Economic Impacts of the Green Transition: Evidence from Korean Gas Stations*

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Abstract

The transition to a carbon-free economy may pose significant risks for industries reliant on conventional energy sources. This study examines how the rising demand for electric vehicles (EVs) influences retail fuel pricing dynamics and the presence of gas stations across regions in South Korea. To address endogeneity concerns, we employ an instrumental variable approach in a two-stage least squares model, leveraging the mandatory EV charger installations in Korean apartment complexes. Our analysis reveals that installing a hundred additional EV chargers per city area decreased gasoline price per liter by 7.4% and diesel price per liter by 8.7% from 2011 to 2023, without affecting the number of gas stations per city area. These findings suggests that the expansion of EV charging infrastructure may reduce fuel costs for conventional vehicle drivers, potentially offsetting emissions reduction benefits. Finally, we highlight policy implications for the effectiveness of command-and-control-type environmental regulations.

Keywords: EV Charger, Gas Station, Gasoline Price, IV Estimation

JEL Codes: Q40, Q51, Q58

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1 Introduction

In the global transition towards a carbon-free and sustainable economy, the adoption of electric vehicles (EVs) has increased significantly, accompanied by a corresponding expansion in EV charging infrastructure (Hall and Lutsey 2017). This charging infrastructure plays a crucial role in supporting the shift to electric mobility, leading to a notable growth in the number of EV chargers (Colato and Ice 2023).

As EVs may serve as substitutes for internal combustion engine vehicles (ICEVs), increases in demand for EVs due to the proliferation of EV chargers is expected to reduce reliance on ICEV fuels like gasoline and diesel, potentially leading to decreased demand and subsequent downward pressure on prices within these fuel markets. Thus, this shift may also manifest in the restructuring of gas station networks: Their numbers and economic viability would be affected more in regions experiencing significant EV uptake. As a result, it is important to understand the implications of EV adoption through charging infrastructure development on traditional energy (fuel) markets and associated infrastructure. However, to our best knowledge, few studies so far have thoroughly examined this issue.

This paper aims to fill this void in the literature by investigating the extent to which increases in the number of EV chargers influence existing industries, with a particular focus on gas station industry in South Korea. South Korea serves as an exemplary case study for several reasons. First, Korea leads globally in EV charging infrastructure, boasting a high density of public chargers relative to plug-in EVs. According to the International Energy Agency (IEA), South Korea had 201,000 public chargers supporting 357,000 plug-in electric passenger cars by the end of 2022, equating to an average of 563 chargers per 1,000 EVs, ranking it first worldwide.[1] Second, the Korean government has implemented policies mandating the installation of EV chargers in large apartment complexes, providing a unique opportunity to utilize exogenous variations

[1] https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer

in EV demand to mitigate potential endogeneity concerns.[2] These factors make South Korea an ideal case for examining how the expansion of EV infrastructure influences the dynamics of traditional fuel markets.

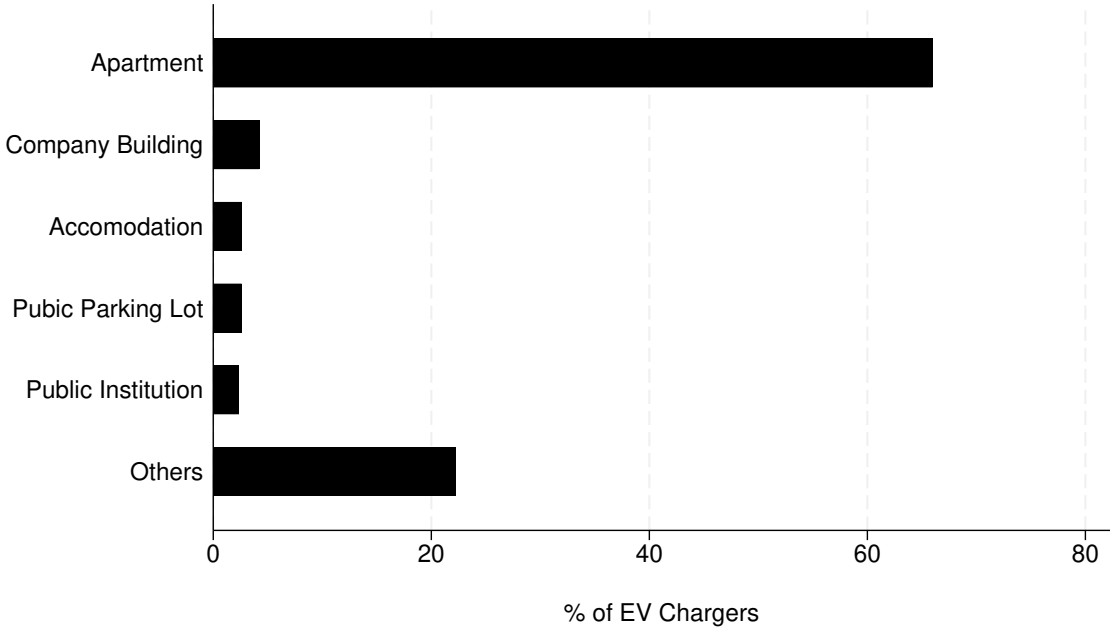
Estimating causal effects of changes in numbers of EV chargers on gas stations is challenging due to numerous confounding factors such as oil price fluctuation, government subsidies for EVs, and shifts in consumers' tastes on cars. To address these complexities and capture exogenous variations in demand, we leverage recent legislative measures in South Korea aimed at enhancing EV charging infrastructure. Specifically, under the revised Environment-Friendly Automobile Act, new apartment complexes are mandated to install EV chargers in at least 5% of their parking spaces, while existing complexes must allocate minimum 2%. This legislative push has resulted in more than 60% of South Korea's EV chargers being installed at apartment complexes as of October 2023, as shown in Figure 1.[3] To estimate the causal impact of EV charger growth on gas stations, we hence utilize the number of apartment units at the regional level *prior to* the introduction of EV chargers in South Korea as an instrumental variable (IV). This IV is selected based on its ability to predict the installation of EV chargers, given the observed prevalence of charger installations at apartments. Importantly, at the time of apartment construction, the legislative requirements were not anticipated, strengthening the exogeneity of this variable. Our analysis confirms that this IV is strongly correlated with changes in the number of EV chargers from 2011 to 2023, while demonstrating no significant correlation with changes in fuel prices and the number of gas stations during the pre-period from 2008 to 2010. This supports the validity of our approach in capturing exogenous variations in EV charger deployment and their potential impacts on traditional fuel infrastructure.

Our empirical findings can be summarized as follows. First, we find that both

[2]The term "apartment" in Korea is equivalent to "condominium" in the U.S.

[3]In Korea, apartments are the most common facility type for EV chargers, accounting for more than 60% of the total number of EV chargers. In contrast, all non-apartment facilities, such as shopping malls, hospitals, public parking lots, company buildings, accommodations, public institutions, schools etc., collectively account for less than 40%. As shown in Figure 1, apartment chargers significantly outnumber those in the 2nd, 3rd, 4th, and 5th positions.

Figure 1: Percentage of EV Chargers by Facility Types (Top Five and Others)



Notes: Apartments are the most common facility type for EV chargers. The second most common type is company buildings, followed by accommodations, public parking lots, and public institutions in third, fourth, and fifth place, respectively. "Others" refers to all other facility types.

gasoline and diesel prices drop significantly due to the rise of EV chargers. Second, the surge in EV chargers does not significantly change the number of gas stations, implying that the green transition in the car industry has not forced existing gas stations to exit the market. Thus, our findings suggest that gas stations respond mainly to the increasing number of neighboring EV chargers by adjusting prices (intensive margin) rather than shutting down or relocation (extensive margin). We conduct a battery of robustness check; considering only the altering current (AC)-type chargers, controlling for a battery of additional factors, using lagged versions of the IV, and applying region-specific deflation to price dependent variables hardly change the results. Furthermore, we perform a back-of-the-envelope calculation to provide an estimate of the positive spillover effect for individuals who originally owned ICEVs, benefiting from

lower gasoline or diesel prices and the corresponding increases in real income.

We finally highlight important policy implications of our findings. In regions where the number of EV chargers has significantly increased, a subsequent decrease in gasoline or diesel price might lead to a positive spillover effect for those driving ICEVs, as they may benefit from lower fuel cost given no changes in accessibility to gas stations. Thus, even with the increased availability of EV chargers, chances are that they may continue to use ICEVs instead of transitioning to EVs, saving on fuel costs and enjoying the boost in their real income. Therefore, if the government adheres to a policy of simply increasing the number of chargers with the goal of encouraging more people to transition to EVs, the policy's effectiveness may be limited. In addition, our findings have a far-reaching implication for changes in government fuel tax revenue, stemming from a potential decrease in the value-added tax levied on retail gasoline and diesel prices.

Several existing studies are closely related to our paper. First, some studies evaluate the value of charging networks by analyzing how various underlying factors influence, or emerge as significant outcomes in, the relationship between charging infrastructure and EV adoption. For example, Li (2023) examines the impact of charging network compatibility on consumer welfare and firm profits, while Li et al. (2017) and Springel (2021) highlight the role of subsidies in expanding EV charger networks and increasing EV adoption. Second, other studies incorporate fuel consumption or fuel prices into the context of EV charging. For instance, Dorsey et al. (2024) forecasts the future value of EV chargers based on current consumer behavior in fuel search and refueling at gas stations. Dong and Lin (2012) investigates how charging infrastructure can reduce gasoline consumption among plug-in hybrid electric vehicle (PHEV) drivers, while Grigolon et al. (2024) demonstrates that higher fuel prices can encourage PHEV owners to rely more on electric mode by increasing the frequency of electric recharging. We build on this body of literature by unveiling a causal link between the growth of EV chargers and fuel price dynamics at gas stations.

Beyond the studies directly connected to our research, other literature explores

various aspects of EV charging infrastructure. These include optimal charger placement and network design (Ahmad et al. 2022; Chandra Mouli et al. 2016; McClone et al. 2024; Myers et al. 2024; Lam et al. 2014; Mastoi et al. 2022), the relationship between individual characteristics and charging behavior (Caperello et al. 2013; Davis 2019; Helmus et al. 2020; Lee et al. 2020; Tal et al. 2014), electric grid systems (Kester et al. 2018; Parsons et al. 2014; Powell et al. 2022; Richardson 2013), and environmental benefits and costs (Filote et al. 2020; Graff Zivin et al. 2014; Nehiba 2024). There is also a rich body of literature on the impact of monetary incentives (Davis and Bradley 2012; Fetene et al. 2017; Kacperski et al. 2022; Langbroek et al. 2017; Motoaki and Shirk 2017) and informational interventions (Nicolson et al. 2017; Nienhueser and Qiu 2016) in shaping drivers' charging decisions. In particular, several papers conduct and analyze experiments to explore the effects of nudges and incentives aimed at encouraging EV owners to shift their charging behavior to midday hours, when solar energy generation is most abundant (Bailey et al. 2023; Burkhardt et al. 2023; Garg et al. 2024; La Nauze et al. 2024).[4] However, as none of these studies directly consider the economic impact of EV chargers on gas stations, we offer a novel contribution to the literature by examining this relationship.

