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

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Abstract

The transition to a carbon-free economy presents challenges for industries dependent on conventional energy. This study investigates how expanding electric vehicle (EV) chargers influences fuel prices and gas station presence in South Korea. Leveraging a unique policy intervention mandating EV charger installations in apartments, we employ apartment units constructed before EV introduction as an instrument. We find that 100 additional chargers per city area lowered gasoline and diesel prices by 7.4% and 8.7%, respectively, from 2011 to 2023, without affecting gas station numbers. This suggests that EV charger expansion may inadvertently slow EV adoption by keeping fuel costs lower.

Keywords: EV Charger, Gas Station, Fuel Prices, IV Estimation

JEL Codes: Q40, Q50, Q58

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1 Introduction

Rising global temperatures and increasing occurrences of extreme weather and climate events have prompted politicians and researchers to actively discuss decarbonization measures, including the reduction of CO_2 emissions, over the past decades. Among these measures, the adoption of electric vehicles (EVs) has emerged as a key strategy in the global transition toward a carbon-free and sustainable economy. Since EVs are likely substitutes for internal combustion engine vehicles (ICEVs) (e.g., Xing et al. 2021), this transition is expected to reduce reliance on conventional ICEV fuels such as gasoline and diesel. Consequently, the shift toward EVs could introduce additional risks, or opportunities, by creating spillover effects on other industries.

This paper seeks to evaluate the potential transition risks associated with this shift, which, to the best of our knowledge, has been largely overlooked in the existing literature; previous research has examined the environmental impacts of EV adoption (Graff Zivin et al. 2014; Holland et al. 2016; and Nehiba 2024), compared its static and dynamic economic costs (Gillingham and Stock 2018; and Holland et al. 2021), analyzed factors influencing EV purchase decisions (Lin and Wu 2018; and Muehlegger and Rapson 2022), and assessed the effectiveness of different government subsidies for promoting EVs (Linn 2022). However, few have explored the spillover impacts of the EV transition. In this paper, we investigate the extent to which EV adoption impacts conventional energy (fuel) markets and associated infrastructure by estimating the causal effects of a substantial increase in EV chargers in South Korea on the gas station industry.[1]

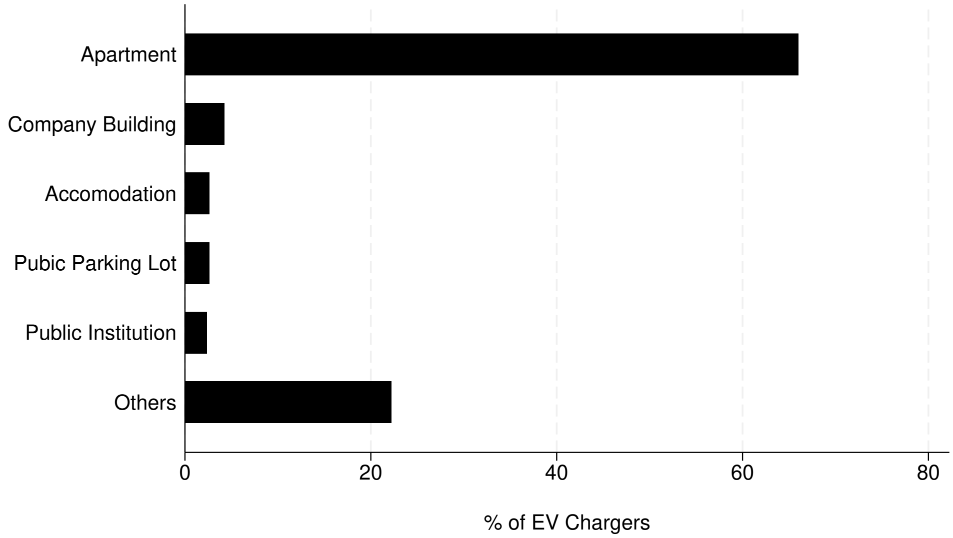
The EV charging infrastructure plays a pivotal role in enabling the transition to electric mobility (Gillingham and Stock 2018; and Colato and Ice 2023). South Korea is a global leader in EV charging infrastructure; according to the International Energy Agency (IEA), the country had 201,000 public chargers supporting 357,000 plug-in electric passenger cars in 2022, i.e., an average of 563 chargers per 1,000 EVs, the highest in the world.[2] The proliferation of EV chargers is likely to reduce demand for conventional fuels, thereby exerting downward pressure on fuel prices. This transition may also lead to structural changes in the gas station network, as their numbers and economic viability are likely to decline in regions with significant EV adoption. This study exploits cross-regional variations within Korea to estimate the causal effects of increased EV charger deployment on the gas station industry.

Estimating the causal effects of changes in the number of EV chargers poses significant challenges

[1] We use "South Korea" and "Korea" interchangeably.

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

Figure 1: EV Charger Installations by Facility Types



Notes: The share of installed EV chargers at different facilities in Korea as of October 2023.

due to numerous confounding factors, such as fluctuations in oil prices, government subsidies for EVs, and shifts in consumer preferences for vehicles. However, South Korea offers an ideal setting for such an analysis, owing to its environmental policy mandating the installation of EV chargers in large apartment complexes to bolster EV infrastructure. This policy creates a unique opportunity to leverage exogenous variations in EV adoption, mitigating potential endogeneity concerns.

Specifically, the revised Environment-Friendly Automobile Act in Korea requires existing apartment complexes to install EV chargers in at least 2% of their parking spaces, while new complexes must allocate a minimum of 5%. This legislative has driven the installation of more than 60% of EV chargers at apartment complexes, as illustrated in Figure 1. We, hence, utilize the number of apartment units at the municipality 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 high prevalence of installations at apartments. More importantly, its exogeneity is enhanced considering that the legislative requirements were not anticipated at the time of apartment construction. We further validate its relevance by showing our IV is strongly correlated with changes in the number of EV chargers from 2011 to 2023 but uncorrelated with changes in fuel prices or gas station counts during the pre-period (2008–2010). In addition, we assess its exogeneity by explicitly accounting for local public transportation accessibility and by testing alternative timings of apartment construction.

Our empirical findings can be summarized as follows. First, we find that the rise in EV chargers significantly reduces gasoline and diesel prices. Second, despite this shift, the number of gas stations remains largely unchanged, suggesting that the green transition in the automotive industry has not forced existing gas stations to exit the market. This implies that gas stations primarily respond to the growing presence of neighboring EV chargers by adjusting fuel prices (i.e., intensive margin) rather than by shutting down or relocation (i.e., extensive margin). We further reinforce this conclusion by examining the direct impact of EV purchases on the gas station industry. Our findings are robust to several alternative specifications, including (i) restricting the analysis to alternating current (AC) chargers only, (ii) applying region-specific deflation to fuel price variables, and (iii) controlling for additional factors that could influence the estimates.

Our findings offer several noteworthy implications. First, a policy focused on expanding EV charging infrastructure may be less effective than anticipated in accelerating EV adoption. Specifically, ICEV drivers in regions experiencing significant growth in EV chargers may benefit from lower conventional fuel costs and continue using ICEVs, particularly in the absence of changes in gas station accessibility. Second, the robust expansion of EV charging infrastructure in Korea has not yet resulted in a transition risk substantial enough to affect the extensive margin, as gas stations have largely remained in operation. Finally, our findings have implications for public finances regarding potential tax revenue losses from fuel price declines. For instance, under a 10% value-added tax on retail gasoline prices, one could estimate the potential revenue impact for the Korean government using our analysis as a basis.

