THREE ESSAYS ON THE ECONOMICS OF TRANSITIONING TO CLEAN ENERGY

By

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ABSTRACT

Human activities have caused widespread, rapid, and intensifying climate change. Overshooting 1.5 °C is inevitable in 2024, while substantial scientists have warned that irreversible changes will settle down in many places over the Earth after a 2 °C increase since 1850-1900. We must find a way to mitigate climate change, study its impact on our society, and build sustainable communities. Nevertheless, it isn't easy to find a socially desirable implementation of an environmental policy due to its complexity and various stakeholders. This dissertation contributes to finding socially desirable ways of tackling climate change in energy transition.

The first chapter, titled "Incentivizing capital investments in electric vehicle attributes to stimulate demand," studies the optimal purchase and investment subsidization of electric vehicles (EV) to stimulate investment. The US government has subsidized electric vehicles (EV) with a constant purchase subsidy of $7500 to replace internal combustion engines (ICE). In this chapter, I analyze the theoretical model consisting of firms' dynamic Bertrand game of price and investment and a government's dynamic Stackelberg game with firms. I run this theoretical model by estimating data for every vehicle model sold in the US from 2008 to 2019 and calibrating the model by the collocation method. I show that the two dynamic policies have the same trend, in which the optimal intervention begins at high values to spur early adoption before falling and approaching zero as EV firms' capital grows. In the two dynamic policies, the optimal policy intervention is very high at the capital level in 2024: $10694 to $16073 (purchase subsidy) and $17.06 billion to $40.58 billion (investment subsidy). Then, the optimal policy shrinks rapidly as EV capital increases. Dynamic purchase and investment subsidy increase the total net present value social net benefit by $2.32 trillion (3.84%) and $1.44 trillion (2.39%) compared to zero policy and by $923 billion (1.49%) and $47.7 billion (0.08%) compared to the current constant policy. Governments should strongly intervene in the market first, gradually reducing their policy as the new business grows.

The second chapter, titled "Peer effects in electric vehicle adoption," captures the peer effect of EV adoption in Michigan. The market competitiveness of EVs has been improved as many countries have introduced policies for stimulating EV adoption. A prior understanding of consumer behavior

is required because those policies try to alter the choices of consumers or firms in the market. There is little literature on the peer effect on EVs, while substantial literature focuses on the consumers' substitution pattern of vehicles. Consumers may hesitate to purchase an EV at first; however, if they observe more EVs in their neighborhood, on the road, or in parking lots, their reluctance to purchase an EV may be resolved. I adopt the spatial error and autocorrelated models and compared the results with other spatial models with panel data by ZIP Code Tabulation Area (ZCTA) from 2013 to 2019 in Lower Michigan to address the spatial dependent trend. It shows that one increase in cumulative EV adoption at the same ZCTA will increase next year's EV adoption by 0.326 to 0.352 cars. One cumulative EV adoption increase in the same ZCTA has the same impact as an income increase of $1125 to $1254. The policy should be set to adopt the EV aggressively to take advantage of the peer effect, which strengthens the aggregate demand for EV adoption.

The third chapter, titled "The impact of transnational municipal networks on local energy consumption," is co-authored with Dr. Sun-Jin Yun and published in Urban Climate. Local governments are essential to the successful implementation of climate policies. They know where funds should be allocated and how to increase efficiency at the local level. Transnational municipal networks (TMNs) have galvanized local climate action by sharing best strategies and supporting communication. This study asks whether and to what extent the International Council for Local Environmental Initiatives – Local Governments for Sustainability (ICLEI), one of the major TMNs in climate action, affects local energy consumption in South Korea. We use a staggered difference-in-differences (DID) method, which is a robust alternative under staggered treatment, with a strongly balanced panel dataset across 226 Korean counties between 2005 and 2019. We find that ICLEI membership leads to a significant decrease in energy consumption per capita 4.53% to 6.62% with county membership, 8.91% to 9.00% with state membership, and 11.8% to 21.4% with both county and state membership. In addition, state membership shows a growing impact on energy consumption reduction, while county membership has a weaker trend. The results are statistical evidence of the role of TMNs in local energy policies. The central government may increase the effectiveness of its energy policy by selectively supporting ICLEI members.

In loving memory of my grandparents and maternal grandfather, who loved me so much. It would have been nice to complete this earlier. I love you always, maternal grandmother.

To my wife, Jieun, for her sincere love and being my unflagging supporter.

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LIST OF ABBREVIATIONS

AFRE Department of Agricultural, Food, and Resource Economics

AIC Akike Information Criterion

ATE Average Treatment Effect

BIC Bayesian Information Criterion

CAFE Corporate Average Fuel Economy

CDP Carbon Disclosure Project

CO2eq Carbon Dioxide Equivalent

COVID-19 Coronavirus Disease 2019

CPI Consumer Price Index

CS Consumer Surplus

CS estimator Callaway & Sant'Anna estimator

DE Damage from social costs of carbon

DID Difference-in-Differences

Eq Equilibrium

EV Electric Vehicle

FFE Two-way Fixed Effect in Group and Time

FOC First-Order Condition

GCom Global Covenant of Mayors for Climate & Energy

GDP Gross Domestic Product

GE Governmental Expenditure

GexCom Global Executive Committee

GHG Greenhouse Gas

HJB Hamilton–Jacobi–Bellman

HP Horsepower

ICE Internal Combustion Engine

ICLEI International Council for Local Environmental Initiatives – Local Governments for Sustainability

IID Independent and Identically Distributed

IPCC Intergovernmental Panel on Climate Change

K-ExCom Korea Executive Committee

KEA Korea Energy Agency

LED Light-emitting Diode

LHS Left-hand Side

LL Log-likelihood function value

MNL Multinomial Logit

MPG Miles per Gallon

MPGe Miles per Gallon of Gasoline-Equivalent

MSRP Manufacturer-Suggested Retail Prices

MSU Michigan State University

NOx Nitrogen Oxides

OLNPP One Less Nuclear Power Plant

OLS Ordinary Least Squares

PS Producer Surplus

R&D Research and Development

RE Renewable Energy

RexCom Regional Executive Committee

RFE Two-way Random Effect in Group and Fixed Effect in Time

RHS Right-hand Side

SAC Spatial Autocorrelation Model

SAR Spatial Autoregressive Model

SCC Social Costs of Carbon

SDM Spatial Durbin Model

SEC U.S. Securities and Exchange Commission

SEM Spatial Error Model

SNB Social Net Benefit

SOx Sulfur Oxide

TMN Transnational Municipal Network

TOE Tonne of Oil Equivalent

TSNB Total Net Present Value Social Net Benefit

TWFE Two-way Fixed Effect

US United States of America

ZCTA ZIP Code Tabulation Area (ZCTA)

ZEV Zero-Emission Vehicle

ZIP Zone Improvement Plan

CHAPTER 1

INCENTIVIZING CAPITAL INVESTMENTS IN ELECTRIC VEHICLE ATTRIBUTES TO STIMULATE DEMAND

1.1 Introduction

One of the most pressing concerns facing humanity is climate change. The IPCC (2022) argued that global temperature increase should be kept below 2°C to avoid irreversible systematic change in global ecology and below 1.5°C to avoid this safely. Achieving either goal requires substantial cuts to carbon emissions. It is in this context that we need to consider transportation, one of the main carbon-emitting sectors. In 2019, 29% of domestic carbon emissions in the US came from transportation (US Environmental Protection Agency, 2020), and over 90% of fuel is petroleum-based (US Environmental Protection Agency, 2020). Fortunately, we have an alternative to reduce heavy carbon emissions: electric vehicles (EV). Curbing the temperature growth urgently requires replacing petroleum-based vehicles with carbon-free vehicles, such as EV.

Growing evidence shows that consumers care more about price and attributes than the power source when purchasing a vehicle (Jackman et al., 2023). Graham (2021) found that commonly accepted advantages of EV are lower operating costs, such as maintenance and repair costs, and better driving and environmental performance with less noise. The disadvantages are high purchase cost, lower driving range, and long charging time. Zhang et al. (2018) found that consumers are concerned about the price and attributes of EVs in their purchase: high price (23%), short driving range (38%), inconvenient charging (21%), and short battery life (13%).

US governments have tried changing the market price factor with a constant subsidy. Changing the market price affects consumer demand. The government has subsidized plugged-in electric and electric vehicles via the American Clean Energy and Security Act (2009) since 2010. This law sets a minimum credit of $2,500 for vehicles with at least 5 kWh battery capacity plus $417/kWh beyond 5 kWh of capacity, capped at a maximum credit of $7,500. In 2022 summer, the new Inflation Reduction Act changed the details and conditions of subsidies; however, it maintained the maximum subsidy at $7500. Therefore, the constant maximum subsidy at $7500 exists from 2010 until now and in the future, considering the difficulties of the US legislative process.

It is worth noting that these decisions are driven to achieve EV adoption goals rather than to maximize social net benefit (Rapson & Muehlegger, 2023). The current constant subsidy may not, however, achieve maximum social welfare for two reasons. First, the optimal subsidy should be changed over time in response to market change. Specifically, the optimal subsidy must be set so that intertemporal marginal benefits and costs are the same, mindful that consumers are concerned about the market price and attributes for their decision. If the EV attributes improve dramatically over time, then consumers may be willing to buy an EV at a higher price, which means that governments will need to provide less subsidy to achieve the same replacement effect. In recent decades, for example, EV driving range has markedly increased: the maximum range from 100 miles to 375 miles, and the median range from 70 miles to 240 miles, between 2011 to 2019 (US Department of Energy, 2021). Maxwell & Decker (2006) found that responsive regulation is required to achieve maximum social welfare because voluntary investment may lead to a suboptimal equilibrium. Recent studies indicated that future implications would need to consider long-term market growth and innovation via investment to achieve social optimality. Clinton & Steinberg (2019) pointed out that subsidies will not improve welfare if they only take benefits from emission reduction. Long-term EV market growth, production cost savings, or accelerated innovation could substantially impact net welfare. Langer & Lemoine (2022) found that technological progress would reduce the government's expenditures by 77% to 95%. Therefore, the optimal policy will shift as EV attributes improve and the price decreases. Second, subsidization in the current market endogenously affects the subsidy in the future market by stimulating EV investment. This is because the current subsidy improves future EV attributes and decreases prices. EV firms' current profit increases with more market sales due to purchase subsidies, allowing them to invest more in EV capital. The firm's investment in its capital will make for better vehicles in the future, which lessens the subsidy required. The literature recognizes the necessity of considering the dynamic mechanism of investment stimulation by the policy. Holland et al. (2016) argued that EV subsidization may lead to lower production costs due to learning by doing and will increase adoption in the future.

Luo et al. (2019) found that the government has to pay a much higher subsidy if it does not consider the efficiency improvement in automated vehicles due to the subsidy itself.

Despite such agreement, the literature has not yet taken market dynamics into account when studying subsidies or taxes. Market dynamics are especially important for products in the early stage of business that are good at addressing externality but not market-competitive due to price and attributes. The improvement of attributes by firms has been missed in previous models (Gulati et al., 2017). In addition, most estimations of regulatory cost disregard the possibility of technological innovation (Harrington et al., 2000). Previous attention focused on the constant optimal policy in a static framework (Holland et al., 2021; Langer & Lemoine, 2022). More recent literature has started to focus on the need to consider the dynamic effect of subsidies. Dynamic subsidization generates better outcomes than subsidies determined in a static framework (Chen & Hu, 2018; Luo et al., 2019). For example, Luo et al. (2019) found that a higher initial subsidy helps to quickly penetrate the initial stage where the benefit from the automated vehicle is lower than its cost. Langer & Lemoine (2022) analyzed the dynamic subsidies for residential solar in California, focusing on the demand side dynamic decisions, and found that the efficient subsidy increases over time.

This chapter makes two main contributions. To the best of my knowledge, this chapter is the first to identify the optimal policy path, considering market dynamics on the production side caused by the subsidy itself. Thus, it meets the recognized need to consider the dynamic impact of subsidization. The recent work of Langer & Lemoine (2022) analyzed the optimal policy path considering consumers' value and price discrimination; however, they assumed that there is no induced technological change, a gap that this chapter addresses. This chapter fills this gap by theoretically and numerically identifying the optimal policy path in the presence of market dynamics arising from capital investments. To do this, I develop a dynamic market model and estimate demand and production relations using real market and investment data. I established a dataset of all vehicle models sold in the US from 2005 to 2019 and SEC filing reports of firms to estimate demand and production functions.

Second, this chapter compares a purchase subsidy and an investment subsidy. As we discussed, consumers care about price and attributes. Therefore, governments may subsidize the purchase price to change the price or subsidize the investment to change attributes. The literature suggests robust evidence of welfare being increased by enacting various types of individual instruments: purchase subsidy (DeShazo et al., 2017; Clinton & Steinberg, 2019), purchase tax (Xiao & Ju, 2014), adoption subsidy of residential solar (Langer & Lemoine, 2022), and investment subsidy (Jiang et al., 2018; De Groote & Verboven, 2019; Dong et al., 2019). Nevertheless, there is little literature that compares policies. Anderson & Sallee (2016) shows important findings that market-based policies are better than standards-based policies in fuel economy, not EV adoption. The main policies for EV production in the US are standards-based: the Zero-Emission Vehicle (ZEV) and Corporate Average Fuel Economy (CAFE) mandates. According to Bloom et al. (2019), an R&D tax credit is the best innovation policy with the highest quality and conclusiveness of evidence and net benefit. Aghion et al. (2016) show that firms innovate more on EVs and less on ICEs when they face higher tax-inclusive fuel prices. Acemoglu et al. (2012) argue that the optimal policy involves both taxes and subsidies so that excessive use of carbon taxes is avoided. Therefore, this chapter compares two market-based policies on price and investment.

1.2 Market Model

I develop a market model that considers consumption, production, and policy decisions, as diagrammed in Figure 1.1. Individual consumer behavior is modeled as a discrete choice, responsive to the vehicles' price and attributes. Consumers have time-invariant preferences and are myopic. Firms decide the price and investments to maximize profits with experience curves enhancing attributes and reducing production costs by accumulated capital—they play a dynamic Bertrand game of price and investment. After observing all market dynamics, the government may provide purchase subsidies to intervene in consumer choice or investment subsidies to alter firms' choices considering the social cost of carbon together. This naturally builds a dynamic Stackelberg game in that a leader (a government) has the advantage of moving first, and followers (firms) move later, taking the leader's action as given (Abou-Kandil & Bertrand, 1987). Archsmith et al. (2022) argue that the rate of EV adoptions in the United States is determined by three forces: intrinsic growth in demand for EVs (attributes improvement), production cost declines (market price decrease), and government stimulus of the industry (capital accumulation). All three factors are embodied in the model.

1.2.1 Consumers

I assume that individual consumer behavior follows a discrete choice model with a multinomial logit (MNL) model. They decide to buy ICE or EV, which means both vehicles are sufficiently substitutable, as assumed by Acemoglu et al. (2012). The discrete choice model is convenient for studying the probability of choice in a given market size. An MNL model is simple and easily gives approximate results in transportation applications Mau et al. (2008), who used MNL because their focus was to estimate aggregate consumer behavior. They assume that each estimated coefficient is identical to all consumers. This chapter accepts this assumption because I have aggregate-level data only, and the US automobile market size has remained constant in recent decades. The total number of new vehicle sales since 2000 has ranged around 17 million (US Bureau of Economic Analysis, 2022), except for the economic crisis (marked as gray) and its recovery. I assume that consumers will buy an ICE or EV no matter what the current subsidy level is. This model fits the US automobile market, which exhibits a constant market size and fierce competition. The discrete choice model shows that if firm A produces a product with the same price and attributes while competitors make the same product with better attributes and lower prices, firm A's market sale decreases.

I assume there are $M = 17 million$ vehicle sales each year, either an EV (indexed by e) or an ICE (indexed by f). There is no non-purchase option for this group. This means that the market for a new car is mature in the US, which makes firms compete for market share. Consumers make their purchase decision in response to the vehicle's price, p_j (for $j \in \{e, f\}$), and attributes. If a government subsidizes the purchase of a vehicle j with η_j, then the purchase price will be $p_j - \eta_j$. Consumers are assumed to be indifferent to price and subsidy but only care about the out-the-door price, following DeShazo et al. (2017) and Li et al. (2017). Consumers have the same preference for price and attributes regardless of their demographics, as Langer & Lemoine (2022). They are not forward-looking and will not delay their purchase with an expectation of future attribute improvement. Consumer i's indirect utility from its discrete choice of a vehicle j is u_{ij}, its average is $\bar{u}_j$, and the market share of a vehicle j is s_j.

$$u_{ij}(p_j, \boldsymbol{x_j}, \boldsymbol{y_j}, z_j, \eta_j) = \boldsymbol{\beta x_j} + \boldsymbol{\gamma y_j} + \delta_j z_j - \alpha(p_j - \eta_j) + \epsilon_i \tag{1.1a}$$

$$\bar{u}_j(p_j, \boldsymbol{x_j}, \boldsymbol{y_j}, z_j, \eta_j) = \boldsymbol{\beta x_j} + \boldsymbol{\gamma y_j} + \delta_j z_j - \alpha(p_j - \eta_j) \tag{1.1b}$$

$$s_j(\boldsymbol{p}, \boldsymbol{x}, \eta_e) = \int_{\epsilon} \prod_{j \neq j'} P(\bar{u}_j - \bar{u}_{j'} - \epsilon) P(d\epsilon) = \frac{e^{\bar{u}_j(p_j, \boldsymbol{x_j}, \boldsymbol{y_j}, z_j, \eta_j)}}{\sum_{j \in \{e,\ f\}} e^{\bar{u}_j(p_j, \boldsymbol{x_j}, \boldsymbol{y_j}, z_j, \eta_j)}} \tag{1.1c}$$

where $\alpha > 0$ is a parameter related to prices. η_j is purchase subsidy per vehicle purchase; and I only consider for EV subsidy, which means $\eta_e \geq 0$ and $\eta_f = 0$. $\boldsymbol{\beta} = (\beta_1, \cdots, \beta_3)$ and $\boldsymbol{\gamma} = (\gamma_1, \cdots, \gamma_3)$ are parameter vectors related to $\boldsymbol{x_j}$ and $\boldsymbol{y_j}$, and δ_j is a parameter related to z_j. I use the similar attributes used in Berry et al. (1995). There are two types of attributes. First, capital-dependent attributes, denoted $\boldsymbol{x_j}^T = (x_{1j}, \cdots, x_{3j})^T$, include: 1 for power-weight ratio (Horsepower per curb weight), 2 for fuel economy (miles per fuel of dollar value), and 3 for maximum driving range (miles). I do not consider charging time in this model because of charging patterns and that charging efficiency is largely due to the technology of charging stations rather than the vehicle [1]. The other attribute type is capital-independent attributes, denoted $\boldsymbol{y_j}^T = (y_{1j}, \cdots, y_{3j})^T$, including 1 for wheelbase, 2 for height, and 3 for width. Firms can make any level of these attributes without significant capital accumulation. $\boldsymbol{y_j}$ are important to resolve omitted variable problems but are not used in the final model. z_j is a binary variable indicating the type of vehicle: EV or ICE. $z_e = 1$ if $j = e$, and 0 if $j = f$ and vice versa. It captures consumer preference for each type. The final term, ϵ_i, is an idiosyncratic preference and is assumed to be independent and identically distributed (i.i.d.). Consumer i will choose vehicle j if and only if $u_{ij} \geq u_{ij'},\ \forall j' \neq j$.

Equation (1.1c) shows the market share for a vehicle j derived from the random utility model following McFadden et al. (1973) and Berry et al. (1995). $\boldsymbol{p} = (p_e,\ \ p_f)$, $\boldsymbol{x} = (\boldsymbol{x_e},\ \boldsymbol{x_f})$, and

[1] According to Lee et al. (2020), 86% of EV owners indicate that home is the most common charging location chosen by PEV owners: at home only (53%), at home and other places (33%), at work only (8%), and at public only (3%). The factors for charging time are battery capacity (how many battery cells are deployed) and technology of charging ports such as level 1, level 2, or DC fast chargers, not EV technology. All EVs have used the same type of batteries until 2024, Li-ion battery. There will be a significant improvement in battery charging and capacity if the solid-state battery is commercialized in the future.

$\boldsymbol{z} = (z_e \;\; z_f)$. Vehicle j's market share is a function of both vehicles' prices and attributes. In Equation (1.1b), $\bar{u}_j$ represents the mean utility from purchasing a vehicle j. The expected market share at the aggregate level, $s_j(\boldsymbol{p}, \boldsymbol{x}, \boldsymbol{z}, \eta_e)$, is deterministic with vehicles' prices and attributes. $\boldsymbol{y_j}$ are removed by assuming that $\boldsymbol{y_e} = \boldsymbol{y_f}$. The market share scales exponentially with a product's attractiveness and exponentially downwards with the sum of price and attributes. The total of all market shares is necessarily 1, i.e. $s_e + s_f = 1$. This is the logical consistency requirement, with no non-purchase option, introduced by Cooper & Nakanishi (1988) (also see Huang et al. (2013), for a review).

1.2.2 Producers

In the model, two aggregated EV and ICE producers compete with each other as per Ma et al. (2020). The two aggregated firms thus articulate the competition between entire ICE and EV firms rather than among individual firms, brands, and models. The investment decision of automobile companies is made at the headquarters of a global company that owns its entire brands, and the benefit of investment returns to entire ICE or EV models within the firm or the entire ICE or EV market through spillover effects. Then, the model includes the experience curve by treating accumulated capital as a state variable and investment as a control variable. Attributes and unit production costs are assumed to follow the experience curve with accumulated capital. This means that the investment will promote technological advances that can increase product value in two ways: cost reduction that leads to lower prices and better performance (Gale & Klavans, 1985).

Therefore, unit production cost and attributes are assumed to depend on capital accumulation on the experience curve. We should consider that EV and ICE have different maturity. ICE has more than 100 years of history and has almost fully developed its technology, market segmentation, and strategy, EV firms, being young, have much more potential to dramatically improve attributes and decrease production costs with capital investment, even if their market prices were initially too high for their attributes (Holland et al., 2021). Acemoglu et al. (2012) argued that the study of environmental policies must include the endogenous response of different technologies to proposed policies. I embody this by having the experience curve concept for technology innovation.

The experience curve means that the cost of production is exponentially decreased with business growth. I assume that the unit production cost depends on capital, not quantity. The unit production costs of j, $c_j(K_j)$, are assumed as a function of cumulative investment in physical capital stock for j, K_j. The same power function is used for attributes because the investment in capital has similar effects in cost reduction and attribute improvement in the early-stage business.

$$c_j(K_j) = \phi_{jc0} \times K_j^{\phi_{jc1}} \tag{1.2a}$$

$$x_{jl}(K_j) = \phi_{jl0} \times K_j^{\phi_{jl1}}, \text{where } l \in \{1, 2, 3\} \tag{1.2b}$$

where ϕ_{jc0} and ϕ_{jc1} are production cost parameters and ϕ_{jl0} and ϕ_{jl1} are attributes parameters. Capital-dependent attributes, $\boldsymbol{x_j}$, are modeled as a function of cumulative capital investment. l indicates each element in $\boldsymbol{x_j}$: $l = 1$ for power-weight ratio, $l = 2$ for fuel economy, and $l = 3$ for maximum driving range. Experience is usually defined as cumulative production (Samadi, 2018); however, Schmidt et al. (2017) found that cumulative investment affects future cost decrease along the experience curve. Therefore, this paper defines experience as the capital stock, the results of cumulative investment. The dependent variable is expressed as a power function of experience (Hayward & Graham, 2013).

The firms' optimization problem with the per-period net income of a firm j, π_j, profit minus investment cost, and the law of motions of capital accumulation are defined as follows. ρ is the discount rate over time. θ_e is the investment subsidy for EV investment, and $\theta_f = 0$ as $\eta_f = 0$. $\boldsymbol{K} = (K_e,\ K_f)$ is a vector of K_j, and $\boldsymbol{\tau} = (\eta_e,\ \theta_e)$ is a policy vector.

$$\max_{p_j,\, I_j} \int_0^\infty e^{-\rho t} \pi_j(\boldsymbol{p}, I_j, \boldsymbol{K}; \boldsymbol{\tau}) dt \quad s.t.\ \dot{K}_j,\ \dot{K}_{-j},\ K_j(0) = K_{0j} \text{and } K_{-j}(0) = K_{0-j} \tag{1.3a}$$

$$\pi_j(\boldsymbol{p}, I_j, \boldsymbol{K}; \boldsymbol{\tau}) = (p_j - c_j(K_j)) s_j(\boldsymbol{p}, \boldsymbol{x}(\boldsymbol{K}); \eta_e) M - \psi_j(I_j) + \theta_j \tag{1.3b}$$

$$\dot{K}_j = I_j - \mu K_j \tag{1.3c}$$

$$\psi_j(I_j) = \nu I_j^2, \nu > 0 \tag{1.3d}$$

$$\rho V_j(\boldsymbol{K}; \boldsymbol{\tau}) = \max_{p_j,\, I_j} [\pi_j(\boldsymbol{p}, I_j, \boldsymbol{K}; \boldsymbol{\tau}) + \frac{\partial V_j}{\partial K_j} \underbrace{(I_j - \mu K_j)}_{\dot{K}_j} + \frac{\partial V_j}{\partial K_{-j}} \underbrace{(I_{-j} - \mu K_{-j})}_{\dot{K}_{-j}}] \tag{1.3e}$$

One firm's net income depends on both firms' capital via attributes in the market share. In addition, firms are assumed to respond to the subsidy myopically as consumers did for attributes. They will not consider that their strategies may affect future subsidies. To simplify the game, I adopt an open-loop game, which means each firm takes the other firm's choices, as well as policy instrument choices, as being time-dependent rather than being specified as feedback rules (Basar & Olsder, 1982). This is not an uncommon approach, but it does mean the game is not subgame-perfect.

In Equation (1.3c), $\dot{K}_j$ is the law of motions, I_j is an investment in a vehicle j, and μ is the depreciation rate of capital, which is the same for all capital stocks. To simplify problems, I assume that the capital is immediately accumulated from investment decisions, which takes much longer in the real automotive business. The aggregated investment of two aggregate firms, EV and ICE, will accumulate the aggregated capital. Thornton & Thompson (2001) shows that learning spillovers are significant in productivity growth, and the market failures may be modest. $\psi_j(I_j)$ is the cost of investment, where ν is a cost parameter related to investment and is expected as $\nu > 0$. In dynamic programming, this results in investments being spread over time rather than all at once to achieve a steady state immediately. The convex investment cost is assumed for EV by Creti et al. (2018). Barnett & Sakellaris (1998) said it is common for researchers to assume a quadratic form for investment cost.

Equation (1.3e) is Hamilton-Jacobi-Bellman equation. V_j is the maximized long-term profit that solves Equation 1.3. Firms have choice variables (price and investment) and state variables (capitals). The right-hand side has current period profits, $\pi_j(\boldsymbol{p}, I_j, \boldsymbol{K}, \boldsymbol{\tau})$, and the other terms represent the marginal value of capital times changes in both firms' capital, which are the longer run value to the firm of changes in the capital stock. $\frac{\partial V_j}{\partial K_j}$ is the price of capital accumulation, and $\dot{K}_j$ is the capital accumulation. The value function has an interaction term between firms, $\frac{\partial V_j}{\partial K_{-j}}\dot{K}_{-j}$. The capital change of a firm can affect the other's value function via this term. Both value functions will be solved together because $V_j(\boldsymbol{K};\boldsymbol{\tau})$ contains both $\dot{K}_j$ and $\dot{K}_{-j}$.

The firms' optimality condition for the price is to set the marginal benefit and marginal cost as the same. The F.O.C. for the price of a vehicle j is $s_j M = -(p_j^* - c_j)\frac{\partial s_j}{\partial p_j}M$. The left-hand side is the marginal effect of price on sales. If there is a marginal increase (decrease) in price, firms will observe a marginal increase (decrease) in revenue as $s_j M > 0$. The right-hand side is the marginal effect of price on market share. If there is a marginal increase (decrease) in price, firms will also observe a marginal decrease (increase) in market share as $\frac{\partial s_j}{\partial p_j} = -\alpha s_e s_f < 0$. Firms find optimal prices when the marginal benefit from a higher price matches the marginal cost from a lower market share, and vice versa. By solving the F.O.C. for the prices, the optimal feedback price rule for each period is gained, $p_j^*(\boldsymbol{K};\boldsymbol{\tau})$, which depends on the capital of both firms subject to given policy instruments.

$$p_e^*(\boldsymbol{p^*}, \boldsymbol{K}; \eta_e) = c_e + \frac{1}{\alpha} + \frac{1}{\alpha}\exp[\boldsymbol{\beta}(\boldsymbol{x_e}(\boldsymbol{K}) - \boldsymbol{x_f}(\boldsymbol{K})) + \delta_e - \delta_f - \alpha(p_e^* - \eta_e - p_f^*)] \tag{1.4a}$$

$$p_f^*(\boldsymbol{p^*}, \boldsymbol{K}; \eta_e) = c_f + \frac{1}{\alpha} + \frac{1}{\alpha}\exp[\boldsymbol{\beta}(\boldsymbol{x_f}(\boldsymbol{K}) - \boldsymbol{x_e}(\boldsymbol{K})) + \delta_f - \delta_e + \alpha(p_e^* - \eta_e - p_f^*)] \tag{1.4b}$$

This optimal price has its term on the right-hand side due to market share. For my numerical analysis, I approximate the equations with Lambert-W equations to get the optimal price as a function of other terms, not including itself. Lambert-W function, w, is the function satisfying $we^w = x$, where $w = W_0(x)$ for $x \geq 0$ (Disney & Warburton, 2012; Lehtonen, 2016). Therefore, we can convert the exponential equations into linear ones using the Lambert-W equation as suggested by Lehtonen (2016). The result is $\check{p}_j^*(\boldsymbol{K};\eta_e)$, described in Equation (1.C.1.3) in the Appendix 1.C.1. Note that the approximated optimal price is now only a function of both firms' capital and given subsidy. One way to validate approximation is to compare the results with the literature.