The remainder of this paper is organized as follows: Section 2 describes the data across cities, counties, and districts in South Korea. Section 3.1 presents the assumptions and inferences that ground our hypothesis and predict how the increasing number of EV chargers can affect the gas station industry. Section 3 introduces our identification strategy with an IV, and then Section 4 reports our findings together with several robustness checks and discusses their economic and policy implications. Section 5 concludes.

[4]Charging EVs during periods of high renewable energy generation, such as midday when solar energy is plentiful, can help reduce the environmental damage of EV usage and support the decarbonization of the power grid (Garg et al. 2024; Imelda et al. 2024).

2 Data

We first describe how we obtain information on average gasoline and diesel prices, the number of gas stations, and the number of EV chargers at the regional level. We also detail the procedures involved in constructing regional-level control variables and the instrumental variable. The geographical unit of analysis is 228 cities, counties, and districts in South Korea.[5] We focus on the period from 2011 to 2023, as the first EV charger in Korea was installed in October 2010,[6] and data on EV chargers are available only for the year 2023.

2.1 Gas Stations Data

Our primary source for the regional level data on gas stations is the Oil Price Information Network (OPINET) website. OPINET, established by the Korea National Oil Corporation in 2008, aims to enhance transparency and price stability in oil product transactions by disclosing relevant price information. From this website, we extract data on the regional number of gas stations as well as the average gasoline and diesel prices for 2011 and 2023.[7] Table 1 summarizes the changes in the variables of interest between 2011 and 2023. In particular, it provides descriptive statistics on the changes in fuel prices per liter and the number of gas stations across 228 cities, counties, and districts in Korea during this period.

As shown in Table 1, average gasoline and diesel prices decreased by KRW 280.02 and KRW 178.71, respectively. The most substantial price drop for gasoline was observed in Nam District (Busan City) with a reduction of KRW 388.17. Dong District

[5] Sejong City, formerly part of Yeongi County, was designated as the administrative capital of the Republic of Korea in 2012. This designation granted it autonomy and reclassified it as a special autonomous city, separate from Chungcheongnam Province. Following this transformation, Sejong City experienced rapid growth in both population and infrastructure. To address concerns that these substantial changes could bias our analysis, we exclude Sejong City from all observations in the regressions.

[6] https://www.lsholdings.co.kr/en/media/news/71375371694e6d5064656267696a784d63312f45574b474d54786

[7] We use the yearly average data for 2011 and 2023.

Table 1: Descriptive Statistics of Data on Gas Stations (2011-2023)

	No. of obs.	mean	std. dev.	min.	max
Δ Gasoline Price (in KRW)	228	-280.02	41.44	-388.17	38.86
Δ Diesel Price (in KRW)	228	-178.71	42.51	-259.73	131.12
Δ # Gas stations	228	-8.74	9.34	-56	8
Δ # Gas Stations per $1km^2$ of City Area	228	-0.20	0.23	-1.08	0.35

Notes: The units of observations are cities, counties, and districts. All variables are calculated by first taking the annual averages for the years 2011 and 2023, and then obtaining the differences between the two. In the fourth row, "city area" refers to the area of a region excluding zones designated for agriculture, forestry, and natural environmental conservation. Sejong City is excluded, since it did not formally exist in 2011.

(Busan City) went through the most severe drop in diesel prices, recording KRW 259.73. Additionally, about nine gas stations exited the market on average across regions, with Changwon City experiencing the most significant decline, losing 56 gas stations over the 13-year period.

In the last row, we report the change in the number of gas stations per square kilometer of city area for each city, county, and district. The concept of "city area" is derived from the City Planning Status data provided by the Korea Land and Geospatial Informatix Corporation. It refers to regions where population and industry are concentrated or expected to concentrate. Notably, this measure excludes agricultural, forestry, and natural environmental conservation zones, which are areas where gas stations are unlikely to be present. Since the concentration of gas stations within a region is likely closely linked to local demand and supply dynamics, normalizing the number of gas stations by city area provides a more accurate reflection of the local gas station industry than simply considering the total number of gas stations in a region.[8] On average, a region in South Korea experienced a market exit of 2 gas stations per 10 square kilometers of city area over the 13-year period, with Cheongsong County experiencing the most severe market exit, losing approximately 11 gas stations per 10

[8]In the normalization process, we use the city area measured in 2011 throughout the paper. Since the city area generally does not change significantly across years in most regions, changing the measurement year to 2023 or other years does not notably affect the descriptive statistics or regression results.

square kilometers of city area.

2.2 EV Chargers Data

For regional-level information on EV chargers, we use data from the "Finding Charger Near Me" section in the pollution-free vehicle integrated website, operated by the Ministry of Environment of Korea. This dataset provides details on charger types, installation facility types, and the precise addresses for each charger in operation as of 2023. Using this dataset, we construct the variable for the number of chargers in 2023 at the city, county, and district levels. However, a limitation of the dataset is the unavailability of information on EV chargers for other years. We address this issue by noting that the EV charging industry is relatively new. Specifically, as mentioned earlier, the first EV charger in Korea was installed in October 2010. This allows us to interpret the variable as reflecting the regional-level increase in the number of chargers from 2011 to 2023, with the number of chargers before 2011 assumed to be zero.[9]

We also compute the normalized number of EV chargers per unit area for each city, county, and district in Korea based on the size of the city area. Following a similar rationale used to normalize the number of gas stations, adjusting the calculation to exclude agricultural, forestry, and natural environmental conservation zones can offer a more precise representation of the local charging infrastructure and demand.[10]

The first to the third rows in Table 2 present descriptive statistics of the changes in the number of EV chargers across cities, counties, and districts from 2011 to 2023. The table shows an average of 1,095.09 chargers, with a minimum of 26 chargers installed in Yeongyang County and a maximum of 6,990 chargers in Yongin City over the 13-year period. The normalized summary statistics by city area are reported in the fourth to

[9] We assume that the number of EV chargers installed from October to December 2010 is negligible.

[10] For example, if two regions have the same number of EV chargers but differ in city area, the region with a larger area may indicate lower demand for EVs. This is because the greater travel distances required to access chargers could make EVs more costly and less convenient for residents in that region.

Table 2: Descriptive Statistics of Changes in the Number of EV Chargers (2011-2023)

	Obs.	Mean	SD	Min	Max
Δ# EV Chargers	228	1,095.09	1,207.21	26	6,990
Δ# AC EV Chargers	228	964.97	1,109.59	5	6,622
Δ# DC EV Chargers	228	100.14	89.27	8	730
		per $1km^2$ *of city area*			
Δ# EV Chargers	228	21.04	24.44	1.31	143.29
Δ# AC EV Chargers	228	18.23	22.93	0.44	135.57
Δ# DC EV Chargers	228	2.23	1.95	0.21	13.54

Notes: The units of observations are cities, counties, and districts. In the second panel, "city area" refers to the area of a region excluding agricultural, forestry, and natural environmental conservation zones. Sejong City is excluded from the sample.

sixth rows. The fourth row shows that, on average, 21.04 EV chargers were installed per square kilometer of city area. Among all Korean regions, Damyang County had the lowest density of EV chargers, with 1.31 chargers per square kilometer of city area. In contrast, Seongdong District had the highest density, with 143.29 chargers per square kilometer of city area.

Two main types of EV chargers are commonly installed: Alternating Current (AC) chargers and Direct Current (DC) chargers. Table 2 shows that the majority of EV chargers in Korea are of the AC type. A detailed discussion of each charger type is provided in Section 4.3.

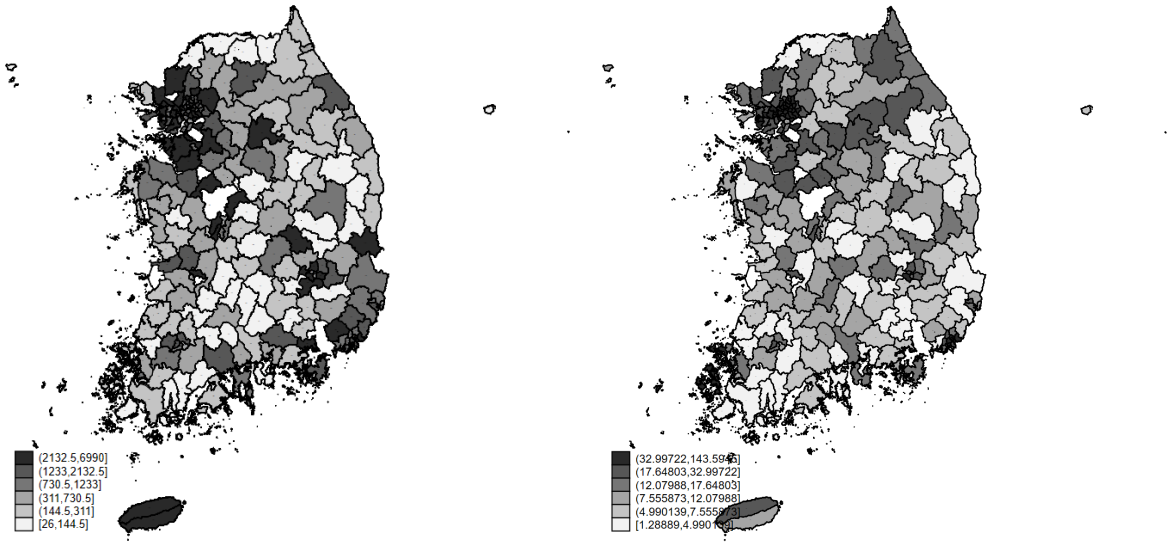
2.3 Regional Level Controls and Living Zones

Figure 2 illustrates the spatial distribution of changes in the number of EV chargers and changes in their density, i.e., the number of EV chargers per city area, from 2011 to 2023. Although considerable regional variation is evident, spatial patterns reveal notable concentrations, particularly in major cities in Korea.[11] These spatial concentrations may reflect local characteristics that could bias our estimates, making

[11]In particular, the colors of regions near Seoul City (northwest) and Busan City (southeast), the two largest cities in Korea, tend to be much darker than other regions.

it essential to control for potential confounders. To address this, we include several control variables in our analysis to account for regional-level characteristics and shocks.

