THE FACTORS LEADING TO A SURGE IN ELECTRIC VEHICLE SALES: A PANEL DATA ANALYSIS FOR OECD COUNTRIES

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ABSTRACT

THE FACTORS LEADING TO A SURGE IN ELECTRIC VEHICLE SALES: A PANEL DATA ANALYSIS FOR OECD COUNTRIES

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This thesis aims to scrutinize the determinants of Electric Vehicle (EV) sales incorporating socioeconomic and other factors through a panel data analysis covering 23 OECD countries over the period from 2010 to 2022. After using panel data analysis for the Fixed Effects model, we extend our study through a one-step difference Generalized Method of Moments (GMM) and system GMM techniques to analyze the data under the possibility of the presence of endogeneity. We show that the first lag of EV sales, the number of charging stations from the previous year, GDP per capita and years of schooling have positive and significant effects on EV sales based on difference GMM estimation. The findings indicate that years of schooling is the most influential factor in the adoption of EVs. It is also revealed that the other variables have no statistically significant effect on EV sales including oil prices, unlike the studies that cover a shorter period of time.

Keywords: Electric Vehicles, Crude Oil Price, Socioeconomic Factors, Panel Data, GMM

ÖZ

ELEKTRİKLİ ARAÇ SATIŞLARININ ARTMASINA YOL AÇAN FAKTÖRLER: OECD ÜLKELERİ İÇİN BİR PANEL VERİ ANALİZİ

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Bu tez sosyoekonomik ve diğer faktörlerin elektrikli araç satışları üzerine olan etkisini 2010-2022 yılları arasında 23 OECD ülkesi için panel veri analizi uygulayarak incelemeyi amaçlamaktadır. Panel veri analizini sabit etkiler modeli için uyguladıktan sonra, araştırmamızı endojenite ihtimali altında inceleyebilmek için tek adımlı fark GMM ve sistem GMM teknikleri ile genişletiyoruz. Fark GMM tahminine göre, elektrikli araç satışlarının ilk gecikmeli değişkeninin, şarj istasyonları sayısının ilk gecikmeli değişkeninin, kişi başına düşen gayrisafi yurtiçi hasılanın (GSYİH) ve okul yılları değişkeninin elektrikli araç satışları üzerine olumlu ve anlamlı bir etkiye sahip olduğunu görmekteyiz. Sonuçlar gösteriyor ki bu faktörler arasında elektrikli araca sahip olmada en yüksek etkiye sahip değişken okul yıllarıdır. Daha dar bir zaman aralığını kapsayan geçmiş çalışmaların aksine, petrol fiyatları da dahil diğer değişkenlerin elektrikli araç satışları üzerine istatistiki olarak anlamlı bir etkiye sahip olmadıkları açıklanmaktadır.

Anahtar Kelimeler: Elektrikli Araçlar, Ham Petrol Fiyatı, Sosyoekonomik Faktörler, Panel Veri, GMM

To My Beloved Mother

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LIST OF ABBREVIATIONS

BEV	: Battery Electric Vehicle
CD	: Cross-Dependence
CO_2	: Carbon Dioxide
COP21	: The 21st Conference of the Parties
EPI	: Environmental Performance Index
EU	: European Union
EV	: Electric Vehicle
FE	: Fixed Effect
GDP	: Gross Domestic Product
GHG	: Greenhouse Gas
GMM	: Generalized Method of Moments
ICEV	: Internal Combustion Engine Vehicle
IEA	: International Energy Agency
MSA	: Metropolitan Statistical Area
OECD	: The Organization for Economic Cooperation and Development
OEM	: Original Equipment Manufacturer
OLS	: Ordinary Least Squares
OPEC	: Organization of the Petroleum Exporting Countries
PHEV	: Plug-in Hybrid Electric Vehicle
POLS	: Pooled Ordinary Least Squares
RE	: Random Effect
St. Err.	: Standard Error
UK	: United Kingdom
USA	: United States of America

CHAPTER 1

INTRODUCTION

The rising prominence of electric vehicles (EVs) is driven by their ability to boost energy efficiency and curb local air pollution, offering a compelling alternative to conventional internal combustion engine vehicles (ICEVs). EVs are pivotal in the ongoing efforts to reduce carbon dioxide (CO_2) emissions and enhance sustainability in the transportation industry. The emissions savings from an EV vary between 28% when compared to a luxury diesel vehicle and 42% when compared to a small petrol vehicle over its average service life of 13 years as long as governments pursue their current policies that aim to cut greenhouse gases (GHGs) substantially (Wietschel et al., 2019). Even future EVs are projected to have an impact on climate change lower than those of today’s EVs with the help of technological improvements in the fields of charging electricity, refurbished battery life cycle and recycling (Cox et al., 2018; Koroma et al., 2022).

The European Commission is trying to reach its aim of mitigating GHG emissions by 55% relative to levels observed in 1990 in liaison with the Paris Agreement setting the objective of restricting global warming to 1.5°C (Fetting, 2020). The aspects mentioned above of EVs highlight their importance in meeting global targets on condition that problems regarding electricity generation and battery production are solved. Therefore, studies on EVs have been drawing more attention amid rising global concerns about carbon emissions, which brings about our research motivation on EVs.

This study primarily seeks to explore the impacts of selected factors on the demand for EVs. Especially, it is questioned whether oil price has an impact on EVs or not. It is assumed that oil prices could be a greater financial incentive for the adoption of EVs inasmuch as policies are trying to switch consumer preferences from ICEVs to

EVs. We should note that in this study the definition of EVs encompasses both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs); therefore, the share of PHEVs using both electricity and gas may impede us from inferring such a relationship. Nevertheless, we find it worthwhile to investigate the presence of crude oil prices affecting EV sales.

In this thesis, we use 23 OECD countries' data on EV sales and its potential determinants. This study differs from previous literature in terms of the time span (includes a longer time horizon from 2010 to 2022 compared to other studies). We also do our estimation using static as well as dynamic estimation methods. The results also tend to differ slightly compared to the previous literature.

In Chapter 2 of this thesis, we give a historical background of EVs starting from the second half of the 19^{th} century. In Chapter 3, we provide information on the relatively new literature on EVs. We go on to present our data set and model in Chapter 4 along with giving empirical findings. In Chapter 5. we summarize the outcomes of econometric analyses as a conclusion of the thesis and provide practical recommendations for policy makers and future works based on these findings.

CHAPTER 2

HISTORICAL BACKGROUND OF ELECTRIC VEHICLES

2.1. The Early Growth and Subsequent Decline of the EVs

Electric vehicles have gained much importance in recent years in an attempt to combat carbon emissions. In fact, the history of EVs begins with the advent of lead-acid batteries around the latter half of the 1800s. French physicist Gaston Plante invented the lead-acid battery in 1859, marking it as the pioneering rechargeable battery. Although the first crude electric vehicle was developed by Robert Anderson in around 1832, it was not practical. With the invention of lead-acid batteries, EVs became more practical since they enable better storage capacity. In the late 1800s, several attempts in the manufacturing of EVs appeared. In 1881, Gustave Trouvé showcased an electric-motor-powered tricycle at the International Electricity Exhibition in Paris. The Flocken Elektrowagen, invented by the entrepreneur Andreas Flocken, is considered the first electric car and made its debut in Germany in 1888. In the United States, around 1890, William Morrison introduced the first successful electric car. In 1897, Walter Bersey introduced London's first self-propelled electric taxis for hire, marking a significant innovation in transportation.

During the latter part of the 19^{th} century and the early 20^{th} century, EV gained so much popularity because of its advantages over its rivals. Most importantly, they were easy to drive whereas gasoline-powered cars required gear changes. Furthermore, they ran quietly and did not make noises. Electricity also became widespread so recharging them was convenient.

Many factors contributed to the decline of EVs in the 1920s. Firstly, Henry Ford’s launch of mass production for ICEVs resulted in their widespread availability and affordability for the public. In 1908, he introduced the Model T, making gasoline-powered cars accessible to a wide range of people. In 1912, the price for a gasoline car was just $650, whereas an electric roadster was priced at a higher price of $1,750. (Matulka, 2014). Also, the early 20th century witnessed the discovery of Texas petroleum reserves. Texas oil boom dramatically reduced the price of oil. Gas stations were proliferated together with the installation of a wide range of road systems in the US. Besides, electricity was still largely confined to urban areas and not yet widely accessible beyond city centres, which made longer trips difficult by EVs. All in all, consumer preferences switched from EVs to ICEVs; as a result, EVs had largely disappeared by 1935.

2.2. The Resurgence of Electric Vehicles

Boeing and General Motors (GM)' subsidiary Delco Electronics contracted by National Aeronautics and Space Administration (NASA) built the Lunar Roving Vehicle for the Apollo 15 mission, and they chose electric power due to the moon's lack of atmosphere. The LRV, affectionately known as the "Moon buggy", sported individual DC drive motors in each wheel, powered by a pair of 36-volt silver-zinc potassium hydroxide non-rechargeable batteries. The electric propulsion system developed by GM also drove several land-based electric vehicles, including the Electrovair I and Electrovair II, as well as the distinction of being the world's inaugural fuel cell vehicle known as the Electrovan.

On October 6, 1973, the Arab-Israeli war broke out. Seeking to exert influence on Western countries and enforce Israel's withdrawal from occupied lands, Arab countries of OPEC (Organization of the Petroleum Exporting Countries) started significant reductions in oil production (Hammes and Wills, 2005). Following OPEC's oil embargo in 1973, which led to a quadrupling of per-barrel prices to $12 overnight, electric cars began to appear as a more attractive alternative.

Moreover, in the 1970s, British chemist M. Stanley Whittingham achieved a milestone by developing the initial rechargeable lithium-ion batteries. These breakthrough advancements revived the interest in EVs once again. Together with environmental concerns, the early 1990s witnessed a wide range of EVs made by different brands. GM's EV1 with its 80-mile range and acceleration from 0 to 50 miles per hour in just seven seconds was one of the most popular electric cars. Nissan Altra produced by Nissan Motors in 1998 was the first electric car to use lithium-ion battery. The Toyota Prius became historically significant as the first hybrid electric vehicle to be produced on a large scale.

The 2010s have been the heyday of EVs' history. Tesla Roadster, which was produced by Tesla Motors in 2008, paved the way for dramatic shifts from gasoline cars to electric cars. In the same year, Chinese manufacturing company BYD debuted its inaugural plug-in hybrid vehicle, the F3DM, on December 15. This first series of production PHEV is said to offer a 100-kilometre (62-mile) range on battery power, followed by an extra 300 kilometres (267 miles) using its conventional 1.0-litre petrol engine (Wang and Kimble, 2010). PHEVs employ batteries for electric motor propulsion and a secondary fuel, like gasoline or diesel, for powering an internal combustion engine or alternative propulsion mechanism. Subsequently, the series production of Chevrolet Volt as a PHEV was delivered to customers in the early 2010s. Also, in the US and Japan markets, the Nissan Leaf was available for battery electric vehicle in 2010.

2.3. Current Trends in Electric Vehicle Adoption

Since the 2010s, the number of models has been immensely increasing and the product range has been widened. In 2022, electric car sales surpassed 10 million (14% of total new car sales) with the following distinction among the three biggest markets: China 60%, Europe 15%, and the USA 8% as shown in Figure 1 (IEA, 2023). Electric vehicle sales continued to thrive in 2023, surpassing the figures from 2022 by roughly 35% year-on-year, achieving a total of nearly 14 million units sold (IEA, 2024).

It is also possible to see original equipment manufacturer (OEM) rankings in 2023 in Table 1. As can be seen, global electric vehicle sales are predominantly led by Chinese automaker BYD and American Tesla. Also, the availability of EV models has dramatically improved.