In addition to the literature on EV adoption, our paper is closely related to research evaluating the economic and environmental impacts of expanding EV charging networks. Several studies examine the effectiveness of various policy measures aimed at accelerating EV charger deployment and promoting EV adoption (Li et al. 2017; Li 2023; and Springel 2021). Some papers assess the costs of the EV charging in terms of electricity generation and resulting emissions (Imelda et al. 2024; and Garg et al. 2024). Other research investigates the economic value of refueling time (Dorsey et al. 2024) and plug-in hybrid users' responses to fuel price fluctuations (Grigolon et al. 2024). However, none of these studies directly investigate the potential risks that EV adoption poses to the conventional energy industry, particularly gas stations. Thus, our study contributes to this literature by offering new insights into the broader implications of the green transition for conventional energy markets and infrastructure.

The remainder of this paper is organized as follows: Section 2 describes the data at the municipality level in Korea. Section 3 illustrates our empirical framework with details on our IV. Section

4 discusses our findings and their economic implications, together with several robustness checks. Section 5 concludes.

2 Data

This section demonstrates 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. The geographical unit of our analysis consists of 228 municipalities in South Korea (i.e., *Si-Gun-Gu*), which are the close to the most granular units used for cross-regional analysis in the country (see Kim et al. (2025), for instance).[3] We focus on the period from 2011 to 2023, as the first EV charger in Korea was installed in October 2010,[4] 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, established by the Korea National Oil Corporation in 2008. We extract data on the regional number of gas stations as well as the average annual gasoline and diesel prices for 2011 and 2023. Table 1 provides descriptive statistics on the changes in fuel prices per liter and the number of gas stations across 228 municipalities in Korea between 2011 and 2023.

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

	number 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 unit of observation is the municipality. All variables are calculated as differences in annual average values between 2011 and 2023. In the fourth row, "city area" refers to the area of a region excluding zones designated for agriculture, forestry, and natural environmental conservation.

In the last row, we report the change in the number of gas stations per square kilometer of city area for each municipality. The concept of "city area" is derived from the City Planning Status

[3]Sejong City is excluded from all our analyses. Designated as the administrative capital of the Republic of Korea only in 2012, the city experienced swift growth in both population and infrastructure. To avoid potential bias from such abrupt development and deal with absence of observations in 2011, we have omitted it from our dataset.

[4]See, for instance, a newspaper article in the link: https://www.lsholdings.co.kr/en/media/news/71375371694e6d5064656267696a784d63312f45574b474d547866346b57776f

data provided by the Korea Land and Geospatial Informatix Corporation, referring to regions where population and industry are concentrated or expected to concentrate. Notably, this measure excludes agricultural, forestry, and natural environmental conservation zones, i.e., areas where gas stations are unlikely to be located. 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.[5] 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.

2.2 EV Chargers Data

We use the number of EV chargers based on the assumption that it is positively correlated with EV demand. This assumption implies that increases in charging infrastructure are associated with greater demand for EVs. Several studies identify the availability of sufficient charging infrastructure as a key determinant for successful EV adoption (Egbue and Long 2012; Li et al. 2017; Schroeder and Traber 2012; and Springel 2021).

We provide support to our assumption by examining the relationship between the number of EV chargers and subsidized EV purchases at the city and county (i.e., *Si-Gun*) level.[6] 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.[7] As shown in Figure 2, 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)).[8]

For municipality-level information on EV chargers, we use data from the "Finding Charger Near Me" section of the pollution-free vehicle integrated website, operated by the Ministry of

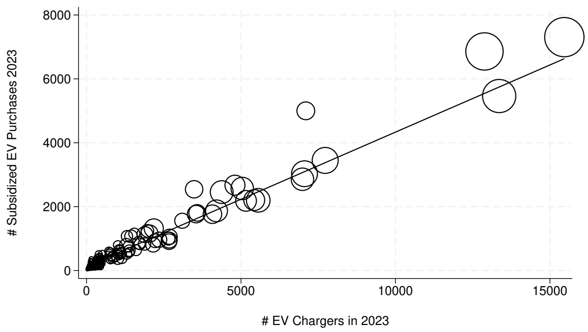
[5] In the normalization process, we use the city area measured in 2011 throughout the paper. Since the city area generally does not change significantly across years in most regions, changing the measurement year to 2023 or other years does not notably affect the descriptive statistics or regression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

[6] The only publicly available EV purchase data in Korea is the annual number of subsidized new EV purchases at the 161 city and county (*Si-Gun*) level from 2019 onward. Under Korea's green transition policy, local governments provide subsidies for certified EVs, and nearly all newly delivered EVs receive these subsidies. It is worth noting that using the *Si-Gun* level rather than the municipality (*Si-Gun-Gu*) level substantially reduces cross-sectional variation, as each *Gu*, a sub-municipal unit comprising large metropolitan areas, is aggregated into a single city unit; for example, Seoul's 25 *Gu*s would be collapsed into one. Section 4.2.2 complements our baseline analysis by presenting additional results using this EV purchase data within a panel framework.

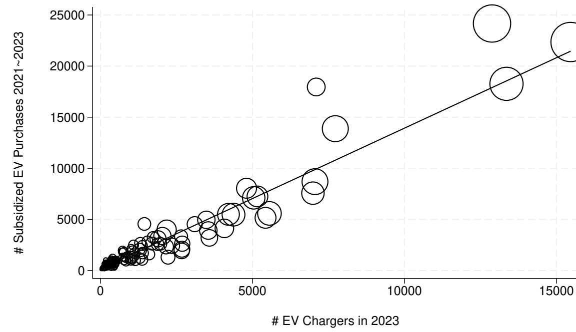
[7] Full regression results are reported in Appendix Table A1. Additionally, the figures and regression results with city area normalization are presented in Appendix Figure A1 and Appendix Table A1.

[8] One potential concern might be 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 2: EV Chargers and Subsidized Purchases by Region



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



(b) Correlation between the number of EV chargers in 2023 and EV purchases 2021-2023

Notes: Data is sourced from the pollution-free vehicle integrated website of the Ministry of Environment, Korea. The number of subsidized EV purchases is available only at the city and county level, and the EV charger data (originally available at the municipality level) is aggregated accordingly. 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 cumulative number of subsidized EV purchases from 2021 to 2023. The size of each circle is proportional to the population in 2023, and the line represents the fitted regression line.

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 a variable representing the number of chargers in 2023 at the municipality level.

One limitation of the dataset is the lack of EV charger information for years other than 2023. We address this by noting that the EV charging industry is relatively new, with the first charger in Korea installed in October 2010, as mentioned earlier. We assume that the number of chargers installed between October and December 2010 was minimal and negligible. Thus, we interpret the 2023 EV charger counts as capturing the cumulative increase in chargers from 2011 to 2023 at the municipality level, with the number of chargers prior to 2011 set to zero.

