Gutiérrez et al. (2022), and Wang et al. (2018). Benchmarks obtained from statistical analysis were used in (Kolibaba et al., 2025; Tucki et al., 2022). The use of logit or probit models in electromobility research can be found in (Almeida Neves et al., 2020).

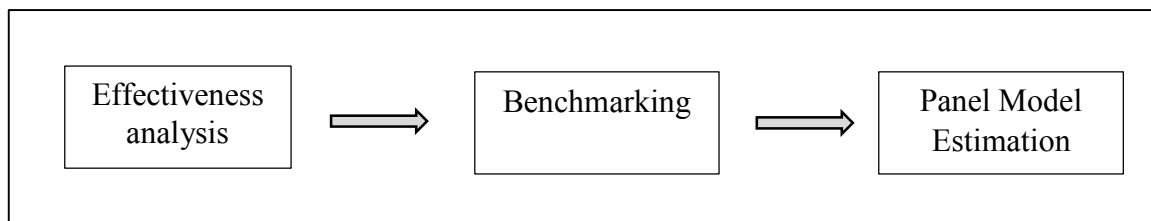
A substantial proportion of the referenced sources concentrate on public policies and charging infrastructure, which are regarded as pivotal to enhancing EV market penetration in Europe. These sources examine the broader context of managing transport innovations, such as Mobility-as-a-Service (MaaS) and autonomous vehicles, to promote more integrated and sustainable urban systems. The rapid growth of electromobility in recent years has prompted further research into this process. In light of the EU's strategic initiative to transition to zero-emission transport in the near future, the development of electromobility has emerged as a pivotal research area. The following research questions were therefore posed:

1. Is the process of introducing electromobility in public transport in European countries proceeding with similar efficiency?
2. Have there been any significant changes among the leaders in the introduction of electromobility in public transport between 2019 and 2023?
3. Which macroeconomic factors have a significant impact on the ability to lead the implementation of electromobility?

### 3. Methods

#### 3.1. Research description

The study was conducted in accordance with the proposed approach, which was divided into three stages. The scheme of this approach is presented in Figure 1 below.



**Figure 1.** Research stages.

Source: own work.

The first stage of the process is to assess the efficiency of electromobility solutions in public transport across all EU countries. Efficiency  $\delta$  is defined here as the relation of multiple outputs to multiple inputs and takes value between 0 and 1. The goal of this stage is to divide the EU countries into two groups: those that demonstrate effective implementation of electromobility processes ( $\delta = 1$ ) and those that demonstrate ineffective implementation ( $\delta \neq 1$ ). The DEA method was used to evaluate efficiency. The DEA is a non-parametric method that does not require the user to specify a formalized input-output relationship. A further advantage is that it does not require inputs and outputs to be in the same units. The efficiency of the implementation of electromobility in public transport was examined separately for each year of the 2019 - 2023 period.

The second stage of the study (benchmarking) aims to identify countries that can be described as so-called “influence leaders”. Based on the results from the first stage, those EU countries that are originally efficient will be identified, and there is at least one inefficient country for which they are a benchmark. This means that not all the countries previously identified as efficient will play the role of influence leaders. The second stage of the procedure results in the creation of a vector containing binary values. A value of 1 indicates that a country should be considered an influence leader, while 0 indicates the opposite.

The final stage of the research is the construction of a probit panel model, which will be used to identify the macroeconomic variables contributing to the leadership of electromobility implementation in public transport. Additionally, this section of the study aims to analyze the direction and strength of their influence in achieving this position. In this model, the explanatory variable is a binary vector of countries that are influence leaders in a given year. The data in this stage has a panel structure, in which observations for countries have been arranged by consecutive years. The explanatory variables used for the construction of the panel model are different from those used in the effectiveness analysis in the first stage.

### 3.2. Efficiency evaluation

A key element in assessing the efficiency with which EU countries are implementing electromobility solutions in public transport is to identify the set of inputs and outputs. The following inputs were selected:

- number of buses at least 10 years old.
- total area of urban agglomerations [ $\text{km}^2$ ].

The first input is justified by the fact that the oldest vehicles are being replaced the fastest. Their replacement by electric vehicles has a measurable effect in reducing CO<sub>2</sub> emissions and other harmful chemicals. The selection of this input is further supported by a variety of government programs that encourage the replacement of outdated transportation fleets with new low-emission ones (Su et al., 2021).