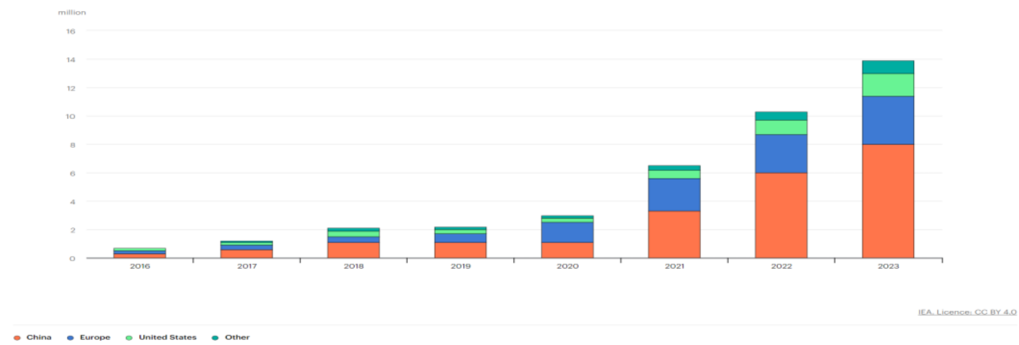

Figure 1. Electric car sales, 2016-2023

Source: IEA (2023)

Table 1. Global EV Sales By OEM for 2023

Rank	OEM	2023	%(y-o-y)
1	BYD	3,012,070	22.0%
2	Tesla	1,808,652	13.2%
3	Volkswagen Group	994,403	7.3%
4	Geely-Volvo	925,111	6.8%
5	SAIC	791,521	5.8%
	Total	13,689,291	

Source: CleanTechnica, 2023

This incessant growth leads us to take a more optimistic view of the future of EVs. As depicted in Figure 2, BEV sales in Europe are expected to prevail over internal combustion engine vehicles in 2025. There are miscellaneous underlying reasons for this soaring interest in EVs, which comprises the nucleus of this study.

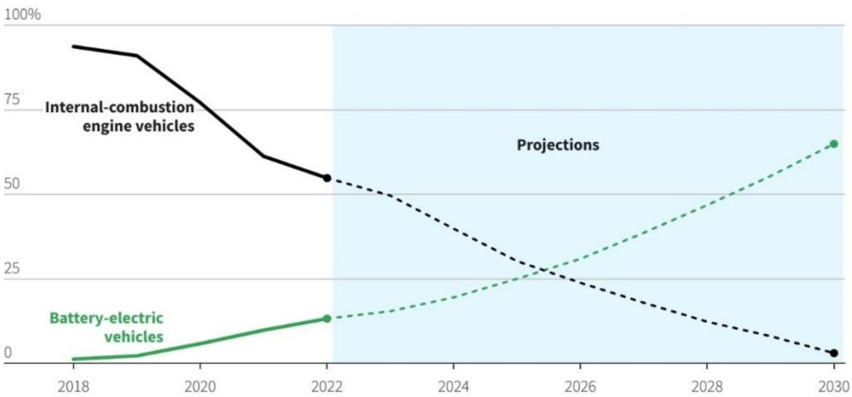

Figure 2. The share of BEV Sales in Europe

Source: Reuters by Sumanta Sen (2023)

Most importantly, EVs offer a solution to reduce CO_2 and pollutant emissions even when considering emissions that arise indirectly from generating electricity and manufacturing batteries. Also, it is anticipated that the costs associated with CO_2 mitigation will decline in the future due to technological advancements and the expanding use of renewables in electricity generation (Weiss et al., 2019). In 2015, in an effort to mitigate the adverse effects of global warming, Paris Agreement came into being. Besides, during COP21, The Paris Declaration on Electro-Mobility and Climate Change & Call to Action was announced. According to this declaration, achieving the objective of restricting the rise in global temperatures to below 2 degrees Celsius necessitates altering the trajectory of transportation emissions, as a result, it is required that at least 35% of all road transport vehicles worldwide will be electrically driven by 2030 to meet the targets. The adoption of electric cars is projected to result in the avoidance of emissions equivalent to around 700 million metric tons of CO_2 in 2030 (IEA, 2023).

The global energy-related GHG emissions from the transportation sector, amounting to nearly one-quarter (24 per cent), are increasing at a faster pace compared to any other energy end-use sector (Ritchie, 2020). Therefore, a rapid transition from fossil fuels to electricity and low-emission fuels is needed, which highlights the importance of EVs. McLaren et al. (2016) also showed that promoting the expansion of renewable energy sources, coupled with the increase in workplace charging facilities, can play a pivotal role in reducing emissions associated with EVs.

Additionally, the driving range of EVs has constantly increased, as shown in Figure 3, which assists customers in transitioning from ICEVs to EVs. Kim et al. (2017) point out that range significantly influences the market share of electric vehicles, making it one of their key characteristics. In 2023, the average driving range of EVs is 377 km, which is still a shorter distance than what many gasoline-powered cars can achieve on a full tank (ev-database.org/2023). According to the survey conducted by EY in 2022, one-third of new car buyers identified range anxiety as their primary concern when considering the purchase of electric vehicles (Samant et al., 2022). It seems to remain one of the great inhibitors for adopting EVs in the near future.

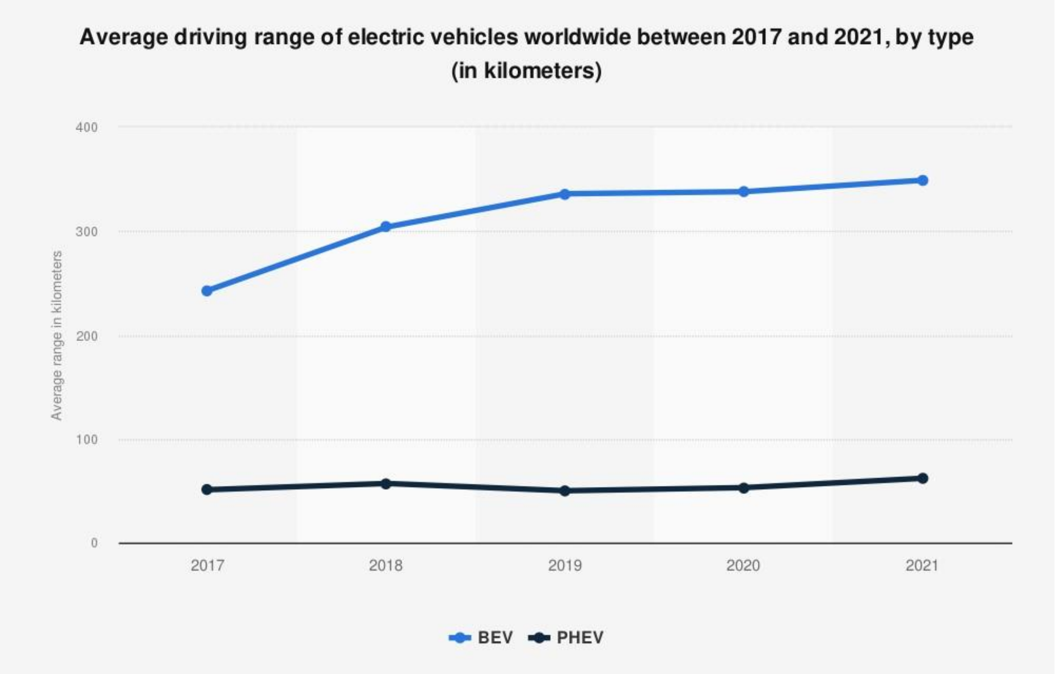

Figure 3. Average driving range of EVs between 2017 and 2021

Source: Statista (2024)

CHAPTER 3

LITERATURE REVIEW

As we discussed in Section 2, the origin of EVs dates back to the 1850s. However, there has been a surge in interest in EVs recently. Figure 4 shows us the frequency which people search for ‘Electric Vehicle’ on Google, as reported by Google Trends. Especially after the second half of 2020, an increasing number of people began to consider having one of them. One of the underlying reasons for this change is that despite reducing the volume of EV sales at the beginning, the Covid-19 pandemic has the effect of spurring the demand for EVs (Wen et al., 2021). After it reached its peak at the beginning of 2022, there has been a small reduction in searches as a result of a number of hikes in interest rates in developed countries corresponding to swelling inflation rates.

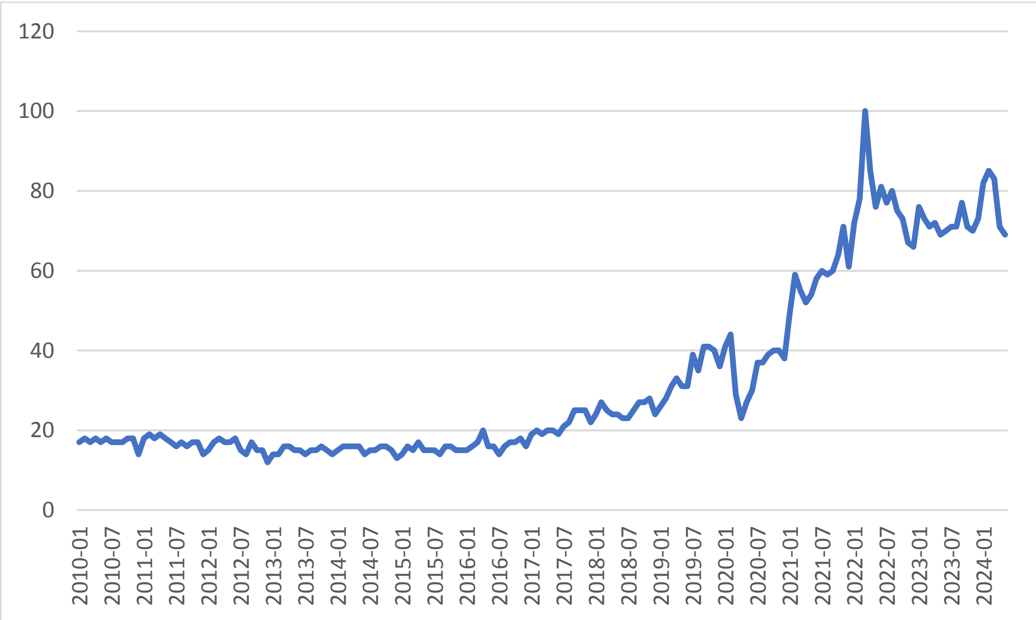

Figure 4. Interest in EV over time

Source: Google Trends (2024)

Recent interest in EVs has also accelerated academic work on EVs. However, in early studies, researchers took the topic at hand by using the data for hybrid vehicles. We begin to analyse the existing literature by reviewing articles on hybrid vehicles. Then, we go on to look at the research for EVs. Table 2 summarizes the lists of main articles that contribute to our study.

Table 2. List of Articles

Article	Focus of Study	Country	Year
Azar, "Electric Cars and Oil Price", (2009).	Oil price and interest in EV	USA	2004 - 2009
Gallagher and Muehlegger. "Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology", (2011).	The effect of state incentives and gasoline prices on hybrid vehicles	USA	2000 - 2006
Beresteanu and Li, "Gasoline Prices, Government Support, And The Demand For Hybrid Vehicles In The United States", (2011).	The effect of gasoline prices and tax incentives on hybrid vehicles	USA	1999 - 2006
Sierzchula et al., "The influence of financial incentives and other socio-economic factors on electric vehicle adoption", (2014).	The relationship between socioeconomic factors and EV market share	Australia, Austria, Belgium, Canada, China, Croatia, the Czech Republic, Denmark, Estonia, Finland, France, Greece, Germany, Iceland, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, Türkiye, UK, USA	2012
Li et al.,"Impacts of renewables and socioeconomic factors on electric vehicle demands – Panel data studies across 14 countries", (2017).	The effect of socioeconomic factors on EV demand	USA, China, Germany, UK, France, Canada, Sweden, Norway, Italy, Spain, Portugal, Japan, South Korea and New Zealand	2010 - 2015
Arnob," Effect of electric vehicle sales on the price of oil", (2021).	The relationship between gasoline prices and EV	Belgium, Brazil, Canada, China, Finland, France, Germany, Greece, India, Italy, Japan, Netherlands, New Zealand, Norway, Poland, South Korea, Spain, Sweden, UK, USA	2010 - 2019
Yan, "The economic and environmental impacts of tax incentives for battery electric vehicles in Europe", (2018).	The effect of vehicle taxes and purchase subsidies on the adoption of EV	28 European Countries	2012 - 2014
Chandra, "Investigating the impact of policies, socio-demography and national commitments on electric-vehicle demand: Cross-country study", (2022).	The influence of policies and incentives, national commitments, and socioeconomic conditions on EV demand	Canada, China, India, Japan, France, Germany, Netherlands, Norway, UK and USA	2013 - 2019
Bushnell et al., "Energy Prices and Electric Vehicle Adoption", (2022).	The effect of gasoline and electricity prices on EV demand	USA	2014 - 2017

Research on hybrid vehicle demand can offer insights into the market for electric vehicles. Gallagher and Muehlegger (2011) analyze the data on hybrid sales, state incentives, and gasoline prices. The authors classify hybrid vehicles as high fuel economy and low fuel economy according to their average gas mileage. It is discovered that an increase of 10% in gasoline prices leads to an 8.6% increase in the sales of high fuel-economy hybrid vehicles per person. Additionally, their research suggests that the cross-price elasticity for low fuel-economy hybrid vehicles is statistically indistinguishable from zero. We learn from their article that an increase of $100 in annual fuel savings corresponds to a 13% rise in hybrid vehicle sales. Similarly, Beresteanu and Li (2011) examine the effect of gasoline prices and federal tax incentives on hybrid vehicle sales at the Metropolitan Statistical Area (MSA) level. Their study conclude that both gasoline prices and federal incentives significantly boost hybrid vehicle sales. Specifically, they note if gasoline prices in 2006 had remained at the 1999 level of $1.53 per gallon, rather than increasing to $2.60, hybrid vehicles sold in 2006 would have been 37% reduced. In addition, Diamond (2009) shows even small fluctuations in gasoline prices could result in dramatic shifts in adopting hybrid vehicles. These articles on hybrid vehicles clearly point out that there exists a positive and statistically significant relationship between gasoline prices and hybrid vehicle sales. Therefore, we expect to see a similar result when we conduct the same analysis for EVs rather than hybrid vehicles.