Figure 2: Regional Variations in EV Chargers and Density (2011-2023)



(a) Changes in the Number of EV Chargers

(b) Changes in the Number of EV Chargers per Square Kilometer of City Area

Specifically, we control for variables that may influence both the EV charging and gas station industries in certain areas. All control variables measured at the 2011 level capture the "predetermined" characteristics of regions at the time EV chargers were introduced. Meanwhile, the "contemporary change" variables indicate (log) changes from 2011 to 2023 and help parse out the effects of confounding shocks during the 13-year period. Detailed information on data sources and measurements for each control variable is provided below.

Demographic Characteristics We use the Year-Centered Census Data from the Population and Housing Census by the National Statistical Office of Korea to construct regional demographic variables, including total population, the proportion of residents aged 25 to 49, and the proportion of residents aged 30 to 69, as of 2011 and 2023.

Vehicle Registration Status Data from the Vehicle Registration Status Report by

the Ministry of Land, Infrastructure and Transport of Korea is used to calculate the number of registered vehicles at the regional level for both 2011 and 2023.

Labor Income Labor income data for residents is sourced from the Korean Labor and Income Panel Study (KLIPS) by the Korea Labor Institute and the Local Area Labor Force Survey (LALFS). Using these sources, we calculate the average monthly wage at the regional level for 2011 and 2023.

Real Estate Market Prices Real estate market prices in a region are strongly correlated with residents' standard of living and wealth accumulation and may also reflect the level of infrastructure development in the area (Davidoff 2006; Diamond and Moretti 2021; Efthymiou and Antoniou 2013; Määttänen and Terviö 2014; Mandell and Wilhelmsson 2015). Such correlations can directly affect regional fuel prices as well as the entry and exit dynamics of gas stations in the market. For example, residents in areas with high real estate prices often have higher incomes or greater accumulated wealth, potentially making them less sensitive to fuel price increases. Such lower sensitivity allows gas stations to raise prices without significantly losing demand.

To control for these effects, we include average real estate transaction prices at the city, county, and district levels in our control variable set. Using data from the Real Transaction Price Open System, operated by the Ministry of Land, Infrastructure, and Transport, we collect transaction prices for three types of residential properties (i.e., apartments, multiplex houses, and single/multi-family houses) and two types of non-residential properties (i.e., land and commercial/business properties). We calculate the market price per square meter for each property in every transaction, then average these values by property type, region, and year. These averages are used to create both 2011-level variables and 13-year change variables as controls.

Numbers of Gas Stations per City Area The number of gas stations per city area in a region is likely to be highly correlated with both market entry or exit decisions as well as the intensity of fuel price competition. To account for the influence of market competitiveness and price fluctuations among gas stations, we control for the number

of gas stations per city area at the regional level in 2011. Additionally, in analyses where gasoline or diesel prices are the dependent variables, we control for the change in the number of gas stations per city area from 2011 to 2023.

Living Zone The Living Zone system, created by the Statistics Development Institute of the National Statistical Office of Korea, consists of 55 mutually exclusive regions designed to reflect actual living areas. Similar to *commuting zones* in the U.S., the system is based on the idea that economic activities and living areas extend beyond administrative boundaries. Considering factors such as geographical proximity and the labor market characteristics, this system categorizes Korea's administrative regions into 21 "Central Urban Zones", 13 "Urban-Rural Linked Zones", and 21 "Rural Living Zones" (Park et al. 2015). Accordingly, this system is used to control for unobserved heterogeneity across actual living spaces (Park et al. 2023).

Table 3 reports descriptive statistics of the aforementioned variables.

3 Empirical Analysis

3.1 Assumptions

Our inferences build on two key assumptions. First, traditional gas stations will experience a (negative) demand shock as more drivers switch to EV and no longer require refueling with traditional fuels. Second, the growing number of EV chargers indicates higher demand for EV, which is expected to create spillover effects on the traditional gas station industry. Consequently, gas stations are likely to be more affected in regions with significant increases in the number of EV chargers compared to those with only marginal changes. We elaborate on these assumptions below.

Assumption 1: EVs and ICEVs are substitutes.

Several studies emphasize the substitute nature of the EV adoption process. We not only reference articles that meticulously dissect the differences between ICEVs and EVs in detail to evaluate them across multiple environmental, ecological, social,

Table 3: Descriptive Statistics of the Control Variables

	Obs.	Mean	SD	Min	Max
Predetermined					
Population	228	219,429	211,465	10,550	1,083,395
Ratio of Residents Aged 25 to 49	228	0.3705	0.0595	0.2430	0.4792
Ratio of Residents Aged 30 to 69	228	0.5602	0.0216	0.5110	0.6198
Average Monthly Wage (10,000KRW)	228	190.70	35.70	113.91	315.85
# Registered Vehicles	228	80,716	78,213	4,201	560,172
# Gas Stations per $1km^2$ of City Area	228	1.20	0.85	0.16	5.23
Real Estate Market Prices (*10,000KRW*)					
Apartment	228	224.23	162.51	52.45	1,069.50
Multiplex House	228	160.36	117.49	40.65	719.59
Single/Multi-Family House	228	166.63	142.02	34.77	907.91
Land	228	78.81	157.11	0.98	1,248.11
Commercial/Business	228	252.65	211.52	36.69	1,780.33
Contemporary Changes					
Δ Population	228	3,209	54,048	-102,775	415,918
Δ Ratio of Residents Aged 25 to 49	228	-0.0701	0.0250	-0.1229	0.0383
Δ Ratio of Residents Aged 30 to 69	228	0.0252	0.0212	-0.0301	0.0871
Δ Average Monthly Wage (10,000KRW)	228	8.76	46.03	-114.18	106.41
Δ # Registered Vehicles	228	32,228	48,024	-6,606	406,973
Δ # Gas Stations per $1km^2$ of City Area	228	-0.20	0.23	-1.08	0.35
Real Estate Market Prices (*10,000KRW*)					
Δ Apartment	228	220.01	250.48	-22.31	1,559.80
Δ Multiplex House	228	-130.03	179.42	-1,331.92	24.53
Δ Single/Multi-Family House	228	-139.88	158.90	-1,184.14	0.83
Δ Land	228	76.77	225.07	-547.81	2,089.01
Δ Commercial/Business	228	175.08	207.78	-477.89	1,602.04

Notes: The units of observations are cities, counties, and districts. The term "city area" refers to the area of a region excluding agricultural, forestry, and natural environmental conservation zones. Sejong City is excluded from the sample.

economic, and technical criteria (Bauer et al. 2015; Faria et al. 2012; Onat et al. 2016), but also resort to the research shedding light on consumers' choice of EVs among other fuel alternatives. Liao et al. (2017) and Kumar and Alok (2020) identify distinctive factors and attributes linked to EV preferences. Xing et al. (2021) conduct a rigorous

counterfactual analysis to determine the type of vehicles that would have been bought if EV were not available in the market. Their findings reveal that EVs primarily replace fuel-efficient gasoline vehicles.[12]

Assumption 2: The number of EV chargers is positively correlated with EV demand.

This assumption implies that the number of EV chargers rises, as the demand for EVs increases. Several studies identify the presence of sufficient charging infrastructure as a crucial factor for successful EV adoption (Bakker et al. 2014; Campbell et al. 2012; Coffman et al. 2017; Egbue and Long 2012; Li et al. 2017; Lopes et al. 2014; Schroeder and Traber 2012; Springel 2021; Tal et al. 2014), affirming this assumption.

We further examine the relationship between the number of EV chargers and subsidized EV purchases at the city and county level.[13] In particular, we regress the number of subsidized new EV purchases in 2023 and the total subsidized EV purchases from 2021 to 2023 separately on the number of EV chargers in 2023.[14] As shown in Figure 3, the number of EV chargers in 2023 is strongly positively correlated with both subsidized new EV purchases in 2023 (panel (a)) and the total subsidized EV purchases from 2021 to 2023 (panel (b)), providing support for Assumption 2.[15]

3.2 Identification Strategy

To examine the causal effect of expanding EV charging infrastructure on the gas station industry in Korea, we analyze regional variations in the change in EV chargers per city area, average gasoline and diesel prices, and the number of gas stations per

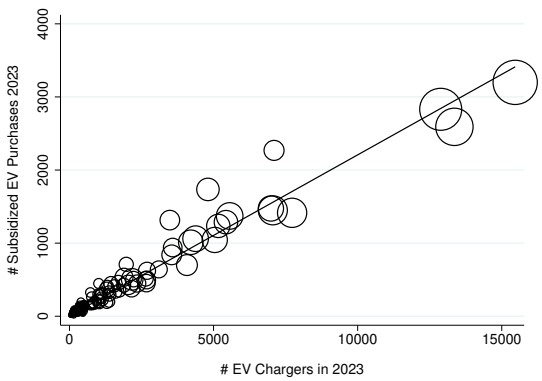
[12]However, some studies such as Burlig et al. (2021) suggest that "EVs may be complements to gasoline-powered vehicles, rather than substitutes for them."

[13]Due to data limitations, we rely on the number of subsidized EV purchases rather than total EV purchases. Under Korea's green transition policy, local governments provide subsidies for certified EVs and nearly all new EVs delivered are subsidized.

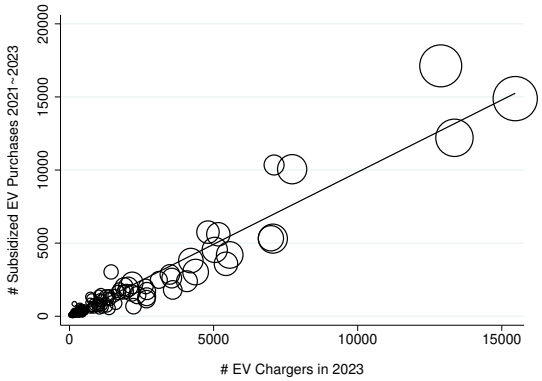
[14]Full regression results are reported in Table A1. Additionally, the figures and regression results with city area normalization are presented in Figure A1 and Table A1.

[15]One potential concern regarding this assumption and inference process is the recently increased demand for hybrid vehicles (HVs). However, since HVs also have a substitutional relationship with EVs (Xing et al. 2021), and HV owners also refuel at gas stations, our framework remains valid even when considering HV demand. Furthermore, we treat plug-in hybrid electric vehicles (PHEVs) as a type of EV within our framework since they rely on EV chargers for operation just like EVs.