From Equation (1.C.1.3), $\frac{\partial p_e}{\partial \eta_e} \approx 0.262$, which means that EV prices will be increased by \$262 under \$1,000 of subsidies, and subsidy-inclusive EV price will be decreased by\$738. $\frac{\partial p_f}{\partial \eta_e} \approx -0.262$, which means that ICE prices become \$262 lower under \$1,000 of EV purchase subsidies. This corresponds to Muehlegger & Rapson (2022) saying that every \$1,000 of subsidies lowers subsidy-inclusive EV prices by \$730 to \$850.

The firms' optimality condition for investment is when marginal benefit and marginal cost are the same. The F.O.C. for an investment in a vehicle j is $\frac{\partial V_j}{\partial K_j} = \psi_e'(I_j)$, where $\frac{\partial V_j}{\partial K_j}$ is the intertemporal values of investment, which equal the marginal value of capital, and $\psi_j'(I_j)$ is the marginal cost of investment. As a result of solving the F.O.C. for an investment, we will get two feedback functions, $I_j(\boldsymbol{K}, \boldsymbol{\tau}) = \frac{1}{2\nu}\frac{\partial V_j}{\partial K_j}$. It may be noted that the optimal investment depends on subsidies. Purchase subsidies affect the optimal subsidy because the firm's profits depend on its market share, which depends on this subsidy. Investment subsidies for EV firms even affect the ICE firm because each firm has interaction terms with each other through the capital accumulation in Equation (1.3a). Capital investment of competitors will affect long-term profit maximizing via competition with price and attributes in the future market. These feedback rules can be substituted into the HJB equation. Appendix 1.C. 1 describes how to get this optimal investment.

The feedback rule for investment is fully identified as a function of capital under a given policy, $I_j^*(\boldsymbol{K}; \boldsymbol{\tau})$. I_j^* has both firms' capital and policy terms via $\frac{\partial V_j}{\partial K_j}$. By substituting the optimal price, the market share is now $s_j(\check{p}_j^*(\boldsymbol{K}; \eta_j), \boldsymbol{x}(\boldsymbol{K}), \eta_e) = s_j(\boldsymbol{K}; \eta_e)$. Now, the HBJ equation in Equation (1.3e) is substituted with the feedback rule for price and investment as follows.

$$\rho V_j(\boldsymbol{K}; \boldsymbol{\tau}) = \pi_j(\boldsymbol{\check{p}^*}(\boldsymbol{K}; \eta_e), I_j^*(\boldsymbol{K}; \boldsymbol{\tau})) + \frac{\partial V_j}{\partial K_j}(I_j^*(\boldsymbol{K}; \boldsymbol{\tau}) - \mu K_j) + \frac{\partial V_j}{\partial K_{-j}}(I_{-j}^*(\boldsymbol{K}; \boldsymbol{\tau}) - \mu K_{-j}) \tag{1.5}$$

With the optimal price and investment, the per-period consumer and producer surplus are described as the function of both firms' capital.

$$E[\mathrm{CS}(\boldsymbol{p}, \boldsymbol{x}, \boldsymbol{y}, \eta_e)] = \frac{M}{\alpha}\ln[\sum_{j \in \{e,f\}} e^{\bar{u}_j(p_j, \boldsymbol{x_j}, \boldsymbol{y_j}, z_j, \eta_j)}] \tag{1.6a}$$

$$PS(\boldsymbol{K}; \boldsymbol{\tau}) = \sum_{j \in \{e,f\}} \left[\left(\check{p}_j^*(\boldsymbol{K}; \eta_e) - c_j(K_j)\right) s_j^*(\boldsymbol{K}; \eta_e) M - \psi_j(I_j^*(\boldsymbol{K}; \boldsymbol{\tau})) + \theta_j\right] \tag{1.6b}$$

From the discrete choice model, the expected individual consumer surplus (CS) is gained by the log-sum of the exponential of the average utility of each choice, suggested by Small & Rosen (1981), in Equation (1.6a). The aggregate consumer surplus is calculated by multiplying individual expected utility by the total market size of M. The rate of return is gained by taking partial derivatives with respect to K_j, which is similar to the adjoint condition in a typical optimal control model.

$$\rho + \mu = \frac{\frac{\partial \pi_j}{\partial K_j}}{\frac{\partial V_j}{\partial K_j}} + \underbrace{\frac{\frac{\partial^2 V_j}{\partial K_j^2}}{\frac{\partial V_j}{\partial K_j}} \dot{K}_j + \frac{\frac{\partial^2 V_j}{\partial K_j K_{-j}}}{\frac{\partial V_j}{\partial K_j}} \dot{K}_{-j}}_{\frac{d(\frac{\partial V_j}{\partial K_j})/dt}{\frac{\partial V_j}{\partial K_j}}} \tag{1.7}$$

The left-hand side is the return adjusted for depreciation, μ, and the rate of return, ρ, that the firm could earn elsewhere, an opportunity cost of its own investment. Therefore, the left-hand side is the depreciation-adjusted rate of return. Optimally, the firm's own investments must generate a return equal to the depreciation-adjusted rate. This return is the RHS of Equation (1.7). The first term of the right-hand side is the marginal profit gains from capital investment, divided by the marginal value of capital to produce a rate of return. The marginal profit term includes a price effect on changing demand due to capital accumulation and, therefore, improved attributes, as well as benefits from reduced production costs. The second term of the right-hand side is a capital gain or loss that reflects proportional increases (gain) or decreases (loss) in the marginal value of its own capital. $\frac{\partial^2 V_j}{\partial K_j^2}$ is the direction and speed of capital gain or loss by their own capital accumulation, and $\frac{\partial^2 V_j}{\partial K_j K_{-j}}$ means the direction and speed of capital gain or loss by the competitor's capital accumulation. Assuming $\frac{\partial^2 V_j}{\partial K_j^2} < 0$, then there is a capital loss when the capital stock is increasing due to their being diminishing returns to capital at given $\frac{\partial V_j}{\partial K_j} > 0$. Vice versa, with $\frac{\partial^2 V_j}{\partial K_j^2} > 0$, there is a capital gain with investment due to increasing returns to capital at given $\frac{\partial V_j}{\partial K_j} > 0$. If $\frac{\partial^2 V_j}{\partial K_j^2} = 0$, there is no motivation to capital gain or loss. The capital gain and loss term also includes a capital spillover effect through the market. The last term indicates the rate of capital gain or loss from the other firm's capital investments. It may capture that other firms' investments may induce (1) capital loss by losing relevant technicians, researchers, and scientists and increasing wage expenses due to headhunting for experts or (2) mutual capital growth due to capital spillover effects.

1.2.3 Government

In this model, governments decide their subsidy level after observing all market dynamics, playing a dynamic Stackelberg game with firms. The Stackelberg game has been widely applied to policy-making problems in which a government is a leader, and the target industries are followers (Rahimi et al., 2021). A substantial literature in environmental economics applies Stackelberg gaming to analyze the interaction between regulators (leader) and industries (followers) over emissions trading (Hong et al., 2017), environmental tax (Carlsson, 2000; Canton et al., 2008; Jiang et al., 2023; Krass et al., 2013), international agreement (Eichner & Pethig, 2015; Finus et al., 2021), acid rain (Baron, 1985) and investment (Maxwell & Decker, 2006). In this game, governments try to maximize their objective goals, such as consumer and producer surplus, subsidization cost, and social cost of carbon.

Government expenditures here are the sum of all government expenditures on subsidization. The per-period government expenditure, GE, is defined as $\mathrm{GE}(\boldsymbol{K};\boldsymbol{\tau}) = \eta_e s_e^*(\boldsymbol{K};\eta_e)M + \theta_e$. The first term is the expenditure for purchase subsidization, and the second is the expenditure for investment subsidization. This chapter does not account for the instrument interaction; therefore, $\eta_e \times \theta_e = 0$. Their interaction is beyond the focus of this study.

This chapter only considers carbon emission as an externality arising from the automobile market because externalities such as NO_x, SO_x, and/or particle matter emissions or batteries' disposal are negligible or insignificant[2]. I consider the carbon emission from driving of EV and ICE. EVs do not emit carbon dioxide during driving, but modern economies heavily depend on fossil fuel power plants to generate electricity. Thus, EV driving's carbon emission comes from

[2]Based on the dataset of Maier et al. (2023), the avoidable social cost of all other air pollution by replacing ICE with EV is just 1.7% to 9.1% of the social cost of carbon by urban, suburban, and rural areas and by small, medium, and large cars. In addition to that, both ICE and EV generate the cost of disposal, and there is growing evidence of decreasing the disposal cost of EV batteries by recycling. Rahman et al. (2017) suggest a way of recycling about 47.34% of the battery active metals.

electricity generation.

Damage of carbon emissions from a vehicle j is the social cost of carbon (SCC) from total carbon emissions during the vehicle j's lifetime. The aggregate social cost is calculated by summing all social costs of vehicle carbon emissions.

$$d_j(K_j) = \underbrace{\frac{\overline{\text{year}}}{\text{vehicle}_j}}_{lifetime} \times \underbrace{\frac{\overline{\text{mile}}}{\overline{\text{year}}}}_{annual\ miles} \times \underbrace{\frac{\text{gallon}_{eq}}{\overline{\text{mile}}}}_{\frac{1}{MPG_j(K_j)}} \times \underbrace{\frac{\text{emission}_j}{\text{gallon}_{eq}}}_{unit\ emission} \times \underbrace{\frac{\text{cost(\$)}}{\text{emission}_j}}_{unit\ cost} \tag{1.8a}$$

$$DE(\boldsymbol{K}, \eta_e) = \sum_j d_j(K_j) s_j(\boldsymbol{K}, \eta_e) M \tag{1.8b}$$

where $d_j(K_j)$ is the social cost of carbon from the lifetime emission of one vehicle j and $D(\boldsymbol{K}, \eta_e)$ is the total social cost of carbon from all new vehicles per period. The social cost is a product of several terms: the social cost of unit carbon emission SCC (\$ per g CO_2), the average mileage per year $\overline{\text{mile}}$ (miles per year), the discounted total life span of a vehicle $\overline{\text{year}}$ (years), and the conversion factor emit_j (g CO_2 per unit fuel),[3] and fuel economy mpg_j (miles per unit fuel). The miles per gallon (MPG) for ICE equals the miles per gallon equivalent (MPGe) for EV. I assume that annual mileage and lifetime are time-invariant, which means no rebound effect. The social cost of carbon emission is also assumed to be time-invariant. Table 1.1 shows the above parameters and their sources. US Environmental Protection Agency (2010) suggests that social costs of carbon will be \$52.04/ton CO_2 under 3% of discount rate. Then, EVs emit 30% of carbon emissions per mile from ICE.

The regulators' per-period social net benefit (SNB) is the sum of consumer surplus (CS), producer surplus (PS), minus government expenditure (GE), and social cost of carbon emission

[3]For ICE, the conversion factor is carbon emission per unit gasoline. For EVs, a gasoline equivalent is needed to reflect the carbon emissions from electricity generation. $\text{emit}_f = \frac{\text{g } CO_2}{\text{gasoline (gallons)}}$ and $\text{emit}_g = \frac{\text{g } CO_2}{\text{electricity (kWh)}} \cdot \frac{\text{electricity (kWh)}}{\text{gasoline (gallon}_{\text{eq}})} = \frac{\text{g } CO_2}{\text{electricity (kWh)}} \cdot \frac{33.7\text{kWh}}{\text{gasoline}_{\text{eq}}}$. EPA defined both 33.7 kWh of electricity and 1 gallon of gasoline as generating the same heat of 115,000 BTU.

(DE). Governments' problem and Hamilton–Jacobi–Bellman's equation are

$$\max_{\tau_x \in \boldsymbol{\tau}} \int_0^\infty e^{-\rho t}\,\mathrm{SNB}(\boldsymbol{K};\boldsymbol{\tau})dt \quad s.t.\ \dot{K}_j,\ \dot{K}_{-j},\ K_j(0) = K_{0j} \text{and } K_{-j}(0) = K_{0-j} \tag{1.9a}$$

$$\mathrm{SNB}(\boldsymbol{K};\boldsymbol{\tau}) = \mathrm{CS}(\boldsymbol{K};\eta_e) + \mathrm{PS}(\boldsymbol{K};\boldsymbol{\tau}) - \mathrm{GE}(\boldsymbol{K};\boldsymbol{\tau}) - DE(\boldsymbol{K};\eta_e) \tag{1.9b}$$

$$\rho\Omega(\boldsymbol{K}) = \max_{\tau_x \in \boldsymbol{\tau}} \left[\mathrm{SNB}(\boldsymbol{K};\boldsymbol{\tau}) + \frac{\partial\Omega}{\partial K_e}\cdot\dot{K}_e + \frac{\partial\Omega}{\partial K_f}\cdot\dot{K}_f\right] \tag{1.9c}$$

where $\Omega(\boldsymbol{K})$ is the net present value of social welfare. $\frac{\partial\Omega}{\partial K_e}\cdot\dot{K}_e + \frac{\partial\Omega}{\partial K_f}\cdot\dot{K}_f$ is the welfare improvement by capital accumulation, where $\frac{\partial\Omega}{\partial K_j}$ is the price of capital accumulation for social welfare.

A government is assumed to know market responses and information, denoted $\check{p}_j^*(\boldsymbol{K};\eta_e)$, $s_j^*(\boldsymbol{K};\eta_e)$, and $I_j^*(\boldsymbol{K};\boldsymbol{\tau})$. Given this information, the optimality condition for the policy instrument is to set the marginal benefit equal to the marginal cost of the policy. The F.O.C. for policy instrument $\tau_e \in \boldsymbol{\tau} = \{\eta_e,\ \theta_e\}$ is

$$\frac{\partial\,\mathrm{SNB}}{\partial\tau_e} + \frac{\partial\Omega}{\partial K_e}\left(\frac{\partial I_e}{\partial\tau_e}\right) + \frac{\partial\Omega}{\partial K_f}\left(\frac{\partial I_f}{\partial\tau_e}\right) = 0 \tag{1.10}$$

The optimal subsidy has economic implications. The first term is the marginal impact of subsidy on the current market. It represents how the consumer and producer surplus and social cost of carbon change due to the subsidy. The second and third terms are the change in the net present value of social benefit by capital accumulation due to investment stimulation caused by the subsidy on EV firms and ICE firms. I get the optimal level of subsidy as a function of capital by solving the F.O.C. Appendix 1.C.2 describes how to get the optimal purchase subsidy. Solving for η_e gives Equation (1.11).

$$\begin{aligned}\eta_e^*(\boldsymbol{K}) = &\Big[(\check{p}_e^*(\boldsymbol{K},\eta_e^*) - c_e(K_e) - d_e(K_e)) - (\check{p}_f^*(\boldsymbol{K},\eta_e^*) - c_f(K_f) - d_f(K_f))\Big] \\ &+ \frac{1+w_1}{(1-w_1)\alpha s_e(\boldsymbol{K},\eta_e^*)s_f(\boldsymbol{K},\eta_e^*)M}\left[\frac{\partial\Omega}{\partial K_e}\left(\frac{\partial I_e}{\partial\eta_e}\right) + \frac{\partial\Omega}{\partial K_f}\left(\frac{\partial I_f}{\partial\eta_e}\right) - \frac{\partial\psi_e(I_e)}{\partial\eta_e} - \frac{\partial\psi_f(I_f)}{\partial\eta_e}\right]\end{aligned} \tag{1.11}$$

$$\eta_e^*(\boldsymbol{K}^\star) = (\check{p}_e^*(\boldsymbol{K}^\star,\eta_e) - c_e(K_e^*) - d_e(K_e^*)) - (\check{p}_f^*(\boldsymbol{K}^\star,\eta_e^*) - c_f(K_f^*) - d_f(K_f^*)) \tag{1.11a}$$

The first part is the marginal effect of the subsidy on changing consumers' discrete choices from ICE to EV in the current market. This first term is markup minus damage of EV minus that of ICE: if the markup minus damage from EV becomes larger, the subsidy increases, and if that of ICE increases, the subsidy decreases. At steady state, this part is directly the optimal purchase subsidy at the state in Equation (1.11a). The second term explains the marginal effect of the subsidy in the future market from the change in net present social welfare by stimulating capital investment. The bracket means a net marginal increase in social welfare by the subsidy: the welfare increase minus investment cost. The optimal purchase subsidy is determined by the balance of marginal impact on the current and future markets.

The optimal investment subsidy, θ_e^*, is calculated from Equation (1.12), and Appendix 1.C.3 describes how to get the subsidy.

$$\left(\frac{\partial \Omega}{\partial K_e}\right)\left(\frac{\partial I_e}{\partial \theta_e}\right) + \left(\frac{\partial \Omega}{\partial K_f}\right)\left(\frac{\partial I_f}{\partial \theta_e}\right) = \psi_e^{'}(I_e)\left(\frac{\partial I_e}{\partial \theta_e}\right) + \psi_f^{'}(I_f)\left(\frac{\partial I_f}{\partial \theta_e}\right). \tag{1.12}$$

The left-hand side is how much social net benefit will be improved by the investment subsidy via both firms' capital accumulation, and the right-hand side is how much investment cost will be caused by the investment subsidy via both firms' capital accumulation. It considers how much investment in each firm will be stimulated by subsidy, $\frac{\partial I_j}{\partial \theta_e}$, and how much benefit and cost are caused by capital accumulation, $\frac{\partial \Omega}{\partial K_j}$ and $\psi_j^{'}(I_j)$.

The rate of return is gained by taking partial derivatives of social net benefit with respect to $K_j, j \in \{e, f\}$, which is similar to the adjoint condition in a typical optimal control model.

$$\rho + \mu = \frac{\frac{\partial SNB}{\partial K_j}}{\frac{\partial \Omega}{\partial K_j}} + \underbrace{\frac{\frac{\partial^2 \Omega}{\partial K_j^2}}{\frac{\partial \Omega}{\partial K_j}}\dot{K}_j + \frac{\frac{\partial^2 \Omega}{\partial K_j K_{-j}}}{\frac{\partial \Omega}{\partial K_j}}\dot{K}_{-j}}_{\frac{d(\frac{\partial \Omega}{\partial K_j})/dt}{\frac{\partial \Omega}{\partial K_j}}} \tag{1.13}$$

The left-hand side indicates the return adjusted for capital depreciation, μ, and the rate of return, ρ, that the government could earn or expend elsewhere, an opportunity cost of subsidization. Therefore, the left-hand side is the risk-adjusted rate of return that the government is required to earn through its subsidization. The first term of the right-hand side is the government's rate of return before subsidization. The marginal benefit includes a rise in consumer and producer surplus brought about by innovation through capital accumulation and a decrease in the social cost of carbon through altered consumption patterns. The second term of the right-hand side is a social welfare gain or loss, which represents proportional increases (gain) or decreases (loss) in the marginal value of both firms' capital. The direction and pace of capital gain or loss by firm j's capital accumulation is represented by $\frac{\partial^2 SNB}{\partial K_j^2}$, and the direction and speed by firm $-j$'s capital accumulation is represented by $\frac{\partial^2 SNB}{\partial K_j K_{-j}}$. Assuming $\frac{\partial^2 SNB}{\partial K_j^2} < 0$, a capital loss occurs when the capital stock rises as a result of declining returns on capital at given $\frac{\partial SNB}{\partial K_j} > 0$. Conversely, with $\frac{\partial^2 SNB}{\partial K_j^2} > 0$, investment results in a capital gain because of rising returns on capital. There is no incentive to profit or lose money if $\frac{\partial^2 SNB}{\partial K_j^2} = 0$. A capital spillover impact via the market is also included in the capital gain and loss term.

1.3 Calibration and Estimation

1.3.1 Calibration

This chapter has two unknown parts in its model: unknown parameters of demand and production and unknown functional forms of value functions. Regarding unknown value functions, I use the collocation method to approximate unknown value functions for both firms and a government. The collocation method has been widely used in analyzing dynamic economic systems since the late 20th Century (Miranda & Glauber, 1995), and is now routinely used in economics to solve non-linear dynamic models (Malin et al., 2011) and to approximate continuous Bellman equations (Homayounfar et al., 2011). The method is flexible, accurate, and numerically efficient for most research in economics and finance (King & Lohano, 2006). The core concept of the collocation is to approximate the unknown value function by a weighted sum of easy functions such as polynomials. We approximate the value function with a polynomial. This polynomial and its derivatives will replace the unknown value function and its derivatives in the objective functions. Objective functions must hold for any value of the state variables. Now, a polynomial with n terms has n coefficients to fit. To get those n coefficients, we hold all value functions exactly at n different combinations of finite points, called collocation nodes. This method replaces the optimal control problems in non-linear programming with a problem of algebraic equations (Khamseh et al., 2021). Increasing n results in better fitting by having more points to hold the equations but requires more computational effort. The detailed collocation process is described in Appendix 1.D.

1.3.2 Estimation

I estimate demand and production functions with real market data and use the coefficients as parameters in the theoretical model. It is to get realistic results for dynamic optimization. For demand estimation, I built a dataset of all 598 vehicle models sold in the U.S. from 2008 to 2019 using a dataset of global automobile marketing companies: Marklines and Wardsauto. The vehicle models are light-duty vehicles, excluding sport, luxury, and commercialized cars, and the rule is described in Appendix 1.B. The data is on the yearly basis of the model year[4]. Table 1.2 shows the descriptive statistics of the dataset.

Prices are manufacturer-suggested retail prices (MSRP) at the beginning of the model year and include destination charges. Then, a federal purchase subsidy or guzzler tax is added to the vehicle model's price, gathered from US Department of Energy (2022). All dollar values of the nominal price are transformed into a real price in 2019 by applying the consumer price index (CPI) from US Bureau of Labor Statistics (2022). The no-purchase option is introduced to secure the sum of market share equal to 1. The number of no-purchases is M (17 million) minus the total sales of each model year. Table 1.3 shows those statistics and annual oil and electricity prices. Oil prices are from US Energy Information Administration (2024), and electricity prices are from US Energy Information Administration (2023), with applying CPI index for each fuel.

I take the log of the market share in Equation (1.1c) and subtract the common term as per Berry et al. (1995). Then, I use two-way mixed effect models with controls on each vehicle model and year. I assume the fixed effect in the year and the fixed or random effect in the vehicle model and compare them with the Hausman test (Hausman, 1978).

$$\ln s_{m,t} - \ln s_{n,t} = \boldsymbol{\beta x_{m,t}} - \alpha(p_{m,t} - \eta_{j,t}) + \boldsymbol{\gamma y_{m,t}} + \delta_m z_m + \zeta_i + \zeta_t + e_{i,t} \tag{1.14}$$

$$\ln s_{n,t} = \ln \sum_{k \in \text{models}} \left[e^{\boldsymbol{\beta x_{k,t}} - \alpha(p_{k,t} - \eta_{k,t}) + \boldsymbol{\gamma y_{k,t}} + \delta_k z_k} \right] \tag{1.14a}$$

[4]The automobile industry's model year runs from October to September, different from its fiscal year. The 2019 model year is from October 2018 to September 2019.

The estimation result is in Table 1.4. The Hausman test shows $\chi^2(17) = 1.24$, and $probability > \chi^2 = 1.000$, which means the hypothesis that the individual-level effects are adequately modeled by a random-effects model cannot be rejected. Therefore, I adopt the two-way mixed effect models with random effect in the vehicle model and fixed effect in a year. According to the results, consumers prefer cheaper, longer, and more powerful and fuel-efficient vehicles that drive longer. \$10,000 increase in price will drop the market share by 29.24%. Each 10% increase in the average power-weight ratio (0.0057HP/lb) and the average fuel economy increase (1.01 mile/\$) has the same effect as a price decrease of \$1,106 and \$1,046. A 100-mile increase in the maximum driving range has the \$5,141 value of price decrease. A one-inch increase in wheelbase has the \$439 value of price discount. Then, there is a clear preference for ICE by observing δ_f, which corresponds to Jackman et al. (2023) saying that EV adopters represent a relatively narrow band of consumer characteristics until now. From 2008 to 2019, the majority of consumers prefer ICE.

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In the real market, it is impossible to get data for cumulative capital, investment, and unit production costs for each of the 598 vehicle models. Therefore, I assume that the two virtual aggregate EV and ICE firms release each representative vehicle model with the same size, $\boldsymbol{y}$, but different price, cost, and capital relevant attributes, $\boldsymbol{x}$ from 2008 to 2019. First, I gathered SEC filing reports and production data for Tesla and Ford, and from the reports, I define "the property, plant and equipment, net in asset" as capital, "research and development in operating expenses" as investment, "the total cost of revenue for automotive sales and lease" as a total cost. I define the total production as a total production from Ward's yearbook to get the unit production cost. Then, considering the volume-weighted average, I convert the capital and investment of Tesla and Ford into those of virtual firms of EV and ICE. The unit production cost is converted from Tesla and Ford to virtual firms, applying their price ratio to other firms. Regarding specification, I get the volume-weighted average specification of the year for both EV and ICE. Table 1.5 shows the descriptive statistics of the dataset. Then, I use Equation (1.2) to estimate the production cost and attribute functions, Equation (1.3c) to estimate the capital depreciation rate, and Equation (1.3d) to estimate the investment cost functions.

The estimation result of production functions is in Table 1.6. For both EV and ICE, coefficients for the slope of experience curves, ϕ_{jc1} and ϕ_{jl1}, are negative for production cost and positive for attributes. This means that the unit cost decreases and attributes improve as capital accumulates. Depreciation rate, μ, is estimated as 5.1%, and the coefficient for convex investment cost, ν, is positive.

1.4 Results

The capital stream flows for both enterprises are depicted in Figure 1.2. The arrows are the optimal movements of each inner point, which is a combination of capital. From any initial allocation of capital, the arrows from that point describe how the system moves, and so following these arrows maps out an optimal path from that initial allocation. Every path is an optimal one linked to the capital combinations along that path. The movement shows the law of motion of capital affected by investment and subsidies in Equation (1.3c) at each combination of capital. In 2024, the capital of both companies—\$276.17 billion (ICE) and \$52.81 billion (EV)—began to flow red. At zero subsidy, there is an equilibrium with a high ICE capital in Table 1.2 and a corner solution with no ICE capital, described in Figure 1.2a. At a constant \$7500 subsidy, the stream flow leads us to the corner solution, and it reaches \$0 billion (ICE) where \$449 billion (EV) in Figure 1.2b. Figure 1.2c shows a corner solution under dynamic purchase subsidy: about \$0 billion (ICE) where \$421 billion (EV). In Figure 1.2d, Dynamic investment subsidy leads us to a steady state with \$42.56 billion (ICE) where \$365.59 billion (EV).

Figure 1.3 shows the optimal subsidy contour plot with the stream flow. Under the dynamic purchase subsidy, we need a very high purchase subsidy starting from the 2024 capital level. However, the optimal subsidy converges to zero as the state moves along with the optimal path in Figure 1.3a. Figure 1.3b shows the optimal investment subsidy contour plot with the stream flow. The path will arrive at a steady state where the net capital accumulation is zero.

1.5 Discussion

Table 1.7 compares four scenarios: zero subsidy, current purchase subsidy (\$7.5k), dynamic purchase subsidy, and dynamic investment subsidy. The first part describes what happens at the beginning of 2024: EV firms have \$52.81 billion, and ICE firms have \$276.17 billion as their capital. In 2024, the optimal subsidy is higher than the current subsidy: $\eta_e = \$15000$ and $\theta_e = \$37.01 billion$. Then, these dynamic subsidies become zero during the path to equilibrium. TSNB means the total net present value of the social net benefit from 2024 to an infinite time horizon with a discount rate. The subsidization increases total benefit compared to zero subsidies by 2.31% (current purchase subsidy), 3.84% (dynamic purchase subsidy), and 2.39% (dynamic investment subsidy). Dynamic subsidies are also better than the current policy, increasing benefits by 1.49% (dynamic purchase subsidy) and 0.08% (dynamic investment subsidy). SNB, CS, PS, GE, and DE are per period term in 2024. The subsidization also immediately increases the current social net benefit, consumer surplus, and producer surplus of EV firms and decreases the producer surplus of ICE firms and the social costs of carbon. Dynamic ones have a greater impact than constant ones. Investment subsidy has no impact on consumer surplus and social costs of carbon in 2024 because they will affect future markets by stimulating EV investment. The SNB in 2024 is about 6.2% to 6.6% of 2023 US GDP (\$27.36 trillion), and it would be about 5% to 6% of US GDP in 2024, considering recent economic growth. This corresponds to analytical reports saying that the auto industry contributes about 5% of total US GDP (Ballew & Schnorbus, 1994; Alliance for Automotive Innovation, 2022).

I performed a sensitivity analysis of the results in terms of discount rate and unit emission to validate the model and to see how TSNB levels respond to change in key assumptions, such as the social cost of carbon or discount rates. I did not do sensitivity analysis related to parameter values because I gain them from estimation of real market data, while this may be needed. The main analysis of this paper uses \$52.04/ton CO_2 under 3% of discount rate and 12,993 g CO_2 emission per 33.7kWh of electricity generation in Table 1.1. First, I consider other scenarios suggested by US Environmental Protection Agency (2010): (1) \$14.87/ton CO_2 under 5% of the discount rate, and (2) \$152.40/ton CO_2 under 3% of the discount rate. Second, I also consider the decarbonization in electricity generation by increasing renewable sources: (3) RE50 (Renewable Energy 50%) - current carbon emission in electricity generation becomes 50%, and (4) RE100 (Renewable Energy 100%) - current carbon emission in electricity generation becomes 0%. The unit emission from electricity generation will be 6,497 g CO_2per 33.7kWh under (3) and 0 g CO_2per 33.7kWh under (4). Table 1.8 shows the sensitivity analysis for different discount rates: (1) and (2), and Table 1.9 shows the sensitivity analysis for different unit emissions: (3) and (4). In general, we can observe that the percentage change of each social net benefit, consumer and producer surplus, expenditure, and social cost of carbon are similar among scenarios. The location of equilibrium is also similar except for scenario (1). Each scenario shows different values of social net benefit and producer surplus. Regarding social net benefit, it decreases with the high value of the social cost of carbon in scenario (2) and increases with decreasing unit emission from EV driving in scenarios (3) and (4). The social net benefit is much smaller in the 5% scenario (1), which along with applying different discount rates over infinite horizons [5]. Therefore, it supports the robustness of the outcomes.