The second input - total area of urban agglomerations is also reasonable. Electric public transportation largely concerns cities. This is determined by both the potential range of vehicles, as well as the spatial availability of charging infrastructure. A further benefit of electrifying city transport is the increased potential for creating connected, pollution-free zones (e.g. in city centers). A country's larger size is indicative of a greater tendency to use road transportation, which is characterized by the highest degree of spatial accessibility.

The outputs used in the study are as follows:

- number of new electric buses registered,
- final consumption of electricity by the road transport sector [GWh].

A natural result of the implementation of electromobility in public transportation is the number of registrations of new electric vehicles (buses). In contrast, the final electricity consumption of the road transport sector is an undesirable effect. An increase in the number of electric vehicles has the potential to increase demand for electricity and put pressure on power grids (Pariz, Keivanimehr, 2024).

As outlined above, we utilized the DEA method to assess the efficiency with which EU countries were implementing electromobility solutions in public transport. One of the earliest and most well-known DEA models is the CCR model, which was proposed by Charnes, Cooper and Rhodes. They defined efficiency as the ratio of the sum of weighted outputs to the sum of weighted inputs (Cooper, Seiford, Tone, 2007). The CCR is a mathematical programming model, more specifically, quotient programming. The objective is to find the optimal quantities of weights using empirical quantities of inputs and outputs, thereby maximizing efficiency. Graphically, the solution is a fragmentary linear function connecting the most effective Decision Making Units (DMUs). This curve is called the efficiency border. DMUs (objects) lying on the curve are identified as efficient, those located beneath the curve are considered dominated. The quotient form of the objective function makes a nonlinear programming problem. However, it is possible to transform it into a linear model, and then solve it in its dual form, which is the most common approach. Following the presentation of the CCR (Charnes-Cooper-Rhodes) model, a number of other models have been proposed. The BCC (Banker-Charnes-Cooper) model with variable economies of scale has proved particularly popular (Banker et al., 1984).

The DEA method is highly sensitive to changes in the number of objects being evaluated, since efficiency is measured relative to other objects. This method is also characterized by a high degree of subjectivity, which is evident in the selection of the inputs and outputs. Efficiency optimization in the DEA can be understood in two ways. The first means reducing the inputs while keeping values of outputs constant. The second way involves increasing outputs while maintaining inputs at their current level. In this study, the second approach was used (variability of outputs and invariability of inputs) because the levels of the proposed inputs could not be changed. Thus, inefficient DMUs will be characterized by an efficiency index value greater than 1. In addition, one of the outputs (final electricity consumption by the road

transport sector) is the undesirable output. This means that its smaller values leads to greater efficiency. The optimization model used is thus as follows:

$$\max \delta_o \quad (1)$$

$$x_{io} \geq \sum_{j=1}^n x_{ij} \lambda_{jo} \quad (2)$$

$$\delta_o y_{ro}^d \leq \sum_{j=1}^n y_{rj}^d \lambda_{jo} \quad (3)$$

$$\delta_o y_{ro}^u \geq \sum_{j=1}^n y_{rj}^u \lambda_{jo} \quad (4)$$

$$\sum_{j=1}^n \lambda_j = 1 \quad (5)$$

$$\lambda_j \geq 0 \quad (6)$$

where:

$\delta_o$  – the efficiency index of the  $o$ -th object,

$x_{io}$  – the  $i$ -th input for the  $o$ -th object,

$y_{ro}^d$  – the  $r$ -th output for the desirable  $o$ -th object,

$y_{ro}^u$  – the  $r$ -th output for the undesirable  $o$ -th object,

$\lambda_{jo}$  – intensity variables,

$i = 1, \dots, m,$

$r = 1, \dots, s.$

In the following part of the paper, benchmarking formulas will be determined for all inefficient DMUs ( $\delta_o > 1$ ). They determine how the outputs should be changed in order for DMU to be on the efficiency border. These formulas are a linear combination of the efficient DMUs outputs. The optimal values of the intensity weights  $\lambda_{jo}$  are parameters in these formulas and determine new output values (Guzik, 2009). However, the purpose of the second stage is not to calculate the new values of the outputs, which inefficient DMUs should obtain. The goal is to identify efficient objects that can be used as benchmarks for inefficient objects. The final result of the second stage is a binary vector indicating influence leaders (Efficient DMUs, which are benchmarks for inefficient DMUs). This vector is the starting point for the construction of the panel model described in the next section of this paper.