We also compute the normalized number of EV chargers per unit area for each municipality based on the size of the city area. Following a similar rationale for normalizing gas station counts, this adjustment can offer a more precise representation of the local charging infrastructure and demand.[9] Table 2 provides summary statistics of EV chargers at the municipality level.

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

[9]For example, if two municipalities have the same number of EV chargers but differ in city area, the one 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)

	number of obs.	mean	std. dev.	min.	max
$\Delta\#$ EV chargers	228	1,095.09	1,207.21	26	6,990
$\Delta\#$ AC EV chargers	228	964.97	1,109.59	5	6,622
$\Delta\#$ DC EV chargers	228	100.14	89.27	8	730
		per $1km^2$ *of city area*			
$\Delta\#$ EV chargers	228	21.04	24.44	1.31	143.29
$\Delta\#$ AC EV chargers	228	18.23	22.93	0.44	135.57
$\Delta\#$ DC EV chargers	228	2.23	1.95	0.21	13.54

Notes: The unit of observation is the municipality. "city area" refers to the area of a region excluding agricultural, forestry, and natural environmental conservation zones.

AC type. A detailed discussion of each charger type is provided in Section 4.3.

3 Empirical Framework

3.1 Instrumental Variable Approach

We leverage exogenous variation from Korea' s apartment complex EV charger installation policy. This approach helps address endogeneity concerns arising from unobserved confounding factors and potential reverse causality. Despite the extensive set of control variables employed (as discussed in Section 3.2), our estimates may still be biased due to omitted factors such as redevelopment, new city construction, income shocks, or underlying preferences for EVs and ICEVs, all of which could simultaneously affect both the EV charger and gas station industries. In addition, the possibility of reverse causality remains, as changes in the gas station sector driven by other unobserved variables could influence EV charger deployment. We therefore turn to institutional variation in EV charger installation mandates to construct our instrumental variable (IV).

Legislation mandating the installation of EV chargers at certain locations in Korea 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 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. Therefore, regions with a higher concentration of apartment complexes likely experienced larger increases in the number of EV chargers, a relationship that we exploit for identification.

Based on the described policy details, we define our IV as the total number of apartment units in region i, including all those constructed up to and in existence by the end of 2010 (APT_{i10}), i.e., prior to the start of the EV charger installation in 2011.[10] We normalize this by city area ($City\,Area_i$) as follows:

$$IV_i \quad = \quad APT_{i10}\,/\,City\,Area_i\;. \tag{1}$$

Our IV approach leverages the strong 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 (as shown further in Section 3.3). Furthermore, this IV provides exogenous variation, as apartments built before 2011 could not have anticipated the subsequent, especially mandated, introduction of EV chargers.

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.[11] Furthermore, since our analysis focuses on the demand-side substitution between EVs and ICEVs, an IV that incorporates supply-side constraints of EV chargers is consistent with the exclusion restriction. Table 3 provides the descriptive statistics of the IV.

Table 3: Descriptive Statistics of the Instrumental Variable

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

Notes: The unit of observation is the municipality. In the second row, "city area" refers to the area of a region excluding agricultural, forestry, and natural environmental conservation zones.

[10] 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.

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

3.2 Econometric Specifications

To examine how increases in the number of EV chargers affect the gas station industry, we construct a model that leverages cross-sectional variations across 228 municipalities (i.e., *Si-Gun-Gu*) in Korea. Our baseline model is as follows:

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

where endogenous variable, 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 municipality i within Living Zone j. The main independent variable, $\frac{\Delta EVC_{ij(11-23)}}{City\, Area_i}$, captures the change in the number of EV chargers per square kilometer of city area in municipality i within Living Zone j from 2011 to 2023. Therefore, the coefficient of interest β_1, multiplied by 100, indicates 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. As noted earlier, the change in EV charger numbers is instrumented using the number of apartment units per city area in i at the end of 2010, implemented through a Two-Stage Least Squares (2SLS) approach.

The vector of control variables[12], 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[13], (log) real estate market prices, and the number of gas stations per square kilometer of city area. Likewise, $\Delta \log(X_{ij(23-11)})$ represents the log differences of the aforementioned variables during the 13-year period from 2011 to 2023.[14,15]

These controls capture key socioeconomic features that may influence both the gas station and EV charging industries, or specifically the gas station industry; the ratio of residents aged 25 to 49, for example, serves as a demographic proxy for the share of prime-age population. The ratio

[12] Details on the data and descriptive statistics are provided in Appendix B.

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

[14] 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.

[15] 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 results presented in Section 4.1 remain largely unchanged under these alternative specifications, which are detailed in Appendix Table C1.

of residents aged 30 to 69 reflects the group most likely to drive EVs.[16] The number of registered vehicles reflects regional demand for vehicles, while regional income likely correlates with preferences for ICEVs or EVs, as well as the development of both the gas station and EV charging industries.[17] Table 4 provides the summary of control variables we exploit throughout this paper.

Table 4: List of Control Variables

Variables	Classification
Population	Baseline Control
Ratio of Residents Aged 25 to 49	Baseline Control
Ratio of Residents Aged 30 to 69	Baseline Control
Average Monthly Wage	Baseline Control
# Registered Vehicles	Baseline Control
Apartment Price	Baseline Control
Multiplex House Price	Baseline Control
Single/Multi-Family House Price	Baseline Control
Land Price	Baseline Control
Commercial/Business Property Price	Baseline Control
# Gas Stations per City Area	Baseline Control
Public Transportation and Accessibility	Analyzed in Section 4.2
Newly Built Apartment Units per City Area	Analyzed in Section 4.2
Gross Regional Domestic Product (GRDP)	Robustness Control (Section 4.3)
Value Added	Robustness Control (Section 4.3)
Tax Revenue	Robustness Control (Section 4.3)
Mileage	Robustness Control (Section 4.3)

Notes: The (contemporary) change of the number of gas stations per city area is excluded when it is the dependent variable.

One remaining 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 control for unobserved effects within Living Zones using fixed effect (γ_j).[18] We also use the 2011 population as the regression weight and cluster the standard errors at the Living

[16] 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. Appendix Table D1 provides detailed figures and proportions of EV registrations by age group as of 2021.

[17] Previous research indicates that early adopters of EVs are often individuals with higher incomes (Canepa et al. 2019; Davis 2019; and 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).

[18] 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). 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.

Zones level to account for potential correlations among regions within the same Living Zone.[19]

3.3 First-Stage Regression

Table 5 presents the formal first-stage regression results. The explanatory variable is our IV, and 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 result with the IV only. Columns (2)-(4) sequentially add controls for predetermined and contemporary change variables, as outlined in Section 3.2, along with Living Zone fixed effects. The 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. The estimates are statistically significant, with high first-stage F-statistics across all columns, confirming the relevance of the IV.[20]

Table 5: First-Stage Regression Results

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
F-Stat	1,140.33	33.20	103.77	173.11
Obs.	228	228	228	228

Notes: The unit of observation is the municipality. The explanatory variable (instrument) is the number of apartment units per $1km^2$ of city area in 2010. 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.

[19] Our Specific choices of fixed effects, standard error clustering level, and regression weighting are not sensitive; using province-level fixed effects, clustering at the municipality level, or omitting regression weights does not alter the result patterns. Results are available upon request.