Figure 3: EV Chargers and Subsidized Purchases by Region



(a) Correlation between the number of EV chargers in 2023 and the subsidized EV purchases in 2023



(b) Correlation between the number of EV chargers in 2023 and the aggregated subsidized EV purchases 2021∼2023

Notes: Data is from the pollution-free vehicle integrated website, Ministry of Environment, Korea. Since the number of subsidized EV purchases is only available at the city and county level, we transform the EV chargers data into the city and county level before examining the correlation. In both panels, we exclude data for Seoul, the capital city of South Korea, as it is an outlier with unparalleled figures for the number of EV chargers in 2023, the number of subsidized EV purchases in 2023, and the aggregated number of subsidized EV purchases from 2021 to 2023. The size of each circle is proportional to the population, and the line represents the weighted fitted line.

city area across 228 cities, counties, and districts.

Two major endogeneity concerns arise. First, EV charger installation in Korea may not have been random, as the number of chargers in each region could be influenced by unobserved confounding factors. Second, reverse causality may exist, where increased EV demand is driven by gas station closures or high fuel prices. To address these issues, we employ an instrumental variable approach, detailed in Section 3.4.

Another concern is that residents may travel to other areas for refueling or charging their vehicles. To resolve this issue, we use the Living Zone system, which represents areas where people live and work and also control for unobserved effects within Living Zones through fixed effect estimation.[16] Furthermore, we cluster the standard error at the Living Zones level to account for potential correlations between regions within the

[16]Since fuel prices at gas stations can vary regionally based on their distance from oil import points, Living Zone fixed effects also help mitigate supply-side bias in fuel price determination.

same Living Zones.

3.3 Econometric Specifications

Equation (1) is the main equation to be estimated:

$$\Delta \log(Y_{ij(11-23)}) = \beta_0 + \beta_1 \frac{\Delta EVC_{ij(11-23)}}{City\,Area_i} + \mathbf{X}_{ij11}{}' \,\beta_{\mathbf{2}} + \Delta \log(\mathbf{X}_{ij(11-23)})' \beta_{\mathbf{3}} + \gamma_j + \epsilon_{ij(11-23)}, \quad (1)$$

where Y_{ij} is one of the following variables: the average gasoline price, average diesel price, or the number of gas stations per square kilometer of city area in region i within Living Zone j. The main independent variable, $\frac{\Delta EVC_{ij(11-23)}}{City\,Area_i}$, represents the change in the number of EV chargers per square kilometer of city area in region i within Living Zone j from 2011 to 2023. Therefore, the coefficient β_1, when multiplied by 100, measures the percentage change in the dependent variable for a one-unit increase in the number of EV chargers per square kilometer of city area, holding all other explanatory variables constant.

The vector of control variables, denoted as X'_{ij11}, captures predetermined characteristics measured as of 2011. It includes the following: (log) population, the ratio of residents aged 25 to 49, the ratio of residents aged 30 to 69, the number of registered vehicles, the (log) average monthly wage of residents, (log) real estate market prices, and the number of gas stations per square kilometer of city area. Likewise, $\Delta \log(Y_{ij(23-11)})$ represents the log differences of the aforementioned variables during the 13-year period from 2011 to 2023.[17,18] Living Zone fixed effects (γ_j) are also included.

These control variables capture key socioeconomic features that may influence both

[17] The change in the number of gas stations per square kilometer of city area over the 13-year period is included only when the dependent variable is the log change in the average gasoline or diesel price.

[18] These contemporary change control variables must be treated with caution. In particular, collider bias may arise if these controls are common causes of both the independent and dependent variables, while case-control bias may occur if these controls are direct causes of only the dependent variable (Cinelli et al. 2022). These issues should be carefully considered even in an instrumental variable regression setting (Deuchert and Huber 2017). Hence, we test two alternative specifications: (i) controlling for predetermined variables only, and (ii) setting the end year for contemporary change variables to 2022 instead of 2023. Reassuringly, our baseline result presented in Section 4.1 remains largely unchanged under these alternative specifications, which are detailed in Appendix Table B1.

the gas station and EV charging industries, or specifically the gas station industry. The ratio of residents aged 25 to 49 serves as a demographic proxy for the share of prime-age population. The ratio of residents aged 30 to 69 reflects the group most likely to drive EVs.[19] The number of registered vehicles reflects regional demand for vehicles, while regional income levels likely correlate with preferences for ICEVs or EVs, as well as the development of both the gas station and EV charging industries.[20] The inclusion of the remaining controls was discussed in Sections 2 and 3.2.

While we control for an extensive set of predetermined factors measured in 2011, as well as their corresponding contemporary changes, concerns on the unobserved confounding shocks remain. For instance, the variables included may not fully capture the effects of redevelopment, new city construction, income shocks, or key factors for EV and ICEV preferences—factors that could influence both the EV charger and gas station industries.[21] Furthermore, the issue of reverse causality persists, as changes in the gas station industry driven by other unconsidered factors could have influenced the EV charging market. To address these concerns, we exploit the EV charger installation policy in apartment complexes in Korea, as detailed in the following section.

3.4 Instrumental Variable Approach

3.4.1 Institutional Background and Idea

Legislation mandating the installation of EV chargers at certain locations has been actively developed and revised since 2016. For instance, newly constructed apartment complexes with more than 500 households were required to include EV chargers for a specified proportion of parking spaces. Starting in January 2022, phased enforcement

[19] A press release from the Ministry of Land, Infrastructure, and Transport indicates that individuals in their 40s and 50s are the primary purchasers in Korea's EV market, followed by those in their 60s and 30s. Table A2 provides detailed figures and proportions of EV registrations by age group.

[20] Previous research indicates that early adopters of EVs are often individuals with higher incomes (Canepa et al. 2019; Davis 2019; LaMonaca and Ryan 2022). As a result, the transition to widespread EV adoption is expected to begin in wealthier neighborhoods and gradually extend to lower-income areas (Jacqz and Johnston 2024).

[21] Of note, we lack information on income sources other than wages, due to data limitation.

of these mandates further required that EV chargers be installed in 5% of parking spaces in newly built apartment complexes with more than 100 households and in 2% of parking spaces in existing apartment complexes of the same size.[22] Therefore, regions with a higher concentration of apartment complexes likely experienced larger increases in the number of EV chargers, a relationship we exploit for identification.

Based on the described policy details, we define our instrumental variable (IV) as the total number of apartment units in region i, including all those constructed up to and existing by the end of 2010 (APT_{i10}), normalized by city area ($City\,Area_i$)[23] :

$$IV_i \quad = \quad APT_{i10} \,/\, City\,Area_i \;. \tag{2}$$

Our IV approach leverages the strong predictive relationship between the total apartment stock in 2010 and the increase in EV chargers from 2011 to 2023, as all apartments existing by that time were subject to the mandatory installation policy for existing buildings (detailed in Section 3.4.2). Furthermore, this IV likely introduces exogenous variation in the independent variable, as it would have been nearly impossible to anticipate the future introduction of EV chargers during the construction of apartments built before 2011.

Another perspective on our instrumental variable strategy relates to a supply-side perspective. As shown in Figure 1, apartments are the most common location for EV chargers in Korea. Combined with the mandatory installation requirements, this indicates that installing EV chargers in apartments is often the easiest and most efficient method of expanding charging infrastructure. Consequently, the availability of EV chargers may be constrained by the number of apartment units in a region.[24] Furthermore, since our analysis focuses on the demand-side substitution between EVs and

[22] https://www.ajupress.com/view/20240213170016379

[23] We use the Census of Housing data from the National Statistical Office, which provides the annual or five-year count of newly built apartment units in Korea. Since all counted apartment units still exist after 2010, measurement error due to disappearing apartment units is not a concern.

[24] This approach is conceptually similar to methodologies in prior studies that leverage supply-side constraints (e.g., Bhuller et al. 2013; Dettling 2017; Falck et al. 2014).

ICEVs, an IV that incorporates supply-side constraints of EV chargers is consistent with the exclusion restriction.

Descriptive statistics of our IV are in Table 4.

Table 4: Descriptive Statistics of the Instrumental Variable

	Obs.	Mean	SD	Min	Max
Δ# APT Units 2010	228	36,514.04	41,842.38	44.00	211,568.00
Δ# APT Units 2010 per $1km^2$ of City Area	228	684.06	848.57	2.58	4,502.70

Notes: The units of observations are cities, counties, and districts. In the second row, "city area" refers to the area of a region excluding agricultural, forestry, and natural environmental conservation zones. Sejong City is excluded from the sample.

3.4.2 First-Stage Regression

Table 5 presents the formal first-stage regression results. The explanatory variable is our IV, while the dependent variable is the change in the number of EV chargers per square kilometer of city area during the 2011–2023 period. Column (1) shows the benchmark regression results with the IV only. Columns (2) through (4) sequentially add controls for predetermined and contemporary change variables, as outlined in Section 3.3, along with Living Zone fixed effects. The coefficient estimate in Column (4) suggests that regions with 100 additional apartment units per square kilometer of city area in 2010 experienced an average increase of 1.4 EV chargers per square kilometer of city area from 2011 to 2023. Across all columns, the estimates are statistically significant, confirming the relevance of the IV.

3.4.3 IV Falsification Tests

The identifying assumption for using our IV is that the number apartment units in 2010 is not correlated with unobserved determinants of the change in the average fuel prices and the quantity of gas stations during the 2011-2023 period. In other words, conditional on the control variables, the IV affects the dependent variables

Table 5: First-Stage Regression

Dependent variable: $\Delta EVC_{ij(11-23)}/City\,Area_i$				
	(1)	(2)	(3)	(4)
IV_i	0.023***	0.012***	0.014***	0.014***
	(0.001)	(0.002)	(0.001)	(0.001)
Predetermined		✓	✓	✓
Contemporary Change			✓	✓
LZ FE				✓
R^2_{adj}	0.679	0.791	0.830	0.803
Obs.	228	228	228	228

Notes: The explanatory variable (instrument) is the number of apartment units per $1km^2$ of city area in 2010. The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones.
*p < 0.10, **p < 0.05, ***p < 0.01.

solely through the change in the number of EV chargers per city area during 2011-2023, which is after 2010, when the first EV charger was introduced in Korea. While it is not possible to fully verify this assumption, we indirectly assess the validity of our instrument by testing whether it is significantly correlated with the pre-period (2008 to 2010) changes in retail fuel prices and the number of gas stations per city area.[25]

Table 6 reports the results of these falsification tests. The pre-period correlations for the three outcome variables - log changes in gasoline prices, diesel prices, and the number of gas stations per city area - are reported in columns (1) through (6), with each dependent variable covered in two columns. Reassuringly, the coefficient estimates in all columns are statistically insignificant. Put differently, the variation we rely on does not correlate with the pre-trends of the outcome variables. These results from the falsification tests support the validity of our instrument for estimating the demand shock effects on gas stations induced by the expansion of the EV charging industry.