DEA models based on Farrell efficiency can be analysed in a dynamic way, without being limited to static analyses. Furthermore, it is possible to study changes in efficiency dynamics. This is based on Shephard's distance. As outlined in the 2007 study by Cooper, Seiford and Tone, this is the inverse of optimal efficiency from an input-oriented model. The most widely used measure of efficiency changes between periods  $t$  and  $t+1$  is the Malmquist index. In its basic form, it is presented as the product of the change in technical efficiency (TE), which determines the relative change in the efficiency of an object between periods  $t$  and  $t+1$  without taking into account the change in the position of the efficiency curve and the technical change related to technological progress (TP). This decomposition was proposed in an article (Färe et al., 1994). Ray and Desli (1997) highlighted the issue of internal inconsistency arising from combining assumptions about constant returns to scale (CRS) and variable returns to scale (VRS). They proposed an alternative decomposition based solely on VRS technology. This is the approach that has been adopted in our article. According to this approach, the Malmquist index (MI) is derived as the product of the following sub-indices:

$$MI = TE_v \cdot TP_v \cdot SE \quad (7)$$

where:

$TE_v$  – change of the input-oriented technical efficiency between periods  $t$  and  $t+1$ , assuming variable economies of scale,

$TP_v$  – change of the position of the empirical production function between periods  $t$  and  $t + 1$ , assuming variable returns to scale,

$SE$  – scale efficiency change.

More variants of the Malmquist productivity index decomposition can be found in (Ćwiąkała-Małyś, Nowak, 2011).

### 3.3. Estimation of panel model parameters

In the final stage of the study, a panel model was constructed in order to describe the data formed by combining observations from different DMUs (countries) over a specified period. There are two key parameters in the panel model: the number of units  $N$  and the number of time periods  $T$ . The behavior of variables depends on individual factors and factors that affect all the variables under consideration (Danska-Borsiak, 2011).

There are two types of panel models (Maddala, 2008):

- fixed effect models (FE),
- random effect models (RE).

In this study a binomial model is used, in which the explanatory variable is equal 1 (efficient countries – influence leaders for inefficient countries, and 0 otherwise). The mathematical model is as follows (Gruszczynski, 2012):

$$y_{it}^* = \alpha_i + \beta' \mathbf{x}_{it} + \varepsilon_{it} \quad (8)$$

$$y_{it} = \begin{cases} 1, & \text{if } y_{it}^* \geq 0 \\ 0, & \text{if } y_{it}^* < 0 \end{cases} \quad (9)$$

where:

$y_{it}^*$  – binomial vector of observations for the explained variable,

$\mathbf{x}_{it}$  – vector of observations for explanatory variables,

$\alpha_i$  – individual effect for the object  $i$ ,

$\beta$  – parameter vector for explanatory variables,

$\varepsilon_{it}$  – random component,

$i = 1, \dots, N, t = 1, \dots, T$ .

If we assume that the random component follows a normal distribution, then we have a probit model. However, if the distribution is specified as logistic, then we have a logit panel model.

In our research, a probit panel model was used, in which individual effects are treated as random variables and included in the stochastic part of the model. They are also independent of the explanatory variables. This type of model, as opposed to the fixed effects model, allows for wider interpretation of estimated parameters. The model allows us to determine the probabilities of the value of the explanatory variable changing from 0 to 1, given the estimated parameter values and the values of the explanatory variables (Bland, Cook, 2019; Hahn, Soyer, 2005). As previously stated, in the used panel probit model, the dependent variable was a binary vector taking the value of 1 when a country was considered to be the influence leader. Influence leaders were appointed separately for each year.

Continuous economic growth (measured by GDP) directly contributes to the development of the road transport sector (Tucki et al., 2020). In order to increase the market share of BEVs, it is essential to make efficient use of resources such as labour (Almeida Neves et al., 2020; Mazur et al., 2024).

The primary obstacle hindering the growth of the electromobility sector in Poland and other nations is the significant disparity in purchase price between electric vehicles and their conventional counterparts. The high prices are primarily due to the cost of batteries and the research and development costs incurred by manufacturers (Kolibaba et al., 2025). In countries with higher GDP and therefore higher incomes, a greater number of combustion engine cars and BEVs per thousand inhabitants can be expected.