[20] The reported first-stage F-statistics for columns (3) and (4) in Table 5 correspond to specifications that include the contemporaneous change in the number of gas stations per city area. The first-stage F-statistics for the specifications excluding this variable are reported in Table 11.

3.4 IV Falsification Tests

Our IV relies on the assumption that the number of apartment units in 2010 is uncorrelated with unobserved factors driving changes in fuel prices and gas station counts during the 2011-2023 period. That is, conditional on the control variables, the IV affects the dependent variables 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. Although this assumption cannot be directly tested, we assess its validity by testing whether the IV is correlated with the pre-period (2008 to 2010) changes in retail fuel prices and the number of gas stations per city area.[21]

Table 6: Falsification Test Results

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	0.041	0.115	-0.040	-0.097	0.145	0.156
	(0.047)	(0.070)	(0.079)	(0.117)	(0.093)	(0.103)
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 unit of observation is the municipality. The explanatory variable (i.e., instrument) is the number of apartment units per $1km^2$ of city area in 2010. 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 100,000 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table 6 reports the results of these falsification tests. The pre-period correlations for the three outcome variables, i.e., log changes in gasoline prices, diesel prices, and the number of gas stations per city area, are reported in columns (1)-(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.

[21] Due to the unavailability of OPINET data before 2008, we use changes between 2008 and 2010.

4 Impacts of EV Charger Installations on Gas Station Industry

4.1 Estimation Results

4.1.1 Impacts on the Average Region-Level Gasoline Price

Table 7: Impact on the Average Gasoline Price

Dependent Variable: Δ ln(Gasoline Price 2011-2023)						
		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 unit of observation is the municipality. Columns (1)–(3) present the Ordinary Least Squares (OLS) regression results, and columns (4)–(6) show the Two-Stage Least Squares (2SLS) regression estimates using the IV. Columns (1) and (4) use only $\Delta EVC_{(ij(11\text{-}23))}$/City Area$_i$; columns (2) and (5) add the controls from Section 3.2; and columns (3) and (6) further include Living Zone fixed effects. 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.

Table 7 presents the impact of the increase in EV chargers on changes in average regional gasoline prices between 2011 and 2023. The OLS results in 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 declines compared to regions with marginal increases.

The above finding hints at a positive spillover effect for ICEV drivers; 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. Consider a driver who owns a gasoline vehicle with average fuel efficiency per liter and travels the national average annual distance.[22,23] Given the 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 municipalities) 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.[24] This amounts to USD $318.79, using the average nannual KRW-USD exchange rate in 2023 (i.e., USD $1.00 = KRW 1306.76).[25] Alternatively, if 143 EV chargers per city area (the maximum across all Korean municipalities) 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, equivalent to USD $2,170.83.[26]

Our finding also suggests that there is a substitution relationship between EVs and gasoline vehicles. To provide further support, we report the average annual mileage by vehicle type, fuel type, and usage purpose in Korea from 2012 to 2022 in Table 8. 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. Moreover, Table 9 highlights that most subsidized EVs purchased are passenger vehicles from 2021 to 2023, particularly for personal use. These statistics reinforce our inference of the substitution relationship. Consistent with our findings, Xing et al. (2021) demonstrated that 78.7% of EVs replaced conventional gasoline vehicles in the U.S.[27]

[22] 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.

[23] 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.

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

[25] Using the coefficient estimates obtained in robustness check sections, this benefit is estimated to range from KRW 292,736 (USD $224.02) to KRW 557,324 (USD $426.29).

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

[27] Xing et al. (2021) conduct a rigorous counterfactual analysis to determine the type of vehicles that would have been bought if EVs were not available in the vehicle market. Their findings reveal that EVs primarily replace fuel-efficient gasoline vehicles. However, Burlig et al. (2021) suggest that EVs are more likely to be complements to gasoline-powered vehicles, rather than substitutes.

Table 8: 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.

Table 9: Annual Number of Subsidized EV Purchases by Vehicle Types (2021-2023)

				Year Average
	2021	2022	2023	(2021∼2023)
Vehicle Type	(1)	(2)	(3)	(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.

4.1.2 Impacts on the Average Region-Level Diesel Prices

Table 10 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)).[28] 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.

Table 10: Impact on the Average Diesel Price

Dependent Variable: Δ ln(Diesel Price 2011-2023)						
	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 unit of observation is the municipality. Columns (1)–(3) present the OLS regression results, and columns (4)–(6) show the 2SLS regression estimates using the IV. Columns (1) and (4) use only $\Delta EVC_{(ij(11\text{-}23))}$/City Area$_i$; columns (2) and (5) add the controls from Section 3.2; and columns (3) and (6) further include Living Zone fixed effects. 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.

The observed decline 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 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 9 seems at odds with our result.

However, Table 8 reveals that the situation in Korea differs significantly from that in the U.S. Diesel vehicle mileage is not primarily associated with vans or trucks; a substantial portion is

[28] 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 (USD $436.21).

attributed to diesel passenger vehicles, creating the potential for substitution between these vehicles and passenger EVs.[29] Moreover, Table 9 shows that while electric passenger vehicles dominate the EV market, electric trucks also represent a notable share, making up approximately 24% to 30% of total EV purchases. Notably, Korea has implemented a program offering free commercial license plates for electric trucks since 2018, to incentivize diesel truck owners to transition to electric trucks. Hence, 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. These considerations further corroborates our finding.

4.1.3 Impacts on the Number of Gas Stations

Table 11: Impact on the Number of Gas Stations per City Area

Dependent Variable: Δln(# Gas Stations per $1km^2$ of City Area 2011-2023)						
		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 unit of observation is the municipality. Columns (1)–(3) present the OLS regression results, and columns (4)–(6) show the 2SLS regression estimates using the IV. Columns (1) and (4) use only $\Delta EVC_{(ij(11\text{-}23))}$/City Area$_i$; columns (2) and (5) add the controls from Section 3.2; and columns (3) and (6) further include Living Zone fixed effects. 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.

Table 11 illustrates how the increasing number of EV chargers influences the changes in the number of gas stations within a region. While all OLS results and the 2SLS result without control variables point to a significant decline, the 2SLS results with controls reported in columns (5) and (6) are not statistically different from zero. 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.

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

Related, it should be noted that 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 USD $73,000). Hence, our finding implies that the impact of rising EV demand was not severe enough to reduce the profits of gas stations to the extent that they would willingly bear such heavy closure costs.[30]

4.2 Discussions

4.2.1 Public Transportation Accessibility and the Exclusion Restriction of IV

One possible concern for our baseline estimates would be the omission of key regional characteristics, which are not fully captured in the main analysis. That is, areas with more apartment units tend to be more urbanized, often featuring lower car ownership, greater access to public transportation, and shorter commutes. These factors could independently affect trends in fuel prices (regardless of EV demand), thereby posing potential threats to the IV exclusion restriction.