Sierzchula et al. (2014) analyze EV adoption incorporating several socioeconomic factors by using the data for 30 countries for the year 2012. In the econometric model, there are the following variables: EV market share, financial incentives, urban density, education level, EPI as an environmentalism indicator, fuel price, EV price, presence of production facilities, per capita vehicles, model availability, introduction date, charging infrastructure and electricity price. According to the results, charging infrastructure and financial incentives have significant and positive coefficients. The charging station has the highest beta values. Fuel price did not show significance in predicting the market share of EVs. It is important to note again that the study is cross-sectional using the year 2012 only. Also, there is no greater variation in fuel prices in those countries. In our study, we examine the selected countries throughout several years. Besides, oil price data across countries show some variations in our study. For instance, the crude oil import price for Australia was 110.7 USD per barrel in 2022 while the USA had 89.7 USD per barrel of oil in 2022. Therefore, we want to retest whether oil prices influence EV sales by following Sierzchula et al.'s recommendation.

Li et al. (2017) try to show the relationship between EV demand and socioeconomic factors for 14 countries for the years between 2010 and 2015. There are seven socioeconomic factors in the model and these variables are the percentage of renewables in electricity generation, gasoline price, charger density, education level, population density, GDP per capita and urbanization. According to the results, all factors have a positive and significant impact on EV sales except for GDP per capita and urbanization rate. The authors find that the coefficient of gas price is positive, which means that higher gasoline price raises EV demand. However, the authors separate the effect of gasoline prices into BEVs and PHEVs, so the impact of gas prices on BEVs is larger than PEVs. Likewise, Chandra (2022) also finds a similar result for the effect of high fuel prices on BEV sales. The authors offer gas taxes as a policy implication in order to help drivers to switch their preferences to BEVs.

There are also other studies investigating the relationship between oil prices and EV demand. Azar (2009) points out that increases in public interest in EVs result in a negative response to oil prices. He states that variations in the interest levels in electric vehicles can account for nearly 50% of the price reduction observed during the latter half of 2008. Arnob (2021) gathers data from 20 countries spanning the years 2010 to 2019 to see the effect of EV sales on oil prices. According to his findings, a 0.04% increase in EV sales leads to a 1% decrease in oil prices. Existing literature clearly demonstrates the importance of gasoline prices in explaining EV demand. Even, the demand for EVs is more strongly influenced by gasoline prices than by electricity prices (Bushnell et al., 2022).

In addition, other factors significantly influence the promotion of EV adoption. A number of tax incentives such as tax exemptions or price subsidies have been implemented by many countries in an attempt to encourage to switch consumers' preferences towards EVs. For instance, in Türkiye, tax incentives are implemented to influence consumer preference for electric vehicles. Before 2018, there was no Motor Vehicle Tax for fully electric cars and after that, only 25% of Motor Vehicle Tax for ICEVs have been charged for EVs (Gündüz and Yakar, 2020). Yan (2018) claims that increasing tax incentives by 10% typically causes the market penetration of BEVs to rise by approximately 3%.

The primary contribution of this thesis lies in its more detailed datasets. After scrutinizing the existing literature, we add selected socioeconomic factors together with crude oil prices and charging points in an attempt to explain the determinants influencing EV sales. In addition, the period covers between the years 2010 and 2022, which makes our study important in a way that it fills the gap there is no study in the literature to cover the post-COVID-19 period. Also, in some countries such as Türkiye, the Paris Agreement entered into force in 2021, which may raise social awareness for net zero carbon emission later than other OECD countries. Therefore, it is important to use the estimations to cover the latest time the data is available to broaden our understanding of the factors influencing EVs.

CHAPTER 4

DATA SET AND MODEL

4.1. Data Set

The study relies on the data collected from 23 OECD countries. The countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Japan, Netherlands, New Zealand, Norway, Poland, Portugal, South Korea, Spain, Sweden, Switzerland, Türkiye, United Kingdom, United States for the time period between 2010 to 2022. The study is based on these selected countries as a result of the availability of the data set for EV sales and the number of charging stations. Also, the countries are selected among OECD countries since they have similar economic characteristics, which decreases the level of heterogeneity.

The dependent variable is electric vehicle sales, which encompasses the number of both BEV and PHEV sales. EV sales data is set per 100,000 people. The main independent variable is crude oil price. The other independent variables are EPI (environmental performance index), charging stations (per 100,000 people), renewables (% of renewables in electricity generation), GDP per capita, years of schooling and urbanization rate (% of total population). In Table 3, we present the variables and their sources.

Table 3. Description and Sources of Data Set

Variable	Data	Source
EV	Number of electrical vehicles per 100 thousand people	IEA Global EV Data 2023
CRUDE	Crude oil import prices, us dollars/barrel	OECD Data
EPI	Environmental Performance Index	Yale University (Wolf et al., 2022)

Table 3. (continued)

CHRG	Number of charging stations per 100 thousand people	IEA Global EV Data 2023
RNW	Share of renewables in electricity generation	World Energy Balances 2023
GDP	GDP per capita, current prices (US$)	The World Bank
YOS	Average number of years adults over 25 years participated in formal education	UNDP, Human Development Report 2022
URB	Urban population (% of total population)	The World Bank

Importantly, EPI score taking values between 0 and 100 offers a numerical basis for analyzing and comprehending the environmental performance of countries. However, EPI is available every two years. Therefore, we use linear interpolation, estimating a missing value by connecting existing data points in ascending order, to fill gaps in the missing years.

In Table 4, descriptive statistics can be found. For EV sales per 100 thousand people, the average is 160.27, with a maximum value of 3186.474 (Norway, 2022) and with a minimum value of 0.0001347 (Türkiye, 2011). We cannot observe EV sales data until 2011 for Australia, until 2011 for Finland, until 2013 for Greece, until 2011 for Switzerland, and until 2012 for Türkiye. In 2022, the USA had the highest number of EV sales with 990,000 sales, but we can see that Norway was ranked first when we set the data by 100 thousand people concerning its low population. Also, Norway has witnessed a rapid increase in EV sales, a trend attributed to the implementation of generous policies so-called 'Klimaforliket' promoting their use through such as exemption from VAT and other taxes (Holtsmark and Skonhoft, 2014). Standard deviations are similar for most of the variables except for EV sales and GDP per capita. For Crude Oil Price, EPI, Renewables, GDP Per Capita, Years of Schooling, and Urbanization, standard deviations are smaller than their mean values, which implies lesser dispersion in the dataset. However, for EV sales and Charging Points, standard deviations show greater variations across selected countries.

Table 4. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
EV	299	160.27	364.77	0.00	3,186.47
CRUDE	299	77.64	25.18	36.57	117.78

Table 4. (continued)

EPI	299	71.16	10.47	26.30	90.68
CHRG	299	38.99	80.41	0.00	702.14
RNW	299	39.36	25.68	1.25	99.07
GDP	299	44,695.03	19,484.43	8,612.90	105,825.90
YOS	299	12.10	1.54	7.09	14.13
URB	299	79.84	9.61	57.12	98.15

Table 5 shows the correlation coefficient matrix. The largest cross-correlation is 0.5879 between GDP per capita and years of schooling, which means there is no linear correlation. It is assumed that we can see a positive correlation between EV sales and crude oil prices; however, they are negatively correlated. We expected a positive correlation between them because when there is an increase in oil prices, this could lead to financial incentives for consumers to switch from ICEVs to EVs.

Table 5. Correlation Coefficient Matrix

	EV	CRUDE	EPI	CHRG	RNW	GDP	YOS	URB
EV	1.00							
CRUDE	-0.07	1.00						
EPI	0.05	-0.51	1.00					
CHRG	0.70	-0.08	0.03	1.00				
RNW	0.42	-0.06	0.26	0.23	1.00			
GDP	0.41	0.10	0.33	0.35	0.44	1.00		
YOS	0.19	-0.08	0.34	0.18	0.13	0.59	1.00	
URB	0.14	-0.02	0.09	0.23	-0.16	0.31	0.32	1.00

To find out a better understanding, it is drawn time-series graph for each country in Figure 5. Norway has the highest growth rate in EV sales together with another Scandinavian nation Sweden. From this graph, we can see that there is no correlation between EV sales and crude oil prices. Especially for Norway, EV sales per 100,000 people immensely increase whereas gasoline prices stay nearly constant over time.

Table 6. List of Countries

Country ID	**Country**	**Country ID**	**Country**	**Country ID**	**Country**
1	Austria	9	Netherlands	17	United States
2	Belgium	10	Poland	18	Australia

Table 6. (continued)

3	Denmark	11	Portugal	19	Japan
4	Finland	12	Spain	20	New Zealand
5	France	13	Sweden	21	Norway
6	Germany	14	Switzerland	22	South Korea
7	Greece	15	Türkiye	23	Canada
8	Italy	16	United Kingdom		

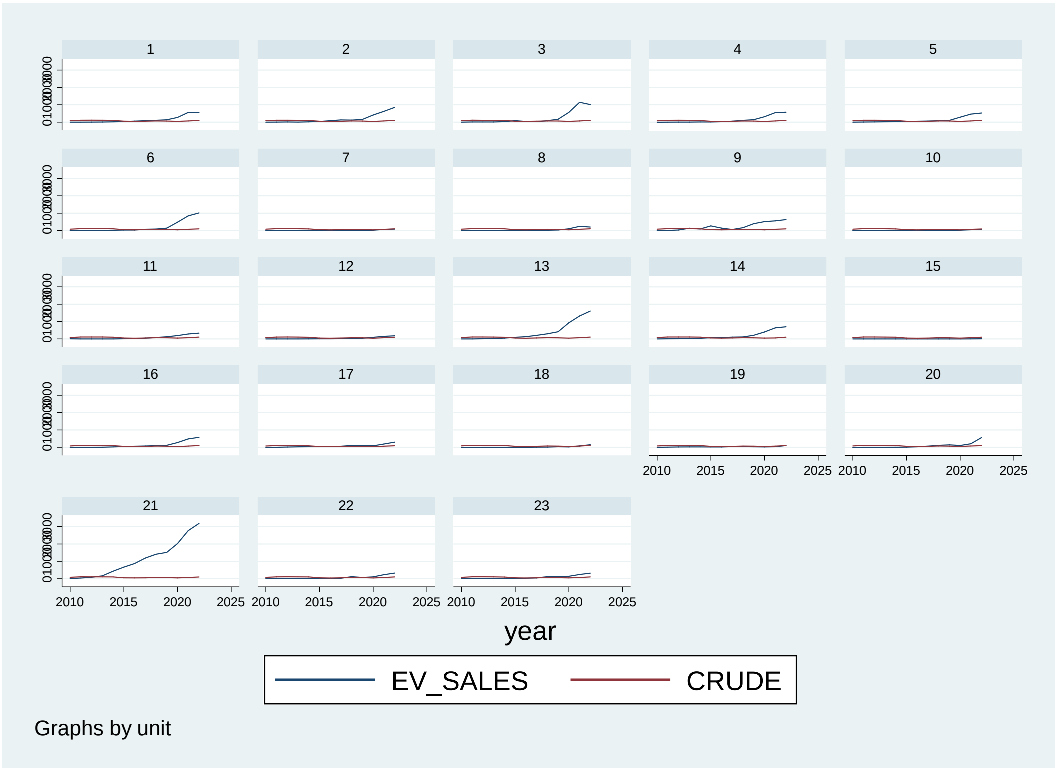

Figure 5. Time-series graph for each country

4.2. Model

The model is established as follows:

$$EV_{it} = \beta_0 + \beta_1 CRUDE_{it} + \beta_2 EPI_{it} + \beta_3 CHRG_{it} + \beta_4 RNW_{it} + \beta_5 GDP_{it} + \beta_6 YOS_{it} + \beta_7 URB_{it} + a_i + u_{it} \quad (4.1)$$

$$log(EV_{it}) = \beta_0 + \beta_1 log(CRUDE_{it}) + \beta_2 log(EPI_{it}) + \beta_3 log(CHRG_{it}) + \beta_4 RNW_{it} + \beta_5 log(GDP_{it}) + \beta_6 log(YOS_{it}) + \beta_7 URB_{it} + a_i + \epsilon_{it} \quad (4.2)$$

where subscription i and t mean i-th country and t-th year, respectively. Log-log model is formed on account of the exponential growth of EV sales as specified in equation 4.2. Also, a_i denotes time-invariant, i.e. fixed effects.