Figure 1.4 shows the path of subsidy and expenditure under each subsidy, which starts from 2024 capital levels, which are not normalized over time. The optimal dynamic purchase subsidy

[5]When applying a discount rate, ρ, over infinite horizons, the infinite geometric series is $\frac{1}{(1-\frac{1}{1+\rho})}$. The ratio of the infinite geometric series under $\rho = 5\%$ to $\rho = 3\%$ is 61.17%. The ratio of TSNB at zero subsidy under $\rho = 5\%$ in Table 1.8, to $\rho = 3\%$ in Table 1.7 is 61.33%.

path (blue solid line) starts from \$15k and continuously decreases over time, while the constant subsidy path (black dashed line) stays at \$7.5k. Along with the subsidy and market share changes, the expenditure under dynamic subsidy (blue pattern area) starts from \$82.06 billion but converges to zero. On the other hand, the expenditure under constant purchase subsidy (grey area) keeps increasing over time. The expenditure under dynamic subsidy (black area) starts from \$37.01 billion, which is 205% of EV investment (blue solid line), but it shrinks to zero very quickly.

Figure 1.5 compares the path of firms' capital under four policies. In Figure 1.5a, EV firms' capital grows over time in any kind of subsidy, and purchase subsidy leads us to equilibrium at higher EV capital. Figure 1.5b shows any form of subsidy will dramatically reduce ICE capital on a path, and purchase subsidy will make it zero. Dynamic purchase subsidy reach the zero ICE capital much faster than constant purchase subsidy.

Table 1.7 clearly shows that dynamic subsidies improve social net welfare. Figure 1.4 indicates dynamic purchase subsidy requires much more expenditure and leads to more welfare improvement. This is because of their nature. This chapter focuses on the twofold impact of subsidies on the current and future markets. Dynamic purchase subsidy intervene in the current market first, then it will indirectly stimulate capital investment by increasing the short-term profit of EV firms. On the other hand, dynamic investment subsidy does not intervene in the current market; instead, it directly affects EV firms' investment decisions, indirectly affecting future markets. Therefore, dynamic purchase subsidy alters the market earlier and is stronger with market size, while dynamic investment subsidy only focuses on innovation on the producer side.

The growth of the market competitiveness of EVs depends on the experience curve. This means this result is based on the assumption that the EV production cost and attributes will be improved at the same speed in the experience curve from the past. If the innovation of EV technology suddenly slows due to technological difficulty or maturity, then the investment in EV capital becomes inefficient. If scientists and engineers find new breakthroughs in EV technology, such as solid-state batteries, which is one of the certain future of batteries (Janek & Zeier, 2023), then investment in EV capital is remarkably attractive.

1.6 Conclusion

I have demonstrated the dynamics of optimal policy on firms' dynamic competition and consumers' purchase behavior. The government promotes EV adoptions by stimulating EV investment using two instruments: EV retail purchase subsidy and manufacturer investment subsidy. This chapter analyzes all agents' behavior and choices to investigate policy intervention. This analysis shows that the optimal path should be a very high level of intervention at the 2024 capital levels; however, all will soon reach zero when the EV capital accumulates. This is because the policy instrument exerts two kinds of impact on the market: impact on the current market and impact on the future market via investment stimulation. The earlier intervention results in an accrued impact over time. On the other hand, as the products' attributes improve and prices decrease, the government may no longer need to intervene at some point – as per Archsmith et al. (2022)'s finding that, if intrinsic demand growth is high, the higher future market share will head to no subsidies required. This result also seems to accord well with Rapson & Muehlegger (2023). Acemoglu et al. (2012) show that it is optimal to redirect technology innovation toward clean technologies immediately and that delaying intervention is costly. They found that long-run growth can be achieved using temporary intervention when the inputs are substitutable.

My finding seems contrary to Langer & Lemoine (2022)'s finding that efficient subsidies increase over time; however, it is justifiable due to the different nature of the research topic. First, the consumer characteristics are different for solar panels and EVs. Langer & Lemoine (2022) analyzed solar panel adoption, which has a fixed total sale and long lifetime of a good exceeding 20 years, while the automobile market has a fixed total sale per year. Therefore, in Langer & Lemoine (2022), early adopters install solar panels first, and they will not be in the market for a long time. So, the result may be considered to avoid overpaying early adopters and to pay more late adopters. If all homeowners install solar panels on their roofs, there will be no new consumers before the installed panels are outdated after 20 years. However, this chapter has 17 million new vehicles consumed every year, considering the recent several decades trend. Therefore, early adopters may buy vehicles every year. Second, the objectives of government are different from each other. Langer

& Lemoine (2022) assume that the government dislikes spending money due to administrative costs and budget limits, and regulators will maximize instantaneous benefit minus cost from adoption. In this chapter, the regulators consider all stakeholders' surplus, and the regulators have no preference for spending money because it will be a tradeoff in society. Thus, regulators maximize consumer and producer surplus with social cost minimization. It makes us focus on how subsidies stimulate capital investment, which will change the social equilibrium, while Langer & Lemoine (2022) focuses on the dynamic and heterogeneous consumer preference at given conditions.

A further implication of this study requires expanding this model. Regarding assumptions, some damage-related parameters are assumed to be constant, even though they are not so in reality. The unit emission from EVs will decrease as the energy source becomes increasingly renewable (Shafique & Luo, 2022; Rapson & Muehlegger, 2023). The social cost of carbon will increase as the carbon budget is exhausted (US Environmental Protection Agency, 2010). Rapson & Muehlegger (2023) argued that there is an active debate about how much EVs are driven, and there may be evidence that average traveled miles of EVs are less than ICEs. Second, future work may consider the consumer's ability to delay the adoption choice and induced technology together. It will include this chapter's findings, how to stimulate investment via subsidies, and Langer & Lemoine (2022)'s findings on how to use subsidies as price discrimination for consumer heterogeneity. There are two competing trends: one to decrease subsidy over time from increasing target technology competitiveness, and one to increase subsidy over time from considering consumers who are unwilling to pay for the technology. Finally, we could apply this model to industries where governments need to intervene to correct externalities, or we could expand this model to other environmental policies such as carbon tax or emission trading schemes. This model is based on market competition and how to promote the target product's market share with policy intervention.

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APPENDIX 1.A: Tables and Figures

Table 1.1 Parameters for damage function

	Variable	Value	Source
$\overline{\text{year}}$	Total lifetime of a car	11.8 year	US Bureau of Transportation Statistics (2021)
$\overline{\text{mile}}$	Annual miles traveled per year	14,263 mile/year	Book (2021)
emit_f	Emission per gallon of gasoline	8,897 g CO_2/gallon	US Environmental Protection Agency (2023)
emit_e	Emission per gallon-equivalent	12,993 g CO_2/gallon$_{eq}$	Calculated by 33.7kWh=1 gallon
	Emission per 1 kWh electricity	385.55 g CO_2/kWh	US Energy Information Administration (2021)
SCC	Social cost of carbon	\$52.04/ton CO_2	US Environmental Protection Agency (2010)
ρ	discount rate	3%	US Environmental Protection Agency (2010)

Table 1.2 The descriptive statistics of the dataset for demand estimation

Variables		Unit	Obs.	Mean	Min	Max
Dependent	$lns_{m,t} - lns_{n,t}$		3,417	−4.467 (2.288)	-15.779	1.058
	Market Share	%	3,417	0.300 (0.488)	5.88×10^{-6}	5.155
	Sale	count	3,417	50,941 (82,932)	1	876,341
p_j	Price	$	3,252	39,220 (19,759)	12,246	132,310
x_1	Power weight ratio	HP/lb	3,258	0.057 (0.015)	0.020	0.134
x_2	Mileage per fuel of dollar value	mile/$	3,238	10.103 (4.954)	4.538	41.776
x_3	Maximum driving range	mile	3,121	415.089 (87.473)	58.0	758.0
y_1	Wheelbase	inch	3,280	111.461 (9.647)	73.5	153.0
y_2	Height	inch	3,279	63.38 (6.752)	53.0	84.6
y_3	Width	inch	3,279	73.547 (3.923)	60.9	89.0
z_e	Type of Vehicle - EV	binary	3,417	0.026 (0.158)	0	1
z_f	Type of Vehicle - ICE	binary	3,417	0.835 (0.371)	0	1

Note: These statistics exclude the portion of no buy options
Parentheses give the standard deviation for each coefficient

Table 1.3 The statistics of annual sale, no-buy options, and fuel price

Year	Total Sale	No-buy options	Oil Price($/gallon)	Electricity Price($/kWh)
2008	14,116,379	2,883,621	2.643	N/A
2009	9,872,487	7,127,513	2.858	N/A
2010	10,906,440	6,093,560	2.826	N/A
2011	12,141,424	4,858,576	2.865	0.104
2012	13,680,451	3,319,549	2.774	0.111
2013	14,889,435	2,110,565	2.702	0.113
2014	15,637,553	1,362,447	2.660	0.108
2015	16,360,077	639,923	2.575	0.103
2016	16,661,898	338,102	2.804	0.099
2017	16,714,252	285,748	2.853	0.098
2018	16,553,388	446,612	2.757	0.097
2019	16,531,617	468,383	2.691	0.097
Average	14,505,450	2,494,550	2.751	0.103

Note: Prices are real prices in 2019 by applying CPI index
Electricity price in 2011 is gained by applying CPI for electricity index

Table 1.4 The demand estimation result of the OLS, FEE, and RFE models

	Variables	Unit		OLS	FFE	RFE
p_j	Price	$	α	-3.61×10^{-5}****	-1.001×10^{-5}***	-2.924×10^{-5}****
				(2.20×10^{-6})	(3.429×10^{-6})	(2.480×10^{-6})
x_1	Power weight ratio	HP/lb	β_1	16.068****	4.539**	3.236*
				(3.415)	(1.960)	(1.912)
x_2	Mileage per fuel of dollar value	mile/$	β_2	0.093****	0.044***	0.030***
				(0.012)	(0.014)	(0.012)
x_3	Maximum driving range	mile	β_3	9.805×10^{-3}****	1.151×10^{-3}***	1.503×10^{-3}****
				(5.428×10^{-4})	(3.853×10^{-4})	(3.578×10^{-4})
y_1	Wheelbase	inch	γ_1	0.002	0.048****	0.013**
				(0.005)	(0.009)	0.006
y_2	Height	inch	γ_2	0.048****	-0.024*	-0.003
				(0.007)	(0.013)	(0.008)
y_3	Width	inch	γ_3	-0.122****	0.013	0.001
				(0.011)	(0.008)	(0.007)
z_e	Type of Vehicle - EV	binary	δ_e	1.791****	N/A	0.071
				(0.382)	N/A	(0.389)
z_f	Type of Vehicle - ICE	binary	δ_f	2.616****	N/A	2.267****
				(0.146)	N/A	(0.162)
	Constant			-5.275**	-10.248****	-8.253****
				(0.404)	(1.308)	(0.645)
	Vehicle model control			None	Fixed	Random
	Time control			None	Fixed	Fixed

Note : $*p < 0.1; **p < 0.05; ***p < 0.01; ****p < 0.001$
Parentheses give the robust standard errors for each coefficient

Table 1.5 The descriptive statistics of the dataset for production estimation

Variables		Unit	Obs.	Mean	Min	Max
EV						
c_e	Unit production cost	\$	7	46,866 (7,958)	35,373	59,930
x_1	Power weight ratio	HP/lb	9	0.052 (0.012)	0.032	0.063
x_2	Mileage per 33.7kWh	mile/33.7kWh	9	106.29 (6.71)	97.98	116.39
x_3	Maximum driving range	mile	9	145.28 (57.53)	73	243.93
K_e	Cumulatice capital	\$ Billion	9	8.12 (7.95)	0.48	19.25
ICE						
c_f	Unit production cost	\$	9	28,563 (1,082)	27,277	30,204
x_1	Power weight ratio	HP/lb	9	0.057 (0.000)	0.056	0.057
x_2	Mileage per gallon	mile/gallon	9	25.47 (0.77)	23.95	26.22
x_3	Maximum driving range	mile	9	437.44 (8.31)	419.89	446.13
K_f	Cumulatice capital	\$ Billion	9	218.98 (27.36)	173.36	248.30
Both						
K_j	Cumulatice capital	\$ Billion	21	22.00 (15.64)	0.32	42.58
I_j	Investment	\$ Billion	21	0.91 (0.36)	0.24	1.51

Table 1.6 The production estimation result

Dependent Variables		coefficient	EV	ICE
c_j	ln(unit production cost)	ϕ_{jc1}	-0.124 (0.044)**	-0.185 (0.084)*
		$\ln \phi_{jc0}$	13.543 (0.996)****	15.091 (2.187)****
x_1	ln(Power weight ratio)	ϕ_{j11}	0.166 (0.034)***	0.037 (0.019)*
		$\ln \phi_{j10}$	-6.663 (0.751)****	-3.841 (0.500)****
x_2	ln(MPG(e))	ϕ_{j21}	0.039 (0.001)***	0.211 (0.040)***
		$\ln \phi_{j20}$	3.809 (0.187)****	-2.262 (1.032)*
x_3	ln(Maximum driving range)	ϕ_{j31}	0.269 (0.047)***	0.111 (0.037)**
		$\ln \phi_{j30}$	-1.060 (1.041)	3.189 (0.961)**
K_j	Cumulative capital	$1-\mu$	0.949 (0.021)****	
I_j	Investment	ν	$8.423 \times 10^{-10} (4.337 \times 10^{-11})$****	

$Note: *p < 0.1; **p < 0.05; ***p < 0.01; ****p < 0.001$

Parentheses give the robust standard errors for each coefficient

Table 1.7 Comparison of policy instruments and their equilibrium

	Unit	Zero subsidy $0	Purchase subsidy Current ($7500)	Purchase subsidy Dynamic (η_e)	Investment subsidy Dynamic (θ_e)
In 2024					
Policy level		$0	$7500	$15026	$37.01 *billion* (206%)
TSNB	$ *trillion*	60.40	+1.40 (+2.31%)	+2.32 (+3.84%)	+1.44 (+2.39%)
SNB	$ *billion*	1700.06	+68.28 (+4.02%)	+122.49 (+7.21%)	+120.31 (+7.08%)
CS	$ *billion*	554.46	+70.86 (+12.78%)	+143.45 (+25.87%)	-
PS (EV)	$ *billion*	91.24	+85.55 (+93.77%)	+162.34 (+177.93%)	+121.43 (+133.09%)
PS (ICE)	$ *billion*	1,094.69	-50.73 (-4.63%)	-102.67 (-9.38%)	-1.11 (-0.10%)
GE	$ *billion*	0	+38.10	+82.06	+37.01
DE	$ *billion*	40.34	-0.71 (-1.75%)	-1.44 (-3.58%)	-
Equilibrium					
Equlibirum		Steady-state	Corner solution	Corner solution	Steady-state
Policy level		$0	$7500	$0	$0 (0%)
EV capital at Eq	$ *billion*	147.77	449	421	365.59
ICE capital at Eq	$ *billion*	665.46	0	0	42.56

** In 2024, EV capital is $52.81 billion and ICE capital is $276.17 billion*

Table 1.8 Senstivity analysis for different discount rates

	Unit	\$0	\$7500	η_e	θ_e
(1) ρ=5%					
In 2024					
Policy level		\$0	\$7500	\$10694	\$21.20 *billion*
TSNB	\$ *trillion*	37.04	+0.72 (+1.95%)	+0.93 (+2.50%)	-0.05 (-0.14%)
SNB	\$ *billion*	1789.66	+57.79 (+3.23%)	+77.21 (+4.31%)	+72.27 (+4.04%)
CS	\$ *billion*	554.46	+70.86 (+12.78%)	+101.49 (+18.30%)	-
PS (EV)	\$ *billion*	138.10	+78.31 (+56.70%)	+108.54 (+78.60%)	+83.45 (+60.42%)
PS (ICE)	\$ *billion*	1108.62	-53.48 (-4.82%)	-77.08 (-6.95%)	-11.18 (-1.01%)
GE	\$ *billion*	0	+38.10	+56.04	+21.20
DE	\$ *billion*	11.53	-0.20 (-1.75%)	-0.29 (-2.52%)	-
Equilibrium					
Equlibirum		Steady-state	Steady-state	Steady-state	Corner solution
Policy level		\$0	\$7500	\$0	\$0 (0%)
EV capital at Eq	\$ *billion*	123.21	328.08	297.83	435
ICE capital at Eq	\$ *billion*	1030.22	34.61	18.12	0
(2) ρ=3% and High SCC					
In 2024					
Policy level		\$0	\$7500	\$16073	\$17.06 *billion*
TSNB	\$ *trillion*	57.59	+1.46 (+2.53%)	+2.55 (+4.43%)	+1.17 (+2.03%)
SNB	\$ *billion*	1622.27	+69.64 (+4.29%)	+131.88 (+8.13%)	+96.46 (+5.95%)
CS	\$ *billion*	554.46	+70.86 (+12.78%)	+153.67 (+27.71%)	-
PS (EV)	\$ *billion*	91.24	+85.55 (+93.77%)	+172.31 (+188.85%)	+90.52 (+99.21%)
PS (ICE)	\$ *billion*	1094.69	-50.73 (-4.63%)	-109.97 (-10.05%)	+5.95 (0.54%)
GE	\$ *billion*	0	+38.10	+88.65	+17.06
DE	\$ *billion*	118.13	-2.07 (-1.75%)	-4.54 (-3.84%)	-
Equilibrium					
Equlibirum		Steady-state	Corner solution	Corner solution	Steady-state
Policy level		\$0	\$7500	\$0	\$0 (0%)
EV capital at Eq	\$ *billion*	147.16	450	422	370.11
ICE capital at Eq	\$ *billion*	665.83	0	0	40.26

** In 2024, EV capital is \$52.81 billion and ICE capital is \$276.17 billion*

Table 1.9 Senstivity analysis for different unit emissions

	Unit	\$0	\$7500	η_e	θ_e
(3) RE50					
In 2024					
Policy level		\$0	\$7500	\$15091	\$30.55 *billion*
TSNB	\$ *trillion*	60.49	+1.40 (+2.31%)	+2.33 (+3.86%)	+1.26 (+2.07%)
SNB	\$ *billion*	1702.35	+68.46 (+4.02%)	+123.27 (+7.24%)	+113.66 (+6.68%)
CS	\$ *billion*	554.46	+70.86 (+12.78%)	+144.09 (+25.99%)	-
PS (EV)	\$ *billion*	91.24	+85.55 (+93.77%)	+162.97 (+178.61%)	+112.30 (+123.08%)
PS (ICE)	\$ *billion*	1094.69	-50.73 (-4.63%)	-103.13 (-9.42%)	+1.36 (+0.12%)
GE	\$ *billion*	0	+38.10	+82.47	+30.55
DE	\$ *billion*	38.05	-0.88 (-2.32%)	-1.82 (-4.77%)	-
Equilibrium					
Equlibirum		Steady-state	Corner solution	Corner solution	Steady-state
Policy level		\$0	\$7500	\$0	\$0 (0%)
EV capital at Eq	\$ *billion*	146.32	450	421	363.97
ICE capital at Eq	\$ *billion*	663.86	0	0	40.85
(4) RE100					
In 2024					
Policy level		\$0	\$7500	\$15087	\$40.58 *billion*
TSNB	\$ *trillion*	60.60	+1.40 (+2.31%)	+2.33 (+3.85%)	+0.91 (+1.50%)
SNB	\$ *billion*	1704.64	+68.64 (+4.03%)	+123.61 (+7.25%)	+123.55 (+7.25%)
CS	\$ *billion*	554.46	+70.86 (+12.78%)	+144.05 (+25.98%)	-
PS (EV)	\$ *billion*	91.24	+85.55 (+93.77%)	+162.93 (+178.57%)	+126.11 (+138.22%)
PS (ICE)	\$ *billion*	1094.69	-50.73 (-4.63%)	-103.10 (-9.42%)	-2.55 (-0.23%)
GE	\$ *billion*	0	+38.10	+82.45	+40.58
DE	\$ *billion*	35.75	-1.06 (-2.96%)	-2.18 (-6.09%)	-
Equilibrium					
Equlibirum		Steady-state	Corner solution	Corner solution	Steady-state
Policy level		\$0	\$7500	\$0	\$0 (0%)
EV capital at Eq	\$ *billion*	146.57	450	418	370.11
ICE capital at Eq	\$ *billion*	666.45	0	0	40.26

** In 2024, EV capital is \$52.81 billion and ICE capital is \$276.17 billion*

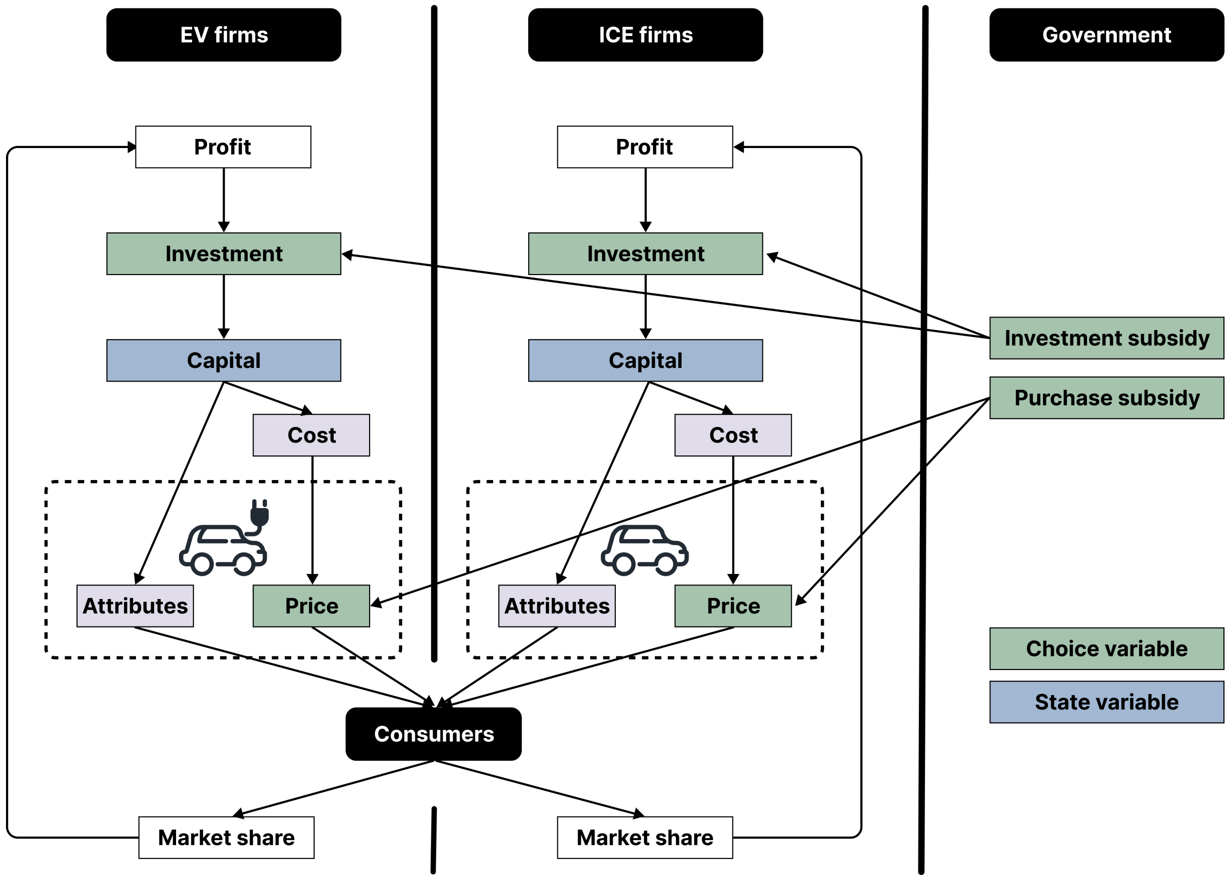
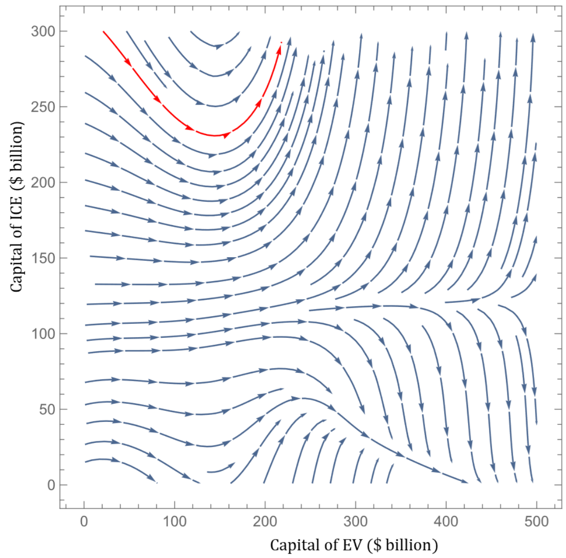
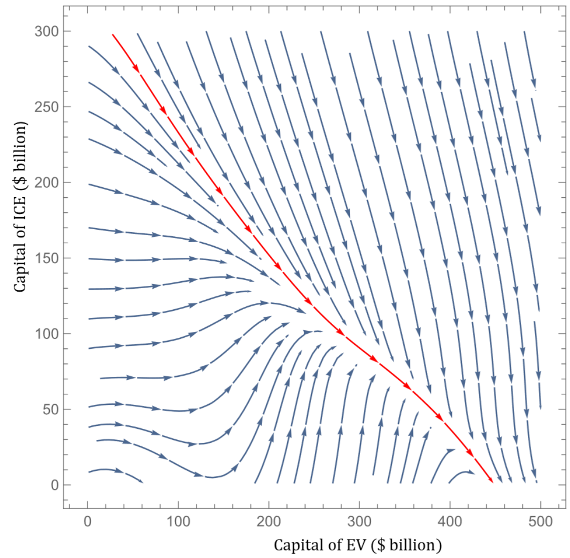


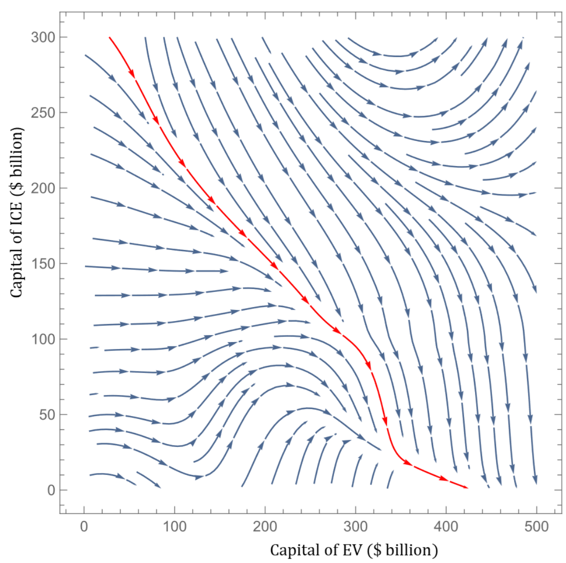
Figure 1.1 A simplified diagram illustrating the model's market dynamics and regulations



