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Electric Vehicle Competitiveness and Environmental Effects of Subsidy

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As cities strive to address environmental issues and contribute to the Sustainable Development Goals, the transportation sector has been a key focus for efforts. In particular, the adoption of electric vehicles (EVs) has been identified as a crucial solution to mitigate air pollution and reduce greenhouse gas emissions. However, EVs are not competitive with internal combustion engine vehicles due to their high price and lack of charging infrastructure, and EV subsidies are being provided to address this. Because EV subsidy effects depend not only on the characteristics of the individual consumers but also on the future technology maturity of the EV and the level of infrastructure deployment, they should be analyzed in an integrated manner. In this study, we analyze the subsidy effect by conducting a stated preference survey and constructing a logit model assuming the vehicle purchase situation of EVs and internal combustion engine vehicles (ICVs). Since the future technical maturity of EVs and the establishment of charging infrastructure are uncertain, we mitigated this through scenario analysis. Our results show the air pollution reduction effects of EV subsidy policies and provide insights for policymakers that EV subsidy policies cannot achieve sufficient effects if they are implemented unilaterally without technological maturity or infrastructure construction.

1. Introduction

Climate change is becoming a global concern due to continuous air pollution and greenhouse gas emissions, and the transportation sector, which accounts for 37% of CO2 emissions in 21st century, is also making efforts to reduce these emissions (IEA, 2022). Unlike vehicles with internal combustion engines (ICE), electric vehicles (EV) have the advantage of producing zero air pollution while driving, therefore, they are attracting significant attention as a solution to reduce air pollution and greenhouse gas emissions (Koo et al., 2022). However, few challenges still exist to increase the penetration of EVs. First, the initial price of EVs remains high, creating a high barrier to entry for the average consumer. According to the Kelley Blue Book (2023), the average price of an EV is 61,488 USD, which is about 20% more expensive than the average price of an internal combustion vehicle (ICV) (49,507 USD). Also, the EV charging time takes longer compared to ICV, and lack of charging infrastructure makes it difficult to drive long distances.

To overcome these challenges and promote the adoption of EVs, governments and related organizations have implemented EV subsidy policies. EV subsidies provide financial incentives to consumers to purchase EVs and stimulate the EV market. However, the effective utilization of EV subsidies requires appropriate adjustments depending on the size of the subsidy and the scenario (Lim et al., 2022). This paper aims to analyze the change in the choice ratio between EVs and ICV due to differences in EV subsidies and operating costs through a Stated Performance (SP) survey, and to evaluate the efficiency of EV subsidies and environmental benefits as the EV penetration rate changes. Since the level of future technological advancement or infrastructure penetration is not clearly known, the subsidies, operating costs, and other future conditions of EVs were set for each scenario to determine the proportion of buyers choosing EVs and allocating them to the network.

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2. Literature review

2.1 Stated Performance (SP) survey

Previous studies have collected data through the SP Survey to analyze various factors affecting EV adoption, including demographic and household characteristics, psychological and social characteristics, technical level and vehicle performance, government policies and economic support, and environmental concerns (Ling et al., 2021). Jia and Chen (2021) analyzed a vehicle fuel choice model based on the SP Survey in Virginia, USA, and found that male gender, higher education, and the availability of fast charging stations positively influence EV adoption. Lin and Wu (2018) analyzed an additional SP survey in cities in China and found that technical factors such as price acceptability, government subsidies, and vehicle performance also have a significant impact on EV choice. Zhang et al. (2011) used logistic regression analysis to show that government policies influence whether and when to choose an EV, while education and peer opinions influence the timing and purchase price. On the other hand, Hasan (2021) conducted a survey to determine the repurchase intention of EVs among consumers who have experienced EVs, providing insights for increasing EV penetration.

2.2 EV subsidy policy and environmental effect

In order to promote the adoption of EVs, governments and companies are promoting the economic benefits of EVs, but the high upfront cost of EVs remains a burden for consumers, and subsidies can address this issue (Liu et al., 2021). Münzel et al. (2019) analyzed EV subsidy policy using European countries and find that a subsidy of €1000 leads to a relative increase in EV sales share of about 5-7%. Clinton and Steinberg (2021) evaluate the impact of vehicle purchase subsidies on EV adoption using different in different methods and synthetic controls and find that they increase at a rate of about 8% per subsidy provided as a direct purchase rebate. However, it is theoretically difficult to increase EV penetration through high levels of subsidy in the long run, so EV penetration should be increased through reasonable levels of subsidy (Ma et al., 2019). Increasing the penetration of these eco-friendly EVs can improve air quality (Knobloch et al., 2020). Ma (2021) found that EV policies can effectively reduce Particulate matter 2.5 (PM2.5), SO_2, and CO_2 by increasing the penetration rate through the Greenhouse Gas and Air Pollution Interactions and Synergy model in the Beijing-Tianjin-Hebei region of China.