Table 12: Results with Public Transportation and Commuting Time Controls

Dependent Variable	Δln(Avg. Gasoline Price)			Δln(Avg. Diesel Price)			Δln(# Gas Stations)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔEVC	-0.050***	-0.062***	-0.100***	-0.060***	-0.075***	-0.114***	-0.003	0.003	0.005
	(0.008)	(0.014)	(0.018)	(0.012)	(0.016)	(0.022)	(0.010)	(0.016)	(0.019)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
LZ FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Transportation Controls									
Controls 1	✓			✓			✓		
Controls 2		✓			✓			✓	
Controls 3			✓			✓			✓
F-stat	364.63	227.74	81.84	364.63	227.74	81.84	382.02	209.11	47.11
Obs.	228	223	228	228	223	228	228	223	228

Notes: The unit of observation is the municipality. The term ΔEVC is equivalent to $\Delta EVC_{ij(11-23)}/City\,Area_i$. All regressions are weighted by 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

[30] An alternative explanation for our finding is that gas station owners may 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.

Accordingly, we control for a comprehensive set of additional variables in the baseline model to account for these factors. These variables include: i) municipality-level average access times to major facilities by time-of-day categories (morning, midday, and evening) and by transport mode (car, public transportation/walking) ("Controls 1")[31], ii) municipality-level number of public transit users and transit volumes ("Controls 2")[32], and iii) survey-based province-level population shares by public transportation access time, transit use frequency, and monthly transit cost categories ("Controls 3")[33]. We include their predetermined levels in their respective first available years as well as their changes relative to the 2022 or 2023 levels. Although these variables are informative, they are not included in the baseline models because their available sample period does not align with that of the main analysis.[34]

Table 12 presents the estimation results from models including the above controls. We confirm that our baseline findings remain robust, suggesting that local factors such as public transit availability or commuting time are unlikely to be key channels driving our results.

4.2.2 Impact of EV Uptake on the Gas Station Industry

This section examines the direct impact of actual EV uptake on the gas station industry. Specifically, we use annual data on subsidized new EV purchases at the city and county (i.e., *Si-Gun*) level from 2020. While this dataset enables panel analysis, it comes with a key limitation: the publicly available subsidized EV purchase data substantially reduce cross-sectional variation, as noted in detail in footnote 6. Nevertheless, we conduct this analysis to complement our main

[31]The data are obtained from the Transport Accessibility Indicators provided by the Korea Transport Institute for the years 2017–2022. The average access time index records, in minutes, the travel time required to access educational, medical, retail, and metropolitan transportation facilities at the municipality (i.e., *Si-Gun-Gu*) level in Korea. Travel times are reported by time of day, i.e., morning (7am-9am), midday (noon–2pm), and evening (6pm-8pm), and by transport mode (car, public transportation/walking).

[32]The data are obtained from the Public Transit Usage Analysis Indicators provided by the Smart Card Big Data System, operated by the Korea Transportation Safety Authority and the Ministry of Land, Infrastructure and Transport. The dataset contains information on the number of public transit users, "trip-based transit volume"—defined as the number of complete trips from the initial boarding to the final alighting counted as one use—and "mode-based transit volume" —defined as the boarding or alighting events that occur each time a bus or subway is used. Both trip-based and mode-based volumes are further decomposed into origin volume and destination volume. All variables sourced from this dataset are log-transformed. For the trip-based and mode-based volume variables, 1 was added prior to taking the logarithm, as several observations had a value of 0.

[33]The data are obtained from the Public Transportation Survey conducted by the Ministry of Land, Infrastructure and Transport. The survey targets individuals who use public transit at least four times a week and collects information on access time to public transportation, average weekly usage frequency, and average monthly transit expenses, with responses categorized into predefined ranges. All variables sourced from this dataset are log-transformed.

[34]Specifically, variables in "Controls 1" group are first available in 2017, "Controls 2' in 2019, and "Controls 3" in 2012. Such delays in the first available observations are unlikely to pose a serious concern, as the policy effects and the resulting rise in EV demand are expected to occur primarily in the latter part of the 2011–2023 period, as discussed in detail in Section 4.2.2.

baseline results and to provide additional evidence on the relationship between EV adoption and the gas station industry. We estimate the following 2SLS model:

$$\Delta \log(Y_{it}) = \beta_0 + \beta_1 \ \log(EV_{it}) + \mathbf{X}_{it-1}{}'\beta_{\mathbf{2}} + \gamma_i + \delta_t + \epsilon_{it}, \tag{3}$$

where $\Delta \log(Y_{it})$ denotes the annual log change in one of the three dependent variables in region i from year $t-1$ to t, for $t = \{2020, 2021, 2022, 2023\}$. These four years at the end of our baseline sample period mark a period of substantial EV adoption. The variable of main interest in this context is the log of the total number of new subsidized EV purchases. Since total EVs include both electric passenger vehicles and electric trucks, we also examine the effects separately for each vehicle type.[35] We additionally include a vector of control variables, $\mathbf{X}_{it-1}{}'$, at the city and county levels.[36] Finally, city-and county-fixed effects (γ_i) and year-fixed effects (δ_t) are considered.

The IV in this setup is constructed as the total number of apartment units in region i (APT_{i10}) as of 2010 interacted with the year-fixed effects, δ_t, for $t = \{2020, 2021, 2022\}$, i.e., $APT_{i10} \cdot \delta_t$.[37] This variable allows for the identification of heterogeneous trends in the diffusion of apartment-based EV charging infrastructure and the resulting EV uptake across regions. Standard errors are clustered at the Living Zones level.[38]

Table 13 reports the first-stage estimation results. We find that the number of apartment units prior to the adoption of EV chargers strongly predicts future EV uptake. Moreover, comparing the F-statistics across electric passenger vehicles (EPVs) and electric trucks (ETs), we find that EPVs are more likely to charge at EV chargers located at apartment complexes than ETs. This suggests that our IV primarily operates through EPVs rather than ETs.

Finally, Table 14 presents the second stage, where EV or EPV purchases are used as main independent variables in place of EV chargers. Importantly, across all three dependent variables, the estimates remain robust, even within the current panel framework.[39] These findings also provide empirical validation for using the number of EV chargers as a credible proxy for EV demand.

[35] Total EVs include electric passenger vehicles, trucks, and buses. Since many regions have zero electric buses, we exclude them from the analysis.

[36] We construct the city and county level control variables from both the baseline control set and the transportation control variable sets.

[37] Using apartment unit counts normalized by city area yields similar results, which are available upon request.

[38] Results are similar when standard errors are clustered at the city and county level and available upon request.

[39] Results change little when control variables related to public transportation accessibility are included. Results are available upon request.