4.2.1. Empirical Results

The methodology used in this study is panel data analysis, which involves a combination of cross-sectional and time series data. Firstly, Fixed Effect (FE) estimation is chosen for this study. FE model puts intercept dummies for each cross-section and estimates the model by Pooled Ordinary Least Squares (POLS) estimator. To be more precise, FE estimation takes into account the cross-sectional heterogeneity by differentiating the intercepts for each cross-section. Table 7 summarizes the results of Fixed Effect estimation.

Table 7. Result of Fixed Effect Panel Regression

	FE
log_CRUDE	-0.41 (0.34)
log_CHRG	0.28** (0.03)
log_EPI	1.10 (0.85)
RNW	0.07** (0.02)
log_GDP	3.75** (1.00)
log_YOS	8.79* (4.92)
URB	0.66** (0.13)
constant	-117.65** (16.68)
observations	299
R-squared	0.75
F(7,269)	117.30**

Values in parentheses are standard errors. *p<0.10, **p<0.01

The F-test is useful to check the validity of FE estimation. Our null hypothesis H_0 is dummies are jointly equal to zero and our alternative hypothesis (H_a) is at least one of them is not equal to zero. If all dummies are equal to zero, it means that the model is the same as POLS. We can see that p-value is less than 0.05 since it is 0.00. So, we can reject the null hypothesis. Therefore, FE estimation must be preferred to POLS. As depicted in Table 7, the coefficients of Charging Points, Renewables, GDP per capita and Urbanization are both positive and significant at 1%. Besides, Years of Schooling has a positive and significant coefficient at 10%. However, Crude Oil Price and EPI score have statistically insignificant coefficients in the model.

When charging points per 100,000 people increases by 1%, EV sales per 100,000 people also increases by 0.28%. This result is consistent with our expectancy. People give great importance to the availability of charging points when they think about the uptake of EVs. Secondly, 1% increase in the share of renewables in electricity generation results in EV sales to increase by 0.07%. Countries with more renewables in their production of electricity tend to have more EV sales. Also, if GDP per capita increases by 1%, EV sales increase by 3.75%. This aligns with the current body of research that positing industrialized and developed countries have a larger number of EV sales. Years of schooling is the most effective variable among other explanatory variables. We can say that a 1% increase in Years of Schooling results in an 8.79% increase in EV sales at 10% significance. Lastly, Urbanization and EV sales exhibit a positive relationship, where a 1% increase in Urbanization corresponds to a 0.66% increase in EV sales.

4.2.2. Assumption Tests

In panel data analysis, the validity of FE estimations pertains to the fulfilment of specific assumptions. This section provides assumption tests to check the validity of our estimation.

4.2.2.1. Hausman Test

First of all, in order to say that FE is appropriate, the validity of FE must be checked via Hausman test, which is applied to ascertain the suitability of either random effects (RE) or FE in conformity with Hausman's computation (Hausman, 1978).

Table 8. shows the result of Hausman test.

H_0: Both RE and FE estimates are consistent

H_1: RE is not valid

Table 8. Result of Hausman Test

Test Cross-Section Random Effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob
Cross-section random	111.74	7	0.0000

The null hypothesis is rejected since p-value (0.00) is less than 0.05. Therefore, we can say that Random Effect is not appropriate. Fixed Effect is chosen since Hausman Test does not support the use of Random Effect.

4.2.2.2. Cross-Sectional Dependence Test

After that, we can check whether there is a cross-sectional dependence problem or not. Cross-sectional dependence refers to the correlation observed among entities within the same cross-sectional group. In order to test cross-sectional dependence, Pesaran test is used because it is useful when time period (T) is small and the number of units (N) is large (Baltagi, 2005). For this study, time period is 13 and the number of units is 23 (N>T).

In his article, Pesaran (2004) posits that

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$$

Where

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{u}it\ \hat{u}jt}{\left(\sum_{t=1}^{T}\hat{u}^2{}_{it}\right)^{1/2}\left(\sum_{t=1}^{T}\hat{u}_{jt}^2\right)^{1/2}}$$

$\hat{\rho}_{ij}$ is the estimated correlation between the residuals in the sample. Under the null hypothesis, Pesaran test says that there is cross-sectional independence and CD statistic has normal distribution when N goes to infinity and T is large (De Hoyos and Sarafidis, 2006). Table 9 depicts the result of Pesaran CD test statistic and its probability.

H_0: There is no cross-sectional dependence

H_1: H_0 does not hold

Table 9. Result of Pesaran's CD Test

Variable	CD test	p-value	corr	abs(corr)
resid_fe	3.31	0.001	0.058	0.383

According to the result, the test statistics is 3.310 and p-value is 0.001. Since p-value is less than 0.05, we reject the null hypothesis. As a result, there is a CD problem in FE specification.

4.2.2.3. Autocorrelation Test

In addition, we should check whether there is an autocorrelation problem or not. Autocorrelation in panel data sets results in biased and less efficient estimates. In order to test it, we resort to Wooldridge Autocorrelation Test because of its robustness. Wooldridge takes the first differences of regression and obtains residuals from the regression in first differences (Wooldridge, 2002; Drukker, 2003).

$$y_{it} = \alpha + X_{it}\beta_1 + Z_i\beta_2 + \varepsilon_{it} \qquad i \in \{1,2,\dots,N\}, t \in \{1,2,\dots,Ti\}$$

$$y_{it} - y_{it-1} = (X_{it} - X_{it-1})\beta_1 + \varepsilon_{it} - \varepsilon_{it-1}$$

$$\Delta y_{it} = \Delta X_{it}\beta_1 + \Delta\varepsilon_{it}$$

Wooldridge asserts ε_{it} are not correlated.

H_0: There is no serial correlation in panel data

H_1: H_0 does not hold

Table 10. Result of Wooldridge Autocorrelation Test

Test statistics	Prob.
6.373	0.0193

We can reject H_0 since the p-value is 0.0193, which is less than 0.05. As a result, there is an autocorrelation problem in the panel regression.

4.2.2.4. Heteroskedasticity Test

Heteroskedasticity arises when the variability of the errors differs among observations, meaning the variance is not constant across them. Hypotheses for the heteroskedasticity test are as follows:

H_0: Homoskedasticity (constant variances)

H_1: Heteroskedasticity (varying variances)

It is used Modified Wald Test for heteroskedasticity in FE regression model. The Modified Wald statistic is calculated as follows (Baum, 2001):

$$\sigma_i^2 = \sigma^2 \; for \; i = 1,2, \ldots, N_g \; where \; N_g \; is \; the \; number \; of cross - sectional \; units$$

$$\hat{\sigma}_i^2 = T_i^{-1} \sum_{t=1}^{T_i} e_{it}^2$$

$$V_i = T_\text{i}^{-1} (T_i - 1)^{-1} \sum_{t=1}^{T_i} \left(e_{it}^2 - \hat{\sigma}_i^2 \right)^2$$

Then it is defined as:

$$\text{W} = \sum_{i=1}^{Ng} \frac{\left(\hat{\sigma}_i^2 - \hat{\sigma}^2 \right)}{V_i}$$

Table 11. Result of Modified Wald Test

Test statistics	Prob.
257.960	0.0000

Since p-value is less than 0.05, the null hypothesis can be rejected. According to the result, there is a heteroskedasticity problem in our model.

4.2.2.5. Robust Hausman Test

It is shown that our panel regression has both cross-sectional dependence and autocorrelation problems and variances of error terms are heteroskedastic. Therefore, it is more appropriate to carry out Robust Hausman Test instead of Hausman Test.

H_0: Both the RE and FE estimates are consistent

H_1: RE is not appropriate

Table 12. Result of Robust Hausman Test

Test statistics	Prob.
58.56	0.0000

According to the result of Robust Hausman Test in Table 13, the null hypothesis can be rejected because the p-value is less than 0.05. Similar to Hausman test, Robust Hausman test also supports the use of Fixed Effect model.

4.2.3. Robust Standard Error Methods

Driscoll and Kraay (1998) estimate consistent standard errors for each coefficient by POLS and FE. Driscoll-Kraay standard errors are estimated because there are both CD problem and autocorrelation problem. Driscoll-Kraay standard errors are designed to handle and remain robust in the presence of CD problem. Firstly, dependent and explanatory variables are transformed.

$$\hat{z}_{it} = z_{it} - \bar{z}_i - \bar{\bar{z}} \ where \ \bar{z}_i = T_i^{-1} \sum_{t=ti1}^{T_i} z_{it} \ and \ \bar{\bar{z}} = \left(\sum T_i\right)^{-1} \sum_i \sum_t z_{it}$$

$$z_{it} \in \{y_{it}, x_{it}\}$$

Then, the transformed regression is estimated by POLS with Driscoll-Kraay standard errors. Here are the results.

Table 13. Result of Fixed Effect Regression With Driscoll-Kraay St.Err.

	FE	Drisc/Kraay
log_CRUDE	-0.41 (0.34)	-0.41 (0.40)
log_CHRG	0.28*** (0.03)	0.28*** (0.05)
log_EPI	1.10 (0.85)	1.10 (1.89)
RNW	0.07*** (0.02)	0.07*** (0.01)
log_GDP	3.75*** (1.00)	3.75*** (0.96)
log_YOS	8.79* (4.92)	8.79** (3.14)
URB	0.66*** (0.13)	0.66*** (0.15)
constant	-117.65*** (16.68)	-117.65*** (24.23)
observations	299	299
R-squared	0.75	0.75
F	117.30***	2387.94***

Values in parentheses are standard errors. *p<0.10, **p<0.05, ***p<0.01

When we use Driscoll-Kraay standard errors, the results are similar to FE model except for years of schooling. At this time, years of schooling has a statistically significant coefficient on 5% level of significance.

4.2.4. Summary and Inference

According to the results, charging points, renewables, GDP per capita, years of schooling and urbanization are both positive and statistically significant. We delve deeper into each variable to clarify the effects of them.

The relationship between charging points and EV sales is positive as expected. When charging points per 100,000 people increase by 1%, EV sales per 100,000 people also increases by 0.28%.

Another significant variable is renewables. There is a positive relationship between the share of renewables in electricity production and EV sales. When the share of renewables increases by 1%, EV sales per 100 thousand people increases by 0.07%. GDP per capita has a positive and significant effect on EV sales. 1% increase in GDP per capita causes EV sales to increase by 3.75%.

Years of schooling has the largest effect on EV sales. A 1% increase in years of schooling causes EV sales to increase by 8.79%.

Urbanization rate is another significant dependent variable in our model. When the urban population increases by 1%, EV sales increases by 0.66%.

We also expected that both crude oil price and EPI factor have positive and significant effects on EV sales based on existing literature. However, this is not the case. We find insignificant relationship between EV sales and them.

4.3. Difference and System GMM Estimation

Endogeneity occurs when the correlation between an explanatory variable and a disturbance term is not zero. Our model includes crude oil import price that can be influenced by the current state of the socioeconomic and political atmosphere. An increasing number of studies reveal the price of oil is endogenous instead of exogenous (Barsky and Kilian, 2001 and 2004; Lin and Li, 2015). As a result, one might suspect the presence of endogeneity in our model. Endogeneity introduces such significant bias that we might not correctly determine the sign of the coefficient (Ketokivi and McIntosh, 2017).