The operating costs of vehicles with conventional engines are influenced by the price of oil, with higher oil prices making electric vehicles more attractive. The development of electromobility is influenced by two key factors: the level of consumption of crude oil and its derivatives, and the pursuit of sustainable forms of transport and alternative fuels (Motowidlak, Bukowska-Piestrzyńska, 2024). Electricity generation from renewable energy sources (RES)

has been shown to have a positive and statistically significant association with a country's efficiency in adopting BEVs, thereby bringing inefficient countries closer to the efficiency frontier (Almeida Neves et al., 2020). In countries where the energy mix is dominated by fossil fuels, the economic benefits of implementing zero-emission buses are limited. The full environmental and economic effects of electromobility on a macroeconomic scale (across the entire country) therefore depend on the simultaneous diversification of energy sources towards RES (Pietrzak, Pietrzak, 2021).

The development of the BEV market is largely dependent on subsidies and financial incentives. Research has demonstrated that financial incentives have a favourable effect on the market share of EVs (Rietman, Lieven, 2018). Another tool used by governments is the taxation of activities that increase CO<sub>2</sub> emissions. Some countries, for example France, use a bonus-malus system that rewards the purchase of cars that emit less CO<sub>2</sub> and penalises those that emit more (by increasing or decreasing the bonus/tax). In countries such as Germany, Denmark, and Norway, policy is not dependent on CO<sub>2</sub> emissions (Nanaki et al., 2022).

The electrification of public transport (including buses) is considered a positive step towards reducing emissions in urban areas (Kucukvar et al., 2021). City buses that do not emit any emissions are given priority when it comes to electrification. This is because they have regular routes, which makes it easier to plan the charging infrastructure and allows for the use of smaller batteries (Pietrzak, Pietrzak, 2021).

Based on the analysis of the literature, the following explanatory variables were selected:

- GDPPC: real GDP per capita [EUR] (Tucki et al., 2019; Tucki, Orynycz, Mitoraj-Wojtanek, 2020).
- UNLAB: the quotient of the number of unemployed to the number of employed (Almeida Neves, Marques, Moutinho, 2020; Mazur, Dybała, Kluczek, 2024).
- CARS1000: number of passenger cars per 1,000 inhabitants] (Tucki et al., 2019, Tucki et al., 2020; Kolibaba et al., 2020).
- PUBTR: share of public transport in total passenger transport (Kucukvar et al., 2021).
- RESELE: share of renewable energy sources (RES) in total produced electricity (Almeida Neves et al., 2020; Pietrzak, Pietrzak, 2021).
- OILCONS: consumption of oil and petroleum products [thousands of tons] (Motowidlak, Bukowska-Piestrzyńska, 2024).
- GHGTRPC: greenhouse gas emissions from the transport and warehouse sector [kg per capita] (Fit for 55, 2021).
- POLTINC: income from taxes on environmental pollution [millions EUR] (Nanaki et al., 2022).

The first two variables refer to a country's economic situation. A rise in real GDP per capita is expected to lead to an increase in the number of electric vehicles purchased, rather than an increase in the number of unemployed people compared to the number of employed. The number of passenger cars per 1000 residents and the share of public transportation in total passenger transportation reflect the tendency to use public transportation services, and thus the tendency to replace traditional vehicles with electric ones. In the first case, the growth of individual transportation is likely to have a negative effect on the number of electric public transport vehicles, as opposed to a positive effect on the use of public transport. The next two explanatory variables (share of RES in total produced electricity and consumption of oil and petroleum products) refer to energy consumption and its impact on electromobility. A higher share of RES in overall energy production reduces the overall cost of electricity, stimulating the tendency to purchase electric vehicles (as it was in Norway, for example), that is, to the detriment of public transportation, as does the increase in oil and gasoline consumption. The final two explanatory variables are intended to indirectly encourage efforts to increase the propensity of traditional fleets being replaced with electric ones. This should be done through government or local government programs (resulting from financial penalties imposed for excessively high greenhouse gas emissions), or through fiscal policy tools that burden producers (and consequently buyers) of traditionally powered vehicles.

Data were collected from the EUROSTAT database. The estimation was carried out using the STATA software package.

#### **4. Results**

The efficiency of each EU country, obtained using the BCC model of the DEA method, is presented in Table 1.