Table 13: First-Stage Estimates

Dependent Variable:	$\ln(EV_{it})$		$\ln(EPV_{it})$		$\ln(ET_{it})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$APT_{i10} * \mathbb{I}\{t = 2020\}$	0.065***	0.065***	0.074***	0.073***	0.049***	0.050***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.017)	(0.018)
$APT_{i10} * \mathbb{I}\{t = 2021\}$	0.081***	0.077***	0.097***	0.091***	0.037***	0.034***
	(0.011)	(0.010)	(0.013)	(0.012)	(0.009)	(0.010)
$APT_{i10} * \mathbb{I}\{t = 2022\}$	0.030***	0.033***	0.031***	0.032***	0.016**	0.023***
	(0.009)	(0.008)	(0.011)	(0.009)	(0.007)	(0.007)
Baseline Controls	✓	✓	✓	✓	✓	✓
Transportation Controls		✓		✓		✓
Region FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
F-stat	35.14	40.54	41.03	45.44	5.73	4.48
Obs.	630	612	625	607	621	603

Notes: The units of observation are cities and counties. The terms $\ln(EV_{it})$, $\ln(EPV_{it})$, and $\ln(ET_{it})$ denote the log number of new (subsidized) purchases in year t of total EVs, electric passenger vehicles (EPV), and electric trucks (ET), respectively. APT_{i10} indicates the total number of apartment units in region i in 2010. "Transportation Controls" refer to "Controls 1" and Controls 2" variables discussed in Section 4.2.1. All regressions are weighted by $population_{it}$. Robust standard errors are in parentheses and clustered by Living Zones. Both point estimates and standard errors have been multiplied by 100,000 for legibility.
*p < 0.10, **p < 0.05, ***p < 0.01

4.2.3 Impacts on ICEV Demand

Did the expansion of EV chargers and subsequent EV uptake also affect ICEV demand? To address this question, we apply our baseline framework using an approximated measure of ICEV ownership. Specifically, we impute the total number of EVs in 2023 by aggregating subsidized new EV purchases from 2019 to 2023, again at the 161 city and county (i.e., *Si-Gun*) level. We then impute the city and county level number of total ICEVs in 2023 by subtracting the imputed total number of EVs in 2023 from the total number of car registrations in 2023. Lastly, assuming that the total number of car registrations in 2011 reflects the total number of ICEVs only, we calculate the log difference in the imputed ICEV numbers from 2011 to 2023 and regress this change on EV charger growth over the same period, in the 2SLS framework similar to our baseline model.[40]

As shown in Table 15, all specifications consistently indicate that the expansion of EV charging

[40] The only variables excluded from our baseline set of controls are those related to the number of car registrations. Additionally, excluding the log change in the number of gas stations, which could potentially be an outcome of changes in ICEV counts, does not alter the result patterns. Results are available upon request.

Table 14: Second-Stage Estimates of EV Purchase

Dependent Variable	$\Delta\ln(\text{Gasoline Price}_{it})$		$\Delta\ln(\text{Diesel Price}_{it})$		$\Delta\ln(\text{\# Gas Stations}_{it})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(EV_{it})$	-0.020***		-0.036***		0.00002	
	(0.006)		(0.010)		(0.00007)	
$\ln(EPV_{it})$		-0.016***		-0.029***		0.00001
		(0.005)		(0.008)		(0.00006)
Baseline Controls	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
F-stat	35.14	41.03	35.14	41.03	36.57	42.10
Obs.	630	625	630	625	630	625

Notes: The units of observation are cities and counties. The terms $\ln(EV_{it})$ and $\ln(EPV_{it})$ denote the log number of new (subsidized) purchases in year $t + 1$ of total EVs and electric passenger vehicles, respectively. All regressions are weighted by $population_{it}$. Robust standard errors are in parentheses and clustered by Living Zones.
*p < 0.10, **p < 0.05, ***p < 0.01

infrastructure reduced the demand for ICEVs. Together with our analysis of the effects of EV uptake discussed in Section 4.2.2, this finding supports the view that increased charging availability spurred EV adoption, which in turn substituted for ICEV demand.

4.3 Robustness Checks

Alternative Timing of the IV and Exclusion Restriction A remaining concern for the validity of our IV's exclusion restriction is its potential correlation with apartment construction outside the baseline reference year. For example, if the number of apartment units in 2010 is systematically related to post-2010 construction, it could affect the outcomes through channels other than EV charger deployment. Regions with a large apartment stock in 2010 may continue to experience significant new construction if they were still undergoing large-scale new town development, while others may see relatively little construction if redevelopment had been already completed or land supply had become constrained. Similarly, the 2010 apartment stock could reflect pre-2010 construction patterns that are correlated with unobserved factors—such as population density or urban development trends, which may independently influence fuel prices or the gas station industry. If either pre- or post-2010 construction is correlated with the 2010 apartment stock and

Table 15: Impact on the Number of ICEVs

Dependent Variable: $\Delta \ln(\widetilde{ICEV}_{ij(11-23)})$				
	(1)	(2)	(3)	(4)
$\Delta EVC_{ij(11-23)}/City\,Area_i$	-0.195*	-0.677***	-0.628***	-0.668***
	(0.108)	(0.157)	(0.090)	(0.079)
Baseline Controls	✓	✓	✓	✓
LZ FE		✓	✓	✓
Transportation Controls 1			✓	✓
Transportation Controls 2				✓
F-stat	119.26	34.04	55.25	58.16
Obs.	147	147	147	143

Notes: The unit of observation is the municipality. $\Delta \ln(\widetilde{ICEV}_{ij(11-23)})$ denotes the change in the imputed number of ICEV between 2011 and 2023 in logs in region i within Living Zone j. Both the predetermined and contemporaneous change versions of the total number of car registrations are excluded from the baseline set of control variables. "Transportation Controls 1" and "Transportation Controls 2" refer to variables discussed in Section 4.2.1. All regressions are weighted by 2011 population. Robust standard errors are in parentheses and clustered by 53 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

directly affects the outcomes, the exclusion restriction of our IV could be violated. To address these concerns, we implement two complementary robustness checks: (i) controlling directly for 2011-2023 new apartment construction and (ii) re-estimating the models using apartment unit counts from earlier years (2009 and 2004) as alternative instruments.

Table 16 reports estimation results. In all of these additional analyses, our main findings remain consistent, with the coefficient estimates on EV chargers retaining its statistical significance. Taken together, these robustness checks provide indirect support for the exclusion restriction by demonstrating that our findings are not sensitive to the exact timing of the baseline IV and are unlikely to be driven by confounding factors related to apartment construction dynamics.

AC vs. DC EV Chargers We differentiate the types of EV chargers and reestimate our baseline model; Alternating Current (AC) chargers are commonly associated with slow charging methods, and 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 housing buildings, while DC chargers are mainly placed in public institutions, facilities, and commercial spaces (LaMonaca and Ryan 2022; and Lee et al. 2020). As illustrated in Figure 1, the majority of EV chargers in Korea are installed within apartments, of which 88% are the AC type

Table 16: 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 unit of observation is the municipality. The term ΔEVC denotes $\Delta EVC_{ij(11-23)}/City\,Area_i$, while New APT refers 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.

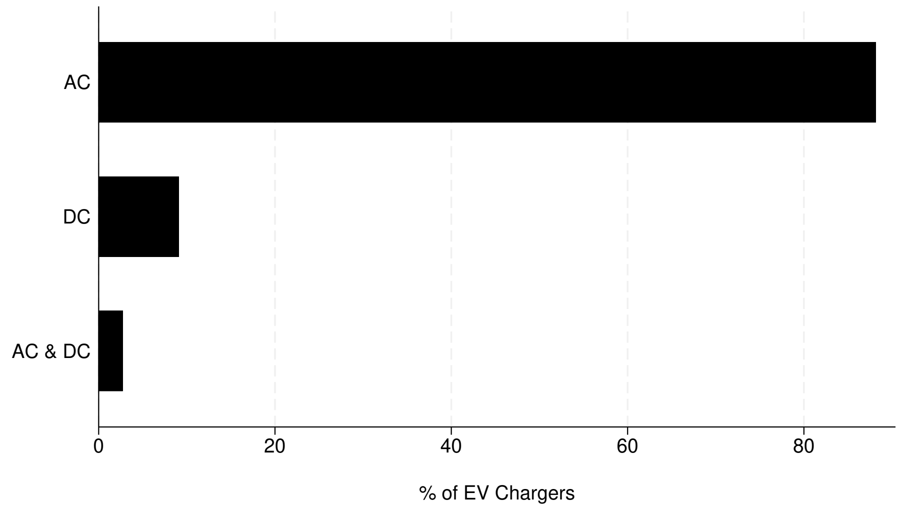
as shown in Figure 3. In essence, most EV owners in Korea likely charge their cars slowly within residential complexes primarily, occasionally engaging in short charging sessions in public spaces.