In addition to endogeneity concerns, we showed in Section 4.2.1.3. and Section 4.2.1.4. that there is an autocorrelation problem and we have heteroskedastic variances. Furthermore, our time period is smaller than the number of units (T=13 < N=23). These conditions prove us to use the generalized method of moments (GMM) in order to decrease the endogeneity problem and solve such issues (Roodman, 2009).

In dynamic panel regression models, the first lag of the dependent variable is used as an explanatory variable. Arellano and Bond (1991) designed a consistent GMM estimator for dynamic panel regression models, which takes into account the lags of the dependent variable and the first differences of the exogenous variables. Schultz et al. (2010) find dynamic GMM specification is resilient to all types of endogeneity when they compare with biased results of POLS and FE models. Similarly, Blundell et al. (2000) state that both the precision can be significantly enhanced and using system GMM can help decrease the finite sample bias. According to their results, OLS generates an upward-biased estimate for the lagged dependent variable, which makes it inefficient. Therefore, it is used difference GMM method in order to get efficient estimates based on the pervasive use of it in academic research dealing with panel data.

Generally, there are two types of GMM: difference GMM and system GMM. After the introduction of difference GMM method based on Arellano and Bond's (1991) article, system GMM is designed according to Arellano-Bover/Blundell-Bond estimation (Arellano and Bover 1995; Blundell and Bond 1998). While the Arellano–Bond estimation process initiates by converting all regressors through differencing and employs the GMM, the Arellano–Bover/Blundell–Bond estimator enhances the Arellano–Bond approach by assuming that the first differences of the instrument variables are uncorrelated with the fixed effects, which increases efficiency (Roodman, 2009).

The primary distinction between difference GMM and system GMM is that system GMM is a more effective estimator because difference GMM can be prone to bias from weak instruments since system GMM permits the inclusion of more instruments. Also, system GMM requires one additional assumption that there is no correlation between instruments and fixed effects. In this study, both techniques are applied for the purpose of comparing their results.

4.3.1. Empirical Analysis and Key Findings

Firstly, one-step robust difference GMM method is followed. In our study, the demand for EVs is also dependent on the number of previous year's EV sales since consumers care about upward or downward trends in the EV market. We add the first lag of our dependent variable into the equation as an explanatory variable. Therefore, our dynamic panel regression is defined as follows:

$$\begin{aligned} log(EV_{it}) = \alpha log(EV_{it-1}) &+ \beta_1 log(CRUDE_{it}) + \beta_2 log(EPI_{it}) + \beta_3 log(CHRG_{it}) \\ &+ \beta_4 RNW_{it} + \beta_5 log(GDP_{it}) + \beta_6 log(YOS_{it}) + \beta_7 logURB_{it} \\ &+ \epsilon_{it} \end{aligned}$$

where $\epsilon_{it} = \mu_i + \nu_{it}$

$$E[\mu_i] = E[\nu_{it}] = E[\mu_i \nu_{it}] = 0$$

The disturbance (ε_{it}) term has two orthogonal components: fixed effects (μ_i) and idiosyncratic shocks (υ_{it}).

i shows the country and t represents the time of the variable.

i=1,2,3,…,23 (the number of countries)

t=1,2,3,…,13 (years from 2010 to 2022)

Adding the lagged term of the dependent variable creates a biasedness and inconsistency problem by increasing endogeneity, which is called the Nickell Bias Problem (Nickell, 1981) in dynamic panel regressions. Difference GMM is one way to solve this problem. Our dynamic panel regression can be rewritten as follows:

$$\begin{aligned} \Delta EV_{it} = \alpha \Delta log(EV_{it-1}) &+ \beta_1 \Delta log(CRUDE_{it}) + \beta_2 \Delta log(EPI_{it}) + \beta_3 \Delta log(CHRG_{it}) \\ &+ \beta_4 \Delta RNW_{it} + \beta_5 \Delta log(GDP_{it}) + \beta_6 \Delta log(YOS_{it}) + \beta_7 \Delta URB_{it} \\ &+ \Delta v_{it} \end{aligned}$$

In our difference GMM estimation, we set crude oil import price as an endogenous variable and charging points as a predetermined variable. While endogenous variables can be affected by current disturbances, predetermined variables are only dependent on past error terms. The number of charging points is influenced by past shocks such as government policies towards the proliferation of charging stations. Furthermore, EV sales are not only influenced by the current charging stations but also by the number of previous year's charging points according to consumers' behaviours.

As a result, we also add the first lagged term of our predetermined variable, which is the log of charging points per 100 thousand people. Our equation turns into this:

$$\Delta EV_{it} = \alpha \Delta \log(EV_{it-1}) + \beta_1 \Delta \log(CHRG_{it}) + \beta_2 \Delta \log(CHRG_{it-1}) + \beta_3 \Delta \log(CRUDE_{it}) + \beta_4 \Delta \log(EPI_{it}) + \beta_5 \Delta RNW_{it} + \beta_6 \Delta log(GDP_{it}) + \beta_7 \Delta log(YOS_{it}) + \beta_8 \Delta URB_{it} + \Delta v_{it}$$

We know that a consistent GMM estimator must lie between FE estimator and POLS estimator, i.e., FE estimate < consistent estimator < POLS estimate since FE estimator is biased downward and POLS estimator is biased upward theoretically. Therefore, we also apply dynamic panel regression based on POLS and FE estimation to compare their results with difference GMM estimation. Table 14 tabulates the findings of dynamic panel regressions for POLS, FE and difference GMM estimation.

Table 14. Result of Difference GMM

	POLS	FE	Difference GMM
log_EV$_{t-1}$	0.538*** (0.037)	0.333*** (0.044)	0.399*** (0.047)
log_CHRG	0.014 (0.028)	0.023 (0.027)	-0.029 (0.029)
log_CHRG$_{t-1}$	0.030 (0.025)	0.004 (0.025)	0.068** (0.027)
log_CRUDE	-0.217 (0.210)	-0.392 (0.239)	-0.333 (0.242)

Table 14. (continued)

log_EPI	-0.557 (0.476)	-0.924 (0.589)	-0.868 (0.586)
RNW	0.004 (0.002)	0.018* (0.011)	0.010 (0.013)
log_GDP	1.194*** (0.187)	0.760 (0.666)	1.293* (0.736)
log_YOS	0.651 (0.512)	5.517* (3.300)	10.857*** (4.215)
URB	0.000 (0.006)	0.097 (0.098)	0.110 (0.108)
constant	-271.748*** (56.539)	-422.414*** (80.414)	no constant
observations	276	276	253
R-squared	0.907	0.8754	-

Values in parentheses are standard errors. *$p<0.10$, **$p<0.05$, ***$p<0.01$

Therefore, the interval for difference GMM estimation should be between 0.333 and 0.538. Since our estimate from Arellano-Bond estimation is 0.399, informal validity proves the use of difference GMM.

For the formal check, it is applied both Autocorrelation test and Sargan test, because GMM estimates are consistent provided that there is no second-order autocorrelation and the instruments are valid.

Since the GMM estimation takes the first difference of the aimed equation, first-order autocorrelation, AR(1), is expected and it does not pose a problem (Roodman, 2009). However, higher-order autocorrelation cannot be seen in errors. Hypotheses for the autocorrelation test are as follows:

H_0: No autocorrelation

H_1: The null hypothesis does not hold

Table 15. Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-6.7272	0.0000
2	1.304	0.1922
3	0.62784	0.5301
4	-0.271	0.7860

As we expected, H_0 is rejected for the AR(1) type of autocorrelation. But there is no higher-order autocorrelation. Besides, instrumental variables used in the estimation must be checked whether they are valid or not. In order to test, we resort to Sargan test, which hypotheses are below:

H_0: instruments are valid

H_1: instruments are not valid

Table 16. Sargan test for overidentifying restrictions

chi2(173)	=	113.57
Prob > chi2	=	0.9999

We fail to reject H_0 since its p-value is greater than 0.05; therefore, we can say that our instruments are valid. By doing this, formal tests are also completed. To sum up, we show that both informal and formal checks support the use of difference GMM.

According to the results, the first lagged term of the dependent variable is statistically significant at 1%. When it increases by 1%, the current EV sales also increase by 0.399%. Years of schooling has also a statistically significant coefficient at 1%. The EV sales increases by 10.857% with a 1% increase in years of schooling. The first lagged term of charging points has a significant effect on EV sales at 5%. If the number of the previous year's charging stations increases by 1%, we expect a 0.068% rise in EV sales. Lastly, the coefficient for GDP per capita is statistically significant at 10%. If GDP per capita increases by 1%, then EV sales also increase by 1.293%. The other variables, crude oil import price, EPI score, the share of renewables in electricity generation, and urbanization rates have no any significant effect on EV sales.

Then, we apply system GMM built upon Arellano-Bover/Blundell-Bond estimation. The legitimacy of the extra instruments in system GMM relies on the premise that alterations in the instrumenting variables are not linked to the fixed effects, so we make this additional assumption. The main difference is that difference GMM uses lagged levels of independent variables as instruments for first differences whereas system GMM allows first differences to be used as instruments for levels.

Table 17. Comparative results for difference GMM and system GMM

	Difference GMM	System GMM
log_EV$_{t-1}$	0.399*** (0.047)	0.550*** (0.038)
log_CHRG	-0.029 (0.029)	-0.046 (0.031)
log_CHRG$_{t-1}$	0.068** (0.027)	0.120*** (0.025)
log_CRUDE	-0.333 (0.242)	-0.518*** (0.194)
log_EPI	-0.868 (0.586)	-2.261*** (0.450)
RNW	0.010 (0.013)	0.028*** (0.008)
log_GDP	1.293* (0.736)	0.069 (0.372)
log_YOS	10.857*** (4.215)	5.515*** (1.354)
URB	0.110 (0.108)	0.021 (0.019)
observations	253	276
instruments	183	217

Values in parentheses are standard errors. *p<0.10, **p<0.05, ***p<0.01

As depicted in Table 17, the system GMM results differ from difference GMM in many aspects. There are also a few similarities. For instance, the coefficient for the first lagged term of the dependent variable is both positive and significant at 1%, which means a 1% increase in the lagged term of EV sales causes a 0.550% increase in EV sales. Similarly, years of schooling has also significant coefficient at 1%. EV sales increases by 5.515% corresponding to a 1% increase in years of schooling. The first lagged term of charging points is significant at 5% instead of 1% in difference GMM estimation. 1% increase in the first lagged term of charging points leads to a 0.120% increase in EV sales. In contrast to difference GMM, crude oil import price and EPI score have both negative and statistically significant coefficients. These are -0.518 and -2.261, respectively. The negative coefficient of crude oil prices is not in liaison with the literature. Besides, the share of renewables has a significant coefficient at 10%, which means when renewables increase by 1%, EV sales also increase by 0.028%. The other variables, charging points, GDP per capita and urbanization rate are not statistically meaningful.

We also apply the same assumption tests, autocorrelation and Sargan test, to assess the validity of system GMM. Table 18 shows the autocorrelation test.

Table 18. Arellano-Bond autocorrelation test for system GMM

Order	z	Prob > z
1	-1.3508	0.1768
2	0.7484	0.4542
3	1.5368	0.1243
4	-0.5793	0.5624

For both first-order and higher-order autocorrelations, p values are not meaningful. We fail to reject the null hypothesis that there is autocorrelation. For second-order and higher-order autocorrelation, there should be no autocorrelation in error terms. However, we do not expect to see there is no first-order autocorrelation, AR(1). This result is not consistent theoretically.

Then, we utilize Sargan test to assess the reliability of the instruments. Table 19 indicates the result of Sargan test.

Table 19. Sargan test for system GMM

chi2(174)	=	176.384
Prob > chi2	=	0.9398

As can be seen, p-value is greater than 0.05 and we fail to reject the null hypothesis that instrumental variables are valid. Although there is no problem according to Sargan test, the absence of AR(1) casts doubt on the validity of system GMM. We can say that difference GMM estimator is useful for interpreting the factors that influence the demand for EVs.