The number of countries with an efficiency index of 1 (100%) in 2019-2023 is 5, 4, 9, 6 and 9 respectively. Moreover, it was possible to indicate several countries whose efficiency was very close to 1. Latvia or Portugal are countries where the efficiency index has not exceeded 1.01 since 2019. This means that outputs of these countries should increase by less than 1% while keeping input unchanged. Approximately 35-55% of countries (depending on the year) can be considered efficient in implementing electromobility processes in public transport over the period considered. Luxembourg, Slovenia, France and the Netherlands achieved the efficiency index equal 1 at least three times.

**Table 1.***Efficiency of implementing electromobility based on the DEA model*

DMU	2019	2020	2021	2022	2023	DMU	2019	2020	2021	2022	2023
AUT	1.144	1.175	1.209	1.113	1.185	LAT	1.03	1.003	1.005	1.005	1.001
BEL	1.154	1.138	1.188	1.228	1.353	LIT	1.043	1.036	1.028	1.015	1.01
CRO	<b>1</b>	1.001	1.002	<b>1</b>	<b>1</b>	LUX	<b>1</b>	<b>1</b>	<b>1</b>	<b>1</b>	<b>1</b>
CZE	1.084	1.067	1.049	1.025	1.03	NET	<b>1</b>	<b>1</b>	<b>1</b>	2.767	1.453
DEN	1.029	1.099	<b>1</b>	<b>1</b>	1.131	NOR	2.367	1.735	2.007	1.016	<b>1</b>
EST	1.017	1.01	1.008	<b>1</b>	1	POL	1.03	1.038	<b>1</b>	1.03	1.041
FIN	1.084	1.124	1.038	1.068	1.204	POR	1.008	1.004	<b>1</b>	1.005	<b>1</b>
FRA	<b>1</b>	1.495	<b>1</b>	<b>1</b>	<b>1</b>	ROM	1.039	<b>1</b>	1.109	1.048	1.001
GER	1.18	1.145	<b>1</b>	1.044	1	SLO	<b>1</b>	<b>1</b>	<b>1</b>	<b>1</b>	<b>1</b>
HUN	1.051	1.054	1.046	1.042	1.037	SPA	1.17	1.217	1.248	1.224	<b>1</b>
ITA	1.16	1.205	1.128	1.295	1.035	SWE	1.068	1.166	<b>1</b>	1.049	1.307

\* AUT - Austria, BEL - Belgium, CRO - Croatia, CZE - Czech Republic, DEN - Denmark, EST - Estonia, FIN - Finland, FRA - France, GER - Germany, HUN - Hungary, ITA - Italy, LAT - Latvia, LIT - Lithuania, LUX - Luxembourg, NET - Netherlands, NOR - Norway, POL - Poland, POR - Portugal, ROM - Romania, SLO - Slovenia, SPA - Spain, SWE - Sweden.

Source: own work.

Noteworthy is the very high inefficiency of the Netherlands in 2022 (also the highest of all 22 countries). Energy prices in the Netherlands were unstable in 2022. In some months, they rose by up to 200% compared to the previous year. This led to high inflation. Compared to internal combustion engines, this could make the operation of electric buses less profitable. In turn, local authorities, the main stakeholders in the implementation of electromobility in public transport, had to limit their investments in new vehicles.

The average efficiency index values for inefficient countries in 2019-2023 are at a similar level:  $1.16 \pm 0.31$ ;  $1.15 \pm 0.18$ ;  $1.16 \pm 0.26$ ,  $1.19 \pm 0.42$ , and  $1.14 \pm 0.15$ . Norway deserves special attention here, as its efficiency should be considered the lowest among all 22 countries (in three consecutive years the efficiency index was close to 2). This is the result of the success in the implementation of electromobility, but in the group of passenger cars. Incentives offered by the Norwegian government have helped to boost BEV sales. Residents who switched to electric cars stopped using public transport. Consequently, the sector experienced a decline and was unable to allocate additional funds to low- and zero-emission mobility.

The average efficiency index of inefficient countries (with the exception of Norway and the Netherlands) has decreased marginally in the period under review and amounts to approximately  $1.09 \pm 0.09$ . The median for all inefficient countries in subsequent years was: 1.07, 1.11, 1.05, 1.05, and 1.04, respectively. Thirteen out of 22 countries have efficiently implemented electromobility processes in public transport at least once in 2019-2023, as evidenced by the values of the efficiency index. These include Croatia, Denmark, Estonia, Germany, Luxembourg, Latvia, France, the Netherlands, Norway, Italy, Poland, Portugal, Slovenia, and Spain. Moreover, the median should be considered as low, which is the result of uniform rules imposed on countries as part of EU's climate policy.