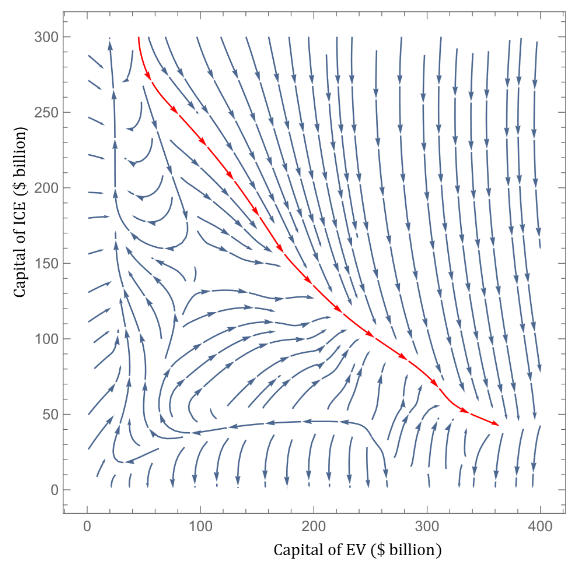
(a) Zero purchase subsidy



(b) Constant $7,500 purchase subsidy

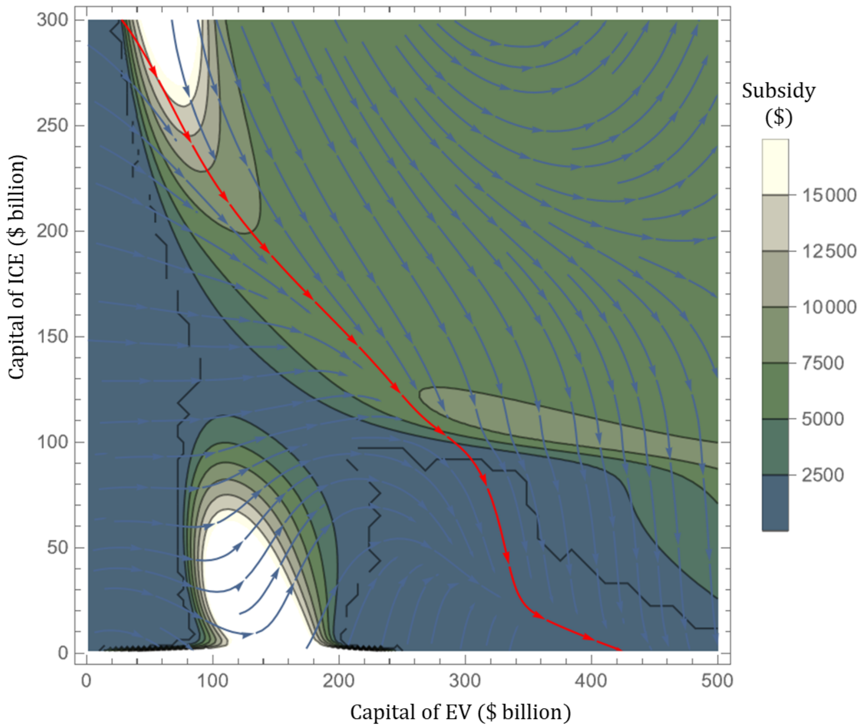


(c) Dynamic purchase subsidy

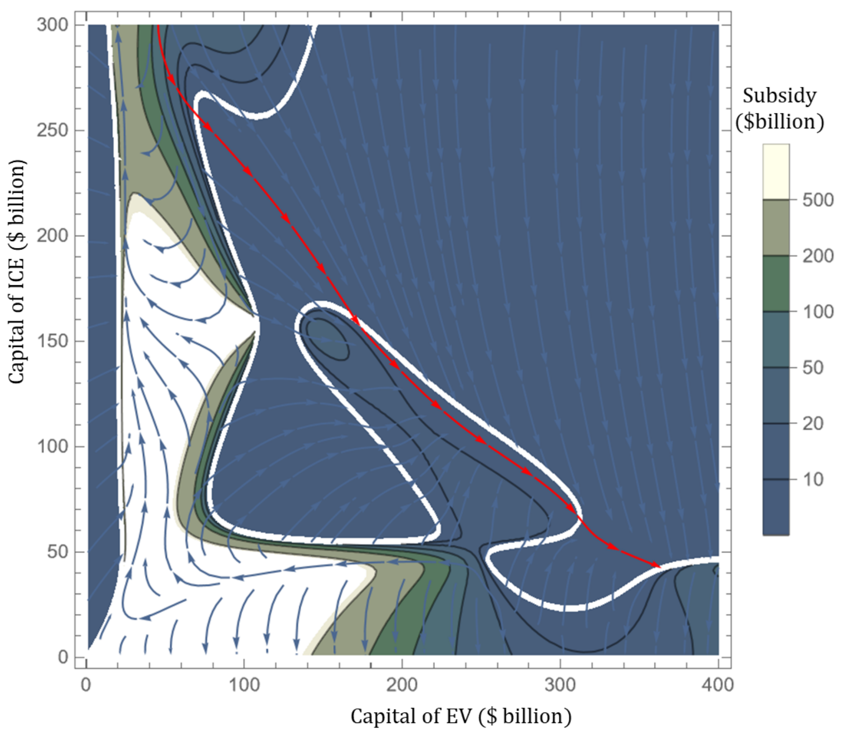


(d) Dynamic investment subsidy

Figure 1.2 Flow chart under each policy



(a) Dynamic purchase subsidy



(b) Dynamic investment subsidy

Figure 1.3 Flow chart with each subsidy

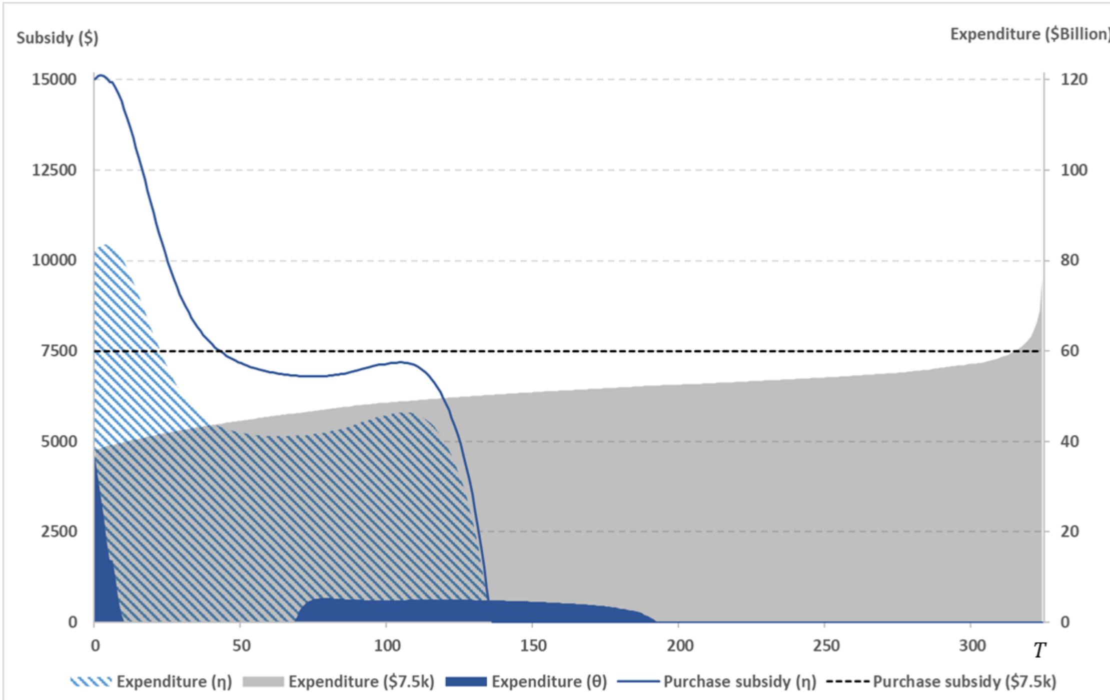
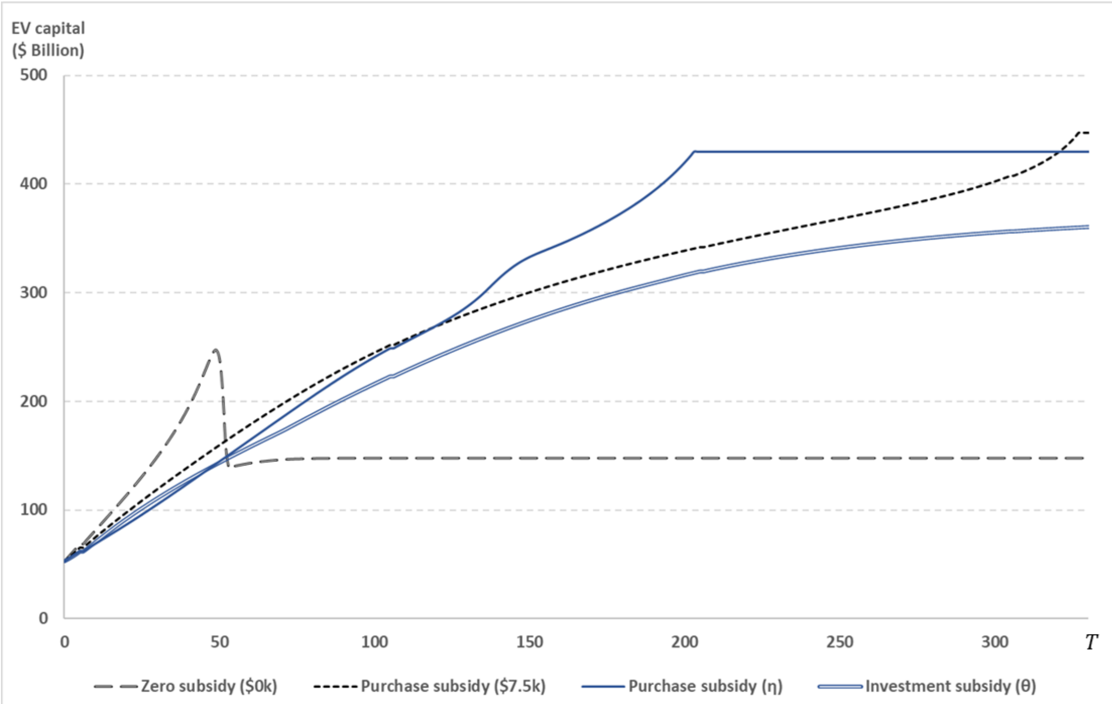
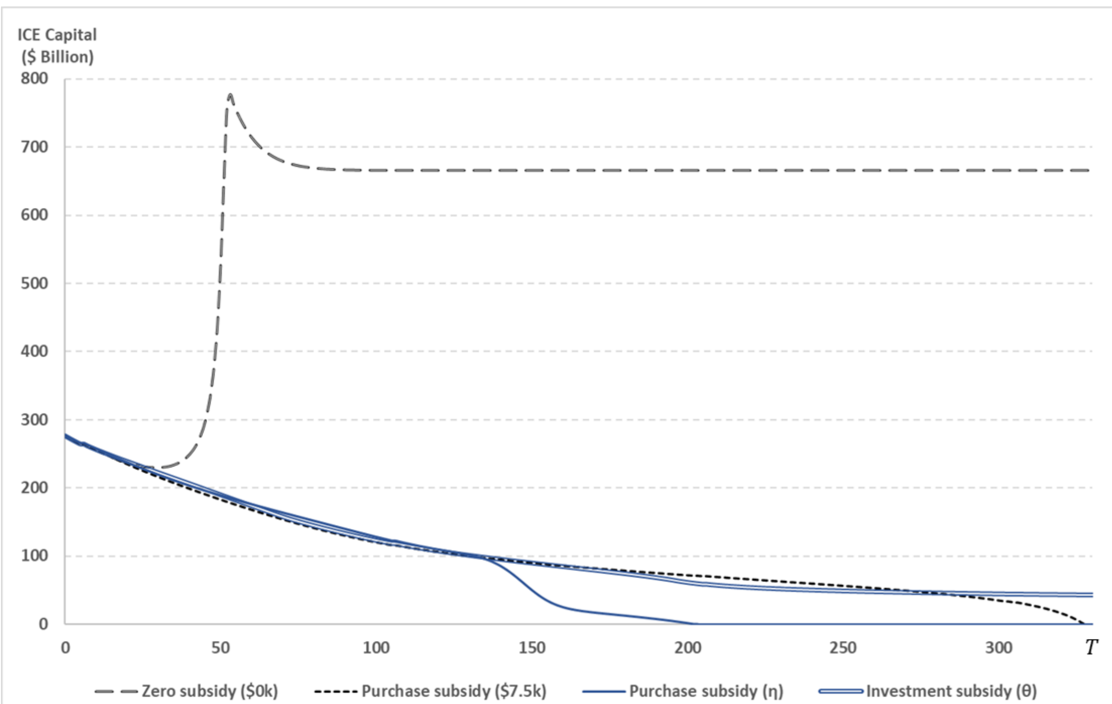


Figure 1.4 The path of subsidy and expenditure under each subsidy



(a) Path of EV capital under four policies



(b) Path of ICE capital under four policies

Figure 1.5 Path of firms' capital under four policies

APPENDIX 1.B: Demand Estimation

To estimate aggregate demand, market data are gathered from global automobile marketing companies: Markline and Wardsauto, and filtered for relevance. First, I excluded commercial vehicles, oversized trucks, and supercars. They have different segments in the market, and there were no commercialized EVs of these types. The list of excluded cars is in Table 1.B.1.

Table 1.B.1 List of excluded vehicle models

Brand	Model
All models in this brand:	Aston Martin, Bentley, Ferrari, Lamborghini, Maserati, Rolls-Royce, Freightliner, Hino, International, Isuzu, Kenworth, Lotus, Mack Trucks, Mitsubishi Fuso, Peterbilt, Sterling, UD Trucks, Volvo Trucks, Western Star
Alfa Romeo	4C
Audi	TT, RS6, R8
BMW	M3, Z4, i8, Z8
Cadillac	XLR
Chevrolet	Camaro, Express cargo, City Express, Silverado médium, Corvette, Kodiak, W, C/T
Chrysler	Truck, Crossfire
Dodge	Challenger, Viper, Sprinter
Fiat	124 Spider
Ford	Truck, Mustang, F-series Medium duty, GT, Transit, Low Cab Forward
GMC	Savana Cargo, Sierra Medium duty, C/T, C/W, Truck(GM)
Honda	S2000, NSX(Acura)
Hyundai	Tiburon
Jaguar	XK, F-Type
Mazda	MX-5, RX-8
Mercedes-Benz	SLC, SLK, CLK, AMG-GT, CL, SL, SLR, SLS, Sprinter
Mitsubishi	Eclipse, Eclipse Spyder
Nissan	350Z, 370Z, GT-R, Truck, Q60(Infiniti)
Pontiac	Solstice, Firebird, GTO
Porsche	Boxster, Cayman, Carrera, Porsche 911, Porsche 918
Ram	Medium duty, Cargo van, ProMaster
Saturn	S-series, Sky
Subaru	BRZ
Toyota	86, Celica, MR2, Supra, FR-S(Scion), RC(Lexus), SC(Lexus), LC(Lexus), LFA(Lexus)
Volkswagen	Eurovan

APPENDIX 1.C: Solving Optimal Decisions

1.C.1 Optimal Price and investment

If we solve Equation (1.3e) with respect to price, the F.O.C. of price is $\rho\frac{\partial V_j}{\partial p_j} = 0 = s_j M + (p_j - c_j)\frac{\partial s_j}{\partial p_j}M$. We can rewrite this with $\frac{\partial s_e}{\partial p_e} = \frac{\partial s_f}{\partial p_f} = -\alpha s_e s_f$, and $\frac{\partial s_e}{\partial p_f} = \frac{\partial s_e}{\partial p_f} = \alpha s_e s_f$.

$$p_e^*(\boldsymbol{p}, \boldsymbol{x}; \eta_e) = c_e(K_e) + \frac{1}{\alpha} + \frac{1}{\alpha}\exp[\boldsymbol{\beta}(\boldsymbol{x_e} - \boldsymbol{x_f}) + \delta_e - \delta_f - \alpha(p_e^* - \eta_e - p_f^*)] \tag{1.C.1.1a}$$

$$p_f^*(\boldsymbol{p}, \boldsymbol{x}; \eta_e) = c_f(K_f) + \frac{1}{\alpha} + \frac{1}{\alpha}\exp[\boldsymbol{\beta}(\boldsymbol{x_f} - \boldsymbol{x_e}) + \delta_f - \delta_e + \alpha(p_e^* - \eta_e - p_f^*)] \tag{1.C.1.1b}$$

To solve this exponential equation, I rearrange Equation (1.C.1.1) using the Lambert W function, that $we^w = x$ can be solved as $w = W_0(x)$ for $x \geq 0$.

$$p_e^*(p_f, \boldsymbol{x}; \eta_e) = c_e(K_e) + 1/\alpha + W_{0e}/\alpha \tag{1.C.1.2a}$$

$$W_{0e} \equiv W_0\Big[\exp\big(\boldsymbol{\beta}(\boldsymbol{x_e} - \boldsymbol{x_f}) + \delta_e - \delta_f + \alpha(p_f + \eta_e - c_e(K_e)) - 1\big)\Big]$$

$$p_f^*(p_e, \boldsymbol{x}; \eta_e) = c_f(K_f) + 1/\alpha + W_{0f}/\alpha \tag{1.C.1.2b}$$

$$W_{0f} \equiv W_0\Big[\exp\big(\boldsymbol{\beta}(\boldsymbol{x_f} - \boldsymbol{x_e}) + \delta_f - \delta_e + \alpha(p_e - \eta_e - c_f(K_f)) - 1\big)\Big]$$

The range of W_{0j} is $[0, 14]$ at the range of $p_j \in [\$10k, \$100k]$, $\eta_e \in [\$0, \$20k]$, and $K_j \in [\$0, \$300 billion]$. In this range, we can approximate $W_0(x) \cong w_1 \ln(x) + w_0$ with $w1 = 0.3546$, and $w_0 = 0.7232$ and R^2 is 0.9095. If we substitute Equation (1.C.1.2) for each other, then the optimal price is now the function of both firms' capital only.

$$\check{p}_e^*(\boldsymbol{K}; \eta_e) = \frac{c_e(K_e)}{1 + w_1} + \frac{1 + w_0 - w_1}{\alpha} + \frac{w_1\big[\boldsymbol{\beta}(\boldsymbol{x_e}(K_e) - \boldsymbol{x_f}(K_f)) + \delta_e - \delta_f + \alpha(c_f(K_f) + \eta_e)\big]}{\alpha(1 + w_1)} \tag{1.C.1.3a}$$

$$\check{p}_f^*(\boldsymbol{K}; \eta_e) = \frac{c_f(K_f)}{1 + w_1} + \frac{1 + w_0 - w_1}{\alpha} + \frac{w_1\big[\boldsymbol{\beta}(\boldsymbol{x_f}(K_f) - \boldsymbol{x_e}(K_e)) + \delta_f - \delta_e + \alpha(c_e(K_e) - \eta_e)\big]}{\alpha(1 + w_1)} \tag{1.C.1.3b}$$

If we solve Equation (1.3e) with respect to investment, we have the F.O.C. of investment: $\rho\frac{\partial V_j}{\partial I_j} = \frac{\partial V_j}{\partial K_j} - \frac{\partial}{\partial I_j}\psi_j(I_j) = 0$. The optimal investment is $I_j^*(\boldsymbol{K}; \boldsymbol{\tau}) = \frac{1}{2\nu}\frac{\partial V_j}{\partial K_j}$.

1.C.2 Optimal Purchase Subsidy

There are two policies to be optimized: η_e (purchase subsidy) and θ_e (investment subsidy). The optimal subsidy is determined by solving Equation (1.9c). First, the F.O.C. of purchase subsidy is $\frac{\partial SNB}{\partial \eta_e} + \frac{\partial \Omega}{\partial K_e}(\frac{\partial I_e}{\partial \eta_e}) + \frac{\partial \Omega}{\partial K_f}(\frac{\partial I_f}{\partial \eta_e}) = 0$. From Equation (1.C.1.3), $\frac{\partial \check{p}_e^*}{\partial \eta_e} = -\frac{\partial \check{p}_f^*}{\partial \eta_e} = \frac{w_1}{1+w_1}$. Then, with these derivatives and Equation (1.1c), we get $\frac{\partial s_e}{\partial \eta_e} = -\frac{\partial s_f}{\partial \eta_e} = \frac{1-w_1}{1+w_1}\alpha s_e s_f$. From Equation (1.9b),

$$\frac{\partial\, \mathrm{SNB}}{\partial \eta_e} = \frac{\partial\, \mathrm{CS}(\boldsymbol{K}, \eta_\mathrm{e})}{\partial \eta_e} + \frac{\partial\, \mathrm{PS}(\boldsymbol{K}, \eta_\mathrm{e})}{\partial \eta_e} + \frac{\partial\, \mathrm{GE}(\boldsymbol{K}, \eta_\mathrm{e})}{\partial \eta_e} + \frac{\partial\, \mathrm{D}(\boldsymbol{K}, \eta_\mathrm{e})}{\partial \eta_e}$$

$$= \frac{1 - w_1}{1 + w_1}[(\check{p}_e^* - \check{p}_f^*) - (c_e - c_f) - (d_e - d_f) - \eta_e]\alpha s_e s_f M - 2\nu I_e\frac{\partial I_e}{\partial \eta_e} - 2\nu I_f\frac{\partial I_f}{\partial \eta_e} \tag{1.C.2.1}$$

Then, we rewrite Equation (1.C.2.1).

$$\frac{w_1-1}{1+w_1}\eta_e+\frac{2w_1}{\alpha(1+w_1)}[\boldsymbol{\beta}(\boldsymbol{x_e}-\boldsymbol{x_f})+\delta_e-\delta_f-\alpha(c_e-c_f)]-(d_e-d_f)$$
$$=\frac{1+w_1}{(1-w_1)\alpha s_e s_f M}[(2\nu I_e-\frac{\partial\Omega}{\partial K_e})\frac{\partial I_e}{\partial\eta_e}+(2\nu I_f-\frac{\partial\Omega}{\partial K_f})\frac{\partial I_f}{\partial\eta_e}] \quad (1.C.2.2)$$

In the above equation, I_j is linear in η_e, and the inverse of the market share term is

$$\frac{1}{s_e s_f}=2+e^{\beta(x_e-x_f)+\delta_e-\delta_f-\alpha(p_e-p_f-\eta_e)}+e^{-\beta(x_e-x_f)-(\delta_e-\delta_f)+\alpha(p_e-p_f-\eta_e)} \quad (1.C.2.3)$$

If we apply Taylor approximation to η_e, the term is approximated as,

$$\frac{1}{s_e s_f}\cong 2+e^{\Delta K}+e^{-\Delta K}+\left(e^{\Delta K}+e^{-\Delta K}+(e^{\Delta K}-e^{-\Delta K})\frac{1-w_1}{1+w_1}\alpha\right)\eta_e \quad (1.C.2.4)$$

$$\Delta K\equiv\beta(x_e-x_f)-\alpha\frac{1-w_1}{1+w_1}(c_e-c_f) \quad (1.C.2.4a)$$

If we substitute this into Equation (1.C.2.2), then we get the quadratic equation of η_e.

1.C.3 Optimal Investment Subsidy

Regarding investment subsidy, $\frac{\partial s_j}{\partial\theta_e}=0$. Therefore, the first-order condition is $(\frac{\partial\Omega}{\partial K_e}-2\nu I_e)(\frac{\partial I_e}{\partial\theta_e})+(\frac{\partial\Omega}{\partial K_f}-2\nu I_f)(\frac{\partial I_f}{\partial\theta_e})=0$.

$$I_j=\frac{1}{2\nu}\frac{\partial V_j}{\partial K_j}=\frac{1}{2\nu}(Z_{j1}\theta_e+Z_{j2}) \text{ where } \frac{\partial V_j}{\partial K_j}\equiv Z_{j1}\theta_e+Z_{j2} \quad (1.C.3.1)$$

Then, $(\frac{\partial\Omega}{\partial K_e}-Z_{e1}\theta_e-Z_{e2})\frac{Z_{e1}}{2\nu}+(\frac{\partial\Omega}{\partial K_f}-Z_{f1}\theta_e-Z_{f2})\frac{Z_{f1}}{2\nu}=0$ with the derivatives: $\frac{\partial I_e}{\partial\theta_e}=\frac{Z_{e1}}{2\nu}$ and $\frac{\partial I_f}{\partial\theta_e}=\frac{Z_{f1}}{2\nu}$. Therefore, we can get the optimal investment subsidy.

$$\theta_e^*=\frac{Z_{e1}(\frac{\partial\Omega}{\partial K_e}-Z_{e2})+Z_{f1}(\frac{\partial\Omega}{\partial K_f}-Z_{f2})}{Z_{e1}^2+Z_{f1}^2} \quad (1.C.3.2)$$

APPENDIX 1.D: Collocation Process

$V_j(\boldsymbol{K};\boldsymbol{\tau})$ is a function of three variables: K_e, K_f, and $\tau_e \in \{\eta_e, \theta_e\}$. I choose a polynomial with 32 terms in three variables, allowing up to third orders for K_j and the first order for η_e. This choice of dimensionality is a balance between having enough scope for good fitting versus computation costs. There are 32 unknown coefficients, $\psi_{nj} \in \boldsymbol{\psi_j}$ and $n \in \{1, ..., 32\}$; therefore, it should interpolate 32 points of variables for each firm j.

$$\check{V}_j(\boldsymbol{K};\eta_e) \equiv \sum_{n=1}^{32} \psi_{nj}\tau_x^a K_e^b K_f^c, \text{ where } a \in \{0,1\}, b, c \in \{0,1,2\} \tag{1.D.1}$$

I solve both firms' problems simultaneously to get a total of 64 unknowns: $\boldsymbol{\psi_e}$ and $\boldsymbol{\psi_f}$. Uniformly distributed points of supports are widely used for determining collocation nodes. 32 nodes are combinations of 10 uniformly distributed points of a support of $\boldsymbol{K}$ and τ_e. We can check the correctness of the collocation by comparing the right-hand side of Equation (1.3e) and Equation (1.D.1) with calibrated $\boldsymbol{\psi_j}$. If the collocation is correct, their difference should be close to zero. The sum of squared errors, $[\frac{V_e(\boldsymbol{K};\tau_x)-\check{V}_e(\boldsymbol{K};\tau_x)}{V_e(\boldsymbol{K};\tau_x)}]^2$, is 1.90×10^{-5} for purchase subsidy and 8.52×10^{-7} for investment subsidy. $[\frac{V_f(\boldsymbol{K};\tau_x)-\check{V}_f(\boldsymbol{K};\tau_x)}{V_f(\boldsymbol{K};\tau_x)}]^2$ is 6.46×10^{-6} for purchase subsidy and 2.85×10^{-6} for investment subsidy.

The government's unknown value function, $\Omega(\boldsymbol{K})$, has two unknown variables: K_e and K_f. I assume the polynomial has 16 terms in two variables with 16 unknown coefficients, $\psi_{ng} \in \boldsymbol{\psi_g}$, necessitating 16 support points.

$$\check{\Omega}(\boldsymbol{K}) \equiv \sum_{n=1}^{16} \psi_{ng} K_e^b K_f^c, \text{ where } b, c \in \{0,1,2\} \tag{1.D.2}$$

Substituting the value function and its derivatives into Equation (1.9c) generates 16 equations with 16 unknown coefficients. I choose 16 uniformly distributed nodes as combinations of $\boldsymbol{K}$. The correctness of the collocation is checked in the same way for firms' value functions. The sum of squared errors, $[\frac{\Omega(\boldsymbol{K})-\check{\Omega}(\boldsymbol{K})}{\Omega(\boldsymbol{K})}]^2$, is 7.18×10^{-9} for purchase subsidy and 1.71×10^{-5} for investment subsidy.

CHAPTER 2

PEER EFFECTS IN ELECTRIC VEHICLE ADOPTION

2.1 Introduction

Individuals communicate and interact with each other, and it significantly affects individual choices and decisions. In many social science disciplines, peer effects have been widely used as an indicator of interaction behavior. Abundant literature considers peer effects in housing (Patacchini & Venanzoni, 2014), productivity (Falk & Ichino, 2006), employment rate (Kondo & Shoji, 2019), sexual behavior (Ajilore, 2015), general consumption (De Giorgi et al., 2020; Agarwal et al., 2021), product adoption (Axsen et al., 2013; Hu & Van den Bulte, 2014; Park, 2019; Simpson & Mishra, 2021; Bailey et al., 2022; Ding et al., 2022), technology adoption (Conley & Udry, 2010; Skevas et al., 2022; Meng et al., 2023), program participation (Dahl et al., 2014), and animation watching (Ameri et al., 2019). In economics, there is growing evidence of whether, how, and to what extent the peer effect affects consumer decisions. Such peer effects play an important role in understanding consumer demand, which is specifically crucial for policymakers and entrepreneurs. Heutel & Muehlegger (2015) find that an increase in initial adopters may positively or negatively affect subsequent diffusions according to the quality of the product. If positive peer effects on product adoption exist, boosting the demand via word of mouth, the actual aggregate demand would be larger than expected from a simple aggregation of individual demand. With negative peer effects, the actual aggregate demand would be lower than expected. McCoy & Lyons (2014) find that mild peer effects could result in large clusters of adopters in certain areas even if adoption is relatively low. This relationship between peer effect and aggregate demand may affect the actual impact of demand-boosting policies, such as purchase subsidies and firms' demand forecasts.

The peer effect is particularly important in the early stage of business when there is no common and widely shared understanding of the product, e.g., eco-friendly goods such as electric vehicles (EV) or renewable energy. The growth and the spread of new technology show an S-shaped curve. Under the initial lack of information, the market grows slowly at the beginning, and then a snowball effect accelerates the adoption according to the Diffusion of Innovation Theory (Rogers, 1976;

Xiong et al., 2016; Barnes et al., 2022). The snowballing can be driven via the peer effect (Bass, 1969; McCoy & Lyons, 2014; Manca et al., 2020) explaining the initial growth in product adoption.

In the United States, the EV market grows continuously but heterogeneously. The EV market share has sharply increased since 2010. It was 0% in 2010, increased to 1.2% in 2019, and to about 9.8% in 2023 (Tefft, 2023). Nevertheless, EV adoption differs between states. According to US Department of Energy (2022), last accessed July 2024, percentages of EV registrations from total vehicle registration at the state level ranged from 0.08% (600 EVs) in North Dakota to 2.50% (903,600 EVs) in California; the average is 0.63% (47,888) with a standard deviation of 0.51% (127,582). There is further geographical variation within states. In the state of Michigan, for example, in 2019, the range of EV adoption by ZIP code ranged from zero to 1033 (in ZIP code 48033), and at the county level, it ranged from zero to 7684 (in Oakland) (Atlas EV Hub, 2023). The average and standard deviation are 6.63 (29.32) for the ZIP code level and 271.82 (969.58) for the county level. From 2011 until now, the US federal government provided an EV purchase subsidy, which is capped at $7500, while Michigan has not provided incentives for purchasing an EV. The wide variations in county and ZIP code tabulation area registrations suggest that further factors affecting EV adoption exist that vary over the region.

Most US daily driving consists of commuting and driving in neighborhood areas. First, the daily driving range is not far. During the second half of 2019, drivers made an average of 3.7 trips per day, of which 1.1 were for commuting and 2.6 for non-work-related purposes (Tefft et al., 2021). Workers specifically made an average of 2.2 trips per day for commuting and 2.0 trips for non-work purposes. In 2021, drivers made an average of 2.56 trips, covering 32.7 miles and taking 61.3 minutes per day (Tefft, 2022). Second, Speidel & Bräunl (2014) found that EVs are mostly charged at business and home locations (55%) while charging stations are only used for 33%. Thus, the probability of EVs being observed is high in areas near EV owners' homes or workplaces.