2.3 Electric vehicle and infrastructure penetration forecast

Charging stations and infrastructure also have a significant impact on EV penetration. Gai et al. (2019) analyzed electricity emission factors and EV charging patterns in Ontario and found that charging station infrastructure can increase penetration by ensuring coverage. Additionally, the deployment of fast charging stations is effective in increasing the driving range of EVs and reducing greenhouse gas emissions (Levinson and West, 2018). Studies have been conducted to determine the optimal location of EV charging stations to build this infrastructure (Ahmad, 2022). Domínguez-Navarro (2019) used Monte Carlo method and genetic algorithm (GA) to optimize the construction and operation of EV fast charging stations to enable effective use of EVs. By analyzing public charging infrastructure and fast charging infrastructure, it was found that EV users prefer to charge at home in the evening when electricity demand is high and suggested that policies to encourage charging at home during non-peak hours, as well as determining strategic fast charging station network locations, are needed for effective infrastructure deployment in the future (Morrissey et al., 2016).

3. Methodology

3.1 Stated Preference (SP) survey and Binary choice model

SP survey can be defined as a set of techniques for finding individual preferences by constructing hypothetical scenarios and presenting them to individuals using statistical experimental design methods. SP survey was conducted using variables shown as Table 1 below.

In this study, the situation of choosing between an EVs and ICVs were considered for the SP survey. Subsidies, operating cost, irregular travel frequency, and charging infrastructure satisfaction were selected to investigate the choice behavior of EVs and ICVs. Although a variety of EVs are competing with ICVs in the market, conducting an SP survey without specifying a specific EV type can lead to respondent confusion, increasing the complexity of the survey and decreasing the reliability of the response results (Hensher, 1994). Therefore, the SP survey was conducted in a context of selecting the most popular (Chu et al., 2019) vehicle families in the EV market (compact, midsize SUVs and sedans) of Korea. The demand for EVs is limited because they have energy efficiency issues if the vehicle size is too large, and they are vulnerable to accidents if they are too small (Weiss, 2020). In addition, consumers of small cars have lower incomes on average, which makes them less attractive to EVs with large initial purchase costs (Chen, 2018).

Table 1: SP survey question list

Variable		Level 1	Level 2	Level 3
Alternative Properties	Subsidy	0	10 M KRW	20 M KRW
	Operation cost	30 KRW/km	50 KRW/km	100 KRW/km
Responder Properties	Irregular travel frequency		Short answer	
	Charging Infra Satisfaction		1(Worst) ~ 5(Best) point	

A binary choice model, commonly used model in transport mode choice behavior (Brownstone, 2001), estimates choice probability based on the utility of each alternative, which is calculated as the sum of observed and unobserved utility. The observed utility is expressed by the explanatory variables, and the effects that are not included in the explanatory variables are expressed by the unobserved utility, as shown as Eq(1).

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

Where, U_{in} is utility of individual n and alternative i , V_{in} is observed utility of individual n and alternative I, ε_{in} is unobserved utility of individual n and alternative i. The logit model, a model that estimates the probability of choosing each alternative by assuming a Weibull distribution of unobserved utility, is a typical binary choice model, represented by Eq(2) below (Cramer, 2003).

$$P_n(i) = Prob\left(U_{in} \geq U_{jn}\right) = \frac{e^{U_{in}}}{e^{U_{in}+e^{U_{jn}}}} \tag{2}$$

Where, $P_n(i)$ is probability when individual n chooses an alternative i. In order to calculate binary choice probability of EV, the utility equation was defined as shown in Eq(3). By using subsidy, operation cost, irregular travel frequency, satisfaction of EV infrastructure as utility function, EV choice model was conducted.

$$U_k = \alpha \cdot Subsidy_k + \beta \cdot OperationCost_k + \gamma \cdot Iregularpassfreq_l + \delta \cdot Infra_m + \varepsilon \tag{3}$$

Where, $Subsidy_k$ is subsidy levels under scenario k, $OperationCost_k$ is operating cost under scenario k, $Irregularpassfreq_l$ is occasional trips by individual l , $Infra_m$ is satisfaction level by individual k.