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, it is rational to expect that using AC chargers only would not alter our baseline findings, while focusing only on DC chargers would lead to an insignificant result.

Table 17 presents the results separating AC and DC chargers. 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 prices dropped significantly, whereas the number of gas stations per city area did not change. Also, the magnitudes of the coefficient estimates are similar to our baseline (Tables 7 and 10), indicating that the effect of AC chargers is the main driver behind the decline in gasoline and diesel prices. Furthermore, it is reassuring that the first-stage F-statistic remains high even after excluding the influence of DC EV chargers. In contrast, the results for DC chargers do not align with the main findings and the first-stage F-statistic becomes marginal (columns (4)-(6) in Table 17), consistent with our prior inference.

Heterogeneous Price Deflation of Fuel Prices Our main analysis does not adjust the average

Figure 3: 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.

gasoline and diesel prices for inflation when computing the log difference between 2011 and 2023. This is based on the assumption that major shocks affecting retail fuel prices, such as oil supply shocks, typically influence the aggregate economy but have limited influence on regional variation in fuel prices. Additionally, even if fuel prices may vary across regions depending on their proximity to oil import locations, the inclusion of Living Zone fixed effects helps mitigate relevant supply-side biases in fuel price determination.

Nonetheless, some shocks may still affect fuel prices heterogeneously across regions within the same Living Zone. For instance, regional differences in industrial composition could influence fuel price dynamics. To mitigate potential biases arising from such possibility, we apply region-specific deflators based on the gasoline and diesel Consumer Price Index (CPI) across cities and provinces, adjusting average fuel prices in 2011 and 2023 accordingly.[41] The results obtained using the log differences of these real prices are presented in Table 18. Columns (1) and (3) show the outcomes using the baseline controls, whereas columns (2) and (4) further deflate monetary control variables using city- and province-specific CPI variations. Although the magnitudes of the coefficient estimates for both gasoline and diesel prices are slightly larger than in the baseline models (Tables 7 and 10), the overall patterns of the outcomes remain unchanged.

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

Table 17: 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 unit of observation is the municipality. $\Delta ACEVC$ and $\Delta DCEVC$ represent $\Delta ACEVC_{ij(11-23)}/City\,Area_i$ 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.

Table 18: Second-Stage, Applying Region-Specific Deflators to Fuel Prices

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 unit of observation is the municipality. 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.

Inclusion of Additional Control Variables To address potential confounding factors correlated with both EV chargers and the gas station industry in certain areas, we include more control variables in the analysis: gross regional domestic product (GRDP), value added, tax revenue, and mileage. Our baseline results remain robust to this change (see Appendix Tables C2 and C3).

5 Conclusion

We investigated how the surge in EV chargers influenced changes in fuel prices and the number of gas stations in Korea between 2011 and 2023. Considering the close relationship between the number of EV chargers and the demand for EVs, we aimed to quantify the economic impacts of the transition to sustainable energy sources by capturing potential spillover effects on competing sectors. To address potential endogeneity, we employed an instrument based on South Korea's unique environmental policy, which mandated the installation of EV chargers in large apartment complexes. Specifically, we used the number of apartment units per city area in 2010, prior to the introduction of the EV chargers.

Our empirical analysis showed that the price of gasoline and diesel decreased in regions where the number of chargers increased. In particular, for every 100 new EV chargers installed per city area 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. However, the rising number of chargers per city area did not significantly contribute to the exit of gas stations from the market. These findings suggested that gas stations' responses to the increasing number of EV chargers were mainly through adjustment of fuel prices (i.e., intensive margin), rather than through relocation or shutting down (i.e., extensive margin).

Our findings provided several implications. First, a policy focused solely on expanding EV chargers may not be as effective in accelerating EV adoption as expected. In regions with significant growth in EV chargers, drivers of ICEVs may benefit from lower fuel costs and continue using ICEVs, especially if gas station accessibility remains unchanged. Second, the extensive expansion of charging infrastructure had not led to enough transition risk to impact the extensive margin, as most gas stations remained operational. Finally, our results highlighted the fiscal impact of the green transition, particularly on tax revenue from declining fuel prices. For instance, based on our analysis, the estimated revenue loss for the Korean government under a 10% value-added tax on retail gasoline could provide a useful gauge of the financial cost of the transition.

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Appendix

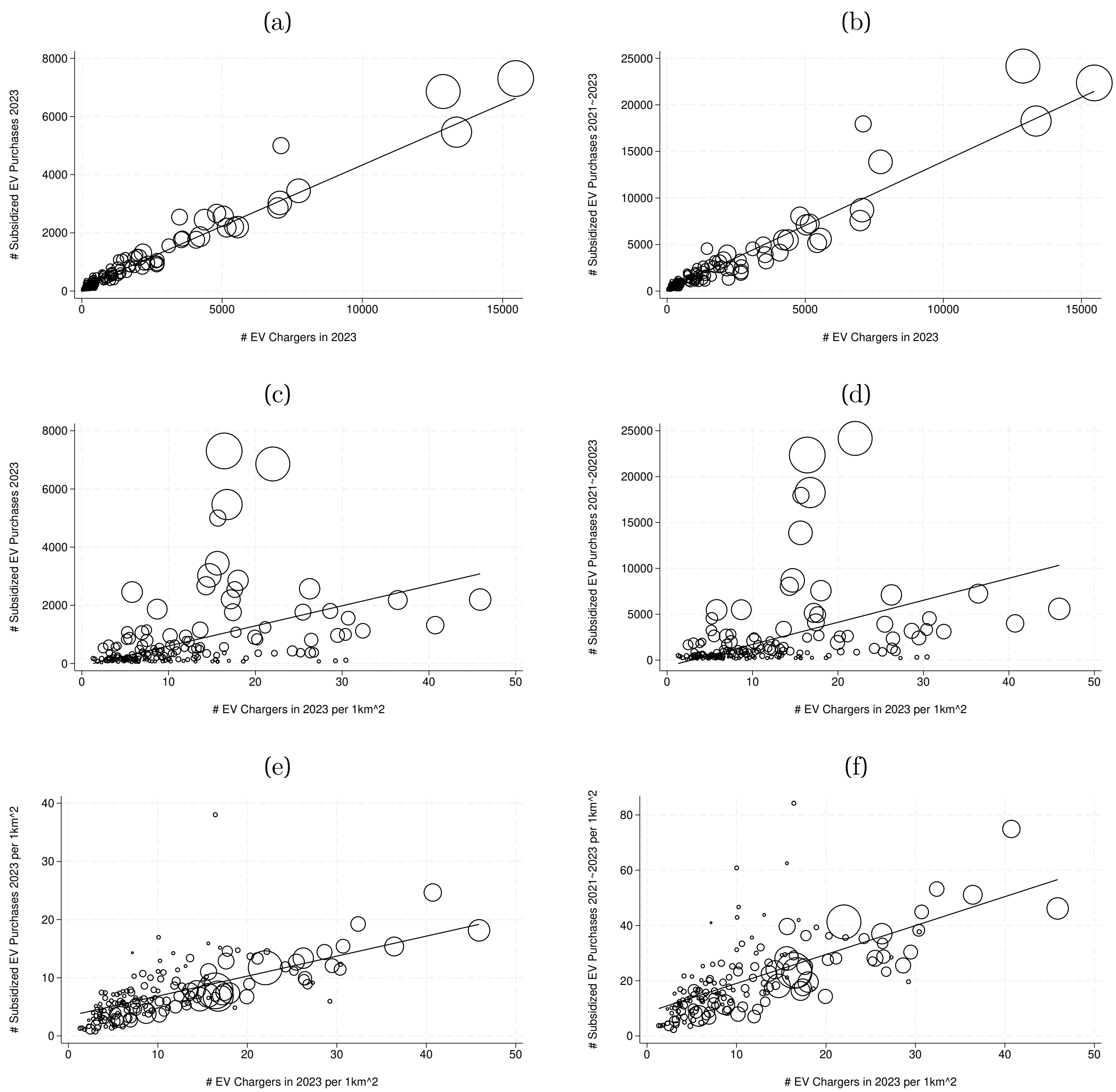
A Additional Anaylsis on the Relation between EV Demand and EV Chargers