In this chapter, I study whether and to what extent peer effects affect EV adoption with EV and charging station data in Lower Michigan from 2013 to 2019. I utilized the spatial panel regression models to address spatial dependence in the peer effect of EV adoption. First, peer effects are defined as the cumulative EV adoption in the same ZIP code, considering the probability of having EV owners among peers and/or being exposed to EVs driving and parking. Second, I include covariates of household variables to disentangle the exogenous peer effect. Third, cumulative installation of charging stations is included to address the correlated peer effect identified by Li et al. (2017).

This chapter contributes mainly to the literature on peer effect in product adoption, specifically considering the probability of observing movable products. There is substantial peer effect literature concerning environmental goods: EV or Hybrid vehicle adoption (Narayanan & Nair, 2013; McCoy & Lyons, 2014; Sexton & Sexton, 2014; Heutel & Muehlegger, 2015; Manca et al., 2020; Mukherjee & Ryan, 2020), solar panel adoption (Bollinger & Gillingham, 2012; Noll et al., 2014; Graziano et al., 2019; Mundaca & Samahita, 2020; Balta-Ozkan et al., 2021; Barnes et al., 2022; Bollinger et al., 2022; O'Shaughnessy et al., 2023; Sokołowski, 2023), low-carbon practice (Jiang et al., 2023; Liu & Xia, 2023). In addition, peer effects have been proven to influence environmental behavior (Bollinger et al., 2020; Wolske et al., 2020; Moncada et al., 2021; Wen et al., 2021; Zhang et al., 2023). They mainly focus on the peer effect of group behavior on individual behavior. Nevertheless, movable products can have additional peer effects through their exposure to nearby residents. Bollinger et al. (2022) find that solar panel installation positively affects peers' solar adoption decisions at distances of at least 500 meters via visibility. That implies that visibility may affect nearby residents. Due to their mobility, EVs' visibility is spread wherever they travel, so they may exert a wider visibility impact than solar panels: people who observe an EV driving on the road and/or EVs parked while passing by will receive an additional peer effect from the EV owners in their peer group. This chapter considers these additional effects together in the case of movable products.

2.2 Theory

Peer effect has been widely used to study consumer behavior and how it works to form aggregate demand. Nevertheless, there is always complexity to address all possible effects correctly. According to Manski (1993), there is a reflection problem when we try to infer if the average behavior of some group may affect others. Manski's reflection problem can be classified into three effects: endogenous, exogenous, and correlated effects. Endogenous effects capture the impact of the interaction between people on their behavior. Exogenous effects mean that consumers' exogenous characteristics may form their behavior. Correlated effects mean that consumers in the same group may tend to behave in a similar way because they face similar institutional surroundings. We must carefully define and estimate each effect to avoid omitted variable problems.

Endogenous effects are the peer effects and are of primary interest to this chapter. The peer groups should be defined in terms of households' geographical proximity to potential adopters, similar to applications in Bollinger et al. (2022). McCoy & Lyons (2014) defines group influence as the proportion of adopters within each agent's social group. I defined the basic unit of geographic scope as ZIP Code Tabulation Areas (ZCTA).[1] Then, the peer effect within the ZCTA is proportional to the cumulative EV adoption in the same ZCTA. This is because the cumulative EV registration in a particular ZIP code area indicates the probability of observing EV driving and parking in the associated ZCTA, which forms the peer effect. Lower Michigan has 801 ZIP codes covering 40,162 sq mi. The average ZIP code area is 50.14 sq mi per zip code, similar to a square with a side of 7.08 miles. According to (Tefft, 2022), in 2021, drivers made an average of 2.56 trips, 32.7 miles per day, which means 12.77 miles per trip. 2.56 trips means every 2 trips per day and 4 additional trips per week. The mean daily traveled miles are similar to the ZIP code area. These may mean the majority of daily trips are ranged within ZIP code or commuting. Therefore, I use the cumulative EV adoption in the same ZCTA as the indicator for the peer effect from the same ZCTA. In the case outside of ZCTA, I defined the EV adoption in the same year as the peer effect. The spatial interaction will explain the influence of other ZCTAs.

Regarding the exogenous effects, I include socioeconomic variables relevant to EV adoption that are aligned with the literature on EV adoption. I consider three types of consumer characteristics: income, political attributes, and urbanization. First, income affects EV adoption due to the high price of EVs. Household income level affects EV adoption decisions because of its high market

[1]ZIP Code Tabulation Areas are a geographic concept of the U.S. Census Bureau. It is mostly similar to the ZIP code areas and was designed by the U.S. Census Bureau to map demographic information.

price compared to internal combustion engines (ICE). Households with enough income and assets may be more likely to purchase EVs. Axsen et al. (2015, 2018); Hamamoto (2019); Manca et al. (2020) consider income level as covariates affecting EV adoption, and Bollinger et al. (2022) include income in studying peer effect on solar PV installation. Second, political attributes affect buying eco-friendly goods, such as EVs. In the US, Democrats usually support climate policy, while Republicans doubt climate policy (Van Boven et al., 2018). Bollinger et al. (2022) use the ratio of Democrats to Republicans as the indicator. Due to data availability, I use education level and age as indicators for the attributes. It is common to include both variables when studying EV adoptions: education (Axsen et al., 2015; Manca et al., 2020; Mukherjee & Ryan, 2020) and age (Mukherjee & Ryan, 2020; Manca et al., 2020). These variables are time-variant due to the net population flow and the number of residents pursuing academic degrees. Lastly, I include the type of land (urban or rural) to consider the urbanization factor. Kotval-K & Vojnovic (2015) shows a distinct difference in travel behavior according to each type of area.

Regarding the correlated effect, I consider both tangible and intangible effects. Tangible effects are caused by factors such as the number of charging stations installed in the same ZCTA. Li et al. (2017) built an indirect network model between EV adoption and charging stations and found that 40% of EV adoption increase is explained by the feedback loops via charging station increase. They show that EV adoption and charging station installation stimulate each other: cumulative EV adoption increases new charging port installation, and cumulative charging station installation increases new EV adoption. Mukherjee & Ryan (2020) also includes the average distance to the nearest charge stations. I include cumulative charging station installation in the same ZCTA. I assume that the charging station is exogenously given and may affect EV adoption, but omit how it is affected by EV adoption in order to focus on the peer effect from the EV adoption side. This assumption is, nevertheless, quite strong because there is clear evidence that charging stations are endogenous and, even more, EV adoption and charging stations exert mutual indirect effects (Li et al., 2017). On the other hand, regarding intangible correlated effects, Michigan does not provide any incentives for buying new or used EVs. Therefore, Michigan residents can get such benefits only from the federal government, which means there is no heterogeneous intangible effect in Michigan.

How do peers affect their neighbors' decisions on whether to purchase an EV? Wang et al. (2022) found that lead users play an important role in future EV adoption, lead users being customers who want to buy cutting-edge products ahead of typical users. According to the diffusion of innovation theory, different adopters can be characterized by when they adopt the new product: early adopters, the early majority, the late majority, and laggards. As adoption progresses through these four groups, the adoption rates show an S-shaped curve, starting slowly among the early adopters, accelerating as the early majority join in, slowing as the later majority adopt, and converging to zero as the laggards finally come on board.

In the first stage, only early adopters or lead users will buy EVs, and their decision is based on limited information and experience. The main influence from peers comes only from those few adopters. The rate of sharing experience and information is too slow; therefore, most households still have limited awareness of EV driving and ownership, making it difficult for them to decide whether to buy an EV. Only a limited amount of EV adoption is observed, and adopters in this stage usually have enough information about EVs from their own backgrounds or they are risk-takers.

In the second stage, early adopters have widely affected consumer decisions regarding EV adoption, and more people have started to receive sufficient information and shared experiences. In this stage, it is not uncommon to observe EVs on roads or parking lots, and consumers only care about the price and specification of EVs versus ICE when they want to get a new car. This dissemination of information, knowledge, and experience is extensive and works through multiple channels described in Figure 2.2. First, when early adopters buy an EV, they share information about EV driving and their experiences with peers such as family, friends, and colleagues in the workplace. Second, non-peers can also get indirect experience with EVs by observing EVs on roads or parking lots. They may come to think that EVs are safer than they had initially expected or are good at accelerating, and these non-peers may share their opinions and experiences with their own peers via word of mouth. Third, consumers may get information from experts via public reports or social media. As more EVs are adopted, more public reports, articles, news, and posts on social media about EVs become available. This information, along with the increased frequency of having EV owners in peer groups or observing EVs on roads or parking lots near hometowns, affects EV adoption by neutral customers. These channels form consumers' valuation of EVs, and they will be essential factors in vehicle adoption choice along with other information such as price, specification, and household characteristics. As more people adopt EVs, the adoption rate becomes faster.

In the third and final stage, the adoption rate starts to slow as the remaining drivers may be against EVs, very risk-averse, or have high inertia that keeps them faithful to familiar technology or special needs for which EVs are not suited. These consumers may not purchase an EV even with full information about EVs. A higher benefit may be required to change their decision, or they may experience special needs that EVs cannot fulfill. According to the dataset and Michigan context, Michigan residents have experienced only the first or second stage because, since the first EV registration in 2013, the EV adoption rate has only gotten faster and has not yet shown any signs of slowing, as in Table 2.1.

2.3 Data

I chose the research area of Lower Michigan from 2013 to 2019 due to several reasons. The first EV registration was in 2013, and I consider only until 2019 to exclude the exogenous shock of COVID-19. Then, most EVs and stations are located in Lower Michigan (Table 2.1). In addition, Michigan has only one border with other states in the South, which minimizes the peer effect from other states. Figure 2.1 shows the EV and charging station in Lower Michigan, 2019. It shows the spatial distribution of EV and charging station data, and EV registration is focused on some geographical areas.

I make the dataset a strongly balanced panel in order to use dynamic spatial panel regression, and Table 2.2 shows the descriptive statistics. First, I combine ZIP code-level data into ZCTA using US Census Bureau (2023b), and I have 801 ZCTAs in my dataset after excluding the 45 ZCTAs which have no full data on all variables. I established a dataset of EV registration and charging stations from Atlas EV Hub (2023) and other variables from US Census Bureau (2023a). The education level is the average duration (in years) of post-secondary education. Each type of final education converted to the duration as the following: High school (0 years), Associate (2 years), Bachelor (4 years), Master (4+2 years), Professional (4+4 years), Doctor (4+2+5 years). Then, I divided the total education duration of residents by the population in the same ZCTA. I coded the land type as 1 if urban or sub-urban area and 0 if rural area.

2.4 Empirical model

Strong spatial dependence is observed in Figure 2.1. In this case, traditional panel regression may be biased due to correlation in error terms and variables (Narayanan & Nair, 2013). Due to identification issues pointed out by Manski (1993) and this possible spatial dependence, I use several spatial models: the spatial error model (SEM), the spatial autocorrelation model (SAC), the spatial autoregressive model (SAR), and the spatial Durbin model (SDM). Comparing these four models allows us to identify spatial interactions which may occur among any of the dependent variables, the independent variables and/or the error terms (Lozano et al., 2023). Equation (2.1) is a general specification of spatial models, the basis for the four models considered here.

$$y_{it} = \rho \boldsymbol{W}_{ij} \boldsymbol{y}_{jt} + \boldsymbol{X_{it}} \boldsymbol{\beta} + \boldsymbol{W}_{ij} \boldsymbol{X}_{jt} \boldsymbol{\theta} + \xi_i + \xi_t + \mu_{it} \tag{2.1}$$

$$\mu_{it} = \lambda \boldsymbol{W}_{ij} \boldsymbol{\mu}_{jt} + \epsilon_{it} \tag{2.1a}$$

$$\boldsymbol{X}_{it} = (\text{Inc}_{it}, \text{Edu}_{it}, \text{Age}_{it}, \text{Urban}_{it}) \text{ and } \boldsymbol{X}_{jt} = (\boldsymbol{Y}_{jt-1}, \mathbf{CS}_{jt-1}) \tag{2.1b}$$

where y_{it} is EV adoption in ZCTA i and year t. $\boldsymbol{y}_{jt}$ is a matrix containing y_{jt} for all of ZCTA j in Lower Michigan. $\boldsymbol{W}_{ij}$ is a contiguity-based spatial weights matrix. We say that there is contiguity if two spatial units have a common border of non-zero length. $\boldsymbol{W}_{ij}$ contains the weight calculated from the contiguity of ZCTAs and represents the spatial relationships through common boundaries in the dataset. w_{ij} is an element of $\boldsymbol{W}_{ij}$, valued at 1 if ZCTAs i and j have a common border, and 0 if there is no common border or if $i = j$. The dimensions of $\boldsymbol{W}_{ij}$ are 801×801. If a ZCTA shares a common border with N ZCTAs, which means $\sum_{j=1}^{801} w_i j = N$, then it has N links with other ZCTAs. The total number of links is 4582, and the average number of links per ZCTA is 5.72, with a minimum of 1 and a maximum of 13. ρ captures the endogenous effect from other ZCTAs, and $\boldsymbol{\beta}$ captures the exogenous effect from demographic characteristics. $\boldsymbol{\theta}$ captures the impact from covariates on the EV adoption of neighbor ZCTAs. ξ_i is a ZCTA-specific fixed effect that captures effects of all time-invariant predictors that only differ across ZCTAs, which pick up the inter-ZCTA differences. The time-specific fixed effect ξ_t explains the effects of all common predictors for all ZCTAs that only differ across years and hence pick up the time trend. ϵ_{it} is assumed to be independent and identically distributed. μ_{it} is the error term specific for ZCTA i and year t. $\boldsymbol{\mu}_{jt}$ is the error term considering spatial dependence on the error terms described in Equation (2.1a) with the spatial influence, λ.

$\boldsymbol{X}_{it}$ is a covariate matrix of exogenous effect including Inc_{it} (median household income applying consumer price index), Edu_{it} (mean post-secondary education years), Age_{it} (mean age), and Urban_{it} (a binary variable indicating urban and sub-urban areas in ZCTA i and year t). I consider that EV adoption may be affected by neighbors' cumulative EV adoption and charging stations, not by their demographic variables.

Each model assumes that spatial dependence exists only in some part of the model: in the error term (SEM), in the dependent variable and error term (SAC), in the dependent variable (SAR), and in both independent and dependent variables (SDM). SAC assumes that $\boldsymbol{\theta} = 0$. SAC can be reduced to SEM by assuming that $\rho = 0$, and to SAR by assuming $\lambda = 0$. SDM considers that $\boldsymbol{\theta} \neq 0$, and it assumes that $\lambda = 0$. I define the endogenous peer effect from the same ZCTA, cumulative EV adoption as follows.

$$Y_{it} = \sum_{\text{year}=2013}^{\text{year}=t} y_{i,\text{year}} \tag{2.2a}$$

$$\text{PE}_{it} = f(Y_{it-1}) = \alpha_1 Y_{it-1} + \alpha_2 Y_{it-1} + \alpha_3 Y_{it-1} = \alpha_Y Y_{it-1} \tag{2.2b}$$

where Y_{it} is cumulative EV adoption in ZCTA i and year t. PE_{it} is the peer effect from the same ZCTA i at year t, and it is a function of the cumulative EV adoption until last year. I assume that peer effect is a linear combination of peer effects from EV owners in the same social network and ZCTA, effects from EV driving, and effects from EV parking, but not any other sources, such as peers from outside of Michigan and/or social media. α_1 captures peer effect from having EV owners in the same ZCTA, which are the conventional peer effects via social networks. It only counts for EV owners who are in the consumer's peer group and live in the same ZCTA. I consider the peer effect from EV owners in other ZCTAs; however, I exclude the peer effect from outside of Michigan, even if consumers may have peers who drive EVs but live outside the state. α_2 captures the peer effect from observing EV driving on roads and thus depends on the probability of being exposed to EV driving. This is governed by the unique transportation infrastructure because transportation practices affect the visibility of EVs driving on the road to passengers, other drivers, and people riding public transportation. α_3 captures the peer effect from observing EV parking on lots and hence depends on the probability of being exposed to EV parking. It is also relevant to the unique structure of parking lots. The architecture of parking lots affects the visibility of EV parking to passengers or other drivers who park their cars in the same lot. $\alpha_Y = \alpha_1 + \alpha_2 + \alpha_3$, and shows the relationship between the endogenous peer effect and cumulative EV adoption in the same ZCTA up to the previous year.

Next, I adopt the static spatial panel regression models in Equation 2.3. SEM is Equation 2.3a, SAC is Equation 2.3b, SAR is Equation 2.3c, and SDM is Equation 2.3d.

$$
\begin{aligned}
y_{it} &= \alpha_{\mathrm{PE}}\mathrm{PE}_{it} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma\mathrm{CS}_{it-1} + \xi_i + \xi_t + \mu_{it} \\
&= \alpha Y_{it-1} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma\mathrm{CS}_{it-1} + \xi_i + \xi_t + \mu_{it} && \text{(2.3a)} \\
y_{it} &= \alpha Y_{it-1} + \rho\boldsymbol{W}_{ij}\boldsymbol{y}_{jt} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma\mathrm{CS}_{it-1} + \xi_i + \xi_t + \mu_{it} && \text{(2.3b)} \\
y_{it} &= \alpha Y_{it-1} + \rho\boldsymbol{W}_{ij}\boldsymbol{y}_{jt} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma\mathrm{CS}_{it-1} + \xi_i + \xi_t + \epsilon_{it} && \text{(2.3c)} \\
y_{it} &= \alpha Y_{it-1} + \rho\boldsymbol{W}_{ij}\boldsymbol{y}_{jt} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma\mathrm{CS}_{it-1} + \boldsymbol{W}_{ij}\boldsymbol{X}_{jt-1}\boldsymbol{\theta} + \xi_i + \xi_t + \epsilon_{it} && \text{(2.3d)}
\end{aligned}
$$

In Equation ($2.3a$), α_{pe} captures the impact of peer effect on the EV adoption; therefore, α is $\alpha_{pe}\alpha_Y$, via Equation ($2.2b$). The only estimable coefficient is α due to data availability. α captures the endogenous peer effect from the same ZCTA. CS_{it} is cumulative charging station installation; therefore, γ means the correlated effect from charging stations. In SDM (Equation (2.3d)), I include the spatial impact from the cumulative EV adoption and charging stations of other ZCTAs. $\boldsymbol{Y}_{jt-1}$ and $\mathbf{CS}_{jt-1}$ are matrices containing Y_{jt-1} and CS_{jt-1} for all of ZCTA j in Lower Michigan.

2.5 Results

In this section, I report the estimation result of Equation 2.3. Table 2.3 shows the estimation results of each model. Measures of goodness of fit for models are at the bottom of Table 2.3: Log-likelihood function value (LL), Akaike information criterion (AIC), and Bayesian information criterion (BIC). I use these three scores to choose the most appropriate model (Belotti et al., 2017). The LL value is meaningless in itself, but informative when comparing several models: the higher the LL value, the better the model. Lower AIC and BIC scores indicate a better fit of the model. The AIC and BIC methods punish the complexity of models by increasing their scores as the number of parameters grows. The punishment also becomes larger in BIC with a larger sample size. According to Burnham & Anderson (2004), AIC captures the difference between the probability distribution of real data and predicted data by the model. Thus, AIC is concerned about predictability, while BIC cares about the real distribution of data. In Table 2.3, according to LL, AIC, and BIC scores, SEM and SAC models better fit the dataset than SAR and SDM. Therefore, I will interpret only the results of SEM and SAC. The spatial dependence in error terms in both SEM and SAC is significant but much smaller than other coefficients.

Regarding endogenous effect, I consider the peer effect from the same ZCTA, α, and outside the ZCTA, ρ. α is consistent across the models, around [0.326, 0.352]. ρ is 0.079 in the SAC model, much lower than α. For the exogenous effects, demographic variables are considered: mean household income, mean education level, mean age, and the type of land. Then, in both models, income and education correlated positively with EV adoption at high significance, while age is negatively correlated with EV adoption, and type of land is insignificant. This means that, if the residents of ZCTA are wealthier, younger, and have more education, EV adoption will increase. A \$1000 increase in average income will lead to 0.260 to 0.313 more EV adoption, a 1-year increase in average education will lead to 11.92 to 13.07 more EV adoption, and a 1-year increase in average age will lead to 0.267 less EV adoption. Lastly, as correlated effects, the number of cumulative charging stations increases EV adoption.

2.6 Conclusions

Due to the nature of new technology, EV adoption follows an S-shaped diffusion curve, and peer effect plays an important role in early adoption. Nevertheless, there has been little consideration of spatial dependence on peer effect. In this chapter, I estimate the endogenous peer effect, which is defined as cumulative EV adoption, the sum of interaction from peers and from being exposed to EVs on roads and parking lots, using different spatial panel regression models. I use the panel data by ZCTA in Lower Michigan from 2013 to 2019, including endogenous, exogenous, and correlated peer effects. To consider exogenous effects, I include demographic characteristics such as median household income, mean education level, mean age, and type of land. I also consider the correlated effect by including the cumulative number of charging stations in the analysis.

The key contributions and implications of this article are twofold. First, I estimate the endogenous peer effect, including exposure to EVs on roads and parking lots, and consider spatial dependence. To address this, I use different spatial panel regression models and gain consistent results. One increase in cumulative EV adoption in any given ZCTA will increase the next year's EV adoption in the same ZCTA by 0.326 to 0.352, and one increase in one year's EV adoption from other ZCTAs will effect a 0.079 increase in that year's EV adoption considering spatial dependence. This effect is of reasonable magnitude when we consider there are additional interactions from observing EV driving and parking. Bollinger et al. (2022) compares the peer effect and the effect of price in solar panels and finds that a peer installation in some conditions increases solar panel adoption by the same amount as a price decline of $577. In SEM and SAC, a cumulative EV adoption increases EV adoption in the same ZCTA by the same amount of an income increase of $1125 to $1254. This means that EV has a more endogenous effect when observed by residents in the same ZCTA. Bollinger et al. (2022) find that solar panels fixed on roofs positively affect peers' adoption over at least 500 meters, while EVs can affect a wider range of residents because they are driven, so their visibility extends over a greater distance. Second, there would be unobservable peer effects spatially dependent at ZCTA levels. SEM and SAC models, which consider spatial dependence in error terms, are better than SAR and SDM, which do not consider them. This implies that we need to address unobserved and spatially correlated variables relevant to EV adoption. It may include accessibility of EV dealerships and charging stations. The number of EV dealerships affects vehicle adoption choices at least before 2020, while more people have tended to purchase a vehicle through online search after COVID-19. Charging ports installed in more crowded places have more influence than those located in less crowded places, as they are observed by more people.

Some limitations of this chapter are raised by the nature of movable products and peer effects. First, measuring the actual exposure to other people when driving or parking is difficult. To capture that, we need to calculate all driving patterns of each EV and calculate the frequency of staying in a specific area. Second, another channel exists to get information and knowledge about EVs, not from EV owners. People can rent an EV and drive it for their vacation or trip. They also can test EVs on the road by visiting the dealerships. They can also learn about EVs remotely, such as watching videos of famous automobile experts and daily experience of EV driving or communicating with their peers from different states. Nevertheless, it would be a small effect because these possible channels only take effect when people are very close to purchasing EVs. Future research may measure the frequency of exposure to other people as a case study or experiment.

This chapter contributes to the literature on peer effect, specifically in adopting EVs and movable products, by quantifying the effect while considering spatial dependence. Policymakers may intensify incentives in areas showing increased EV adoption because cumulative EV adoption will increase EV adoption in the future. Peer effect, including observations, intensifies the aggregate demand, increasing EV subsidization's policy efficiency. The current status is that of the early adopter or early majority ones in the S-shaped diffusion of innovation theory. These results imply that incentivizing EV adoption in the early stage may have a greater impact by stimulating aggregate demand via peer effect.

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APPENDIX 2.A: Tables and Figures

Table 2.1 The number of EV and charging stations in Lower and Upper Peninsula of Michigan

	Lower Peninsula			Upper Peninsula	
Year	**EVs**	**Charging stations**	**Total vehicles**	**EVs**	**Charging stations**
2013	1	14	3,492,280	0	1
2014	292	20	3,536,550	2	1
2015	509	42	3,602,120	4	1
2016	546	85	3,665,530	4	1
2017	5,629	110	3,728,410	47	2
2018	6,437	147	3,787,930	49	4
2019	23,792	230	3,829,965	209	10

Table 2.2 Descriptive statistics for variables in each ZCTA

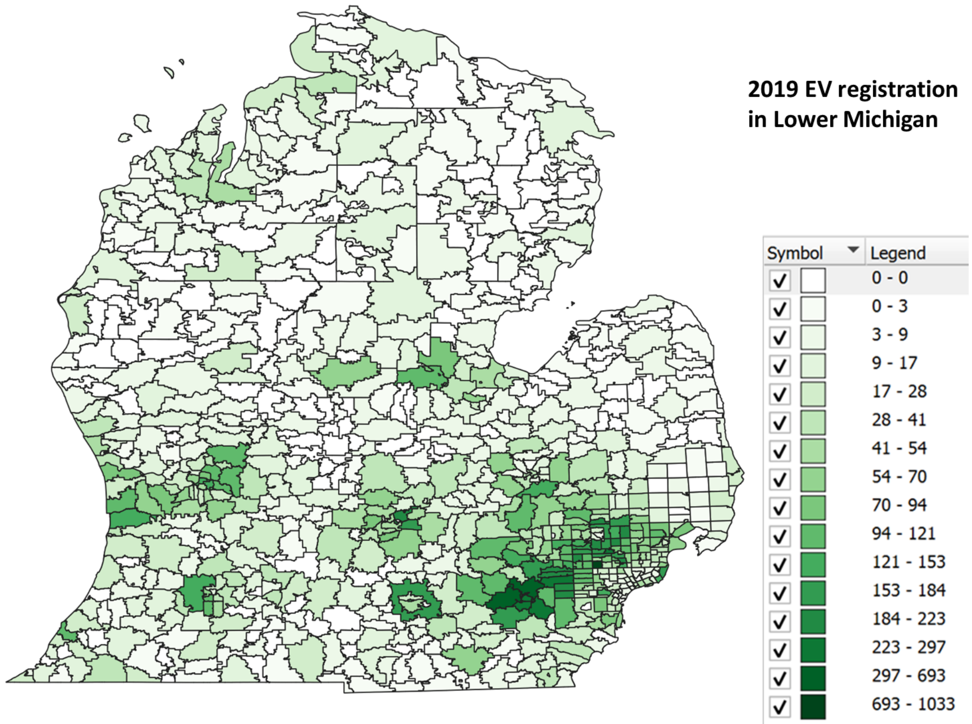
Variable	**Symbol**	**Unit**	**Mean (SD)**	**Min**	**Max**
New EV adoption	y	count	4.944 (21.855)	−41	748
Cumulative EV adoption	Y	count	7.732 (31.536)	0	1033
Cumulative charging station installation	CS	count	0.132 (0.725)	0	15
Median household income	Inc	\$ 1000	136.444 (67.054)	22.400	804.300
Mean education level	Edu	year	0.931 (0.545)	0.096	3.283
Mean age	Age	year	42.861 (6.515)	21.1	66.1
Urban/Rural	$Urban$	binary	0.743 (0.437)	0	1

Note: N=4,806 (801 ZCTAs over 6 years from 2014 to 2019)

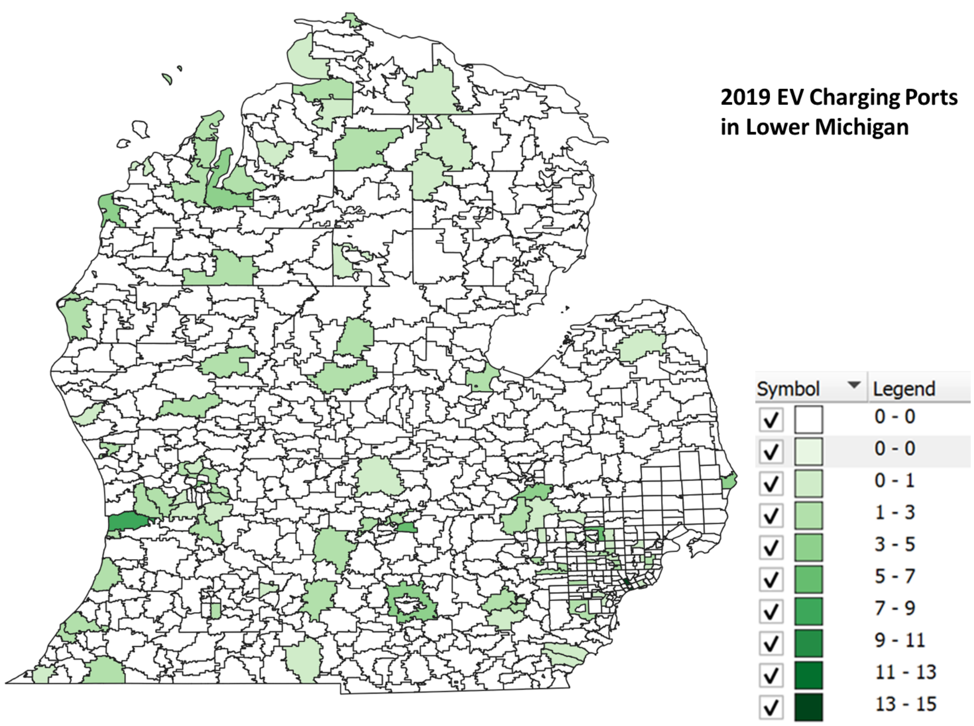
Table 2.3 Estimation results of each model

variable	coefficient	unit	SEM	SAC	SAR	SDM
Y_{it-1}	α	count	0.352****	0.326****	0.307****	0.325****
			(0.020)	(0.019)	(0.025)	(0.025)
y_{jt}	ρ	count		0.079****	0.302****	0.302****
				(0.006)	(0.000)	(0.000)
Inc_{it}	β_1	$ 1000	0.313****	0.260***	0.487****	0.429****
			(0.090)	(0.085)	(0.115)	(0.113)
Edu_{it}	β_2	year	13.074***	11.919***	11.863**	12.782**
			(4.038)	(3.781)	(5.201)	(5.084)
Age_{it}	β_3	year	−0.266	−0.267*	−0.169	−0.135
			(0.167)	(0.156)	(0.215)	(0.210)
Land_{it}	β_4	binary	0.450	0.742	−0.468	−0.177
			(3.165)	(2.939)	(4.073)	(3.981)
CS_{it-1}	γ	count	3.940****	3.612****	3.446****	3.467****
			(0.685)	(0.643)	(0.882)	(0.862)
Y_{jt-1}	θ_1	count				−0.136****
						(0.010)
CS_{jt-1}	θ_2	count				−1.797****
						0.343
μ_{jt}	λ		0.010**	−0.089****		
			(0.004)	(0.009)		
Year			Control	Control	Control	Control
ZCTA			Control	Control	Control	Control
LL			−20,347	−20,323	−22,243	−22,074
AIC			40,719	40,673	44,512	44,195
BIC			40,804	40,764	44,597	44,351

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$
and parentheses contain the robust standard errors for each coefficient.