3.2 Scenario separation

Predicting future market share has uncertainty due to various variables such as market changes and economic conditions. The EV market is constantly growing, and changes in EV-related components and policies are expected to affect initial purchase cost and EV penetration rate. To estimate future policy and technological levels, EV subsidies and infrastructure levels were selected as scenario variables to predict the EV penetration rate. Therefore, this study assumes that the EV operating cost in 2025 is similar to the current 70 KRW/km, and in 2035, the operating cost changes to 30 KRW/km, 50 KRW/km, and 70 KRW/km for 3 scenarios, as shown in Table 2 below.

Table 2: Scenario setting for analysis: Subsidy 0 M/10 M/20 M KRW

Category		2025	2030	2035
Scenario 1	Optimism	70 KRW/km	50 KRW/km	30 KRW/km
Scenario 2	Base	70 KRW/km	60 KRW/km	50 KRW/km
Scenario 3	Pessimism	70 KRW/km	70 KRW/km	70 KRW/km

3.3 Environmental benefits

Previous studies have mentioned that CO, SO2, HC, NOx are the main causes of air pollution among emissions of ICV, and EV do not generate air pollution on road because there are no emissions from ICE during driving (Zhao, 2020). Therefore, we calculated the environmental benefits of the predicted change in penetration of EV through the value of pollution cost savings (PS) using the Eq(4), Eq(5) and Eq(6).

$$\mathrm{PS} = PS_{after} - PS_{before} \tag{4}$$

$$PS_{before} = \sum_{v=1}^{V}\sum_{l=1}^{L}\sum_{k=1}^{K} D_{lk}E_{lk}^{v} \tag{5}$$

$$PS_{after} = \sum_{v=1}^{V}\sum_{l=1}^{L}\sum_{k=1}^{K} D_{lk}^{'}E_{lk}^{v} \tag{6}$$

Where, PS_{after} and PS_{before} is cost of air pollution reduction after and before EV penetration rate changes, D_{lk} *and* D_{lk}' is vehicle travel distance by link l and vehicle type k. E_{lk}^{v} is air pollution cost per km, link l, vehicle type k and speed v . link l was conducted based on Korea nationwide network.
Emissions metrics based on vehicle kilometers traveled (VKT) and vehicle hours traveled (VHT) by mode and speed were used via Eq(5) and Eq(6). Korea development institute (KDI) air pollution cost unit (Figure 1) was used to estimate the amount of reduction in air pollutant. Air pollution from road driving is mainly generated in urban centers and cities, and the increasing penetration of electric vehicles is expected to improve the environment in urban centers.

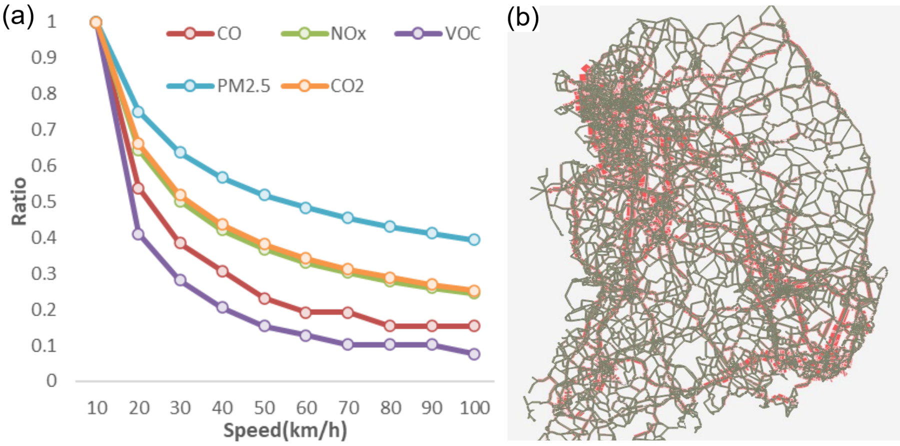

Figure 1: (a): Pollutant emission costs by passenger car speed (E_{lk}^{v}), (b): Traffic assignment result

4. Result Analysis

In this study, 855 samples were collected by SP survey, and logit model was used to conduct EV choice model based on the results of the SP survey. The result of the logit model is shown in Table 3 below. P value was calculated less than 0.05, which is confirmed as a significant level.