A preliminary review of the performance indicators in Table 1 indicates clear variations between countries. The averages and corresponding standard deviations provide a clearer indication of these trends. They remain visible even when Norway is excluded. Therefore, the answer to the first research question is in the affirmative. The same table also shows that a small group of countries were effective for most, or even all, of the period under review. This addresses the second question raised.

The second part of the study was to establish benchmarking formulae for all inefficient countries to identify the efficient DMUs that are influence leaders. Influence leaders were countries that appeared at least once in the benchmarking formula for any country with an efficiency index of  $\delta > 1$ . Table 2 presents twelve countries for which the efficiency index was equal to 1 at least once in the years 2019-2023 and which were also influence leaders at the same time.

**Table 2.**

*The frequency of occurrence of efficient countries that created benchmarks*

DMU	2019	2020	2021	2022	2023	Sum
CRO	2	0	0	7	9	18
DEN	0	0	3	9	0	12
EST	0	0	0	2	0	2
FRA	5	0	1	1	2	9
GER	0	0	1	0	0	1
LUX	14	4	7	15	2	42
NET	2	5	0	0	0	7
NOR	0	0	0	0	2	2
POL	0	0	11	0	0	11
POR	0	0	0	0	13	13
ROM	0	15	0	0	0	15
SLO	10	13	9	0	1	33
SPA	0	0	0	0	2	2
SWE	0	0	1	0	0	1

Source: own work.

The values in Table 2 indicate the number of times a given country appeared in the benchmarking formula in a given year for a country considered inefficient, i.e. it was an influence leader for that country. Luxembourg and Slovenia were the most common benchmarks for inefficient countries. They were the influence leaders every year. Croatia, Poland, Portugal and Romania are also included among the countries that are frequently used as benchmarks for the largest number of countries. In 2021 and 2020, Poland and Romania achieved the efficiency index of one, respectively. However, they appeared in a significant number of benchmarking formulas (11 and 15 times, respectively).

The second objective of the study was to identify macroeconomic factors impacting the achievement of influence leader status in the implementation of electromobility in public transportation, and to examine the direction and strength of their influence on this status. In order to do so, the parameters of a probit panel model were estimated. All variables included 88 observations – 22 observations for each of the four years of the study period. Although the

study covered five years, a one-period lag was applied. Hence, the data series were limited to the years 2020–2023.

Of the potential explanatory variables mentioned earlier, only two were found to be significant: GDPPC - real GDP per capita [EUR] and dPOLTINC - the difference between the POLTINC variable for a given year and the previous year [millions EUR]. The results of the panel model estimation are presented in Table 3.

**Table 3.**

*The results of the panel model estimation*

Variable	Coef.	Std. Err.	z	P> z	Odds ratio
GDPPC	0.00002	0.00001	1.89	0.058	1.00002
dPOLTINC	0.0018	0.011	1.65	0.099	1.0018
const	-1.4705	0.4419	-3.33	0.001	

Source: own work.

The signs of the coefficients correctly reflect the direction of the changes previously assumed (Coef. – the second column of the table). Research indicates that an increase in real GDP per capita is associated with a higher probability of becoming an influence leader in the implementation of electromobility in public transport. It is estimated that an increase of 1000 EUR in real GDP per capita would result in a 2% rise in the DMU's chances of becoming an efficient country and an influence leader (see the Odds ratio column).

The sign at the estimated coefficient of the dPOLTINC variable is also positive. It was not the level of the income from taxes on environmental pollution that proved significant; rather, it was the increase compared to the previous year that was important. In this manner, national and local budgets are able to obtain funds that can be allocated to reduce the negative impact of human activity on the environment. One potential solution to this issue would be to reduce emissions from public transport by introducing electric vehicles. According to the odds ratio, an increase in revenue growth of 1 million EUR would increase the chances of achieving full efficiency by 0.2%.

The estimated parameters of the probit panel model will form the basis of further analysis. It is possible to formulate scenarios in which the probability of a DMU's status changing from zero to one and becoming an influence leader can be affected by a predetermined change in the value of the explanatory variables. Such scenarios were specified for those countries that had an efficiency index  $\delta > 1$  in 2023. Two “improvement” scenarios were assumed. The first one assumes a 5% increase in GDPPC and dPOLTINC, while the second one assumes a 10% increase in these variables. These scenarios do not assume a specific time horizon, only the probability of a positive change. Therefore, these are optimistic scenarios. The results of the calculations are presented in Table 4.