(a) EV registrations in Lower Michigan, 2019



(b) Charging stations in Lower Michigan, 2019

Figure 2.1 EV registrations and charging stations in Lower Michigan, 2019

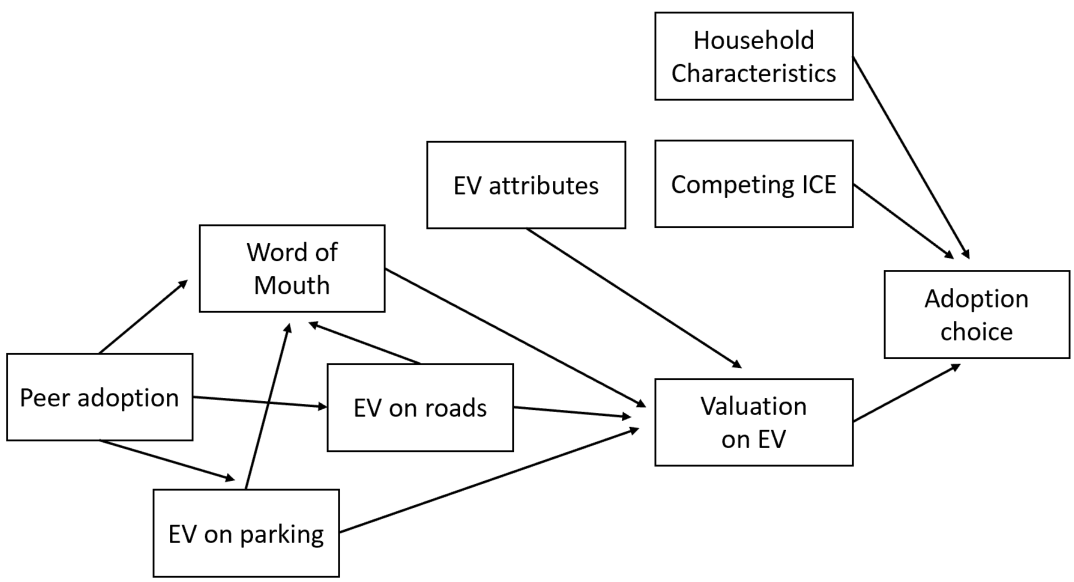


Figure 2.2 Descriptive diagram of how peer effect works

CHAPTER 3

THE IMPACT OF TRANSNATIONAL MUNICIPAL NETWORKS ON LOCAL ENERGY CONSUMPTION

3.1 Introduction

Climate change is one of the most urgent international issues of the 21st century, and local governments are the key to climate policies (Gordon & Johnson, 2017). Local governments know how a policy should be designed: which areas have more priority for implementation given budget limitations and how to lead public opinion toward less resistance by considering the geographic, economic, and political landscape (Picavet et al., 2023). Local governments even act when a national government hesitates. For example, U.S. local governments have moved ahead with climate actions even after the federal government refused to promote climate policies during the Bush and Trump administrations (Byrne et al., 2007, 2022; Kousky & Schneider, 2003; Rabe & Mills, 2017). In Australia, local governments actively engage in renewable energy policy despite unfavorable national political conditions in 2016 (Mey et al., 2016). Furthermore, local actions can become a driving force for enhanced action (Kuramochi et al., 2020).

Transnational municipal networks (TMNs) support local governments by sharing policy implementation experience. A TMN is an international network of local authorities with distinct characteristics: autonomous membership, non-hierarchical structure, and network structure (Kern & Bulkeley, 2009). There is growing evidence that members can benefit from getting to know other members' experiences and reducing the amount of trial and error (Bulkeley et al., 2003; Davidson et al., 2019; Fünfgeld, 2015; Kern & Bulkeley, 2009). After the end of the Cold War in the early 1990s, there was rapid growth in TMNs; one of their main subjects is climate change (Kern & Bulkeley, 2009). The International Council for Local Environmental Initiatives – Local Governments for Sustainability (ICLEI) is one of the main TMNs in climate actions, and it has more than 2,500 member cities that comprise 25% of the world's population. These TMNs support internal mobilization, formulate carbon inventory and goals, and offer project support and incentives like certificates (Busch et al., 2018; Kern & Bulkeley, 2009).

Substantial prior literature shows growing evidence of the role of TMNs with some limitations: lack of quantitative studies, incomplete data analysis, and little focus on policy outcome. First, a lot of literature identified the role of TMNs with qualitative analyses (Bansard et al., 2017). Heikkinen et al. (2020) argued that a lack of quantitative evidence exists regarding the actual impact of network membership. Qualitative analyses include governance analysis (Kern & Bulkeley, 2009), using qualitative survey data (Busch et al., 2018), network analysis (Woodruff, 2018), and comparative analyses of member cities (Adesanya et al., 2020; van Doren et al., 2020; Emelianoff, 2014; Lee & Painter, 2015; Picavet et al., 2023). Second, another mainstream is analysis with selective data. Substantial case studies compare pioneer cities in climate policy (Adesanya et al., 2020; Aylett, 2013; Emelianoff, 2014; Hodson et al., 2013; Jaglin, 2014; Lee & Painter, 2015; Leffel, 2022; Linton et al., 2022; Rocher, 2017). Several studies tried to use a large number of cities in analyses, but only including member cities (Busch et al., 2018; Krause et al., 2016) or only including local governments in a specific state (Pablo-Romero et al., 2016), or using cross-sectional data (Yi, 2013). Third, some literature tried to analyze the impact of TMNs on local policy; however, it did not consider the policy outcome. Krause (2012) and Hakelberg (2014) found the impact of TMN membership on the number of local policies, and Steffen et al. (2019) argued that TMN membership increases solar panel investment. It did not count if the increased number of activities really reduced carbon emissions. Yi (2013) identified that ICLEI membership increased the number of green jobs. There is little literature on the emerging role of urban networks on urban policies (Busch et al., 2018; Davidson et al., 2019; Steffen et al., 2019).

To the best of our knowledge, this chapter is the first quantitative analysis to answer whether TMNs really help local authorities achieve local energy policy outcomes. In this article, we adopt staggered difference-in-differences (DID) methods with a panel dataset to address the staggered joins in ICLEI over time in estimating the impact of ICLEI membership. This method is better for estimating staggered treatment, such as ICLEI memberships over time, than traditional DID. We built a dataset that included all ICLEI and non-ICLEI members for long periods before and after ICLEI membership. The dataset is based on South Korea from 2005 to 2019 and focuses on final energy consumption per capita as the main outcome; the reasons for choosing the spatial and time scope are as follows. First, Korean governments have built extensive, abundant local datasets crucial to statistical analysis. Second, Korea has very active ICLEI networks with a reasonable number of members and non-members. Korea has one of the nine regional secretariats and one of the 12 country offices in ICLEI, and 13 of 17 states and 46 of 228 counties had joined ICLEI by 2019[1]. Third, the time scope is from 2005 to 2019 because the Korean dataset for all counties starts in 2005, and COVID significantly impacted energy consumption starting in 2020 (Jang et al., 2021; Kang et al., 2021). We define final energy consumption per capita as the local energy policy outcome because it is the target of ICLEI. It evaluates how the ICLEI membership affects the policy outcome, which complements Krause (2012) and Hakelberg (2014).

This study finds that Korean local governments significantly reduce energy consumption after joining the ICLEI network, and the reduction becomes larger in the order of county, state, and both county and state membership. We focus on the Korean ICLEI network due to its well-established local-level dataset, active engagement in the ICLEI network at all levels of decision-making, and substantial numbers of ICLEI members. These findings can be extended to other geographic regions with data availability and real activities in the local ICLEI network. We first discuss the theoretical and contextual background of the Korean ICLEI network. We then show key methodologies and variables that explain energy consumption in Korea. Political implications are also provided in the conclusion.

3.2 Background, Data, and Methods

3.2.1 The Role of ICLEI as a TMN in Korea

Learning mechanisms are required to promote innovation in the public sector. Learning is indispensable for local governments, especially in challenging new areas of public policy, such as climate change. Growing evidence emphasizes policy implementation's role in local energy transition (van Doren et al., 2020; Neij & Nemet, 2022). According to Zambrano-Gutiérrez &

[1] The Korea has one Central Government, 17 Broad Local Government (BrLG), and 226 Basic Local Government (BaLG). We define a "state" as a BrLG and a "county" as BaLG because a BrLG is similar to a state or a province, and a BaLG is similar to a county or a city.

Puppim de Oliveira (2022), the collective learning process of governments moves from internal and external learning to governance and then innovation. There are three types of internal learning and six types of external learning: one of the sources of external learning is from foreign organizations or other cities. Grønnestad & Bach Nielsen (2022) and Zambrano-Gutiérrez & Puppim de Oliveira (2022) said TMNs are key places for local governments to obtain knowledge and information about local policy implementation. Therefore, TMNs function as one of the main external learning mechanisms for local governments. On the TMN side, TMNs are built to support local governments' policy implementation. There are three types of internal governing stratagies in TMNs (Kern & Bulkeley, 2009). First, information and communication are indispensable for networks via developing and sharing best practices. There is growing evidence that local governments recognize this benefit of membership (Kern & Bulkeley, 2009; Zambrano-Gutiérrez & Puppim de Oliveira, 2022). Second, TMNs provide a more direct intervention with project funding and cooperation. Lastly, TMNs use recognition, benchmarking, and certification. These strategies encourage political leaders of members who may need outcomes to win reelection.

ICLEI is one of the most successful TMNs in climate action. ICLEI has more than 2600 members of local governments from 130 countries, which address 20% of the world's population. ICLEI is one of the first TMNs in climate change since the 1990s and has become an influential advocate for international agreements on greenhouse gas reduction (Fünfgeld, 2015). According to Gordon and Johnson (2017), a substantial number of ICLEI members included climate change in their core policy area. ICLEI has a multi-level governance system so member cities can participate in decision-making. ICLEI has a president, a board, and a general assembly, and the board comprises the Global Executive Committee (GexCom), Regional Executive Committee (RexCom), and Management Committee. Gexcom has six members from the RexCom for each continent and eight from sub-networks for portfolio seats. RexCom has nine committees from the regional secretariat. ICLEI has one world secretariat in Germany, nine regional secretariats, and seven country offices worldwide. ICLEI helps local governments create climate actions and set specific targets for their climate actions. Therefore, literature considers ICLEI membership part of local climate efforts (Krause, 2012; Krause et al., 2016; Yi et al., 2017; Deslatte et al., 2021). Krause (2012) found that ICLEI membership increased the number of GHG-reducing activities. ICLEI has a global initiative, the Global Covenant of Mayors for Climate & Energy (GCoM). Local governments in the GCoM provide their carbon emission inventory, climate resilience analysis reports, and climate mitigation targets within 2 years and establish a climate action plan and sustainable energy plan within 3 years. In 2019, ICLEI and the Carbon Disclosure Project (CDP) merged into a CDP-ICLEI unified reporting system in which local governments in CDP and ICLEI report the targets, actions, and inventories of their climate actions.

The Korean ICLEI network has been actively engaged in all levels of decision-making in ICLEI. The mayor of Seoul was elected as the president of ICLEI for 2015-2018 as a result of the 2015 ICLEI assembly in Seoul. In 2023, the Korean network had two of the five members of East Asia RexCom and one of 22 of GexCom. The Korean ICLEI network hosted one of nine regional secretariats (the East Asia secretariat in Seoul) and one of the 12 country offices (the Korea office in Ilsan). In 2021, the ICLEI Korea network launched the ICLEI Korea executive committee (K-ExCom) for 2021-2023. ICLEI K-ExCom has 7 members from Korean ICLEI members representing each policy field: climate and energy, sustainable economy, biodiversity, eco transportation, and urban agriculture. It is unique in the ICLEI network to build a national executive committee.

In the Korean ICLEI network, there are several channels and mechanisms for how ICLEI membership leads to decreased energy consumption: active sharing of best practices and experiences among members and project funding. These are TMN's main strategies to achieve its goal (energy consumption reduction is one of ICLEI's main goals), as suggested by Kern & Bulkeley (2009). The first is information and communication. The Korean ICLEI network provides monthly newsletters with members' best practices and international meeting results. Then, they produce case study reports on Korean ICLEI members' activity in Korean and English. The network holds an annual assembly among Korean members and shares the annual report. Public officers in local governments that joined ICLEI have received the newsletters and reports. Then, the ICLEI Korea office regularly educates those public officers and provides workshops and seminars to teach them about climate, energy, and sustainable policies. Second, the Korean network provides project funding and cooperation. It supports local governments' participation in international meetings, such as the ICLEI Congress, the United Nations, and the United Nations Framework Convention on Climate Change. It also organizes the mutual participation of local governments in project funding advanced by ICLEI. In 2019, the ICLEI Korean office spent 30.6% of its total expenditures on local government projects (ICLEI Korea Office, 2020). In Korea, 21 ICLEI members joined GCoM, and they also joined Race to Zero, which was launched in 2020 by the United Nations. They should set a goal of 50% emission reduction by 2030 and 100% reduction by 2050. Two Korean ICLEI members also joined the 100% RE Cities & Regions Network supported by ICLEI. Through this information sharing and project funding, ICLEI members are able to take steps to implement energy policy to reduce energy consumption.

Korean governments consist of one central government, 17 states, and 228 counties. Each level of government has its own department for each policy area. Then, at the discretion of the political leader, a new department may be launched to address the implementation of a new policy. In the case of climate and energy policy, some local governments order existing departments of the environment to take responsibility, and others launch new departments to implement these new policies. Their discretion heavily depends on the budget conditions. Sometimes, wealthier counties have more influence on policy implementation than poorer states. Nevertheless, states usually have more power based on the budget size. In Korea, upper-level governments favor using a match to implement a policy; therefore, they can have dominant power. To describe the policy case propelled by local governments, One Less Nuclear Power Plant (OLNPP) by Seoul, the capital of Korea and a state government, is a good example. Seoul joined ICLEI in 1999, and 8 of 25 counties in Seoul joined ICLEI between 2012 and 2017. OLNPP was designed in 2012 after the Fukushima nuclear accident and national blackout, and the goal is to reduce energy consumption to 2 million TOE, which is equivalent to energy production from one nuclear power plant (Seoul Metropolitan Government, 2017). Subgoals are to reduce wasted energy consumption, increase energy efficiency, and promote renewable energy production. Seoul subsidized mini solar panels on balconies and solar panels on roofs supported building energy self-supporting villages (they substituted old bulbs with LEDs and adopted a smart grid in the town) and introduced eco-mileage (consumers get payback when reducing energy consumption). The mini solar PV was designed by a county, Nowon, Seoul, and it was actively adopted by Seoul, and Seoul spread it to its counties and other states (Han & Yun, 2021).

Figure 3.1 shows how the Korean ICLEI network affects its members. This internal governing is indicated as black lines in Figure 3.1. All states and counties in ICLEI have a direct impact from the ICLEI Korea office (thick line), and counties in an ICLEI state have an indirect impact from the policy of the state and vice versa (dashed line). It is a hypothetical diagram of the network. State 1 and some of its counties joined in ICLEI. This includes cases in which a county and a state joined ICLEI simultaneously. They are connected to other members via a thick line, and some non-ICLEI counties in State 1 are indirectly affected by State 1 via a dashed line. Then, State 2 does not join ICLEI, while only some counties join ICLEI. Only those member counties are connected to the ICLEI network, and they indirectly affect State 2 via the dashed line. In State 3, only State 3 joins ICLEI, with no county members. State 3 is connected to the ICLEI network and indirectly affects its counties. State 4 has no ICLEI members, states, or counties.

The scope of our research covers almost all 226 local Korean governments from 2005 to 2019. We have several adjustments in the data. First, Korea has 17 states and 226 counties. Two states, Sejong and Jeju, have no counties; therefore, we define them as a state and also a county. Then, we consider the unified counties from 2005 to 2019 as one county from 2005 to 2019. Masan, Jinhae, and Changwon were unified into Changwon in 2010. Yeongi was changed to Sejong in 2012. Cheongwon and Cheongju were unified into Cheongju in 2014. Finally, we excluded two counties: Geumsan and Hoengseong. According to the ICLEI Korea office, they were withdrawn from ICLEI Geunsan in 2015 and Hoengseong in 2019. They are excluded in order to use staggered difference-in-difference methods, which require no reverse treatment.

By 2019, 13 of 17 states and 46 of 226 counties in Korea had joined ICLEI, according to the ICLEI Korea Office. 38 of 46 counties joined ICLEI in 2019, and their states also joined ICLEI.

Table 3.1 shows the number of ICLEI members in Korea by county and state from 2005 to 2019. Among all 228 counties, only 2 counties withdrew ICLEI membership during the period. In the other 226 counties, the number of ICLEI memberships is monotonically increasing. 180 had not joined ICLEI by the end of the period, 13 had joined ICLEI before 2005, and many joined in different years. Eight states joined ICLEI before 2005; 4 states had not joined ICLEI by the end of the period; and two states joined in 2008, one in 2009, and one in 2014. This shows the robust ICLEI network in Korea, although international ICLEI membership dropped significantly from 2010 to 2012 (Yi et al., 2017).

3.2.2 Data

We define the log of energy consumption per capita as the dependent variable and the indicator of local energy policy outcome because it explains a substantial part of carbon emissions. It is defined as the final energy consumption of gas, oil, and electricity per capita in the unit of TOE[2] [3]. According to Waheed et al. (2019), there is substantial evidence of causal relations between energy consumption and carbon emissions. For example, Korea emitted 701 million CO2eq in 2019, and 87.2% of the emission came from energy consumption (Korean Ministry of Environment, 2021). We exclude coal consumption because the local dataset is not built for coal in every county. In addition, coal is usually consumed at coal power plants in Korea, which makes it difficult to separate consumption at the county level. Electricity consumption by a county covers the coal consumption. We defined final energy consumption as the sum of electricity, gas, and oil, and it accounts for 83.5% of total energy consumption in 2019 (Korean Ministry of Trade, Industry and Energy, 2022), while coal accounts for 13.2%.

The final energy consumption of electricity, gas, and oil is merged into one variable using the TOE. Conversion coefficients (Korean Energy Economics Institute, 2022) in Table 3.2. The basic unit of the database is a barrel for oil, kM^3 for gas, and MWh for electricity, and is described

[2] TOE is abbreviated for a ton of oil equivalent. It is a unit of energy as the amount of energy comes from burning one ton of crude oil. It is 41.868 gigajoules.

[3] tCO2 would be a better unit because we can easily calculate social costs of carbon from this, and carbon emissions are a final target. Nevertheless, we could not get the annual Korean tCO2/kWh conversion factors from 2005 to 2019 because Korean governments has not release the term annually.

in the column, Unit, in Table 3.2. Korea Energy Agency (2023) provides conversion coefficients between TOE and liter for oil, kg for propane and butane, M^3 for gas, and kWh for electricity, which are in the column, KEA coefficients, in Table 3.2. We got the Conversion to TOE coefficients in Table 3.2 that fit the database by considering that 1 barrel of oil is 158.987l, 1 barrel of propane is 80.775kg, and 1 barrel of butane is 91.912kg. We aggregate the following oil consumption of the followings: propane, butane, gasoline, kerosene, diesel, bunker-A oil, bunker-B oil, bunker-C oil, jet fuel, By-products I & II [4], which are usually used by combustion. Naphtha, solvent, asphalt, and lubricant are excluded because they are irrelevant to carbon emission except for unintentional leaks. We got electricity consumption by county from Korea Electric Power Corporation (2023), oil consumption by county from Korea National Oil Corporation (2023), and gas consumption by county from Korean Local Governments (2021).

The final energy consumption per capita is defined as:

$$y_{it} = (Gas_{it} + Oil_{it} + Electricity_{it})/P_{it} \tag{3.1}$$

where y_{it} is the energy consumption per capita of county i in year t; Gas_{it}, Oil_{it}, and $Electricity_{it}$ are the gas, oil, and electricity consumptions of county i in year t, and P_{it} is the population of county i in year t.

It is difficult and infeasible to implement an expeirment on ICLEI joins that randomly assigns local governments into a treated group which will join ICLEI and a control group which will not join ICLEI and keep eye track on their energy consumption. Therefore, we use a quasi-experimental design (DID), in which the assignment of governments is based on observed behavior. ICLEI members are classified into the treated group, and non-ICLEI members are classified into the control group for the quasi-experimental design. In this setting, ICLEI membership is the treatment. In

[4] By-products I and II are byproduct gas from naphtha-related processes during oil purification. By-product I is Hi-sene, which can replace diesel and kerosene. By-product II is C-9, and it can replace bunker oils.

the canonical DID setting, the estimator comes from the following regression:

$$ln(y_{it}) = \alpha_0 + \alpha_1 ctIC_{it} + \alpha_2 Year_t + \alpha_3 ctIC_{it} \times Year_t + \alpha_4 X_{it} + \epsilon_{it} \tag{3.2a}$$

$$ln(y_{it}) = \alpha_0^{'} + \alpha_1^{'} stIC_{it} + \alpha_2^{'} Year_t + \alpha_3^{'} stIC_{it} \times Year_t + \alpha_4^{'} X_{it} + \epsilon_{it}^{'} \tag{3.2b}$$

$$ln(y_{it}) = \alpha_0^{''} + \alpha_1^{''} btIC_{it} + \alpha_2^{''} Year_t + \alpha_3^{''} btIC_{it} \times Year_t + \alpha_4^{''} X_{it} + \epsilon_{it}^{''} \tag{3.2c}$$

$$X_{it} = (Gvnor, Mayor, Ltax, Ltax^2, FIR, Mnpc, Carpc) \tag{3.2d}$$

where $ctIC_{it}$ is a dummy variable for ICLEI membership of county i in year t and $stIC_{it}$ is a dummy variable for ICLEI membership of the state county i belongs to in year t. $btIC_{it}$ is a dummy variable for ICLEI membership of the county i and the state county i belongs to in year t. If they joined before 2005, we consider them as having joined ICLEI in 2005. These variables are irreversible and are 1 after they were treated. $Year_t$ is a time dummy variable, and ϵ_{it} and $\epsilon_{it}^{'}$ are independent and identically distributed error terms with zero-mean.

We include X_{it}, covariates of energy consumption, and its mechanism is in Figure 3.2. These attributes are classified into five groups: political, financial, industrial, and transportation. First, political variables are the political parties of the county mayor and state governor. In Korea, democrats strongly support climate policies, while conservatives place a low priority on climate actions. We coded 1 if the governor or mayor was affiliated with the democratic party; otherwise, 0. Data were gathered from Statistics of Successful Candidates (Korean National Election Commission, 2022). Second, financial attributes include local income tax collected and the financial independence ratio. Local income tax indicates the county's available budget and income level. The energy-environmental Kuznets curve shows an inverted-U shape for the relationship between income and energy consumption or environmental pressure. Baek & Kim (2013) found empirical evidence of the energy-environmental Kuznets curve in Korea for income and carbon emissions. Therefore, we include a quadratic form of local income tax to consider the inverted-U shape relations. The financial independence ratio is the amount the local government can use for its purposes out of the total budget. Local income tax and the financial independence ratio were gained from Korean Local Governments (2021) and the Local Finance Integrated Open System

(Korean Ministry of the Interior and Safety, 2023a). Third, the industrial attribute is defined as the gross value added per capita in manufacturing. Manufacturing is one of the most energy-intensive sectors, and Korea has one of the world's largest manufacturing economies, with 27.5% of its GDP from manufacturing in 2019 (Statistics Korea, 2022a). The gross value-added dataset came from Korean Local Governments (2021), and populations came from Resident Registration Population Status (Korean Ministry of the Interior and Safety, 2023b). Fourth, the transportation variable is the number of cars per capita. More cars per capita make traffic more crowded and means more energy consumption in transportation. The number of cars per capita was obtained by dividing total car registration numbers from Korean Local Governments (2021) by population. Local tax and gross value added in manufacturing are nominal values each year; they were converted to the 2019 value using the Korean Consumer Price Index (Statistics Korea, 2022b).

We chose observables that may not be the result of the energy policy stimulated by TMN membership in the Korean context. Participation in ICLEI in Korea would not affect other variables. The main factors that decide who will win the election for Mayor/Governor are the economy and political issues, and ICLEI membership would not significantly affect the election result. ICLEI membership also will not significantly affect the financial independence ratio and local income tax. ICLEI membership fee is negligible compared to the annual expenditure of local governments. It is also the same for financial variables. ICLEI membership almost does not affect the FIR ratio or local income tax. Then, in the Korean context, local governments do not want to prohibit manufacturing because it supports local finance a lot. The only exception was to move the industrial complex out of the capital due to environmental concerns in the last 20th century. From 2005 to 2019, Korean local governments never tried to prohibit manufacturing to reduce energy consumption, and I may not believe that there are any local governments who want to kick out manufacturing industries only for energy reduction purposes. Nevertheless, including manufacturing may explain the unavoidable energy consumption from economic activities. Local governments may support green investment; however, the policy instruments for green investment are typically funded by the central government in Korea. Transportation is also the same. Korean local governments do not try to prohibit using personal vehicles with tax or other instruments. Rather than this, they usually do increase the efficiency and accessibility of public transportation and build more roads to decrease traffic jams. So, the number of cars can indicate the traffic and energy cunsumptions in transportation, but not be affected by ICLEI membership. Descriptive statistics are in Table 3.3, and the mean of variance inflation factors is 1.19, which means there is almost no correlation between ICLEI memberships and other variables.

3.2.3 Staggered DID estimator

We use a staggered DID method and compare it with a two-way fixed effect DID model to answer the research question. In the conventional DID format, there are 2 x 2 time and group settings: no one is treated at Time 1, and some are treated at Time 2. Researchers want to estimate the treatment effect of an applied policy. The treatment effect is gained by comparing the outcomes of groups over time. The two-way fixed effect DID model considers fixed effect in group and time together with the 2x2 DID setting. Due to its intuitive and powerful explanation, DID has been widely used in natural and social science to estimate the impact of treatment. Specifically in social science, many studies adopt this model even into datasets of staggered treatment because social scientists often have to design quasi-experiments with given datasets on society, which we cannot easily set experimental settings. However, if we have staggered intervention of policies over time, which means more periods and groups, we need another approach because the result of a traditional DID could be biased and may contain Type I and Type II errors when there are staggered interventions (Baker et al., 2022).

Recently, several robust alternatives to DID under staggered treatments, called staggered DID methods, have been suggested to remedy this staggered setting, and we have chosen the CS estimator suggested by Callaway & Sant'Anna (2021). Baker et al. (2022) suggested a way to evaluate staggered treatment settings using Callaway & Sant'Anna (2021), Sun & Abraham (2021), or stacked regressions. Callaway & Sant'Anna (2021) suggested a CS estimator that estimates the group and time-specific treatment effects (allowed to be heterogeneous) and aggregates them to generate an overall estimator like Goodman-Bacon (2021). CS estimator means the average treatment effect calculated from each DID estimator in all possible combinations. The CS estimator under staggered treatment is close to what is under the 2 x 2 settings. In addition, the CS estimator has more flexibility in using the not-yet treated group as a control, allows covariates, and allows parallel trend assumptions to hold only for conditional covariates and observed anticipation. To check the robustness of the result, we include a static DID estimator with an event study setting to get rid of timing differences among groups.

Callaway & Sant'Anna (2021) suggested using a nonparametrically point-identified average treatment effect with outcome regression, inverse probability weighting, or a doubly robust estimator; we use the latter as also proposed by Sant'Anna & Zhao (2020). In addition, we use not-yet-treated units as a comparison group. First, we define IC as a group that includes all treated counties if their join years are the same. Then, IC_{ic} is a dummy variable that is 1 if a county joined ICLEI in year ic. According to Callaway & Sant'Anna (2021), the average treatment effect for units in group ic of counties joining ICLEI in year ic and year t is defined as:

$$ATT(ic,t) = E[(\frac{IC_{ic}}{E[IC_{ic}]} + \frac{\frac{p_{ic,t}(X)(1-D_t)}{1-p_{ic,t}(X)}}{E[\frac{p_{ic,t}(X)(1-D_t)}{1-p_{ic,t}(X)}]})$$

$$\times (ln(y_t) - ln(y_{ic-1}) - E[ln(y_t) - ln(y_{ic-1})|X, D_t = 0, IC_{ic} = 0])] \quad (3.3)$$

$$p_{ic,t}(X) = Prob(IC_{ic} = 1|X, IC_{ic} + (1 - D_t)(1 - IC_{ic}) = 1) \quad (3.3a)$$

where $ATT(ic,t)$ is the average treatment effect, and D_t is a dummy variable that is 1 if a county remains in ICLEI at year t and otherwise 0. Therefore, D_t is $stIC_t$ if we test the impact of state ICLEI membership, and D_t is $ctIC_t$ if we test the impact of county ICLEI membership. $p_{ic,t}(X)$ is the generalized propensity score indicating the probability of being first treated at time ic.