CHAPTER 5

CONCLUSION AND POLICY RECOMMENDATION

5.1. Conclusion

EV sales increased quite a bit in recent years but there seems to be large differences among countries in terms of the number of sales. While some countries such as Norway and Sweden have the highest EV sales per 100,000 people in 2022, which is 3186 and 1605 respectively, other countries among OECD countries have very low number of EV sales. For instance, Poland witnessed 69 EV sales per 100 thousand people in 2022 and even this number for Türkiye is too low only 8 EVs per 100 thousand people were sold in 2022. Understanding the underlying factors for this discrepancy is of a pivotal importance in analyzing the future of EVs. The aim of achieving net zero level of global carbon dioxide emissions by the year 2050 may stimulate the efforts of adopting EVs, therefore we believe this study will help future works in comprehending significant factors and help policy actors take necessary steps to combat with ICEVs.

In this study, we aim to find the factors impacting EV sales by using panel data from 2010 to 2022 in selected OECD countries. This is the first study that covers this time horizon in terms of econometric estimations and the only study covering the period after COVID-19. An econometric framework for analyzing EV sales is developed, incorporating seven independent variables. These variables are crude oil import price, charging points, EPI score, the share of renewables in electricity generation, GDP per capita, years of schooling and urbanization rate. This thesis uses both static and dynamic panel data estimation techniques in order to analyze the effects of independent variables on EV sales. With this approach, this thesis is the first study in the literature that comprises difference GMM and system GMM estimations and compares their results with static panel regressions. Moreover, this study tries to fill the gap that there is an absence of panel data analysis covering multiple countries with a broader range of time.

According to our findings, static panel data results show that charging points, renewables, GDP per capita, years of schooling and urbanization rate are statistically significant and have positive impacts on EV sales. These estimates are based on FE, which is chosen by Hausman Test. Also, assumptions tests are applied to check the validity of FE and we show that there is cross-sectional dependence, autocorrelation in error terms and heteroskedasticity problem, which leads to less efficiency. As a result of biased estimates, we also estimate the model by using Driscoll/Kraay standard errors since they are robust to such issues. The only difference between FE and Driscoll/Kraay is that we find years of schooling has a positive and significant coefficient at 5% rather than 10% significance level. Besides, years of schooling is the best predictor of EV sales because a 1% increase in years of schooling brings about an 8.79% increase in EV sales. We expect countries with more years of schooling are inclined to have more environmental concerns, which has the effect of spurring EV demand. Governments should take educational policies into consideration provided that they want to increase their EV market share.

Other variables, crude oil import price and EPI score have no power in explaining EV sales. In particular, we find oil price is meaningless to have explanatory power on EV sales, which contradicts later findings of existing literature. This might arise from our definition of EVs consisting of both BEVs and PHEVs. Li et al. (2015) separate the effect of oil price on BEV and on PHEV, then the authors posit that gas price has a larger effect on BEV. Another conclusion is that after the debut of modern EVs in the 2010s, the price elasticity of EVs is higher because of their consideration as a luxury good. Technological learning enabling decreased production costs could result in declining prices for EVs (Weiss et al., 2018). Therefore, gradually the demand for EVs becomes less and less elastic and it is no longer highly sensitive to the volatility of oil prices.

Endogeneity concerns led us to implement dynamic panel regression by using both difference GMM and system GMM. The first lag of the dependent variable, the first lag of charging stations, GDP per capita and years of schooling have both positive and significant coefficients in having the impact on EV sales under difference GMM technique. The other independent variables are statistically insignificant. For system GMM, the first lag of EV sales, the first lag of charging points, crude oil import price, EPI score, renewables and years of schooling have significant effects on EV sales. However, assumption tests such as autocorrelation and Sargan test for overidentification prove us to use difference GMM. We can say that socioeconomic factors have no meaningful impact on EV sales except for years of schooling that is the average number of years adults over 25 years participated in formal education. Rather than social and economic variables, people give more attention to EV-specific factors such as charging points (adjusted for population) and EVs sold in the previous year.

5.2. Policy Recommendation and Suggestion for Future Research

According to our results, we suggest that the increasing number of charging stations is very critical since it is concluded that EV-specific factors should be given priority when governments set policies for the adoption of EVs. Regulations for the installation of charging stations might be eased. For future studies, it should be questioned that the heterogeneous distribution of charging points could be an obstacle to opting for EVs within a country.

Another suggestion is that policy actors may include country-level net-zero commitments in their curriculum and students might be taught how the transportation sector contributes to carbon emissions because both static and dynamic panel data analyses guide us to underscore the importance of educational attainment. Therefore, vehicles powered by clean fuels such as electricity, hydrogen and natural gas could draw more attention with the help of raising concerns among educated people.

We recommend that future research concentrate on the interdependence between EV and GDP. It is concluded that countries with higher GDP per capita also witnessed more EV sales. Also, the growth of the EV market has an impact on GDP by resulting in investment for charging infrastructure, reduced CO_2 emissions, and increasing consumer expenditure through subsidies and lower maintenance costs. For instance, according to the Australian Energy Market Operator (AEMO), consumers will have an additional $370 per annum as a fixed operating and maintenance cost savings. As a result, Australia expects the adoption of EVs to increase real GDP by %0.2 compared to the 2016-17 Australian GDP (Electric Vehicle Council, 2018). Besides, Nieto et al. (2024) find that the transition to electric vehicles could achieve an additional 0.5% annual growth in GDP for the UK.

Another recommendation is that funding for direct-current (DC) fast-charging installation should be on the agenda of governments. The latest KPMG survey threw a spotlight on American consumers' preferences when there would be the same price and features for all types of vehicles, standard gas-powered, hybrid or EV (KPMG American Perspectives Survey, 2024). Only 1 person out of 5 would choose an EV even with the same price, which casts doubt on the future of the EV market. The most outstanding concern is EV charging times since 60% of Americans would prefer 20 minutes or less to charge their cars from zero battery to 80%. As a result, DC fast charger stations should be proliferated. A DC fast charging station is capable of providing from 15kW to over 350 kW, which allows a standard EV with a 60kW average-size battery to be charged in 10 to 60 minutes.

In addition, the latest developments in increasing duties pose a threat to the EV market. The United States quadrupled tariffs on EVs from China by increasing from 25% to 100% in May 2024. Then, the European Commission will impose duties for Chinese EVs up to 38.1% by July 2024 for the sake of protectionism. SAIC and BYD will be subjected to tariffs of 38.1% and 17.4%, respectively. However, according to Fitch Ratings, it is not expected that the tariffs will affect the EV market share of China in Europe. While BYD is planning to build a factory in Hungary, Chery will establish a joint venture in Spain, which localisation could be one way to circumvent the tariffs. Even so, we suggest for future works tariffs data could be added to models in order to see their effects on the rate of adoption of EVs.

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APPENDICES

A. TURKISH SUMMARY / TÜRKÇE ÖZET

Bu çalışma 23 OECD ülkesi için 2010-2022 yılları arasında elektrikli araç satışlarını etkileyen faktörleri araştırmayı amaçlamaktadır. Elektrikli araçlar, Paris Anlaşması'nın hedefleri doğrultusunda karbon emisyonunun azaltılmasında önemli rol oynamaktadır (Wietschel vd., 2019; Weiss vd., 2019). Özellikle teknolojik gelişmeleri de hesaba kattığımızda gelecekteki elektrikli araçların günümüzdeki elektrikli araçlara kıyasla çevreye etkilerinin çok daha az olacağı beklenmektedir. Örneğin, elektrik üretiminde yenilenebilir enerjilerin kullanımının artmasıyla elektrikli araçların salgıladığı karbon emisyon miktarı çok daha az olacaktır. 2030 yılına gelindiğinde elektrikli araçların 700 milyon metrik ton karbondioksit eşdeğerinin önüne geçeceği tahmin edilmektedir (IEA, 2023). Elektrikli araçların küresel çapta kabul gören 2050 yılına kadar net sıfır emisyon hedefine ulaşmak için önemli rol oynadığından önemi ortaya konulmuş oluyor. Elektrikli araçların bu önemi de bu çalışmanın ana araştırma motivasyonunu oluşturmaktadır.

Elektrikli araçların tarihine baktığımızda, ilk elektrikli aracın 1832 yılında Robert Anderson tarafından geliştirildiğini görüyoruz. Özellikle Fransız fizikçi Gaston Plante'nin kurşun asit bataryaları icat etmesi ile elektrikli araçlar yaygınlaşmaya başladı çünkü kurşun asit bataryalar elektrikli araçların depolama kapasitesini büyük ölçüde artırdı. 1881'de Gustave Trouve, Paris'teki Uluslararası Elektrik Sergisi'nde elektrikle çalışan üç tekerlekli aracını tanıttı. Almanya'da ise 1888'de Andreas Flocken tarafından ilk elektrikli araba olan Flocken Elektrowagen üretildi. Elektrikli araçların rakiplerine karşı da önemli avantajları vardı. Vites değişimi olmadığı için kullanmak çok kolaydı, aynı zamanda sessiz çalıştığı için gürültü kirliliği oluşturmuyordu. Tüm bu faktörler 19. yüzyılın sonundan 20. yüzyılın başlarına kadar elektrikli araçların popülerlik kazanmasında rol oynadı.

Fakat 1920’lere gelindiğinde Henry Ford’un içten yanmalı motora sahip araçların seri üretimindeki katkılarıyla elektrikli araçlar sektördeki ağırlığını kaybetmeye başladı. 1912’de benzinli bir arabanın fiyatı 350 dolarken elektrikli bir araç için 1750 dolar gerekiyordu (Matulka, 2014). Bununla birlikte 1920’lerde Teksas’ta petrol rezervleri keşfedilmeye başlandı ve bu gelişme petrol fiyatlarında ciddi bir düşüşe neden oldu. Elektrik ise hala şehir merkezlerinde sınırlıydı. Bu gelişmeler, elektrikli araçların yüzyılım hemen başında kazandığı popülerliği kaybetmesine neden oldu. 1970’de ise NASA’nın Apollo 15 görevinde elektrikli ay gezgin taşıtı kullanması, yine aynı dönemlerde Arap-İsrail savaşı sonucu OPEC ülkelerinin ambargo uygulayıp petrol fiyatlarının ciddi bir şekilde yükselişe yol açması ve bataryalarda lityum-iyon kullanılmaya başlanmasıyla depolama kapasitesinde ciddi artışlar elde edilmesi gibi gelişmeler elektrikli araçları tekrar popüler hale getirmiş oldu.

Günümüze baktığımızda ise 2022 yılında elektrikli araç satışları 10 milyonu geçti (IEA, 2023). Market payını ise %60 ile Çin, %15 ile Avrupa ve %8 ile Amerika Birleşik Devletleri elinde bulunduruyor. 2025 yılında elektrikli araç satışlarının daha da artarak içten yanmalı motora sahip araç satışlarından daha fazla olacağı tahmin ediliyor. Paris Anlaşması çerçevesinde ilan edilen Elektro-Mobilite Paris Deklarasyonu’na göre küresel ısınmayı 2 derece ile sınırlamak istiyorsak 2030’a kadar tüm taşıtların en az %35’inin elektrikli araç olması gerekmektedir. Gelecekteki elektrikli araçların daha az emisyon üreteceği ve sürüş menzilinin de giderek artacağı gibi faktörler göz önüne alındığında elektrikli araçlara olan talebin artacağını öngörüyoruz, bu çalışma da bu talebi etkileyen faktörleri incelemeyi amaçlamaktadır.

Son zamanlarda elektrikli araçlara yönelik ilgi artmış durumdadır. Bu artan ilgiyi Google Trends’in yayınladığı Google arama sekmesine ‘Electric Vehicle’ yazan kişi sıklığını gösteren grafikle de görebilmekteyiz. Covid-19 pandemisinin 2020 yılı başlarında elektrikli araçlara olan ilgiyi ilk başta kısıtladığını fakat daha sonra ilginin artmasına yol açtığını görmekteyiz. Wen vd. (2021) Covid-19’un elektrikli araçlara yönelik ilgiyi kısa dönemde satış rakamlarını azaltıcı etkisine rağmen uzun dönemde artıracağını ileri sürmektedir.