[25]Data prior to 2008 are unavailable from OPINET, so we use changes between 2008 and 2010.

Table 6: Falsification Tests

Dependent Variable: (2008∼2010)	Δ ln(Gasoline Price)		Δ ln(Diesel Price)		Δ ln(# Gas Stations per $1km^2$ of City Area)	
	(1)	(2)	(3)	(4)	(5)	(6)
IV_i	0.004	0.012	-0.004	-0.010	0.015	0.016
	(0.005)	(0.007)	(0.008)	(0.012)	(0.009)	(0.010)
Predetermined (2008)	✓	✓	✓	✓	✓	✓
Contemporary Change (2008 ∼ 2010)		✓		✓		✓
LZ FE	✓	✓	✓	✓	✓	✓
R^2_{adj}	0.008	0.078	0.405	0.424	0.479	0.482
Obs.	228	228	228	228	228	228

Notes: The explanatory variable (instrument) is the number of apartment units per $1km^2$ of city area in 2010. The units of observations are cities, counties, and districts. Sejong city is excluded from the sample. All regressions are weighted by the 2008 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for IV_i have been multiplied by 10,000 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

4 Impacts of EV Charger Installations

4.1 Estimation Results

Tables 7 to 9 report the regression results for the three primary dependent variables. In all tables, columns (1), (2), and (3) report the Ordinary Least Squares (OLS) regression results, while columns (4), (5), and (6) display the Two-Stage Least Squares (2SLS) regression outcomes using the IV. Specifically, columns (1) and (4) show the results from the model that includes only $\Delta EVC_{(ij(11-23))}/City\,Area_i$ as a regressor. Columns (2) and (5) add the control variables introduced in Section 3.3. Finally, columns (3) and (6) incorporate both the control variables and Living Zone fixed effects.

Gasoline price Table 7 presents the impact of the increase in EV chargers on changes in average regional gasoline prices over the 2011–2023 period. The OLS results in

Table 7: Impact on the Average Gasoline Price

Dependent Variable: Δ ln(Gasoline Price 2011$\sim$2023)

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta EVC_{ij(11-23)}/City\,Area_i$	0.011	-0.001	-0.007	-0.013***	-0.080***	-0.074***
	(0.008)	(0.011)	(0.016)	(0.003)	(0.022)	(0.017)
Controls		✓	✓		✓	✓
LZ FE			✓			✓
R^2_{adj}	0.013	0.248	0.176			
F-Stat				1,140.33	103.77	173.11
Obs.	228	228	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for $\Delta EVC_{ij(11-23)}/City\,Area_i$ have been multiplied by 100 for legibility.
*p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

columns (1)-(3) indicate that, on average, gasoline prices per liter do not significantly change. In contrast, the 2SLS regression results in column (4) indicate that a 100-unit increase in EV chargers per city area results in a 1.3% decrease in average gasoline prices per liter. With full controls and Living Zone fixed effects, the coefficient in column (6) indicates a 7.4% decrease in gasoline prices per liter, statistically significant at the 1% level. In sum, regions with substantial growth in EV charging facilities experienced more pronounced gasoline price decreases compared to regions with marginal increases.

The above finding hints at a positive spillover effect; in regions with significant increases in the number of EV chargers, the reduction in gasoline prices may have benefited individuals who continue to drive gasoline vehicles. A simple back-of-the-envelope calculation using our coefficient estimates can help quantify this effect. Suppose a driver owns a gasoline vehicle with average fuel efficiency per liter and travels

the national average annual distance.[26,27] Given the approximate average gasoline price in 2011 (KRW 1,928), a driver in a region where 21 EV chargers per city area - the average number of installation across all Korean regions — were installed over the 13-year period is estimated to experience an unexpected income gain of approximately KRW 416,586 in 2023, compared to 2011.[28,29] Alternatively, if 143 EV chargers per city area - the maximum number of the independent variable across all Korean regions - were installed in that region, the estimated benefit for the representative gasoline vehicle owner over the 13-year period becomes around KRW 2,836,751.[30]

Diesel price Table 8 provides the results pertaining to the average diesel price change. Similar to the case of gasoline prices, the OLS results in columns (1)-(3) show insignificant changes in diesel prices. In contrast, after addressing the endogeneity issue and controlling for all variables, the average price of diesel per liter decreases by 8.7% on average when 100 EV chargers per city area are installed (column (6)).[31] This result is also statistically significant at the 1% level, indicating a noteworthy impact of the expansion of the EV charging industry on the average diesel prices.

Number of gas stations Table 9 illustrates how the increasing number of EV chargers influence the changes in the number of gas stations within a region. While all OLS

[26] Using data from the Korea Energy Agency on the fuel economy of 1,785 domestic and imported gasoline vehicles purchased between 2008 and 2024, we calculate that the average fuel economy is approximately 10.309 km per liter.

[27] The average annual mileage for gasoline vehicles is calculated using the daily average driving distance per vehicle information from the dataset provided by the Statistical Office of Korea, which is available for the years 2012 to 2023. We compute the average of the yearly values for the daily driving distances per vehicle, multiply by 365 days, and then by 13 to estimate the total mileage over the 13-year period. This calculation results in approximately 143,338.542 km. For an alternative calculation, we assume that the average annual mileage in 2011 is identical to that of 2012, multiply each year's daily average driving distance per vehicle by 365, and sum the predicted yearly mileage for all 13 years. This method results in approximately 143,591 km. We use the former calculation result in the back-of-the-envelope calculation process to provide a more conservative estimate.

[28] Using the coefficient estimates obtained in robustness check sections, this benefit is estimated to range from KRW 292,736 to KRW 557,324.

[29] $[(\text{KRW } 1,928/\ell \times 0.074)] \times \left(\frac{21}{100}\right) \times \left(\frac{143{,}338.542 \text{ km}}{10.309 \text{ km}/\ell}\right) \approx \text{KRW } 416,586$

[30] $[(\text{KRW } 1,928/\ell \times 0.074)] \times \left(\frac{143}{100}\right) \times \left(\frac{143{,}338.542 \text{ km}}{10.309 \text{ km}/\ell}\right) \approx \text{KRW } 2,836,751$

[31] Using a similar calculation method, the magnitude of the potential positive spillover effect of a diesel price decrease on a representative diesel driver residing in a region where 21 EV chargers per city area were installed over the 13-year period is estimated to be around KRW 570,022.

Table 8: Impact on the Average Diesel Price

Dependent Variable: Δ ln(Diesel Price 2011$\sim$2023)

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta EVC_{ij(11-23)}/City\,Area_i$	0.010	-0.004	-0.013	-0.016***	-0.093***	-0.087***
	(0.009)	(0.010)	(0.015)	(0.004)	(0.028)	(0.019)
Controls		✓	✓		✓	✓
LZ FE			✓			✓
R^2_{adj}	0.008	0.282	0.180			
F-Stat				1,140.33	103.77	173.11
Obs.	228	228	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for $\Delta EVC_{ij(11-23)}/City\,Area_i$ have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

results and the 2SLS result without control variables point to a significant decrease, the 2SLS results with controls reported in columns (5) and (6) do not show statistical significance. These findings suggest that despite the proliferation of EV chargers and a corresponding increase in the demand for EVs, the number of gas stations did not exhibit a significant decline.

4.2 Discussions and Policy Implications

Our baseline findings can be summarized as follows; between 2011 and 2023, an increase in the number of EV chargers per unit of city area was associated with a significant decline in both the average gasoline price per liter and the average diesel price per liter, while the number of gas stations per unit of city area remained largely unchanged. We discuss more on our findings below.

First, our finding of a significant negative impact of EV charger increases on re-

Table 9: Impact on the Number of Gas Stations per City Area

Dependent Variable: Δln(# Gas Stations per $1km^2$ of City Area 2011$\sim$2023)

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta EVC_{ij(11-23)}/City\,Area_i$	-0.023***	-0.009***	-0.007**	-0.022***	0.001	0.000
	(0.001)	(0.003)	(0.003)	(0.002)	(0.010)	(0.013)
Controls		✓	✓		✓	✓
LZ FE			✓			✓
R^2_{adj}	0.294	0.503	0.384			
F-Stat				1,140.33	78.82	159.08
Obs.	228	228	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for $\Delta EVC_{ij(11-23)}/City\,Area_i$ have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

gional gasoline prices suggests a substitution relationship between EVs and gasoline vehicles. Table 10 reports the average annual mileage by vehicle type, fuel type, and usage purpose in Korea from 2012 to 2022. It shows that gasoline-fueled, personal-use passenger cars account for more than half of the total mileage for passenger vehicles. The distribution of gasoline mileage across vehicle types also confirms that passenger vehicles dominate gasoline usage. Furthermore, Table 11 highlights that most subsidized EVs purchased are passenger vehicles, particularly for personal use in Korea from 2021 to 2023. These statistics reinforce our inference of a substitution relationship. Related, Xing et al. (2021) demonstrated that 78.7% of EVs replaced conventional gasoline vehicles in the U.S. vehicle market, in line with our finding.

Second, however, the observed decrease in diesel prices may initially seem puzzling, as Xing et al. (2021) reports negligible substitution patterns between EVs and diesel vehicles. Diesel vehicles are widely used for vans, trucks, or specialty vehicles due

Table 10: The Average Annual Mileage by Vehicle Type, Fuel Type, and Usage Purpose (2012-2022)

			Usage Purpose	
		Total (km)	Non-Commercial (km)	Commercial (km)
Vehicle Type	Fuel Type	(1)	(2)	(3)
Passengers Vehicle	Gasoline	115,073,710	109,994,951	5,078,759
	Diesel	71,900,505	67,5155,819	4,384,685
	LPG	34,929,822	19,986,661	14,943,161
	Etc.	6,908,650	6,128,448	780,202
Van	Gasoline	46,188	43,766	2,423
	Diesel	13,770,214	8,948,878	4,821,336
	LPG	1,687,245	1,658,091	29.153
	Etc.	2,733,782	62,411	2,671,461
Truck	Gasoline	135,509	134,842	667
	Diesel	60,139,446	43,414,561	16,724,885
	LPG	2,200,149	1,590,039	610,111
	Etc.	1,037,339	611,695	425,644
Specialty Vehicle	Gasoline	508	283	225
	Diesel	3,696,811	363,182	3,333,630
	LPG	4,334	2,092	2,242
	Etc.	11,501	8,776	2,725

Notes: The data was obtained from the Korea Transport Safety Authority's Statistics on Vehicle Travel Distance. The formula for the annual mileage is as follows: (Average daily travel distance×365)×the number of registered vehicles. The mileage is calculated not based on the actual travel distance but on the average distance traveled during the period between the previous inspection and the most recent inspection for vehicles that have undergone annual inspections. In parentheses, the percentages of mileage covered by each fuel type are reported for each vehicle type and purpose category.

to their superior fuel efficiency for heavy loads (see Heywood 2018, for instance). The relatively small proportion of electric van and truck purchases shown in Table 11 seems at odds with our result.