The main assumptions of the DID method are parallel trends and no anticipation. The parallel trend assumption is that the treated and control groups show the same trend before treatment. The no anticipation assumption is that there is no observed displacement right before policy implementation. Callaway & Sant'Anna (2021) said that the CS estimator is suitable when units can anticipate participating in the treatment and may adjust their behavior before the treatment is implemented. Local governments should pay substantial admission fees to join ICLEI; therefore, it is highly likely that they will recognize they will join ICLEI. Therefore, the no anticipation test is unnecessary. There are two ways of testing parallel trends: statistical tests and reading graphs.

Baker et al. (2022) mentioned that static DID estimates should be accompanied by an event-study design to identify the timing of outcome differences between treated and control groups. We run the following regressions to evaluate parallel trend assumptions.

$$\begin{aligned} ln(y_{it}) = \beta_0 + \sum_{\tau=-14}^{-2} \beta_\tau \times 1[ctJoin_i - t = \tau] + \sum_{\tau=0}^{14} \beta_\tau \times 1[ctJoin_i + t = \tau] \\ + \beta_X X_{it} + \zeta_i + \zeta_t + u_{it} \end{aligned} \tag{3.4}$$

$$\begin{aligned} ln(y_{it}) = \beta_0^{'} + \sum_{\tau=-14}^{-2} \beta_\tau^{'} \times 1[stJoin_i - t = \tau] + \sum_{\tau=0}^{14} \beta_\tau^{'} \times 1[stJoin_i + t = \tau] \\ + \beta_X^{'} X_{it} + \zeta_i^{'} + \zeta_t^{'} + u_{it}^{'} \end{aligned} \tag{3.5}$$

$$\begin{aligned} ln(y_{it}) = \beta_0^{''} + \sum_{\tau=-14}^{-2} \beta_\tau^{''} \times 1[stJoin_i - t = \tau] + \sum_{\tau=0}^{14} \beta_\tau^{''} \times 1[stJoin_i + t = \tau] \\ + \beta_X^{''} X_{it} + \zeta_i^{''} + \zeta_t^{''} + u_{it}^{''} \end{aligned} \tag{3.6}$$

where $ctJoin_i$ is the year county i joined ICLEI, $stJoin_i$ is the year the state of county i joined ICLEI, and $btJoin_i$ is the year the state of county i and the county i joined ICLEI. If they did not join by 2019, we define $stJoin_i$ or $ctJoin_i$ as equal to t. ζ_i, $\zeta_i^{'}$, $\zeta_i^{''}$ are county-specific, and ζ_t, $\zeta_t^{'}$, $\zeta_t^{''}$ are year-specific fixed effect, and u_{it}, $u_{it}^{'}$, $u_{it}^{''}$ are independent and identically distributed error terms with zero-mean.

3.3 Results

We drew event study plots for CS estimators (solid line) and event study estimators of conventional DID (dashed line) with and without covariates, along with 95% confidence intervals in Figure 3.3. Pre-treatment estimates of CS estimators indicate that there are almost no parallel trends. The post-treatment estimates of CS estimators are the treatment effect. In Figure 3.3a, without covariates, all pre-treatment estimates are close to zero; the average is -0.0016 (0.0048)[5] with a p-value of 0.737. On the contrary, post-treatment estimates have an average of -0.0589 (0.310) and a p-value of 0.057, which means clear energy consumption reduction after joining ICLEI. In Figure 3.3b, the

[5] parenthesis means the standard errors.

average pre-treatment is -0.0053, and the average post-treatment is -0.0699 with covariates. CS estimators and event study estimators show similar flat trends before the treatment, which means there are no pre-trends and a sudden fall just after the treatment. The noise after the treatment is caused by the small number of counties that joined ICLEI in the same year.

Figures 3.3c and 3.3d show CS estimators estimators on the state ICLEI membership with and without covariates. There are no pre-trends, and there are clear treatment effects. Without covariates, the average pre-treatment effect is -0.0152 (0.0034) with a p-value of 0.000, while the post-treatment effect is -0.0927 (0.0257) with a p-value of 0.000. With covariates, the average pre-treatment is 0.0013, while post-treatment is -0.0920. Although there may be a pre-trend under event study estimators, there is no pre-trend under the CS estimator, which is enough to justify the result under Callaway & Sant'Anna (2021). Event study estimators with static DID show the violation of no anticipation assumption on the plot; however, if we assume a county can anticipate its future joining, it would be okay to use CS estimators (Callaway & Sant'Anna, 2021).

Figures 3.3e and 3.3f are CS estimation results on county and state ICLEI membership with and without covariates. There is clearly no pre-trend and substantial decrease in post-treatment. Without covariates, the pre-treatment average is -0.0125 (0.0056), and the post-treatment average is -0.1651 (0.0311). With covariates, the pre-treatment average is -0.0233 (0.0233), and the post-treatment average is -0.3997 (0.0923). In each group-year 2 x 2 setting, there are almost no pre-trends.

CS estimators for each case of ICLEI memberships are in Figure 3.4. Green and triangular ones are for county membership, red and rectangular ones are for state membership, and black and round ones are for both memberships. Thick lines are for with covariates, and dashed lines are for without covariates. There is no pre-trend in all cases and a clear decrease after joining ICLEI. The magnitude becomes greater from county to state and to both memberships.

Table 3.4 shows the average treatment effect estimated using CS estimators on the impact of county and state ICLEI membership with and without covariates. First, we compare the result with static two-way fixed effect (TWFE) DID methods. The TWFE row shows estimates of a post-treatment effect from TWFE DID, a conventional DID design. CS estimators in Table 3.4 mean the weighted average treatment effect described in Equation 3.3. Both report a significant decrease in energy consumption after joining ICLEI. County-specific effects report average treatment effects by the timing of joining ICLEI, and *ic* means the year a county joined. Year-specific effects indicate average treatment effects in year *t*. The event study row of Table 3.4 reports average treatment effects by the length of ICLEI membership years, and post-term means the number of years since joining ICLEI. The numerical value of ATEs after year 0 is shown in Table 3.4. Without covariates, energy consumption per capita is estimated to decrease by 4.53% after joining ICLEI. In the first year after a county joined ICLEI, the energy consumption per capita decreased by 3.67%, and it is estimated to decrease by 6.95% in the 4th year, 7.52% in the 5th year, 7.28% in the 7th year, and 21.65% in the 12th year. This is similar to the estimation with covariates. There is no clear fortifying trend after joining ICLEI by a county.

We observe a much clearer treatment effect with a state ICLEI membership. Table 3.5 shows a growing energy consumption reduction after joining ICLEI. Without covariates, there is no significant decrease in energy consumption for 3 years; after 3 years, there is a 5.09% decrease in energy consumption per capita. This keeps growing and becomes a 14.32% decrease in the 12th year of joining ICLEI. With covariates, the significant decrease shows up after 6 years, and the magnitude keeps growing over time. The aggregated treatment effects by group and year are also consistent with the hypothesis that ICLEI membership will decrease energy consumption on a county level compared to non-CLEI members. The CS estimators are similar with and without covariates.

Table 3.6 shows the treatment effect with both county and state membership. The magnitude is bigger than the sole membership of a county or a state. Then, we can observe the growing impact of membership over time. Without covariates, the treatment grew from a 2.68% decrease in 1st year to a 40.64% decrease in the 12th year. With covariates, the treatment becomes significant after 4 years: 21.82% decrease in the 4th year to 84.36% decrease in the 12th year.

The parallel trend assumption needs to be justified, but we do not need to check no-anticipation assumptions using CS methods (Callaway & Sant'Anna, 2021). The CS methods lean on the idea that the decision to join ICLEI is made at a county or state level, and other social, political, or economic conditions may not affect their decisions. Counties or states may anticipate when they will join ICLEI, and the CS methods is suitable for this case (Callaway & Sant'Anna, 2021). First, we check the parallel trend assumption with and without covariate. Figure 3.5 shows the point estimates and 95% confidence levels for pre- and post-treatment periods clustered at the county level without covariates. Green points before 0 indicate the pre-treatment effects, and red ones after 0 indicate the post-treatment effects. Under the null hypothesis of parallel trends, the pre-treatment effect should equal 0. The post-treatment effect may deviate from 0 if ICLEI membership has any impact on energy consumption. Each group shows the set of counties that joined ICLEI each year. In most cases, the parallel trend assumptions are justified, though Groups 2010, 2017, and 2019 have some deviations from 0. Group 2016 shows an increase in energy consumption after joining ICLEI. Figure 3.6 shows better results with covariates, while Group 2017 still shows a violation of the assumption. This may be because a few counties joined ICLEI in the same year. The number of counties that joined ICLEI in the same year ranged from one to eight Table 3.3. Regarding state ICLEI membership, we clearly identify no pre-trend and significant deviation after the treatment in Figures 3.7. Figures 3.8 and 3.9 show that there is almost no pre-trend in estimating both county and state membership. Some groups in 2017 and 2019 showed sudden increases before treatment; however, this is due to the low numbers of treated groups: one in 2017 (Songpa) and two in 2019 (Icheon and Yuseong).

3.4 Discussion

Overall, the estimation had several meaningful results. First, using the CS methods, we find evidence that ICLEI membership reduces energy consumption per capita at a county level, and state membership has a stronger impact than county membership, and both county and state membership have the biggest impact. The total average effect of county ICLEI membership is a 4.53% decrease in energy consumption per capita without covariates and a 6.62% decrease with covariates. The aggregated treatment effect of state membership is a 9.00% decrease without covariates and an 8.91% decrease with covariates. With both memberships of a county and a state, energy consumption is decreased by 11.8% without covariates to 21.4% with covariates. In Korea, the average energy consumption per capita at the county level from 2005-2019 is 3.968 TOE/person, which means the energy consumption reduction is 0.184 to 0.2420.180 to 0.263 TOE/person with a county membership and 0.354 to 0.357 TOE/person with a state membership, and 0.467 to 0.848 TOE/person with both memberships. It may point out that multi-level governance can generate a bigger impact on policy outcomes when each agent tends to cooperate and support the shared goal. Second, unlike county ICLEI membership, state ICLEI membership shows a stronger and fortifying trend in local energy consumption over time. State membership shows an increase in energy consumption reduction over time after joining ICLEI. The reduction becomes significant after 3 years without covariates and 6 years with covariates. Third, there is a significant difference between the results of TWFE DID and CS methods, which means we avoid the potentially biased result of the canonical DID setting.

The policy implementation power of local governments made greater energy consumption reduction with state membership. In the Korean context, state governments have greater influence and discretion in policy implementation compared to county governments. First, states can spend much more money at their discretion. According to the Local Finance Integrated Open System (Korean Ministry of the Interior and Safety, 2023a), the average financial independence ratio of states is 72.7, and that of counties is 59.4. The average budget is 7,027 billion Korean won for states and 619 billion Korean won for counties. This means that states can initiate a more powerful drive if they want to do so. Furthermore, in Korea, higher-level governments often utilize matches for policy implementation. Central or state governments do a project a match: i.e. if they want to subsidize charging station installation, the central government may suggest a 5:3:2 match (central:state:county). States also do this kind of match for their counties; however, the county has no other lower-level governments. It makes local governments tend to accept the policies of the higher governments (Han & Yun, 2021). Second, states have bigger political and policymaking power than counties. They have more negotiation power against the central government and more influential political leaders (governors are usually more popular and well-known than mayors), and it is the same for the local congress. Governors and state congressmen are closer to National congressmen than mayors and county congressmen. This makes it easier for state governments to lead the national budget and policy favorable to them. Third, states have greater populations, which they can affect. Korea has 17 states and 228 counties, and each state can affect all the populations of its counties.

Policy learning is the key mechanism for explaining how ICLEI membership affects local policy outcomes. When a local government wants to learn how to implement climate policy effectively, the most required resources are the capacity of public officers, budget, and experience. Grønnestad & Bach Nielsen (2022); Zambrano-Gutiérrez & Puppim de Oliveira (2022) assert that TMNs provide knowledge and information about their policy fields. The ICLEI Korea network provides capacity building for local public officers, sharing knowledge and information of successful policy implementation cases from domestic and international member cities to its members. The network has also spent a substantial budget to support project funding for member cities. Through these channels, ICLEI Korean members can build their capacity to implement climate policy and sometimes can secure project funding. In contrast to Grønnestad & Bach Nielsen (2022); Zambrano-Gutiérrez & Puppim de Oliveira (2022), who estimate the impact of each channel, we estimate the impact of TMN membership on the final outcome of local energy policy. Therefore, we did not compare the external learning from TMN membership with other channels of learning climate policy. Nevertheless, the finding shows that the impact of external learning from TMNs is highly significant to improve the final policy outcome.

In terms of global stocktake under the Paris Agreement, this high impact of ICLEI membership is remarkable but still not enough to achieve the overarching climate goals agreed upon in Paris, 2015, or Glasgow, 2021. This chapter analyzes to what extent ICLEI membership decreases "Energy Consumption," not "Greenhouse Gas Emissions." The 4.5% to 11% decrease in energy consumption is the average impact of ICLEI membership. First, after joining ICLEI, local governments may start to take care of the low-hanging fruit, such as increasing energy efficiency, installing solar PV, subsidizing electric vehicle adoption, and advertising energy policy. However, after harvesting them, local authorities will face high-hanging fruit, such as energy consumption in manufacturing, agriculture, or retailing. It is impossible to reduce energy consumption in those sectors unless we produce goods without energy consumption. In these fields, we need to invest in new technology to produce the same quality products with less carbon emissions or energy consumption; however, it is out of the local government's control. For the last, the most essential point is that the ultimate climate goal is to reduce carbon emissions, not reduce energy consumption. At this point, they have the same meaning because most energy comes from burning fossil fuels. However, if we consume energy without carbon emissions, we can still have a chance to meet overarching climate goals with substantial energy consumption. Therefore, the high impact of ICLEI membership may support the initiation of climate policy over the nation, and it should be spread nationwide. Then, we should follow up if further innovation is made to meet the national and global goals. Korea has national goals for greenhouse gas emissions: reduction of up to 40% of 2018 emissions by 2030 and 100% by 2050.

Our findings of the impact of ICLEI membership on energy consumption can be transferable to other contexts. To extend the results, researchers should consider the following factors. First, local governments should have guaranteed local autonomy. Communication between local governments should be safe, active, frequent, and encouraged. Assured representative democracy is one of the parts that make it possible. Korean local governments are highly democratized, and the Korean constitution guarantees local autonomy. Second, local governments should have a sufficient local budget to build their capacity. Implementing climate and energy policy is difficult for beginner cities, and both budget and knowledge are required. Only with enough capacity on both sides can TMNs stimulate local policy implementation. Local governments should have enough budget or be ready to utilize external resources and funds under a low level of corruption. Third, national public opinions should be somewhat favorable for climate and energy policy. Otherwise, it is difficult to observe meaningful numbers of ICLEI members or significant activities of ICLEI members.

Nevertheless, there are several important limitations to the finding. First, some groups of counties may deviate from 0 in the pre-treatment periods, which may violate the parallel trend assumption. It may be close to 0 if we include covariates, while some groups remain deviated from 0. This is inevitably caused by the small number of counties that joined ICLEI in the same year. The total number of counties in South Korea is 228, and it is not easy to observe more than 20 counties joining ICLEI in the same year. Second, we treat the impact of joining ICLEI as the same for every county, although there is some heterogeneity among ICLEI members in their actual efforts to pursue the goal of ICLEI. Thus, the estimated impact of ICLEI membership should be interpreted as the average treatment effect. The main reason we include political factors as covariates is to address this concern.

3.5 Conclusion

This chapter has identified the impact of TMN membership on local energy policy outcomes. It adopted a staggered DID to address the potential bias from using a canonical DID on staggered interventions. Some local governments persistently implement climate policies despite the central government's neglect. Some of the external learning for their successful policy implementation comes from TMNs. TMNs offer members the best strategies, success cases, and communication opportunities. Therefore, they are informative and valuable places for beginners to learn new climate policies. This study is the first attempt to estimate the impact of TMN membership on local policy outcomes. Using a database of all 228 local governments in Korea between 2005 and 2019, this chapter identified the impact of ICLEI membership on local energy consumption.

The primary contribution of this chapter is to identify the significant role of ICLEI, one of the TMNs in climate actions, on local climate policy in Korea. This chapter shows that member cities actually drive the policy outcome alongside the goal of ICLEI. This is the first chapter to identify the impact of TMN membership on the final policy outcome. It means local governments have tried to meet the goal via multiple channels, and it achieves remarkable differences. If central governments want to implement climate policies under budget limits, they should seriously consider selectively supporting ICLEI members, which have better policy performance than non-ICLEI members, as European countries have done (Kern & Bulkeley, 2009). This suggests the possibility of global urban governance from the international urban network. Gordon & Johnson (2017) state that cities can substantially contribute to meeting global climate goals and suggest the orchestration framework to analyze politics and power dynamics in global urban governance. They pointed out that cities were remarkably moving beyond simple symbolic pledges and consolidating urban climate governance in the 2010s, while TMNs showed low levels of activation at first in the 1990s. Acuto & Leffel (2021) also argued that urban networks lead to further internationalization of city leadership. They said that institutionalized boundaries of networks would be a stretch for a bigger picture of global urban governance.

Second, this chapter sheds light on the impact of ICLEI on local climate policy through quantitative analysis, given that previous literature was mainly qualitative. We systematically compared the impact of ICLEI membership on local energy consumption for all members and non-members of TMNs in Korea. The results reveal that county and state ICLEI membership has significantly decreased local energy consumption. Specifically, if a county becomes an ICLEI member, there is a 4.53% to 6.62% decrease; if a state becomes an ICLEI member, there is an 8.91% to 9.00% decrease; and if both county and state become an ICLEI member, there is an 11.8% to 21.4% decrease in energy consumption per capita. These findings show a statistically significant effect of TMN membership, which fortifies qualitative findings in previous literature. We also found a growing impact of ICLEI membership over time. When a state joins ICLEI, it shows significant energy consumption reduction after 3 to 6 years of membership. This means energy consumption is reduced more if a state maintains membership longer.

Third, to the best of our knowledge, this study is the first to adopt staggered DID for staggered intervention at the county level using all the county data in a nation. There is growing evidence that traditional DID results may be biased if there is staggered treatment timing. The CS estimator shows robust results, and the required assumptions are justified. The results are similar with or without covariates, which means the impact of ICLEI membership significantly affects local energy consumption reduction. Those results significantly differ from the TWFE and event study estimators. We can avoid this bias in canonical DID under staggered treatment by using staggered DID.

Our findings lead researchers to further studies. First, researchers may use carbon emission reduction as the target with TMN membership if they can build a carbon inventory database by county. We use energy consumption rather than carbon emissions because of data feasibility at a county level. Korea has started to build a carbon inventory by county; in 2022, the Greenhouse Gas Inventory & Research Center of Korea (2022) published tentative carbon emissions by county for 2016-2019. Second, researchers may apply these approaches to other studies of local policies across a broader geographical scale. Extending these findings to other TMN areas or other geographic regions requires careful consideration of data availability. Our theoretical background was based on robust evidence from previous literature on the role of TMNs in climate change. When a researcher tries to expand this to other TMNs, robust evidence of the relationship between target TMNs and local governments should be identified. Third, Callaway & Sant'Anna (2021) is one part of the rapidly growing literature on staggered DID settings. We chose this method based on its fit with our research. A researcher can get knowledge about this staggered DID method from Baker et al. (2022).

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APPENDIX 3.A: Tables and Figures

Table 3.1 The number of counties or states that joined ICLEI

Year	County	State (# of its counties)	County and State
Joined before 2005	Ansan, Bucheon, Damyang, Gimpo, Gumi, Jeju, Jeongseon, Jeonju, Pyeongchang, Suncheon, Suwon, Wonju	Busan (16), Chungnam (15), Gangwon (18), Gwangju (5), Gyeonggi (36), Jeju (1) Seoul (25), Ulsan (5)	Ansan, Bucheon, Gimpo, Jeju, Jeongseon, Pyeongchang, Suwon, Wonju
2007	Changwon, Gwacheon		Gwacheon
2008	Hadong, Seongnam	Daegu (8), Gyeongnam (18)	Changwon, Hadong, Seongnam
2009	Gapyeong, Namyangju	Incheon (10)	Gapyeong, Namyangju
2010	Yeosu		
2011	Seocheon		Seocheon
2012	Buyeo, Cheongyang, Seongbuk		Buyeo, Cheongyang, Seongbuk
2013	Anyang, Gangneung, Osan, Seodaemun, Taean, Yeongju		Anyang, Gangneung, Osan, Seodaemun, Taean
2014	Cheongju, Gangdong, Inje Jongno, Sejong, Uiwang	Sejong (1)	Gangdong, Inje Jongno, Sejong, Uiwang
2015	Asan, Dangjin, Dobong, Nowon Pohang, Siheung, Yuseong		Asan, Dangjin, Dobong, Nowon, Siheung
2016	Eunpyeong, Namgu (Incheon)		Eunpyeong, Namgu (Incheon)
2017	Songpa		Songpa
2019	Icheon	Daejeon (5)	Icheon, Yuseong
Non-Members (as of 2019)	180 counties	Chungbuk (11), Gyeongbuk (23) Jeonbuk (14), Jeonnam (22)	188 counties
Total in data	226 counties	17 states (226 counties)	226 counties
Excluded	Geumsan, Hoengseong		

Table 3.2 Conversion factors for energy unit conversion

Type	Sources	Unit	KEA coefficients		Conversion to TOE	
Oil	Gasoline	bbl	0.000781	toe/l	0.124	toe/bbl
	Kerosene	bbl	0.000877	toe/l	0.139	toe/bbl
	Diesel	bbl	0.000903	toe/l	0.144	toe/bbl
	Bunker-A	bbl	0.000931	toe/l	0.148	toe/bbl
	Bunker-B	bbl	0.000967	toe/l	0.154	toe/bbl
	Bunker-C	bbl	0.000996	toe/l	0.158	toe/bbl
	Jet fuel	bbl	0.000872	toe/l	0.139	toe/bbl
	By-products I	bbl	0.000886	toe/l	0.141	toe/bbl
	By-products II	bbl	0.000953	toe/l	0.152	toe/bbl
	Propane	bbl	0.001204	toe/kg	0.097	toe/bbl
	Butane	bbl	0.001182	toe/kg	0.109	toe/bbl
Gas	Natural Gas	kM^3	0.001043	M^3	1.043	toe/kM^3
Electricity	Electricity	MWh	0.000211	toe/kWh	0.211	toe/MWh

Table 3.3 Descriptive statistics for variables

Variable	Symbol	Unit	Mean (SD)	Min	Max
Ln (Energy Consumption per capita)	Ln(Enpc)		1.177(0.572)	0.119	3.511
Energy Consumption per capita		TOE/person	3.960(3.405)	1.127	33.473
Energy Consumption		TOE	767,854(943,786)	21,645	9,208,969
ICLEI membership of a state	ST	Binary	0.632(0.482)	0	1
ICLEI membership of a county	CT	Binary	0.124(0.330)	0	1
ICLEI membership of both	BT	Binary	0.096(0.295)	0	1
a party of a Governor	Gvnor	Binary	0.442(0.497)	0	1
a party of a Mayor	Mayor	Binary	0.367(0.482)	0	1
Local Income Tax	Ltax	₩1 million	50,610(101,218)	480.610	1,257,906
Financial Independence Ratio	FIR	%	62.969(11.299)	28.280	93.900
Gross Value Added per capita in Manufacturing	Mnpc	₩1 million/person	7.605(11.871)	0.022	90.373
The Number of Cars per Capita	Carpc	Car/person	0.404(0.108)	0.191	2.011

Note: N=3,390 (226 counties over 15 years from 2005 to 2019)

Table 3.4 Average treatment effect of county ICLEI membership

Without covariates								
	Partially aggregated estimator							Aggregated estimator
TWFE								-0.0734**
								(0.0311)
CS estimators								-0.0453*
								(0.0234)
County-specific effects	ic=2007	ic=2008	ic=2009	ic=2010	ic=2011	ic=2012		County-Average
	-0.0984****	0.0776	-0.0445	-0.0237**	-0.2412****	-0.0571****		-0.0460**
	(0.0259)	(0.0926)	(0.0616)	(0.0094)	(0.0082)	(0.0148)		(0.0187)
	ic=2013	ic=2014	ic=2015	ic=2016	ic=2017		ic=2019	
	0.0280	-0.1066	-0.0836***	0.0560	-0.0673****		0.0249****	
	(0.0400)	(0.0820)	(0.0251)	(0.0383)	(0.0057)		(0.0031)	
Year-specific effects	t=2007	t=2008	t=2009	t=2010	t=2011	t=2012		Year-Average
	0.0605	0.0238	0.0088	0.0093	-0.0406	-0.0457*		-0.0245
	(0.0489)	(0.0396)	(0.0472)	(0.0471)	(0.0345)	(0.0273)		(0.0225)
	t=2013	t=2014	t=2015	t=2016	t=2017	t=2018	t=2019	
	-0.0208	-0.0262	-0.0445*	-0.0553**	-0.0564**	-0.0626*	-0.0695**	
	(0.0189)	(0.0197)	(0.0231)	(0.0266)	(0.0258)	(0.0328)	(0.0338)	
Event study	post-term 0	post-term 1	post-term 2	post-term 3	post-term 4	post-term 5		Pre-Average
	-0.0175	-0.0367**	-0.0290	-0.0408	-0.0695**	-0.0752*		-0.0016
	(0.0116)	(0.0177)	(0.0245)	(0.0282)	(0.0303)	(0.0396)		(0.0048)
	post-term 6	post-term 7	post-term 8	post-term 9	post-term 10	post-term 11	post-term 12	Post-Average
	-0.0389	-0.0728*	-0.0693	-0.0154	-0.0313	-0.0529	-0.2165****	-0.0589*
	(0.0333)	(0.0385)	(0.0611)	(0.0569)	(0.0630)	(0.1023)	(0.0392)	(0.0310)
With covariates								
	Partially aggregated estimator							Aggregated estimator
TWFE								-0.0494**
								(0.0290)
CS estimators								-0.0662*
								(0.0583)
County-specific effects	ic=2007	ic=2008	ic=2009		ic=2011	ic=2012		County-Average
	-0.0728	0.2257**	-0.0018		-1.2562****	-0.1519**		
	(0.0779)	(0.0882)	(0.0551)		(0.0303)	(0.0803)		
	ic=2013	ic=2014	ic=2015	ic=2016			ic=2019	
	0.0516	-0.1030	-0.0270				0.1372****	
	(0.0323)	(0.0714)	(0.0384)				(0.0172)	
Year-specific effects	t=2007	t=2008	t=2009	t=2010	t=2011	t=2012		Year-Average
	0.0845	0.0724*	-0.0443	-0.0917	-0.0625	-0.0363		-0.0260
	(0.0803)	(0.0382)	(0.0576)	(0.0648)	(0.1139)	(0.0467)		(0.0471)
	t=2013	t=2014	t=2015	t=2016	t=2017	t=2018	t=2019	
	-0.0171	-0.0557	-0.0752	-0.0917	-0.0796	-0.1103	-0.1028	
	(0.0348)	(0.0595)	(0.0559)	(0.0658)	(0.0593)	(0.0763)	(0.0767)	

Table 3.4 (cont'd)

Event study	post-term 0	post-term 1	post-term 2	post-term 3	post-term 4	post-term 5		Pre-Average
	-0.0202	-0.0229	-0.0218	-0.0640*	-0.0872*	-0.1283*		-0.0053
	(0.0278)	(0.0244)	(0.0307)	(0.0511)	(0.0586)	(0.0859)		
	post-term 6	post-term 7	post-term 8	post-term 9	post-term 10	post-term 11	post-term 12	Post-Average
	-0.1070	-0.2454	-0.2664	-0.0597	-0.0692	-0.0910	-0.1661	-0.0699
	(0.0959)	(0.1817)	(0.2874)	(0.0958)	(0.0949)	(0.1687)	(0.1791)	

Note : $*p < 0.1; **\ p < 0.05; ***p < 0.01; ****\ p < 0.001$, and parentheses mean the standard errors for each coefficient