Bu çalışmaya etkisi olan belli başlı çalışmalar listelenmektedir. Literatüre baktığımızda ilk olarak hibrit araçlara yönelik çalışmalarla karşılaşmaktayız. Bizim elektrikli araç tanımımız hem plug-in hibrit araçları (PHEVs) hem de tamamen elektrikli araçları (BEVs) kapsamaktadır. Plug-in elektrikli araçlar hem benzin hem de elektrikle çalışırlar, bu yüzden hibrit araçlara yönelik olarak yapılan araştırmaların bizim çalışmamıza katkı sağlayacağına inanıyoruz Bu çalışmaların ortak bulgusu elektrikli araçlar ile benzin fiyatları arasında istatistiki olarak anlamlı bir ilişki olduğuna yöneliktir (Diamond, 2009; Gallagher ve Muehlegger, 2011; Beresteanu ve Li, 2011). Diamond (2009) benzin fiyatlarındaki çok küçük bir değişikliğin bile hibrit araç elde etmede önemli bir katkıya yol açacağını ortaya koymaktadır. Aynı şekilde, Beresteanu ve Li (2011) 2006 yılındaki benzin fiyatları 1999 yılındaki fiyatlarla aynı kalsaydı, bir başka deyişle bir galon için 2.60 dolar yerine 1.53 dolar olsaydı, 2006 yılında satılan hibrit araç sayısının %37 azalacağını söylemektedir. Gallagher ve Muehlegger (2011) ise benzin fiyatlarındaki %10’luk bir artışın hibrit araç satışlarında %13’lük bir artışa neden olacağını göstermektedir.

Elektrikli araç için yapılan çalışmalara baktığımızda, Sierzchula vd. (2014) 30 ülke için 2012 yılı verilerini kullanarak sosyoekonomik faktörlerin elektrikli araç satışları üzerine bir etkisinin olup olmadığını araştırmıştır. Yapılan çalışmada elektrikli araç pazar oranları, finansal teşvikler, şehirleşme yoğunluğu, eğitim düzeyi, çevrecilik göstergesi olarak EPI, benzin fiyatları, elektrikli araç fiyatları, üretim tesislerinin varlığı, kişi başına düşen araç sayısı, model çeşitliliği, elektrikli araç satışlarının başlangıç tarihi, şarj altyapısı ve elektrik fiyatları kullanılmıştır. Sonuç olarak şarj istasyonları elektrikli araç pazar payında en çok etkiye sahip olan faktör olarak bulunmuştur. Benzin fiyatlarının istatistiki olarak bir etkisinin olmadığı sonucuna varılmıştır. Li vd. (2017) ise 2010-2015 yılları arasında 14 ülke için benzer bir çalışma yapmıştır. Li ve arkadaşları elektrik üretiminde yenilenebilir enerjinin payının, şarj istasyonu yoğunluğunun, eğitim seviyesinin, nüfus yoğunluğunun ve benzin fiyatlarının elektrikli araç satışları üzerine pozitif ve anlamlı bir etkiye sahip olduğunu göstermektedir. Yine benzer bir çalışmada Chandra (2022), benzin fiyatlarının elektrikli araç satışlarının üzerine pozitif ve anlamlı bir etkiye sahip oluğunu ortaya koymaktadır. Azar (2009) elektrikli araçlara yönelik ilginin artmasının benzin fiyatlarında olumsuz bir etkiye sahip olacağına dikkat çekmektedir.

Literatürde diğer faktörlerin de elektrikli araçlarla olan ilişkisi ortaya konmaktadır. Birçok ülkede insanların içten yanmalı motora sahip araçlardan elektrikli araçlara yönelmelerini sağlamak için elektrikli araçlara yönelik vergi muafiyetleri ve fiyat sübvansiyonları sağlanmaktadır. Örneğin Türkiye'de2018'e kadar alınmamakta olan motorlu taşıtlar vergisi, 2018'den sonra içten yanmalı motora sahip araçlara olan verginin %25'i olarak tahsil edilmiştir (Gündüz ve Yakar; 2020). Yan (2018)'e göre vergi teşviklerindeki %10'luk bir artış BEV satışlarını %3 artırmaktadır.

Biz de literatüre bakarak yedi tane faktör seçerek bu faktörlerin elektrikli araç satışları üzerine anlamlı bir etkiye sahip olup olmadığını incelemeyi amaçlıyoruz. Bu çalışmanın literatüre en büyük katkısının 2010-2022 yılları arasını inceleyerek diğer çalışmalara nazaran çok daha geniş bir zamanı kapsaması ve özellikle Covid-19 pandemisi sonrası elektrikli araç satışlarını inceleyen ilk çalışma olma özelliği taşıması olduğuna inanıyoruz. Ek olarak, hem statik hem de dinamik panel regresyon sonuçlarını vererek literatüre katkı sağlamayı amaçlıyoruz.

Daha önce de belirttiğimiz gibi bizim çalışmamız 23 OECD ülkesini kapsamaktadır. Bu ülkeler: Avustralya, Avusturya, Belçika, Kanada, Danimarka, Finlandiya, Fransa, Almanya, Yunanistan, İtalya, Japonya, Hollanda, Yeni Zelanda, Norveç, Polonya, Portekiz, Güney Kore, İspanya, İsveç, İsviçre, Türkiye, Birleşik Krallık ve Amerika Birleşik Devletleri'dir. Modelimizde kullandığımız bağımlı değişkenimiz elektrikli araç satışlarıdır. Fakat yoğunluğu görmek istediğimiz için bu veriyi 100.000 kişi başına düşen elektrikli araç satışı olarak veriyoruz. Bağımsız değişkenlerimiz ham petrol ithalat fiyatı, çevreciliği ölçen EPI puanı, 100.000 kişi başına düşen şarj istasyonlarının sayısı, elektrik üretiminde yenilenebilir enerjilerin oranı, kişi başına düşen gayrisafi yurtiçi hasıla, 25 yaşın üzerindeki yetişkinlerin formal eğitime katıldıkları yıl sayısı ve şehirleşme oranıdır. EPI puanı ülkelerin çevresel performansını ölçer ve 0 ile 100 arasında bir değer alır. Fakat EPI, Yale Üniversitesi tarafından 2 yılda bir açıklanır. Biz de EPI puanının açıklanmadığı yılları doldurmak için lineer interpolasyon yöntemini kullandık. Seçtiğimiz değişkenler için korelasyon matrisine baktığımızda çoklu korelasyon sorunu olmadığını görüyoruz.

Modelimizi log-log model olarak kuruyoruz çünkü elektrikli araç satışları üstel artış sergiliyor. Aynı zamanda tam logaritmik model kullanmak sonuçları elektrikli araç satışlarının esnekliği olarak yorumlamamıza imkan sağlayacak.

Bu çalışmada zaman serisi ve yatay kesit yöntemlerini birleştiren panel veri analizi kullanılmıştır. Ekonometrik veri analizimizi sabit etkiler modeli kullanarak gerçekleştiriyoruz. Sabit etkiler, her bir yatay kesit için kesme noktalarına kukla değişken koyar ve havuzlaştırılmış en küçük kareler yöntemi ile modeli tahmin eder. Regresyon analizi sonucuna göre 100.00 kişi başına düşen şarj istasyonları sayısı %1 düzeyinde anlamlıdır ve katsayısı 0.28'dir. Yine, yenilenebilir enerjinin oranı, kişi başına düşen gayrisafi yurtiçi hasıla ve şehirleşme oranı %1 anlamlılık düzeyinde pozitif bir etkiye sahiptir. Katsayıları sırasıyla 0.07, 3.75 ve 0.66'dır. Eğitim yıllarının katsayısı %10 anlamlılık düzeyinde 8.79'dur. Sabit etkiler modeline göre, ham petrol ithalat fiyatları ve EPI puanı istatistiki olarak anlamlı değildir.

Sabit etkiler modelinin geçerliliğini test etmek için bir dizi varsayım testini uygulamak gerekmektedir. Öncelikle sabit etkiler modelini mi yoksa rassal etkiler modelini mi seçeceğimize yönelik Hausman testi yapıyoruz. Hausman testinin sıfır hipotezi rassal etkileri kullanmanın daha doğru olacağı yönündedir. Fakat p değerimiz %5'ten küçük olduğu için hipotezi reddederiz, böylece Hausman testi sabit etkiler modelini desteklemektedir sonucuna ulaşırız. Daha sonra modelimizde yatay kesit bağımlılığının olup olmadığını test ediyoruz. Baltagi (2005), yatay kesitlerin sayısının zaman verisinden fazla olduğu durumlarda yatay kesit bağımlılığını test etmek için Pesaran testini önerir. Bu yüzden Pesaran testi seçilmiştir. Sıfır hipotezi yatay kesit bağımlılığının olmadığıdır fakat %5 anlamlılık düzeyinde hipotez reddedilmektedir. Dolayısıyla modelimizde yatay kesit bağımlılığı sorunu vardır. Aynı zamanda otokorelasyon testi için Wooldridge testi seçilmiştir. Test sonucuna göre otokorelasyon problem vardır. Varyansların heteroskedastik mi yoksa homoskedastik mi olduğuna yönelik ise modifiye edilmiş Wald testi kullanılmıştır. Test sonucuna göre varyanslar sabit değildir, bir başka deyişle heteroskedastiktir.

Yaptığımız test sonuçlarına göre modelimizde, yatay kesit bağımlılığı, otokorelasyon ve heteroskedastisite sorunları mevcuttur. Bu durumda sabit etkiler modeli sonuçları güvenilir değildir çünkü tahminler yanlı ve tutarsızdır. Bu sorunları bertaraf etmek için sabit etkiler modeli Driscoll/Kraay standart hata terimleri kullanılarak ile tahmin edilir. Driscoll-Kraay yöntemi ile modeli tahmin ettiğimizde sabit etkiler modeline göre tek fark eğitim yılları değişkeninin anlamlılık düzeyinin %10 yerine %5 çıkmasıdır. Katsayılar tüm değişkenler için aynıdır.

Statik modelden sonra dinamik model sonuçlarını veriyoruz. Dinamik model, bağımlı değişkenin ilk gecikmeli değerinin bağımsız değişken olarak denkleme eklenmesiyle oluşturulur. Modele bağımlı değişkenin gecikmeli değerinin bağımsız değişken olarak eklenmesi endojenite sorununa yol açar ve buna literatürde Nickell Bias denir (Nickell, 1981). Endojenite açıklayıcı değişkenler ile hata terimi arasında korelasyonun sıfır olmadığı durumları ifade eder. Dinamik modelde hata terimi hem sabit etkileri hem de idiyosenkrazik şokları kapsar. Sabit etkiler zamanla değişmez, bu yüzden sabit etkilerde bir şok hem gecikmeli bağımlı değişkeni hem de hata terimini etkilemiş olur ki bu durumda modeldeki bağımsız bir değişkenle hata terimi arasında korelasyon gözlemlenmiş olur. Ek olarak, ham petrol fiyatlarının endojen bir değişken olduğuna yönelik literatürde çalışmalar vardır (Barsky ve Kilian, 2001 ve 2004; Lin ve Li, 2015).

Literatürde dinamik modellerdeki endojenite sorununu çözmek için en iyi yollardan biri olarak fark Genelleştirilmiş Momentler Yöntemi (GMM) metodu önerilir. Fark GMM, tüm değişkenlerin birinci farkını alır ve araç değişkenler kullanır (Arellano ve Bond, 1991). Sistem GMM ise kullanılan araç değişkenlerin sabit etkiler ile arasında korelasyon olmadığına dair ek bir varsayım yapar (Arellano ve Bover, 1995; Blundell ve Bond, 1998). Sistem GMM kullanılan araç sayısını artırarak modelin etkinliğini yükseltir. Karşılaştırma yapabilmek adına hem fark GMM hem de sistem GMM sonuçlarını veriyoruz.

Fark GMM, modelde endojen ve önceden belirlenmiş olarak seçmemize olanak sağlar. Biz de ham petrol fiyatlarını endojen seçtik. Aynı zamanda, şarj istasyonu sayısı değişkenini de önceden belirlenmiş olarak seçip ilk gecikmeli değerini modele ekliyoruz. Şarj istasyonu sayısını önceden belirlenmiş değişken olarak düşündük çünkü geçmiş yıllarda hükümetler tarafından şarj istasyonlarına yönelik bir teşvik paketi açıklandığı gibi durumlarda, politikaların etkilerini gecikmeli olarak görürüz. Ek olarak, ilk gecikmeli değerini açıklayıcı değişken olarak modele ekledik çünkü elektrikli araç satışları bir önceki yılın şarj istasyon sayısından etkilenebilir.