However, Table 10 reveals that the situation in Korea differs significantly. Diesel vehicle mileage is not primarily associated with vans or trucks; a substantial portion is attributed to diesel passenger vehicles, creating the potential for substitution between these vehicles and passenger EVs.[32] Moreover, as shown in Table 11, while electric passenger vehicles dominate the EV market, electric trucks also represent a notable

[32]Diesel passenger vehicle mileage accounts for more than 30% of total passenger vehicle mileage.

Table 11: Annual Number of Subsidized EV Purchases from 2021 to 2023 by Vehicle Types

Vehicle Type	2021 (1)	2022 (2)	2023 (3)	Year Average (2021∼2023) (4)
Passengers Vehicle	65,583	109,806	94,792	90,060.333
	(69.823%)	(74.307%)	(67.687%)	(70.775%)
Van (Electric Bus)	1,335	1,688	2,034	1,685.667
	(1.421%)	(1.142%)	(1.452%)	(1.325%)
Truck	27,010	38,280	43,219	35,503
	(28.756%)	(24.551%)	(30.861%)	(27.900%)
Total	93,938	147,774	140,045	127,292
	(100%)	(100%)	(100%)	(100%)

Notes: The data was obtained from the 'Purchase Subsidy Payment Status' section of the pollution-free vehicle integrated website, operated by the Ministry of Environment, Republic of Korea. The term "van" in this dataset refers exclusively to the number of electric buses.

share, accounting for approximately 24% to 30% of total EV purchases.

Notably, since 2018, Korea has implemented a program offering free commercial license plates for electric trucks, likely incentivizing diesel truck owners to transition to electric trucks. Therefore, although EVs naturally exhibit a stronger substitution relationship with gasoline vehicles, Korea' s unique policy framework appears to have fostered a substitutional relationship with diesel vehicles as well. This mechanism corroborates our findings further.

Finally, the results pertaining to the number of gas stations imply that the impact of EV-induced demand shock on ICEVs was not substantial enough to force gas stations out of the market. Gas stations in Korea face significant barriers to closure due to high associated costs. For instance, the average cost of land decontamination alone is reported to exceed KRW 100 million (approximately $70,000). Our results imply that the impact of rising EV demand on gas stations has not been severe enough to reduce

their profits to the extent that they would willingly bear such heavy closure costs.[33]

Our findings provide several interesting policy implications. First, our results suggest that lower gasoline prices might deter some ICEVs drivers from switching to EVs, even with the increased availability of EV chargers. Consequently, the decline in gasoline and diesel prices could place a ceiling on the growth of EV demand. This implies that a policy solely centered on expanding the number of EV chargers may be less effective than anticipated in promoting EV adoption. In contrast, our finding that the growth of EV charging industry has not led to the market exit of gas stations suggests that the transition risk may be less significant than expected. This provides the government with an opportunity to expand EV charging infrastructure more aggressively and implement supporting policies with greater confidence. Lastly, the reduction in gasoline and diesel prices due to the increase in EV chargers offers an interesting insight regarding government tax revenue. In regions with significant growth in EV charger installations, a drop in gasoline and diesel prices may have reduced fuel tax revenue, assuming general fuel consumption patterns and quantities remain unchanged. For instance, since the Korean government levies a 10% value-added tax on retail gasoline prices, the associated revenue loss could serve as an indicator of the financial cost of the transition. This insight highlights the importance of accounting for potential revenue impacts when evaluating policies aimed at accelerating the transition to EVs.

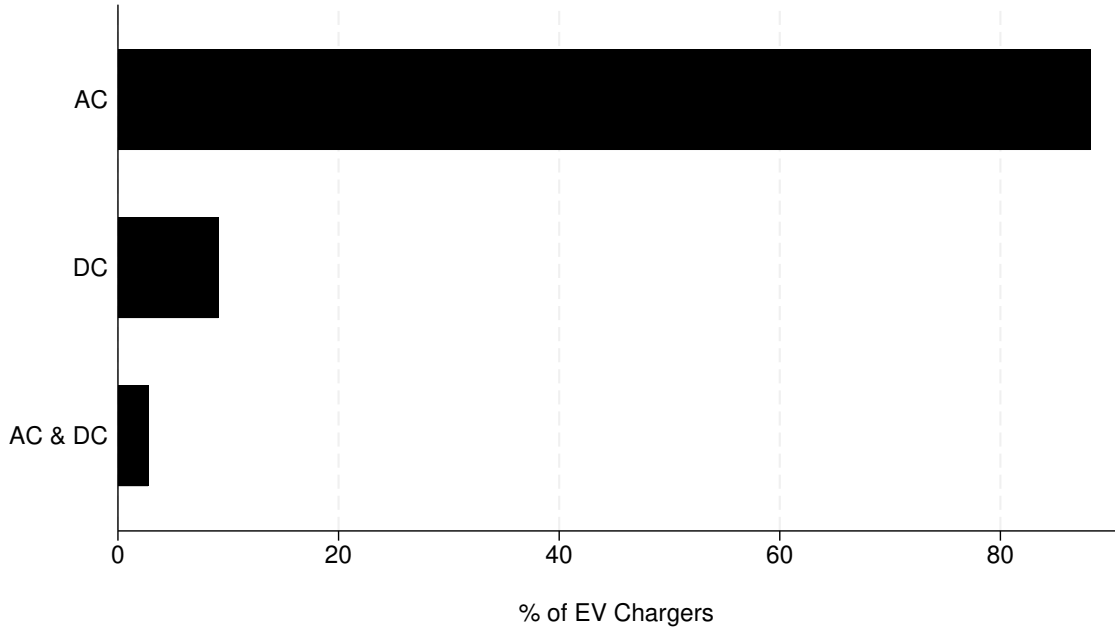
4.3 Robustness Checks

AC vs. DC EV Chargers. As the first robustness check, we examine the effects separately for different types of EV chargers. Alternating Current (AC) chargers are commonly associated with slow charging methods, whereas Direct Current (DC) chargers generally utilize fast charging methods. This distinction has led to the predominant installation of AC chargers in residential areas, such as apartments and multi-family

[33] An alternative explanation for our finding is that gas station owners have strategically adopted EV chargers at their stations to continue selling fuel while also attracting EV drivers. However, since EV chargers located in gas stations account for only 0.36% of the total EV chargers in our data, we do not consider this possibility to be the main driving mechanism.

housing buildings, while DC chargers are mainly placed in public institutions, facilities, and commercial spaces (LaMonaca and Ryan 2022; Lee et al. 2020). As illustrated in Figure 1, the majority of EV chargers in Korea are installed within apartments, with Figure 4 indicating that 88% of chargers are of the AC type. In essence, most EV owners in South Korea primarily charge their cars slowly within residential complexes, occasionally engaging in short charging sessions in public spaces.

Figure 4: Percentage of EV Chargers by Charger Types (AC vs DC)



Notes: Data on EV chargers provide detailed information on each charger's charging type. Specifically, each charger is classified as one of the following: AC single phase, AC three phase, DC CHAdeMO, DC Combo, DC CHAdeMO + AC three phase, DC CHAdeMO + AC three phase + DC Combo, and DC CHAdeMO + DC Combo. We classify AC single phase and AC three phase chargers as "AC" chargers; DC CHAdeMO, DC Combo, and DC CHAdeMO + DC Combo chargers as "DC" chargers; and DC CHAdeMO + AC three phase and DC CHAdeMO + AC three phase + DC Combo chargers as "AC & DC" chargers.

Given that the daily charging method used by EV consumers primarily involves slow chargers at home, the change in the number of DC chargers may not be correlated with the change in EV demand. Hence, according to the hypothesized mechanism

elucidated in Section 3.1, it is rational to predict that concentrating only on the effect of AC chargers would not change the main result, while focusing only on DC chargers would lead to a null result.

Table 12 presents the results for AC and DC chargers separately. The first row presents the results considering only the change in the number of AC chargers per city area as the main independent variable, while the second row shows the results when we instead take the change in the number of DC chargers per city area into account. The overall results for AC chargers align closely with the main findings: the average gasoline and diesel price dropped significantly, whereas the number of gas stations per city area did not change. Specifically, the estimated coefficients in column (1) and column (2) indicate that the introduction of a hundred additional AC chargers per square kilometer of city area results in an average reduction of 7.6% in gasoline prices per liter and 8.9% in diesel prices per liter over the 13-year period. These magnitudes of the coefficient estimates are similar to that obtained in Table 7 and Table 8, indicating that the effect of AC chargers is the main driving force behind the decline in gasoline and diesel prices. Furthermore, it is reassuring that the first-stage F-stat remains high even after excluding the influence of DC EV chargers. On the contrary, as predicted, the results for the DC chargers do not align with the main findings, and the first-stage F-stat becomes marginal, reflecting the fact that EV chargers installed in apartments are mostly of the AC type.

Additional Control Variables. In order to mitigate the concern that additional factors may be correlated with both EV chargers and the gas station industry in certain areas, we can consider more control variables. First, we control for both the predetermined levels in 2011 and contemporary changes from 2011 to 2021 in the log value of gross regional domestic product (GRDP) and the value added.[34] We consider these variables as additional controls because it is possible that the installation of EV chargers and the market behavior of gas stations can both be significantly influenced

[34]Data are sourced from the websites of individual city and provincial offices. We use the 2021 data since information on regional level GRDP and value added after 2021 is not yet publicly available.

Table 12: Second-Stage, Separating AC and DC EV Chargers

Dependent Variable	Δln(Gasoline Prices)	Δln(Diesel Prices)	Δln(# Gas Stations)	Δln(Gasoline Prices)	Δln(Diesel Prices)	Δln(# Gas Stations)
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta AC\ EVC$	-0.076***	-0.089***	0.000			
	(0.017)	(0.020)	(0.013)			
$\Delta DC\ EVC$				-5.654	-6.659	0.000
				(4.343)	(5.046)	(0.965)
First Stage Regression						
IV	0.014***	0.014***	0.014***	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Controls	✓	✓	✓	✓	✓	✓
LZ FE	✓	✓	✓	✓	✓	✓
F-stat	215.07	215.07	196.90	1.65	1.65	1.47
Obs.	228	228	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. Terms $\Delta ACEVC$ and $\Delta DCEVC$ are equivalent to $\Delta ACEVC_{ij(11-23)}/City\ Area_i$ and $\Delta DCEVC_{ij(11-23)}/City\ Area_i$, respectively. Δln(# gas stations) refers to the change in the number of gas stations per city area. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for both $\Delta ACEVC$ and $\Delta DCEVC$ have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

by the intensity of regional economic activities.