Appendix Figure A1 supplements Figure 2 from the main text. Panels (a) and (b) are identical to Figure 2a and Figure 2b, respectively, while 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.

Appendix Table A1 consolidates all results related to Figure 2 and Appendix Figure A1. Specifically, columns (1) and (2) present the regression results corresponding to Figure 2a and Figure 2b, respectively. Columns (3) and (4) show the results associated with panels (c) and (d) in Appendix Figure A1, while columns (5) and (6) display the results corresponding to panels (e) and (f) in Appendix 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.[42] 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.

[42]Despite some missing values, using the cumulative number of subsidized EV purchases from 2019 to 2023—rather than from 2021 to 2023—produces similar patterns of results.

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 of the Ministry of Environment, South Korea. Since the number of subsidized EV purchases is available only at the city and county level that is less granular than the other data used in our main analysis, we transform the EV charger variable and other variables into the city and county level to maintain consistency. 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 fitted regression 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	2021∼2023	2023	2021∼2023	2023	2021∼2023
	(1)	(2)	(3)	(4)	(5)	(6)
# EVC	0.249***	1.095***				
	(0.025)	(0.053)				
# EVC per City Area			43.93***	207.6***	0.434***	1.358***
			(9.666)	(54.22)	(0.084)	(0.183)
(Log) Population	426.8**	826.6**	1,144***	3,927**	-0.750	-0.739
	(170.3)	(377.2)	(412.7)	(1,506)	(0.492)	(1.575)
(Ratio) 25∼49 Popul.	-3,209	-14,150*	-7,751**	-34,758**	-18.95*	-97.95**
	(2,291)	(7,095)	(3,525)	(13,819)	(9.883)	(38.13)
(Ratio) 30∼60 Popul.	-2,906	3,502	-16,077**	-53,784*	33.31	158.6
	(3,196)	(9,126)	(7,538)	(27,971)	(39.93)	(119.8)
(Log) Wage	-91.29	112.8	-271.8	-380.1	-0.519	-0.360
	(209.1)	(535.5)	(597.6)	(2,402)	(3.823)	(9.194)
(Log) APT Price	-71.31	74.74	-457.5	-1,626	2.760	10.42*
	(152.5)	(535.6)	(384.7)	(1,542)	(2.845)	(5.947)
(Log) MH Price	-33.78	-202.5	172.5	712.0	-0.693	1.261
	(160.6)	(426.2)	(316.6)	(1,197)	(3.462)	(7.158)
(Log) S/M-FH Price	-75.11	-150.3	1,209	5,471	-3.777*	-8.650*
	(202.2)	(487.5)	(1,074)	(4,503)	(2.004)	(4.966)
(Log) Land Price	140.4	342.8	149.3	323.6	0.498	-0.057
	(93.16)	(246.2)	(302.4)	(1,046)	(0.587)	(2.191)
(Log) CM/BS Property Price	-63.78	-229.4	-386.7	-1,665*	-0.277	-3.164
	(72.19)	(220.0)	(232.8)	(966.5)	(1.062)	(3.146)
Constant	-601.5	-6,110	-3,724	-20,880	8.132	-53.01
	(1,401)	(5,444)	(5,197)	(22,149)	(18.27)	(38.32)
LZ FE	✓	✓	✓	✓	✓	✓
R^2_{adj}	0.943	0.959	0.684	0.589	0.563	0.617
Obs.	160	160	160	160	160	160

Notes: The units of observation are cities and counties. Robust standard errors are in parentheses and clustered by 55 Living Zones.
*p < 0.10, **p < 0.05, ***p < 0.01.

B Details on Regional Level Data

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. In addition, they may also reflect the level of infrastructure development in the area (Davidoff 2006; Diamond and Moretti 2021; and Määttänen and Terviö 2014). 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 greater wealth or income, potentially making them less sensitive to fuel price increases and further allowing gas stations to raise prices without significantly losing demand.

To control for these effects, we include average real estate transaction prices at the municipality level 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.

Appendix Table B1 reports descriptive statistics of the aforementioned variables.

Table B1: 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 unit of observation is the municipality. The term “city area” refers to the area of a region excluding agricultural, forestry, and natural environmental conservation zones.

C Further Analysis and Robustness Checks

Collider Bias and Case-Control Bias. Contemporary change control variables included in the main regression should 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. Appendix Table C1 presents the results: columns (1), (3), and (5) show the outcomes when condition (i) is applied, while columns (2), (4), and (6) show the outcomes under condition (ii). Reassuringly, our baseline results presented in Section 4.1 remain largely unchanged under these alternative specifications.

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 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.[43] 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 by the intensity of regional economic activities.

The second additional control variable is local tax revenue, by including log level of the variable in 2011 as the predetermined variable and log difference between 2011 and 2022 as contemporary changes.[44] 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 proxy for regional income levels.

The third set of controls includes both the predetermined level and the contemporary log change

[43] 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.

[44] 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.

in regional average mileage.[45] 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.

Appendix Table C2 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 5.2% to 7.2%. Similarly, average diesel price per liter declines significantly, ranging from 6.6% 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 C3.

Table C1: Second-Stage, Mitigating Potential Collider Bias and Case-Control 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 unit of observation is the municipality. 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.

[45] 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 C2: 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 unit of observation is the municipality. 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 C3: 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 unit of observation is the municipality. 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.

D Supplementary Tables

Table D1: 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.