**Table 4.***The scenario analysis for non-efficient countries in 2023 (probability of status change [%])*

DMU	$\delta$	5% improv.	10% improv.	DMU	$\delta$	5% improv.	10% improv.
AUT	1,185	29.2	31	LAT	1,001	13.6	14.1
BEL	1,353	31.8	35.4	LIT	1,001	19.8	20.8
CZE	1,03	15.5	16	NET	1,453	86.6	93.9
DEN	1.131	37.8	41.7	POL	1,041	18.2	20.3
FIN	1,204	28	29.5	ROM	1,001	11.4	11.7
HUN	1,037	10.2	10.9	SWE	1,307	29.7	32.2
ITA	1,035	23.1	25.7				

Source: own work.

Improvements to GDP per capita and the income from taxes on environmental pollution by 10% do not result in a substantial increase in the likelihood of becoming an influence leader for other countries. It is also worth noting that the countries that were closest to the efficiency border ( $\delta < 1.01$ ), i.e. Latvia, would still need significant improvements to become influence leaders. Quite high probabilities appeared for the Scandinavian countries: Denmark, Finland, and Sweden. These countries have been engaged in sustainable development activities for many years.

## 5. Discussion

Let us compare first the list of influential leaders in Table 2 with the leaders in electromobility identified in the literature. As it turns out, the same countries appear in both cases. Research has been carried out in a number of countries, including Norway (Tucki et al., 2019; Rietman, Lieven, 2018) and the Netherlands (Rietman, Lieven, 2018; Kolibaba et al., 2025; Tucki et al., 2022). With regard to the cumulative number of new electric car registrations, the Netherlands, France, Germany, the United Kingdom, and Norway are mentioned (Tucki et al., 2019). In turn, Kucukvar et al. (2022) identified the countries that are most effective in terms of environmental efficiency in the use of BEVs. The following countries are the leaders in the article by Kucukvara et al. and in Table 2: Slovenia, Sweden, France, the Netherlands, Portugal and Denmark. The results of our study have been corroborated by existing literature, while concurrently adding value through the identification of leaders in the electrification of public transport.

The development of electromobility in public transport is primarily driven by the European Union's ambitious policy goals, which are focused on achieving climate neutrality. The overarching objective is to achieve climate neutrality by 2050, with a targeted intermediate goal of reducing greenhouse gas emissions by a minimum of 55% by 2030 (Fanti et al., 2017; Marotta et al., 2023). In accordance with EU Regulation (EU) 2019/631, a ban on the registration of new vehicles with internal combustion engines (ICE) in EU member states is to

come into force in 2035 (Mazur et al., 2024). The findings of our study suggest that top-down measures by the authorities may prove effective, at least in the case of the electrification of public transport.

As shown in Table 4, the countries with the highest probability of achieving full efficiency in electromobility adoption for public transport are also the countries best placed to transform the current mobility model (3.0) into the Mobility 4.0 model described by Motowidlak and Bukowska-Piestrzyńska (2024). It assumes the creation of new value through interactions between the transport sector, the automotive industry, the electricity sector, and other industries. This appears to be a logical conclusion, given the substantial impact of GDP on the panel model. Overall economic development is both the driver and beneficiary of electromobility.

As Nanaki et al. (2022) have noted, such scenarios can inform government decisions. However, it should be noted that, in their opinion, at least in the case of Greece, subsidies are the most effective measure, and they considered the CO<sub>2</sub> tax to be insufficiently effective in making EVs more competitive.

The second research question addressed the issue of changes in efficiency over the five-year period covered by the study. Therefore, Table 5 includes the values of the Malmquist productivity index and sub-indices.

As shown in Table 5, there are significant differences between countries in terms of the implementation of electromobility in public transport. MI values range from 0.22 to 5.639. The most significant enhancement in efficiency was achieved in Italy, with an increase exceeding 450%. Portugal, Spain, Romania and Poland also recorded very high increases. In contrast, the Netherlands and Luxembourg recorded declines of 70-78%. Half of the countries surveyed had an MI index of no more than 0.779, indicating a decline in efficiency of over 20%. An increase was recorded in nine countries.