The second set of additional controls includes the predetermined log level in 2011 and the contemporary log change from 2011 to 2022 in local tax revenue.[35] These variables complement the baseline wage control variables in capturing the total regional income level, which may be associated with individuals' vehicle demand and the development of gas station and EV charging industries. Since local tax revenues encompass a wide range of tax categories, including property tax, automobile tax, leisure tax, real estate income tax, inheritance tax, and others, their magnitude serves as a reliable

[35]Data are sourced from the Local Tax Statistics managed by the Ministry of the Interior and Safety. We use the 2022 data because information on local tax revenue beyond 2022 is not yet publicly available.

proxy for regional income levels.

The third set of controls includes both the predetermined level and the contemporary log change in regional average mileage.[36] These variables, which reflect the distance traveled at the regional level, are incorporated to complement the number of registered cars in capturing the actual demand for vehicle usage and the extent to which vehicles are integrated into people's daily lives.

Table 13 presents the results when each additional control variable is included in the estimation. In congruence with the primary findings in Section 4.1, the results indicate that, on average, the installation of a hundred new EV chargers per square kilometer of city area brings about a statistically significant reduction in average gasoline price per liter, ranging from 6.5% to 7.2%. Similarly, average diesel price per liter declines significantly, ranging from 7.9% to 8.6%. Nevertheless, no discernible shift is observed in the number of gas stations per city area in response to the increase in EV chargers per city area. These consistent patterns reinforce the reliability of our main findings. Furthermore, these patterns persist even when the aforementioned additional controls altogether are incorporated into the estimation. The regression results are provided in the Appendix Table B2.

More Checks on the IV. A remaining concern regarding the exclusion restriction condition of the IV is its potential correlation with the number of newly built apartment units after the adoption of EV chargers. For instance, regions with a greater number of apartment units in 2010 may see more apartments built after 2010 if they are still undergoing new town construction. On the other hand, fewer apartments might be built in such regions if redevelopment processes were completed around 2010. In these scenarios, if unobserved or uncontrolled factors link the number of newly built apartments after 2010 to the unobservable determinants of the dependent variables, the exclusion restriction condition could be violated.

[36]Data are obtained from the Automobile Driving Distance Statistics by Korea Transportation Safety Authority. The predetermined average mileage is measured in 2012, and its change is calculated from 2012 to 2022 due to data limitations.

Table 13: Second-Stage, Additionally Controlling for Various Set of Controls

Dependent Variable	Δln(Avg. Gasoline Price)			Δln(Avg. Diesel Price)			Δln(# Gas Stations)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔEVC	-0.065***	-0.052**	-0.072***	-0.079***	-0.066***	-0.086***	0.004	0.003	0.000
	(0.015)	(0.014)	(0.017)	(0.017)	(0.017)	(0.019)	(0.015)	(0.014)	(0.012)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
LZ FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Additional Set of Controls									
GRDP & VA	✓			✓			✓		
Tax Revenue		✓			✓			✓	
Mileage			✓			✓			✓
F-stat	152.16	161.38	183.40	152.16	161.38	183.40	96.19	88.56	152.45
Obs.	228	228	228	228	228	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\ Area_i$. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for ΔEVC have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

To address this concern, we construct the number of newly built apartment units per city area from 2011 to 2023 at the regional level and examine whether controlling for it alters our key findings. Columns (1), (4), and (7) of Table 14 report the relevant results. It is reassuring that the overall patterns, as reflected by the statistical significance of the coefficient estimates for the number of EV chargers per city area, remain consistent with the previous results.

In addition, to conduct further indirect examination of the exclusion restriction of the IV, we test whether using a more lagged number of apartment units per city area works as an alternative instrument. Specifically, columns (2), (5), and (8) of Table 14 present the results when the number of apartment units per city area as of 2009 is used as the IV, while columns (3), (6), and (9) present the results when the number of apartment units per city area as of 2004 is used as the IV. Overall, these alternative IVs perform well without significant issues, generating consistent patterns with the previous findings.

Table 14: Second-Stage, More Checks on the IV

Dependent Variable	Δln(Avg. Gasoline Price)			Δln(Avg. Diesel Price)			Δln(# Gas Stations)		
	(1)	2009 IV (2)	2004 IV (3)	(4)	2009 IV (5)	2004 IV (6)	(7)	2009 IV (8)	2004 IV (9)
ΔEVC	-0.084***	-0.072***	-0.062***	-0.106***	-0.086***	-0.083***	0.005	0.001	-0.001
	(0.023)	(0.016)	(0.019)	(0.025)	(0.019)	(0.021)	(0.013)	(0.012)	(0.013)
New APT	0.001			0.002***			-0.001**		
	(0.001)			(0.001)			(0.000)		
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
LZ FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
F-stat	78.70	142.53	76.80	78.70	142.53	76.80	98.18	124.66	75.02
Obs.	228	228	228	228	228	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\ Area_i$. The term New APT is equivalent to $\sum_{t=2011}^{2023} NewAPT_{it}/City\ Area_i$. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for ΔEVC have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

Hetereogenous Price Deflation. In the main analysis, we do not adjust the average gasoline and diesel prices in the real terms when computing the log difference between 2011 and 2023. This is based on our assumption that major shocks affecting retail fuel prices, such as oil supply shocks, typically influence the aggregate economy and do not significantly impact the regional variations in fuel prices. Also, even though fuel prices may vary across regions depending on their distance from the point of oil import, the inclusion of Living Zone fixed effects helps eliminate relevant supply-side biases in fuel price determination.

However, there may still be some shocks that affect fuel prices heterogeneously across regions within the Living Zones. For example, the differences in industry composition across regions could contribute to variations in fuel price determination. To mitigate potential biases arising from this possibility, we utilize the variation in the gasoline and diesel Consumer Price Index (CPI) across cities and provinces, applying

Table 15: Second-Stage, Deflated Price Dependent Variable

Dependent Variable	Δln(Real Avg. Gasoline Price)		Δln(Real Avg. Diesel Price)	
	(1)	(2)	(3)	(4)
ΔEVC	-0.098***	-0.099***	-0.113***	-0.114***
	(0.017)	(0.017)	(0.020)	(0.020)
Controls (Original)	✓		✓	
Controls (Deflated)		✓		✓
LZ FE	✓	✓	✓	✓
F-stat	173.11	168.52	173.11	168.52
Obs.	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\ Area_i$. "Controls (Original)" refers to the baseline control variables, whereas "Controls (Deflated)" refers to the control variables adjusted to real terms. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for ΔEVC have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

region-specific, heterogeneous deflation to the average gasoline and diesel prices for 2011 and 2023.[37] The results obtained after computing the log differences of the real price dependent variables are presented in Table 15. Columns (1) and (3) report the outcomes using the baseline controls, whereas columns (2) and (4) present the outcomes when monetary control variables are similarly deflated using city- and province-specific CPI variations. Although the magnitudes of the coefficient estimates for both gasoline and diesel prices are slightly higher compared to the results displayed in Table 7 and Table 8, the overall patterns of the outcomes remain unchanged.

5 Conclusion

In this paper, we investigate how the surge in EV chargers influences changes in fuel prices and the number of gas stations in Korea between 2011 and 2023. Consid-

[37] The data is sourced from the National Statistical Office's Consumer Price by Commodity Survey.

ering the close association between the number of EV chargers and the demand for EVs, we attempt to quantify the economic impacts of the transition to sustainable energy sources. To address potential endogeneity, we employ an instrumental variable approach based on the observation that the majority of chargers in Korea are located in residential areas due to the mandatory EV charger installation policy. Specifically, we use the number of apartment units per city area in 2010 as our IV.

The empirical analysis confirms that, indeed, the price of gasoline and diesel decreased in regions where there was an increase in the number of chargers. In particular, if a hundred new EV chargers per city area were installed in a region over the 13-year period from 2011, the price of gasoline per liter in that region decreased by 7.4% and the price of diesel per liter dropped by 8.4% during the time. On the contrary, the rising number of chargers per city area did not significantly contribute to the exit of gas stations from the market. Subsequent analysis shows that gas stations' price adjustment responses are primarily driven by the increase of AC-type EV chargers. We lastly provide important implications regarding government tax revenue and green transition policies.

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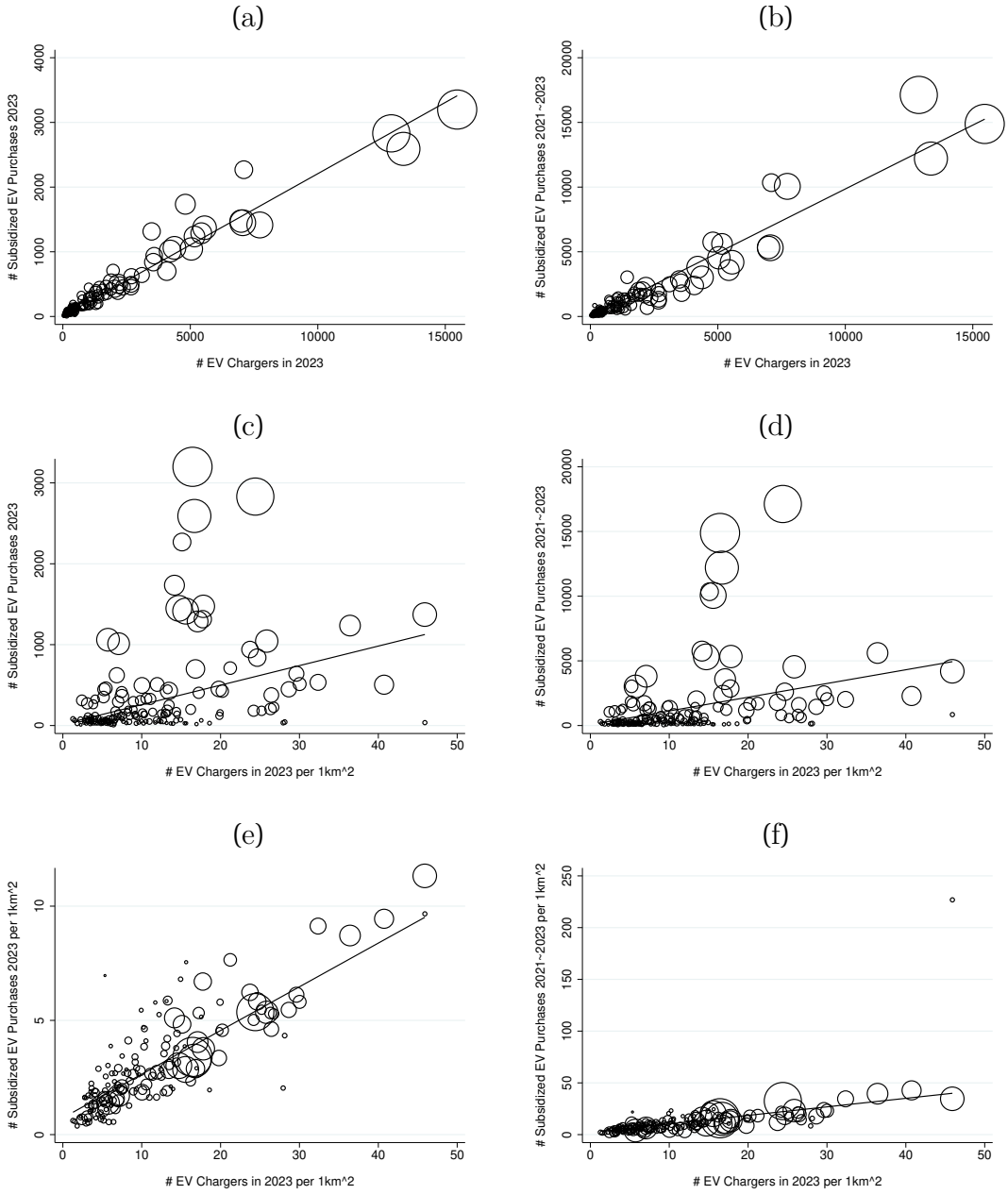
Appendix