Table 3: Logit model results using SP survey data

Category	Coefficient	Std. err.	Z value	[95% conf. interval]	
Subsidy	.0005714***	.0000982	5.82	.0003789	.000764
Operation Cost	-.020608***	.0026357	-7.82	-.0257739	-.015442
Irregular pass frequency	-.0280693***	.0123449	-2.27	-.0522648	-.0038739
Charging station Satisfaction	.4968765***	.15723	3.16	.1887115	.8050416
_cons	1.464792***	.2376195	6.16	.9990666	1.930518

Number of obs = 855, LR chi2(4) = 109.98, Prob > chi2 = 0.0000, Pseudo R2 = 0.1023,
Log likelihood = -482.77626, ***: |p| < 0.001, **: |p| < 0.01, *: |p| < 0.05
The probabilities were calculated by each scenario; 1. Optimism, 2. Base, 3. Pessimism. Figure 2 depicts the change in the probability of choosing an EV by scenario from 2025 to 2035 based on subsidies of 0, 10, and 20 M KRW. By analyzing the number of EVs sales by scenario and subsidy per year, it was found that in the pessimistic case, where the current level of operating costs is maintained, the number of EV sales gradually decreases; when subsidies were 0KRW, sales remained at 70,000 vehicles. In the optimistic and base scenarios, where operating costs decrease in the future, the number of sales continues to increase, and over 150,000 EVs will be sold in 2035 if the subsidy is 20 M KRW. Increased subsidies and decreased operating costs are expected to reduce the financial burden on consumers and thereby increase the choice of EVs. Irregular pass frequency is expected to be long-distance traffic such as hobbies and leisure activities, and the lack of infrastructure in suburban areas is expected to reduce the choice of EVs. Similarly, the more electric charging stations there are, the higher the satisfaction level and the more likely they are to choose an electric vehicle.
To calculate the environmental benefits of each scenario, the total number of vehicles, travel time, and travel distance nationwide were calculated using Transportation demand program as shown in Table 4.
Next, the number of sales of ICVs and EVs based on the total sales of Korea (Republic of Korea) EVs in 2022 was concerned, and the number of EVs sales per year was calculated by multiplying the growth rate of passenger vehicle traffic from KTDB (Korea Transportation Database). Based on this, the air pollution reduction

benefit of replacing ICVs with EVs was calculated by multiplying the average distance traveled by EVs per year and the speed unit presented in Table 5.

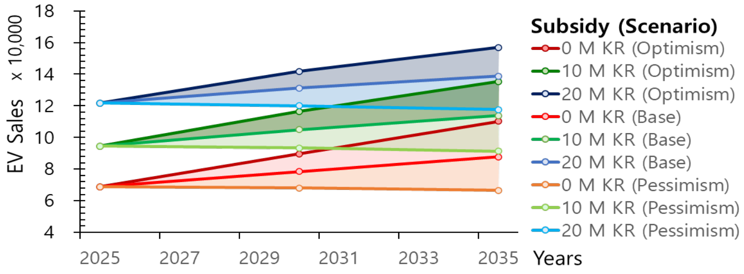

Figure 2: EV sales by Subsidy and Scenario

Table 4: Transportation demand program analysis result

Category	Total travel distance	Total travel time	Travel distance/vehicle	Average speed/vehicle
Contents	14.5 M Veh*km	628 M Veh*Hr	11.93km	43.4km/h

Table 5: Air pollution reduction benefits by subsidy and scenario (Unit: B KRW/y)

Scenario	Optimism			Base			Pessimism		
Subsidy	2025	2030	2035	2025	2030	2035	2025	2030	2035
0	4.8	6.3	7.7	4.8	5.5	6.1	4.8	4.7	4.6
10 M KRW	6.6	8.1	9.5	6.6	8.1	9.5	7.0	6.9	8.6
20 M KRW	8.5	9.9	11.0	8.5	9.9	6.8	8.9	8.8	8.6

5. Conclusion

Previous studies have confirmed that it is difficult to maintain high level of government support, and that reducing the level of subsidy from a high level of subsidy also affects the penetration rate of EVs. Therefore, this study analyze the level of subsidy to secure the penetration rate of EVs for future net-zero by scenario.
The result showed that the probability of choosing EV increased when subsidies and charging infrastructure satisfaction increased. Conversely the probability of choosing an EV decreased as operating costs and the number of irregular trips increased. The results show that the proportion of people choosing EVs increases with EV subsidies and operating costs. By calculating penetration, we found that in 2035, best scenario(20 M KRW subsidy, optimism) produce 6.4 B KRW air pollution reduction benefits per year additionally, compared to worst scenario(no subsidy, pessimism). When subsidy increased 0 to 20 M KRW, environmental benefits increased at optimism from 4.8 to 8.5 B KRW/y. Also in pessimism in 2035, increased from 4.6 to 8.6 B KRW/y. Subsidies can increase EV adoption and therefore reduce air pollution. The results are expected to contribute to the upcoming analysis of the impact of EV subsidies on the rate of environmental benefits.
In future research, it is anticipated that effective analysis can be conducted by considering demographic characteristics, all vehicle types and taking into account factors such as charging time and charging station locations. It would also be beneficial to investigate the impact of integrating electric charging stations with smart grids on the adoption rate of EVs.

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