An analysis of the sub-indices reveals the reasons for this situation. It is important to note that only two countries (Italy and Portugal) demonstrated an increase in technical efficiency. The median  $TE_v$  was only 0.357. A decline of considerable significance was observed in most countries, with a concomitant shift away from the efficiency frontier.  $TP_v$  values fluctuate around 1 (with a median of 1.004). It is notable that Norway is the only country in which there has been an increase, and that increase is almost 140%. From 2019 to 2023, no significant changes in the efficiency of electromobility implementation in public transport due to technological changes were observed in Europe.

**Table 5.***Efficiency dynamics between 2023 and 2019*

	MI	TE <sub>v</sub>	TP <sub>v</sub>	SE		MI	TE <sub>v</sub>	TP <sub>v</sub>	SE
AUT	0.361	0.191	0.965	1.965	LAT	0.700	0.275	1.029	2.473
BEL	1.186	0.993	0.853	1.399	LIT	0.685	0.292	1.032	2.274
CRO	0.700	0.421	1.000	1.663	LUX	0.289	0.289	1.000	1.000
CZE	0.682	0.444	1.053	1.459	NET	0.220	0.240	0.688	1.329
DEN	1.301	0.487	0.910	2.938	NOR	0.878	0.174	2.366	2.134
EST	0.646	0.630	1.017	1.008	POL	3.261	0.750	0.989	4.394
FIN	0.857	0.346	0.900	2.751	POR	4.134	1.138	1.008	3.604
FRA	1.618	0.305	1.000	5.312	ROM	3.908	0.750	1.038	5.019
GER	2.379	0.321	1.180	6.282	SLO	0.588	0.368	1.000	1.596
HUN	0.692	0.403	1.013	1.694	SPA	3.911	0.273	1.170	12.269
ITA	5.639	1.120	1.120	4.497	SWE	0.390	0.182	0.817	2.623

MI – Malmquist productivity index, TE<sub>v</sub> – change in technical efficiency, TP<sub>v</sub> – change in the position of the empirical production function, SE – scale efficiency change.

Source: own work.

All countries except Luxembourg experienced a significant increase in economies of scale. This was particularly evident in Spain, but the median of 2373 clearly demonstrates a qualitative change in the utilisation of electric rolling stock in the countries surveyed over the five-year period.

## 6. Conclusions

The first goal of the article was to identify European countries that demonstrated a high degree of efficiency in implementing electromobility processes in public transport during the 2019-2023 period. For this purpose, the DEA method, specifically the BCC model, was used. This approach enabled the identification of a group of countries that, with minor exceptions, demonstrated a relatively high level of success over the five-year period: Croatia, Denmark, Estonia, France, Germany, Luxembourg, Netherlands, Portugal, Poland and Slovenia. Some of them: Luxembourg, Slovenia, Denmark, Croatia and France have taken on the role of influence leaders for other countries

The second goal of the paper (and the third research question) was to identify the macroeconomic factors that were important in becoming an influence leader in the implementation of electromobility in public transportation. The factors identified in this study included real GDP per capita and the difference between the income from taxes on environmental pollution for a given and the previous year. The panel model results confirmed the predicted direction of change for the explanatory variables. Furthermore, they enabled the estimation of the likelihood of positive changes in the implementation of electromobility in public transport, a key consideration for countries with inefficient processes.

The scenario analysis based on the panel model presented in section 4 is a useful tool to support government decisions. It demonstrates which factors should be selected and how they should be modified to enable the country to successfully introduce electric public transport. This approach offers significant benefits in both scientific research and macro-level management.

The study's limitations have been identified by other researchers. Rietman and Lieven (2018) suggested that a sample of 20 countries might be considered too small, but ultimately deemed it sufficient. There were 22 countries in our study. Almeida Neves et al. (2020) highlighted in the section of their study utilising DEA that only a limited number of countries were positioned on the efficiency frontier. In their view, this may impact how well the model aligns with the data. We too encountered this issue.

The authors are aware that their study, which examined the efficiency of electromobility processes in public transport, does not cover the entire problem. The results obtained using the DEA method may be sensitive to the number of DMUs, which has been limited as a result of data availability. Therefore, further efforts should be made to fully complete the data. In addition, the authors considered the sole appearance of the effective DMU in the benchmarking formula, ignoring the number of its appearances in all formulas. Future research should evolve to apply a procedure for determining the target share of inputs in a target technology based on the inputs “contributed” to the target technology by the benchmark DMU (Guzik, 2009). Following the implementation of this procedure, we will obtain a share of that part of the target input (output) contributed by effective DMU's technology in the final technology.

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