A Detailed and Additional Results Supporting Assumption 2

In Figure A1, panels (a) and (b) are identical to Figure 3a and Figure 3b, respectively. Panels (c) and (d) show the correlation between the number of EV chargers per square kilometer of city area and the number of subsidized EV purchases. Panels (e) and (f) illustrate the correlation between the number of EV chargers per square kilometer of city area and the number of subsidized EV purchases per square kilometer of city area.

Table A1 consolidates all results related to Figure 3 and Figure A1. Specifically, columns (1) and (2) present the regression results corresponding to Figure 3a and Figure 3b, respectively. Columns (3) and (4) show the results associated with panels (c) and (d) in Figure A1, while columns (5) and (6) display the results corresponding to panels (e) and (f) in Figure A1. Across all columns, the coefficient estimates for the number of EV chargers or the number of EV chargers per city area are statistically significant and positively signed. These findings highlight a strong positive correlation between the number of EV chargers and the number of EV purchases, both with and without city area normalization.

Figure A1: Number of EV Chargers (per City Area) in 2023 and the Number of Subsidized EV Purchases (per City Area) at the City- and County-Level



Notes: Data is from the pollution-free vehicle integrated website, Ministry of Environment, South Korea. Since the number of subsidized EV purchases is only available at the city and county level, we transform the EV chargers data into the city and county level before examining the correlation. In all figures, data for Seoul, the capital city of South Korea, are excluded as it is an outlier with exceptionally high values. The size of each circle is proportional to the population, and the line represents the weighted fitted line.

Table A1: Correlation Between The Number of EV Chargers (per City Area) and The Number of EV Purchases (per City Area) at the City- and County-Level

Dependent Variable	Level of EV Purchases				EV Purchased per $1km^2$ of City Area	
	2023 (1)	2021∼2023 (2)	2023 (3)	2021∼2023 (4)	2023 (5)	2021∼2023 (6)
# EVC	0.027***	0.222***				
	(0.009)	(0.068)				
# EVC per City Area			4.284*	35.35***	0.180***	0.684***
			(2.207)	(7.502)	(0.008)	(0.021)
Population	147.5***	-357.1**	113.1**	-637.4**	0.487**	1.094
	(42.65)	(143.5)	(56.17)	(266.4)	(0.227)	(0.895)
25∼49 Popul.	-96.07	-14,118**	42.31	-13,022*	-4.942	-98.93
	(594.4)	(6,332)	(644.2)	(6,913)	(5.174)	(32.78)
30∼60 Popul.	-9,958***	6,907	-10,188***	5,042	-26.02**	114.2***
	(2,122)	(8,864)	(1,854)	(11,999)	(10.82)	(39.66)
# Vehicles	0.001***	0.009***	0.002***	0.012***	-0.000***	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Wage	334.3*1	1,071	433.9**	35.5***	0.180***	0.684***
	(171.1)	(1,361)	(177.4)	(7.502)	(0.008)	(0.021)
APT Price	45.58	703.0	89.03	1,057*	0.237	7.795**
	(137.4)	(546.4)	(148.5)	(601.4)	(0.878)	(3.356)
MH Price	51.71	-566.6	86.14	-287.7	-0.297	-2.888
	(138.3)	(449.3)	(134.4)	(492.1)	(0.813)	(3.198)
S/M-FH Price	40.14	1,276*	141.3*	2,104***	-2.591***	-3.102
	(89.10)	(753.2)	(79.34)	(778.5)	(0.836)	(2.452)
Land Price	47.55	-13.36	-14.41	-521.7***	1.241***	2.488**
	(30.56)	(172.4)	(47.67)	(184.7)	(0.307)	(1.034)
CM/BS Property Price	28.66	103.1	33.78	146.6	-0.260	-3.653*
	(57.39)	(406.1)	(63.31)	(454.3)	(0.448)	(1.959)
Constant	1,270	-10,375	289.8	-18,412	21.62***	-53.01
	(906.5)	(13,359)	(1,155)	(13,679)	(6.589)	(38.32)
LZ FE	✓	✓	✓	✓	✓	✓
R^2_{adj}	0.999	0.999	0.998	0.999	0.964	0.984
Obs.	160	160	160	160	160	160

Notes: The units of observations are cities and counties. Sejong City is excluded from the sample. All regressions are weighted by the 2023 population. Robust standard errors are in parentheses and clustered by 55 Living Zones.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table A2: Electric Vehicle Registration Status by Age Group at the End of 2021

Age Group	# Registered EVs	Percentage
- 10s	60	0.0%
20s	3,886	2.5%
30s	26,469	16.7%
40s	45,091	28.5%
50s	43,207	27.3%
60s	31,793	20.1%
70s	7,173	4.5%
80s	639	0.4%
90s -	65	0.0%
Total	158,383	100%

Notes: This data was obtained from a press release published by the Ministry of Land, Infrastructure and Transport in 2022. The statistics on EV registrations by age group were compiled based on individual purchasers excluding corporate buyers.

B Further Analysis and Robustness Checks

Table B1: Second-Stage, Mitigating Potential Collider Bias

Dependent Variable	Δln(Gasoline Price)		Δln(Diesel Price)		Δln(# Gas Stations)	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEVC	-0.069***	-0.065***	-0.079***	-0.077***	-0.008	-0.002
	(0.015)	(0.014)	(0.020)	(0.014)	(0.014)	(0.011)
Predetermined	✓	✓	✓	✓	✓	✓
Contemporary Change (2011 ∼ 2022)		✓		✓		✓
LZ FE	✓	✓	✓	✓	✓	✓
F-stat	115.46	148.35	115.46	148.35	115.46	201.90
Obs.	228	228	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\,Area_i$. Contemporary change control variables are measured for the period from 2011 to 2022. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for ΔEVC have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table B2: Second-Stage, Additionally Controlling for Various Set of Controls

Dependent Variable	Δln(Avg. Gasoline Price)	Δln(Avg. Diesel Price)	Δln(# Gas Stations)
	(1)	(2)	(3)
ΔEVC	-0.053***	-0.072***	0.003
	(0.012)	(0.015)	(0.015)
Controls	✓	✓	✓
LZ FE	✓	✓	✓
Additional Set of Controls			
GRDP & VA	✓	✓	✓
Tax Revenue	✓	✓	✓
Mileage	✓	✓	✓
F-stat	68.91	68.91	38.69
Obs.	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\,Area_i$. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for ΔEVC have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table B3: Second-Stage, Urban Subsample or Urban Control

Dependent Variable	Δln(Gasoline Price)		Δln(Diesel Price)		Δln(# Gas Stations)	
	Subsample (1)	Urban Control (2)	Subsample (3)	Urban Control (4)	Subsample (5)	Urban Control (6)
ΔEVC	-0.074***	-0.077***	-0.090***	-0.088***	0.001	-0.001
	(0.015)	(0.016)	(0.019)	(0.019)	(0.012)	(0.013)
$Urban$		-0.610**		-0.207		-0.163
		(0.306)		(0.279)		(0.210)
Controls	✓	✓	✓	✓	✓	✓
LZ FE	✓	✓	✓	✓	✓	✓
F-stat	107.58	182.91	107.58	182.91	124.25	179.13
Obs.	144	228	144	228	144	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\ Area_i$. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for ΔEVC have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table B4: Second-Stage, Separating Self-Operated vs General Gas Stations

Dependent Variable	Δln(Gasoline Price)		Δln(Diesel Price)		Δln(# Gas Stations)	
	Self (1)	General (2)	Self (3)	General (4)	Self (5)	General (6)
ΔEVC	-0.055***	-0.053**	-0.066***	-0.063***	0.004	-0.006
	(0.010)	(0.018)	(0.014)	(0.017)	(0.009)	(0.022)
Controls	✓	✓	✓	✓	✓	✓
LZ FE	✓	✓	✓	✓	✓	✓
F-stat	167.40	170.72	167.40	170.72	159.08	159.08
Obs.	222	227	222	227	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\ Area_i$. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for ΔEVC have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table B5: Second-Stage, Excluding Thrifty Gas Stations

Dependent Variable	Δln(Gasoline Price)		Δln(Diesel Price)		Δln(# Gas Stations)	
	Total (1)	No Thrifty (2)	Total (3)	No Thrifty (4)	Total (5)	No Thrifty (6)
ΔEVC	-0.074***	-0.075***	-0.087***	-0.088***	0.000	0.001
	(0.017)	(0.018)	(0.019)	(0.020)	(0.013)	(0.014)
Controls	✓	✓	✓	✓	✓	✓
LZ FE	✓	✓	✓	✓	✓	✓
F-stat	173.11	173.11	173.11	173.11	159.08	159.08
Obs.	228	228	228	228	228	228

Notes: The units of observations are cities, counties, and districts. Sejong City is excluded from the sample. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\,Area_i$. All regressions are weighted by the 2011 population. Robust standard errors are in parentheses and clustered by 55 Living Zones. Both point estimates and standard errors in parentheses for ΔEVC have been multiplied by 100 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.