Resmi olmayan doğrulama yöntemine göre GMM'nin tutarlı sonuçlar verebilmesi için ilk gecikmeli bağımlı değişkenin katsayısının havuzlandırılmış en küçük kareler yöntemi ile sabit etkiler modeli tahminlerinin arasında olması lazımdır. Sonuçlarımıza göre ilk gecikmeli bağımsız değişkeninin katsayısı fark GMM'e göre 0.399, havuzlandırılmış en küçük kareler yöntemine göre 0.538 ve sabit etkilere göre 0.333'tür. Dolayısıyla, fark GMM sonuçlarının resmi olmayan doğrulamaya göre tutarlı olduğunu söyleyebiliriz. Formal test için fark GMM'in Arellano-Bond otokorelasyon testini ve Sargan testini geçmesi beklenmektedir. Arellano-Bond otokorelasyon testinde sıfır hipotezi otokorelasyonun olmadığı varsayımıdır. GMM modellerinde birinci dereceden otokorelasyon beklenen bir durumken yüksek dereceden otokorelasyon istenmez. Test sonucuna göre birinci derece için sıfır hipotezi reddedilir ve modelde birinci dereceden otokorelasyon vardır deriz. İkinci, üçüncü ve dördüncü derecelere baktığımızda sıfır hipotezini kabul ederiz ve yüksek dereceden otokorelasyon yoktur sonucuna ulaşırız. Sargan testi ise kullanılan araç değişkenlerinin geçerli olup olmadığını test eder. Sargan testinde sıfır hipotezi araç değişkenlerinin geçerli olduğudur ve sonuca göre sıfır hipotezi kabul edilir. Kısaca, fark GMM hem pratik olarak hem de formal olarak doğrulanmıştır.

Fark GMM sonuçlarına göre, 100.000 kişi başına düşen elektrikli araç satışlarının ilk gecikmeli değeri %1 anlamlılık düzeyinde istatistiksel olarak anlamlıdır. İlk gecikmeli değer %1 değiştiğinde, elektrikli araç satışları da %0.399 değişmektedir. %1 anlamlılık düzeyinde eğitim yılları %1 arttığında elektrikli araç satışları da %10.857 artmaktadır. 100,000 kişi başına düşen şarj istasyonlarının sayısının ilk gecikmeli değerinin %5 anlamlılık düzeyinde elektrikli araç satışları üzerinde etkili olduğu sonucuna varılmıştır. Şarj istasyonlarının ilk gecikmeli değerinin %1 arttığı durumda, elektrikli araç satışları da %0.068 artmaktadır. Son olarak, kişi başına düşen gayrisafi yurtiçi hasıla %10 anlamlılık düzeyinde istatistiksel olarak anlamlıdır. Kişi başına düşen gayrisafi yurtiçi hasıla %1 arttığında, elektrikli araç satışları da %1.293 artar. Fark GMM'e göre ham petrol fiyatları, EPI, elektrik üretiminde yenilenebilir enerjinin oranı ve şehirleşme oranı istatistiki olarak anlamsız bulunmuştur.

Daha sonra, araç değişkenlerin sabit etkilerle korelasyonunun olmadığı varsayımı yapılarak sistem GMM metodu kullanılmıştır. Sistem GMM'e göre bağımsız değişkenin ilk gecikmeli değeri 0.550'dir. Pratik olarak bu değerin havuzlandırılmış en küçük kareler yöntemi ile sabit etkiler yöntemi tahminlerinin arasında olması gerekirken teoride yukarı yönlü eğilimi olan havuzlandırılmış en küçük kareler yöntem tahmininin de üzerindedir. Formal test olarak sistem GMM'e de Arellano-Bond otokorelasyon testi ve Sargan testi yapılmıştır. Arellano-Bond otokorelasyon testine göre birinci dereceden otokorelasyon için p değeri 0.1768 bulunmuştur. Dolayısıyla, sıfır hipotezi kabul edilir. Sonuca göre, modelde birinci dereceden otokorelasyon yoktur. Yüksek dereceden de otokorelasyon olmadığı sonucuna varılır. Her ne kadar yüksek dereceden korelasyon olmaması gerekse de teorik olarak birinci dereceden otokorelasyon olması gerekir. Bulduğumuz sonuç teoriyle tutarsız olduğundan sistem GMM'nin güvenilirliği açısından şüphe uyandırmaktadır. Sargan testine göre sıfır hipotezi reddedilip kullanılan araç değişkenlerin geçerli olduğu sonucuna varılır. Fakat, sistem GMM'nin bağımlı değişkenin ilk gecikmeli değeri için bulduğu katsayının havuzlandırılmış en küçük kareler tahmincisine göre yukarıda olması ve modelde birinci dereceden otokorelasyon bulunmaması durumlarından fark GMM sistem GMM'e tercih edilmiştir.

Elektrikli araç satışları ülkeler için büyük farklılıklar göstermektedir. Örneğin, Norveç ve İsveç gibi ülkelerde 100.000 kişi başına düşen elektrikli araç sayısı çok yüksekken Polonya için 69, Türkiye için 8 ile 100.000 kişi başına düşen elektrikli araç sayısı incelediğimiz ülkeler arasında en düşüktür. Bu farklılığa sebep olan potansiyel faktörleri bulmak bu çalışmanın amacıdır. Ayrıca elektrikli araçlar üzerine yapılan araştırmaların sayısının artmasının 2050 yılına kadar net sıfır emisyon hedefine ulaşılmada önemli bir rol oynayacağını düşünüyoruz.

Özet olarak, bu çalışmada panel veri analizi kullanılarak 23 OECD ülkesi için 2010-2022 yılları arasında elektrikli araç satışlarını etkileyen faktörler incelenmiştir. Kullandığımız değişkenler elektrikli araç satışları, ham petrol ithalat fiyatları, şarj istasyonları sayısı, EPI, elektrik üretiminde yenilenebilir enerjilerin oranı, kişi başına düşen gayrisafi yurtiçi hasıla, eğitim yılları ve şehirleşme oranıdır. Bu tez, elektrikli araç satışlarıyla ilgili Covid-19 pandemisi sonrasını da kapsayan ilk çalışma olma özelliğindedir. Aynı zamanda hem statik hem de dinamik model sonuçları verilmiştir. Statik panel veri sonuçları şarj istasyonları sayısı, elektrik üretiminde yenilenebilir enerji oranının, kişi başına düşen gayrisafi yurtiçi hasılanın, eğitim yıllarının ve şehirleşme oranının elektrikli araç satışları üzerinde istatistiki olarak anlamlı ve pozitif bir etkiye sahip olduklarını göstermektedir. Statik sonuçlar sabit etkiler modeli kullanılarak elde edilmiştir. Sabit etkiler modeli ise Hausman testi ile seçilmiştir. Yapılan varsayım testlerine göre sabit etkiler modelinde yatay kesit bağımlılığı, hata terimleri arasında otokorelasyon ve heteroskedastik varyans sorunları tespit edilmiştir. Bu problemler tahminlerin yanlı ve tutarsız olmasına neden olacağından sabit etkilerin güvenilirliği konusunda endişemiz oluşmuştur. Bu yüzden model Driscoll-Kraay standart hataları kullanılarak tahmin edilmiştir. Driscoll-Kraay yöntemi ile sabit etkiler arasındaki tek fark eğitim yılları değişkeninin anlamlılık düzeyinin %5 olmasıdır. Eğitim yılları verisi elektrikli araç satışlarını etkileyen en önemli faktör olarak bulunmuştur. Eğitim yıllarında %1'lik bir artış 100.000 kişi başına düşen elektrikli araç satışlarında %8.79'luk bir artışa yol açmaktadır. Bunun dışında literatürün aksine ham petrol fiyatlarının elektrikli araç satışları üzerine istatistiki olarak anlamlı bir etkiye sahip olmadığı görülmüştür. Bunun nedenlerinden biri olarak elektrikli araç tanımımızda hem PHEV hem de BEV kapsanmaktadır. Li vd. (2015) benzin fiyatlarının elektrikli araç üzerine olan etkisini ikiye ayırıp benzin fiyatlarının BEV üzerine daha fazla etkisi olduğunu ortaya koymuştur. Bir diğer açıklama olarak, elektrikli araçların lüks tüketim malı olduğu algısının kırıldığını söyleyebiliriz. Elektrikli araçlar 2010 başlarında lüks olarak algılanıp benzin fiyatlarına karşı çok duyarlıydılar. İnsanlar benzin fiyatlarındaki oynaklık nedeniyle kendilerini elektrikli araç satın alarak korumak istiyorlardı. Fakat zamanla bu esneklik azalarak elektrikli araçlar benzin fiyatlarına daha duyarsız hale geldi.

Statik analizden sonra fark GMM ve sistem GMM ile dinamik panel veri analizi yapıldı. Sistem GMM pratik ve teorik yöntemlere göre test edilerek güvenilir olmadığı sonucuna ulaşıldı. Daha güvenilir olan fark GMM'e göre, 100.000 kişi başına düşen elektrikli araç satışlarının ilk gecikmeli değeri, 100.000 kişi başına düşen şarj istasyonları sayısının ilk gecikmeli değeri, kişi başına düşen gayrisafi yurtiçi hasıla ve eğitim yılları istatistiki olarak anlamlı bulunmuştur. Bir başka deyişle kişi başına düşen gayrisafi yurtiçi hasıla ve eğitim yılları dışında kalan sosyoekonomik faktörlerin ve petrol fiyatlarının elektrikli araç satışları üzerine bir etkisinin olmadığı tespit edilmiştir. Bu yönüyle dinamik model sonuçları Sierzchula ve arkadaşlarının (2014) bulgularıyla örtüşmektedir.

Sonuçlarımız şarj istasyonu sayısının elektrikli araç satışları üzerinde önemli bir etkiye sahip olduğunu ortaya koymuştur. Bu yüzden şarj istasyon projelerinin teşvik edilmesi gerektiğini öneriyoruz. Teşvikler, şarj istasyonu kurma önündeki güçlüklerin kaldırılıp regülasyonların esnetilmesi yoluyla da olabilir.

Diğer bir politika önerisi olarak ülkeler sıfır karbon hedeflerini ders programlarına ekleyip çevreye daha duyarlı öğrencilerin yetişmesine olanak sağlayabilir. Hem statik hem de dinamik panel veri analizlerine göre eğitimin önemi vurgulanmış oldu. Bu yüzden eğitimli insanlarda çevre konusunda endişe yaratarak temiz yakıtla çalışan araçlara olan ilgiyi artırabiliriz.

Aynı zamanda ileride yapılacak olan çalışmaların elektrikli araçlar ve kişi başına düşen gayrisafi yurtiçi hasıla arasındaki karşılıklı bağımlılığa odaklanmaları gerektiğini düşünüyoruz. Kişi başına düşen gayrisafi yurtiçi hasılası yüksek olan ülkeler aynı zamanda yüksek elektrikli araç satış sayılarına ulaşıyor. Fakat, elektrikli araç piyasasının gelişmesi de şarj istasyonu altyapı yatırımları, azalan karbon emisyonu, sübvansiyonlar ile düşük bakım ücretleriyle artan tüketim harcamaları kanallarıyla kişi başına düşen gayrisafi yurtiçi hasılaya etki ediyor. Örneğin, Avustralya'da yapılan bir çalışmaya göre elektrikli araç sahipleri düşük bakım ücretleriyle yılda 370 dolar tasarruf edebiliyorlar. Nieto vd. (2024), Birleşik Krallık için elektrikli araç sahibi olmanın kişi başına düşen gayrisafi yurtiçi hasılayı yılda %0.5 artırdığını bulmuştur.

Diğer bir tavsiye ise doğru akım (DC) hızlı şarj istasyonlarının sayısını artırmak gerektiğidir. KPMG raporuna göre elektrikli araç fiyatları içten yanmalı motora sahip araç fiyatlarıyla aynı olsa bile sadece beş kişiden biri elektrikli aracı tercih ediyor. (KPMG American Perspectives Survey, 2024). Bunun nedenlerinden biri insanların batarya şarj sürelerinin yirmi dakika ve altında olması gerektiğini düşünmeleridir. Bu yüzden en hızlı şekilde şarj etmeye olanak sağlayan DC hızlı şarj istasyonları sayısına önem verilmelidir.

Son olarak, önce Amerika Birleşik Devletleri daha sonra da Avrupa Komisyonu Çin menşeili elektrikli araçlara yönelik gümrük vergilerini arttırdılar. Bu gelişmenin elektrikli araç piyasasına etkisinin sınırlı olacağına yönelik görüşler olsa da gelecekteki çalışmaların gümrük vergisini modellerine etkileyip etkisini test etmeleri gerektiğine inanıyoruz.

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