Table 3.5 Average treatment effect of state ICLEI membership

Without covariates							
	Partially aggregated estimator						Aggregated estimator
TWFE							-0.0437
							(0.0320)
CS estimators							-0.0900****
							(0.0250)
County-specific effects	ic=2008	ic=2009	ic=2014	ic=2019			County-Average
	-0.0461*	-0.1901****	-0.5838****	-0.0350****			-0.0918****
	(0.0256)	(0.0376)	(0.0101)	(0.0077)			(0.0195)
Year-specific effects	t=2008	t=2009	t=2010	t=2011	t=2012	t=2013	Year-Average
	0.0218*	-0.0017	-0.0115	-0.0337	-0.0512**	-0.0717***	-0.0854****
	(0.0114)	(0.0171)	(0.0180)	(0.0215)	(0.0210)	(0.0269)	(0.0238)
	t=2014	t=2015	t=2016	t=2017	t=2018	t=2019	
	-0.0963****	-0.1225****	-0.1376****	-0.1523****	-0.1742****	-0.1941****	
	(0.0285)	(0.0310)	(0.0339)	(0.0378)	(0.0446)	(0.0436)	
Event study	post-term 0	post-term 1	post-term 2	post-term 3	post-term 4	post-term 5	Pre-Average
	-0.0105	-0.0219	-0.0356	-0.0509**	-0.0851***	-0.0936***	-0.0152****
	(0.0118)	(0.0192)	(0.0229)	(0.0255)	(0.0271)	(0.0340)	(0.0034)
	post-term 6	post-term 7	post-term 8	post-term 9	post-term 10	post-term 11	Post-Average
	-0.1016***	-0.1180****	-0.1314****	-0.1460****	-0.1744****	-0.1432***	-0.0927
	(0.0306)	(0.0313)	(0.0336)	(0.0404)	(0.0441)	(0.0472)	(0.0257)
With covariates							
	Partially aggregated estimator						Aggregated estimator
TWFE							-0.0453***
							(0.0295)
CS estimators							-0.0891**
							(0.0375)
County-specific effects	ic=2008	ic=2009					County-Average
	-0.0301	-0.2566****					-0.0930***
	(0.0364)	(0.0699)					(0.0342)
Year-specific effects	t=2008	t=2009	t=2010	t=2011	t=2012	t=2013	Year-Average
	0.0413**	-0.0075	0.0090	-0.0032	-0.0435	-0.0736*	-0.0861**
	(0.0165)	(0.0258)	(0.0271)	(0.0325)	(0.0379)	(0.0445)	(0.0364)
	t=2014	t=2015	t=2016	t=2017	t=2018	t=2019	
	-0.0999**	-0.0994**	-0.1073**	-0.1390**	-0.1569**	-0.3531****	
	(0.0445)	(0.0457)	(0.0495)	(0.0569)	(0.0709)	(0.0992)	
Event study	post-term 0	post-term 1	post-term 2	post-term 3	post-term 4	post-term 5	Post-Average
	0.0006	-0.0139	0.0013	-0.0075	-0.0672	-0.0674	0.0013
	(0.0211)	(0.0242)	(0.0285)	(0.0348)	(0.0416)	(0.0449)	
	post-term 6	post-term 7	post-term 8	post-term 9	post-term 10	post-term 11	Post-Average
	-0.0962**	-0.1027**	-0.1208**	-0.1486**	-0.2674***	-0.2141**	-0.0920
	(0.0475)	(0.0462)	(0.0510)	(0.0687)	(0.0908)	(0.0839)	

Note : $*p < 0.1; **p < 0.05; ***p < 0.01; ****p < 0.001$, and parentheses mean the standard errors for each coefficient

Table 3.6 Average treatment effect of both ICLEI membership

Without covariates								
	Partially aggregated estimator							Aggregated estimator
TWFE								-0.0957***
								(0.0325)
CS estimators								-0.1183****
								(0.0244)
County-specific effects	ic=2007	ic=2008	ic=2009		ic=2011	ic=2012		County-Average
	-0.1884****	-0.0103	-0.1311***		-0.3112****	-0.1148****		-0.1129****
	(0.0274)	(0.0929)	(0.0426)		(0.0099)	(0.0173)		(0.0198)
	ic=2013	ic=2014	ic=2015	ic=2016	ic=2017		ic=2019	
	0.0575	-0.1843**	-0.1026****	-0.0255***	-0.0996****		0.0031	
	(0.0403)	(0.0933)	(0.0189)	(0.0095)	(0.0087)		(0.0045)	
Year-specific effects	t=2007	t=2008	t=2009	t=2010	t=2011	t=2012		Year-Average
	0.0577	0.0223	-0.0093	-0.0117	-0.0701**	-0.0663**		-0.0758***
	(0.0492)	(0.0403)	(0.0416)	(0.0462)	(0.0331)	(0.0289)		(0.0235)
	t=2013	t=2014	t=2015	t=2016	t=2017	t=2018	t=2019	
	-0.0648***	-0.0865****	-0.1137****	-0.1299****	-0.1479****	-0.1703****	-0.1955****	
	(0.0233)	(0.0232)	(0.0263)	(0.0298)	(0.0292)	(0.0346)	(0.0359)	
Event study	post-term 0	post-term 1	post-term 2	post-term 3	post-term 4	post-term 5		Pre-Average
	-0.0268**	-0.0564***	-0.0755***	-0.1029****	-0.1430****	-0.1820****		-0.0125**
	(0.0127)	(0.0190)	(0.0245)	(0.0290)	(0.0313)	(0.0395)		(0.0056)
	post-term 6	post-term 7	post-term 8	post-term 9	post-term 10	post-term 11	post-term 12	Post-Average
	-0.1649****	-0.2001****	-0.2323****	-0.1551**	-0.1718***	-0.2293**	-0.4064****	-0.1651****
	(0.0302)	(0.0381)	(0.0592)	(0.0602)	(0.0613)	(0.1001)	(0.0418)	(0.0311)
With covariates								
	Partially aggregated estimator							Aggregated estimator
TWFE								-0.0648**
								(0.0312)
CS estimators								-0.2136****
								(0.0582)
County-specific effects	ic=2007	ic=2008	ic=2009		ic=2011	ic=2012		County-Average
	-0.2515*	0.2175	-0.2952***		-0.6678****	-0.1788****		-0.1920****
	(0.1291)	(0.3998)	(0.0890)		(0.0290)	(0.0471)		(0.0517)
	ic=2013	ic=2014	ic=2015					
	0.0460**	-0.1717*	-0.1335					
	(0.0231)	(0.0920)	(0.2408)					
Year-specific effects	t=2007	t=2008	t=2009	t=2010	t=2011	t=2012		Year-Average
	0.0951	0.0681	-0.0362	0.0143	-0.0893	-0.0936***		-0.1605***
	(0.0996)	(0.0913)	(0.0314)	(0.0608)	(0.0815)	(0.0318)		(0.0496)
	t=2013	t=2014	t=2015	t=2016	t=2017	t=2018	t=2019	
	-0.0858**	-0.0763	-0.1785***	-0.2340***	-0.4287**	-0.4700**	-0.5710****	
	(0.0354)	(0.0769)	(0.0617)	(0.0788)	(0.1778)	(0.2057)	(0.1307)	

Table 3.6 (cont'd)

Event study	post-term 0	post-term 1	post-term 2	post-term 3	post-term 4	post-term 5		Pre-Average
	-0.0463	-0.0788**	-0.0493	-0.1258	-0.2182***	-0.2891****		-0.0233
	(0.0334)	(0.0359)	(0.0775)	(0.1374)	(0.0795)	(0.0814)		(0.0233)
	post-term 6	post-term 7	post-term 8	post-term 9	post-term 10	post-term 11	post-term 12	Post-Average
	-0.2635**	-0.3579**	-0.6067**	-0.5285**	-0.7548***	-1.0335***	-0.8436****	-0.3997****
	(0.1232)	(0.1469)	(0.2764)	(0.2525)	(0.2373)	(0.3540)	(0.2263)	(0.0923)

Note : $*p < 0.1; **p < 0.05; ***p < 0.01; ****p < 0.001$, and parentheses mean the standard errors for each coefficient

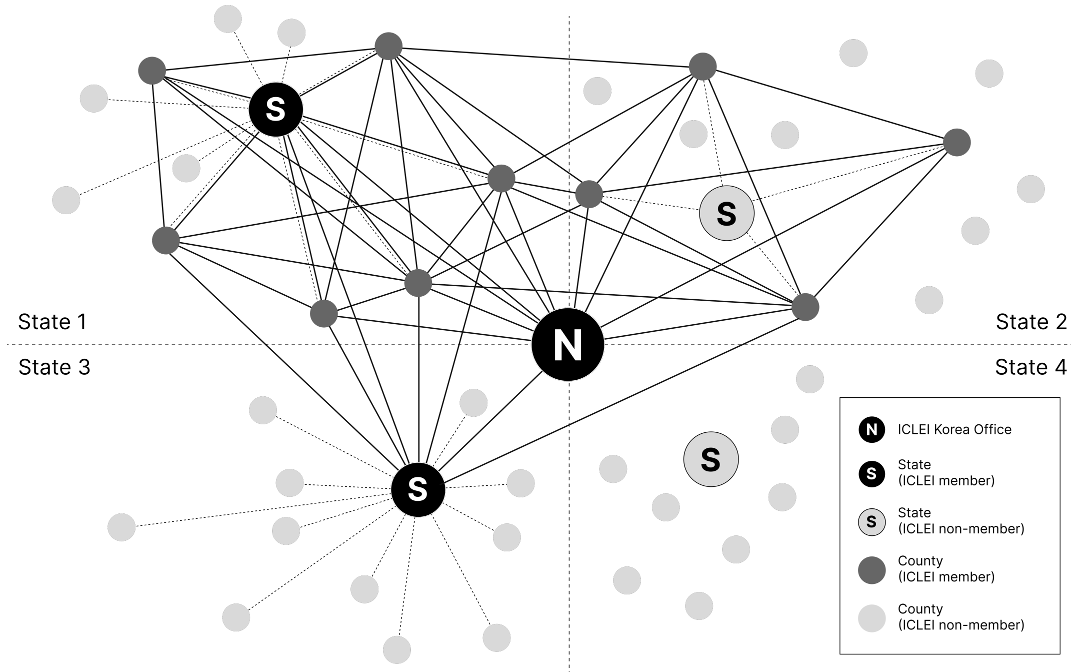


Figure 3.1 Korean ICLEI network

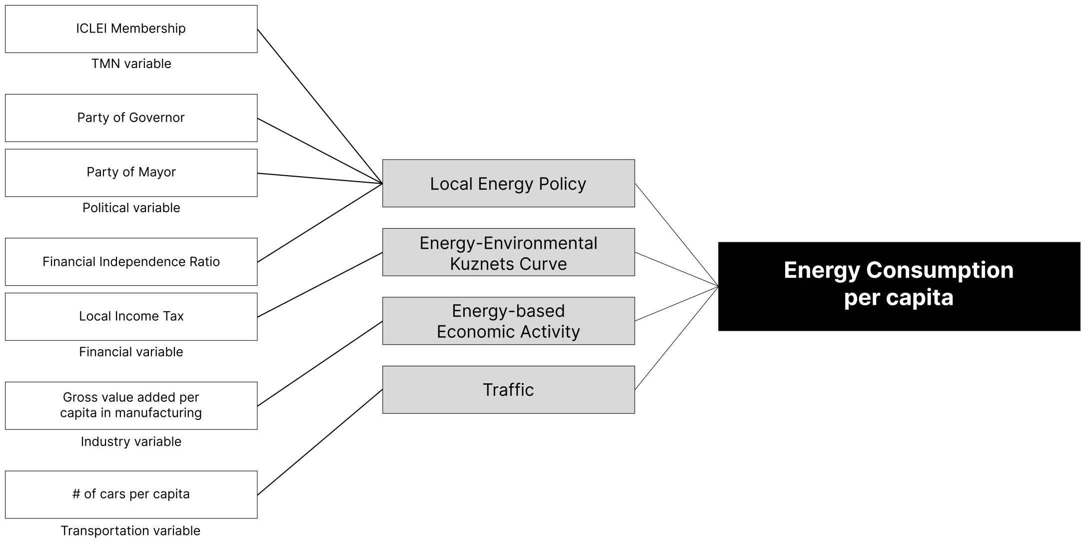
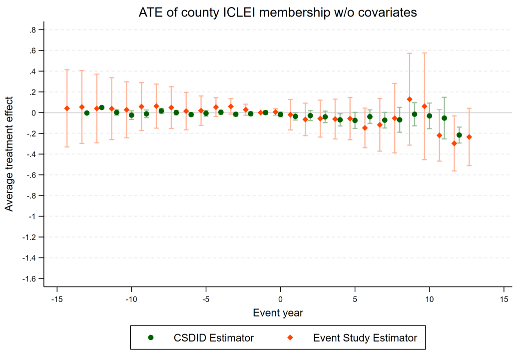
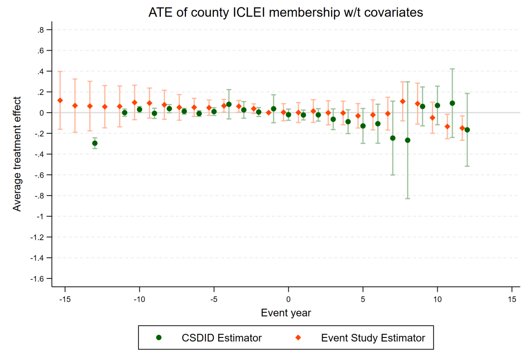


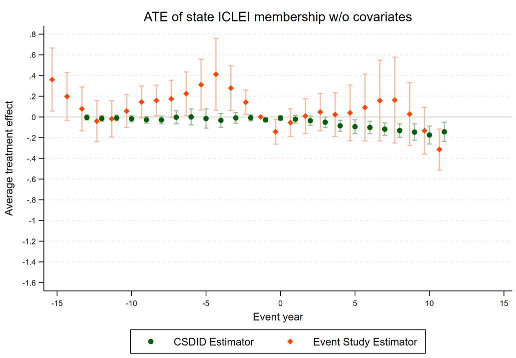
Figure 3.2 Main variables affecting local energy consumption



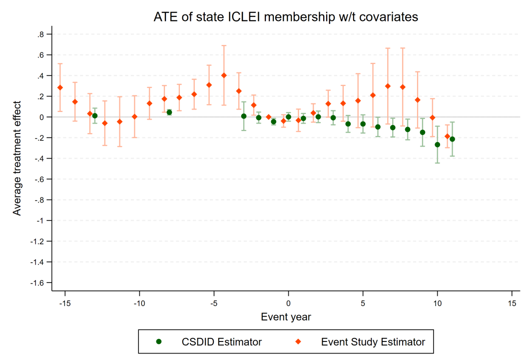
(a) ATE of county membership without covariates



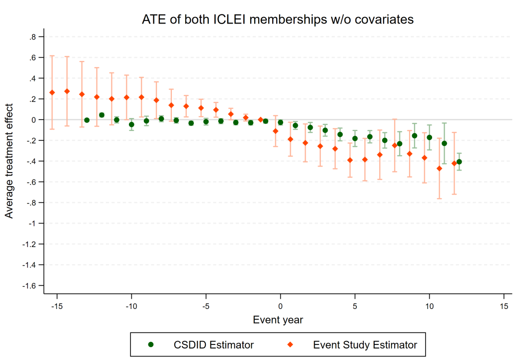
(b) ATE of county membership with covariates



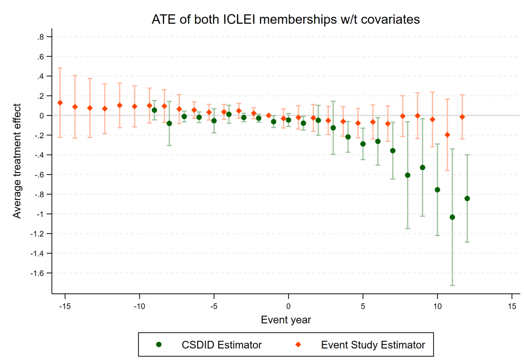
(c) ATE of state membership without covariates



(d) ATE of state membership with covariates



(e) ATE of both memberships without covariates



(f) ATE of both memberships with covariates

Figure 3.3 CS estimators on county and state ICLEI membership w/ and w/o covariates

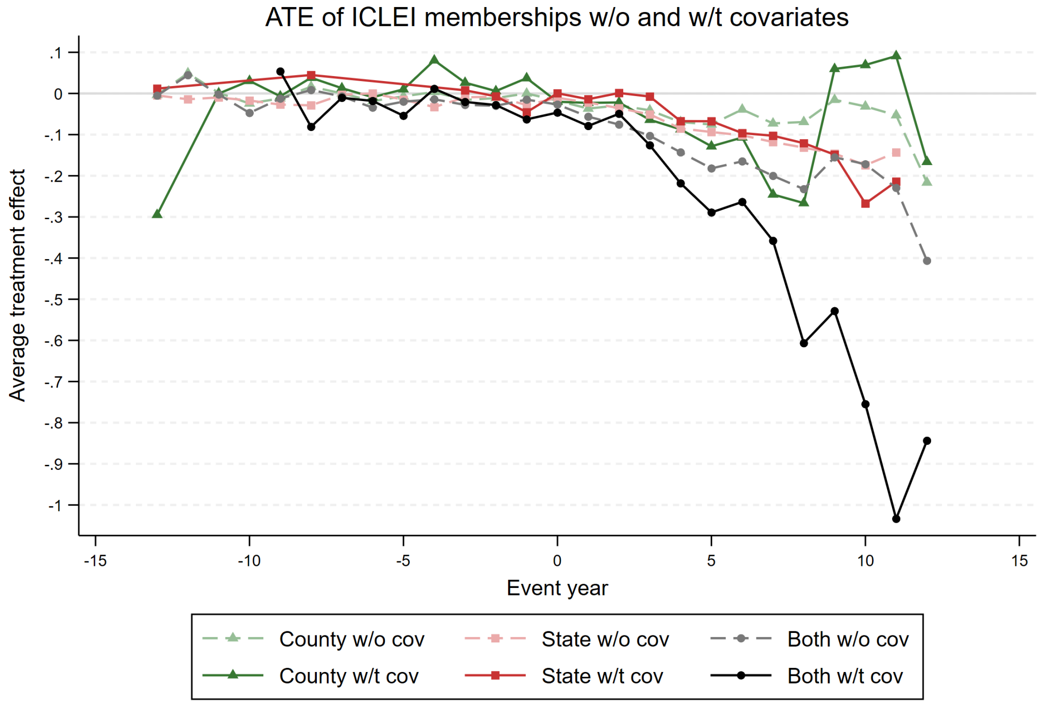


Figure 3.4 ATE of ICLEI memberships by CS estimators

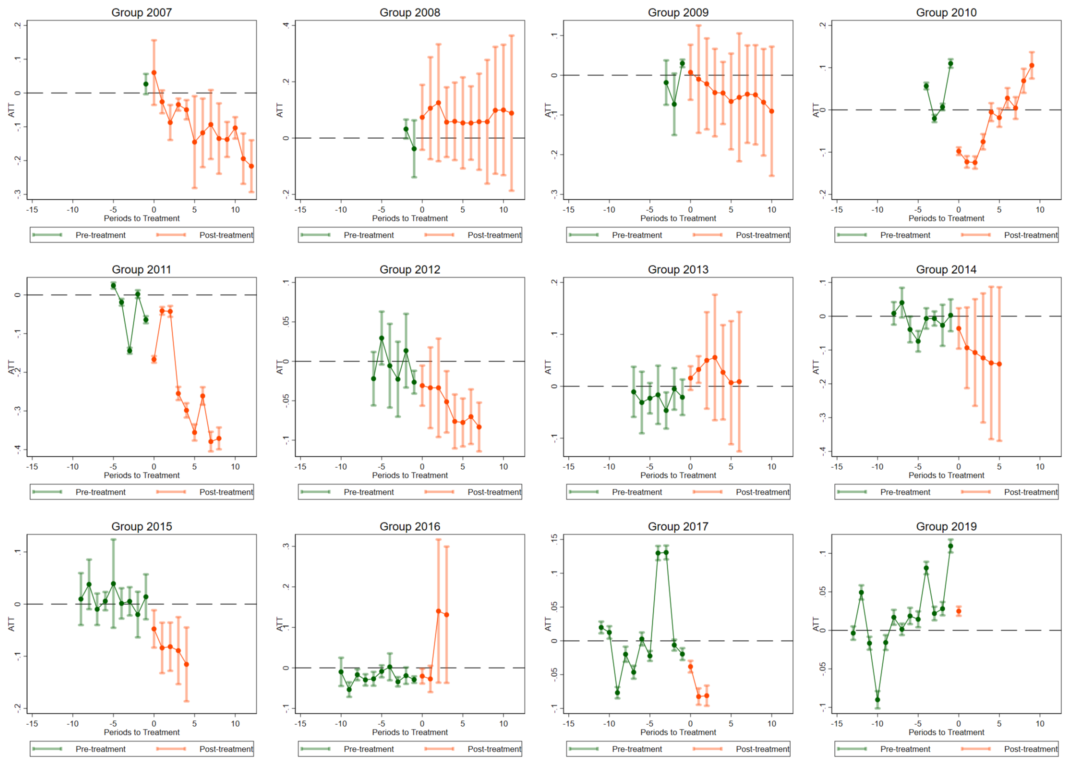


Figure 3.5 county-time ATE of county ICLEI membership - unconditional parallel trends

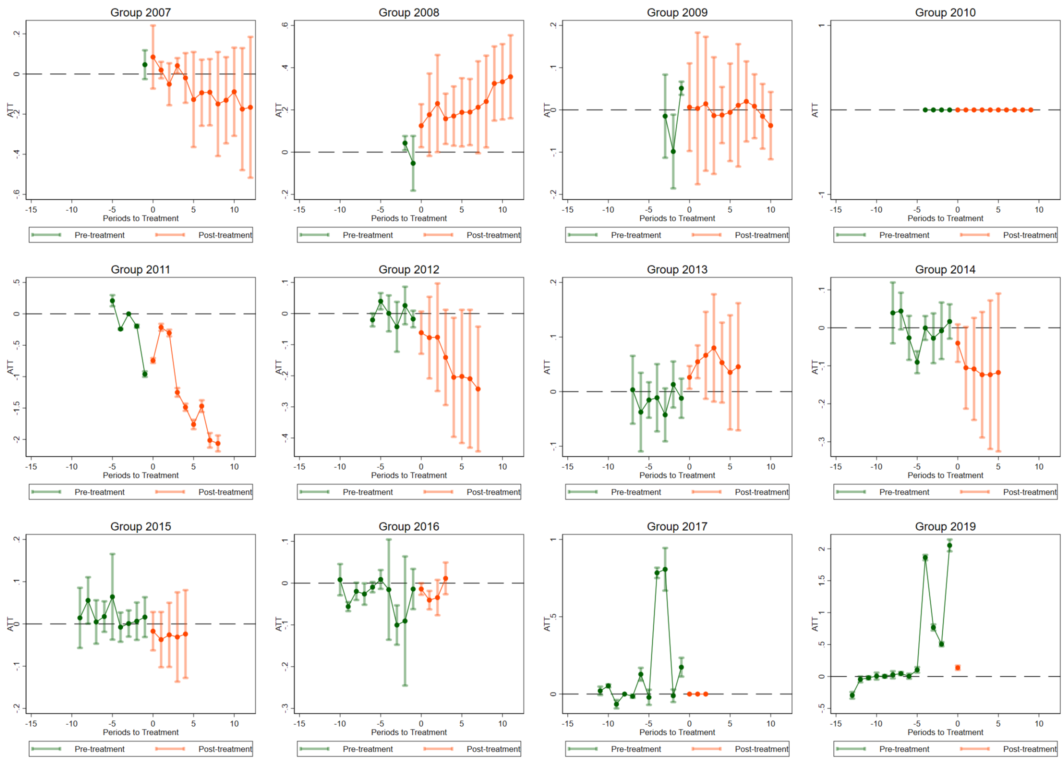
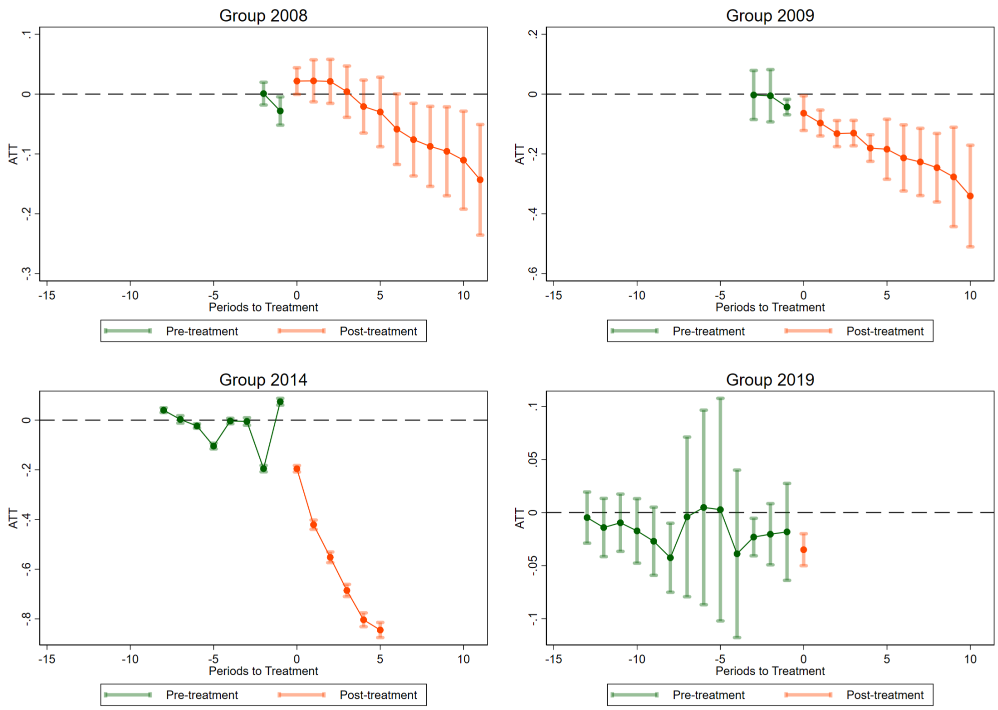
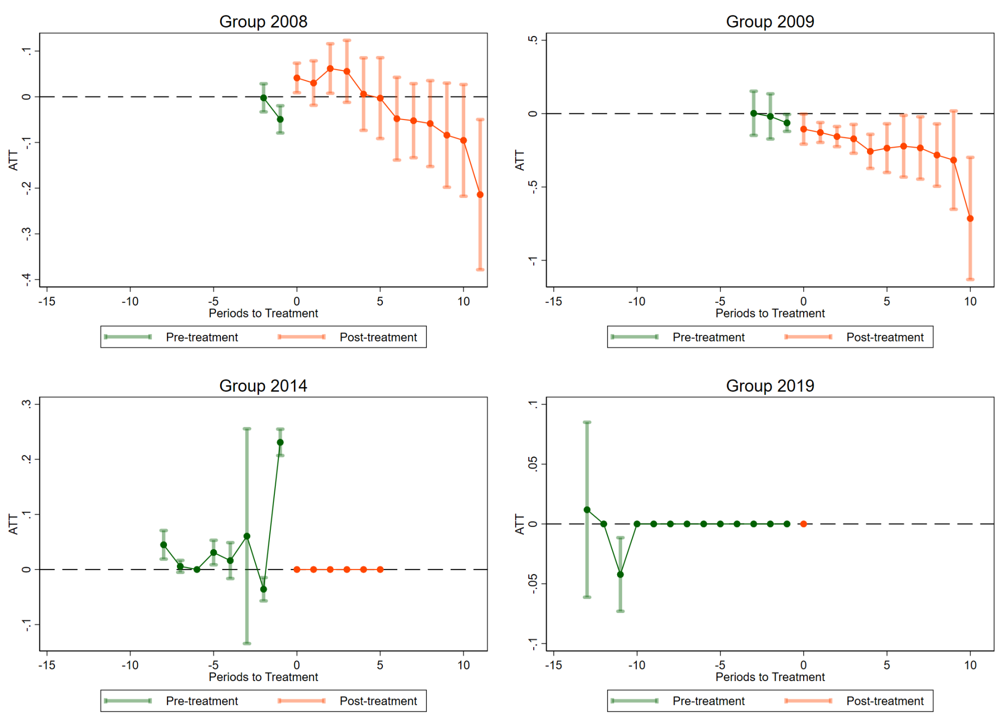


Figure 3.6 county-time ATE of county ICLEI membership - conditional parallel trends



(a) Unconditional parallel trends



(b) Conditional parallel trends

Figure 3.7 County-time ATE of state ICLEI membership

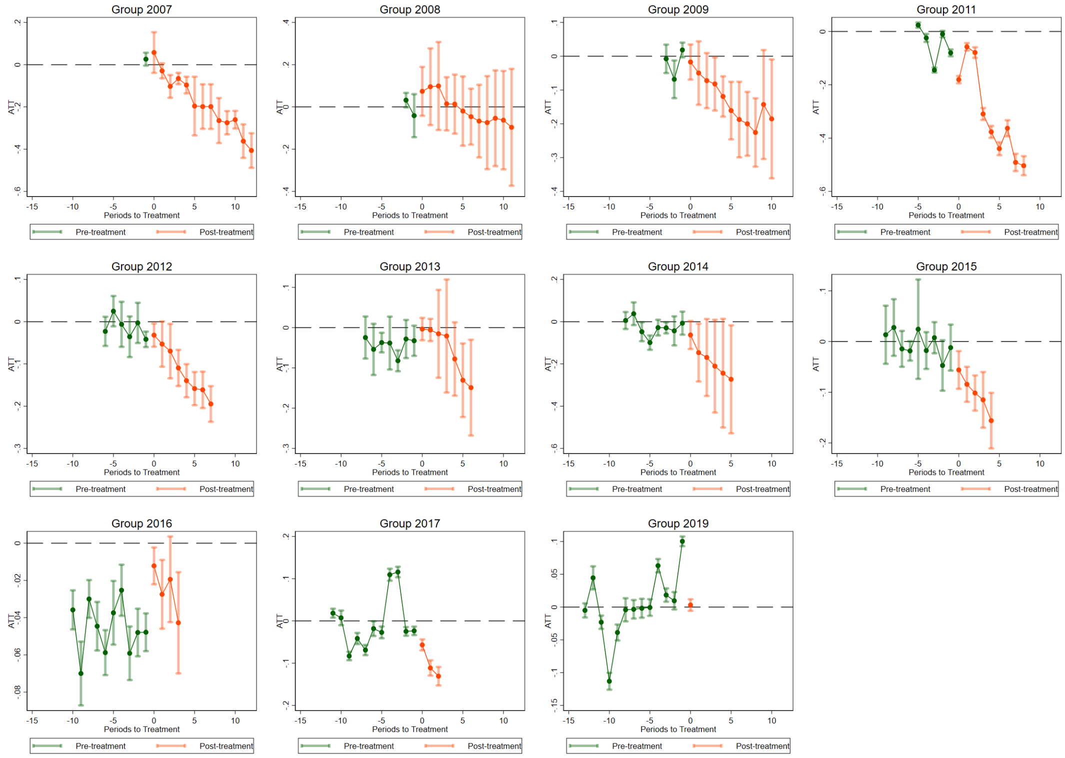


Figure 3.8 county-time ATE of both ICLEI membership - unconditional parallel trends

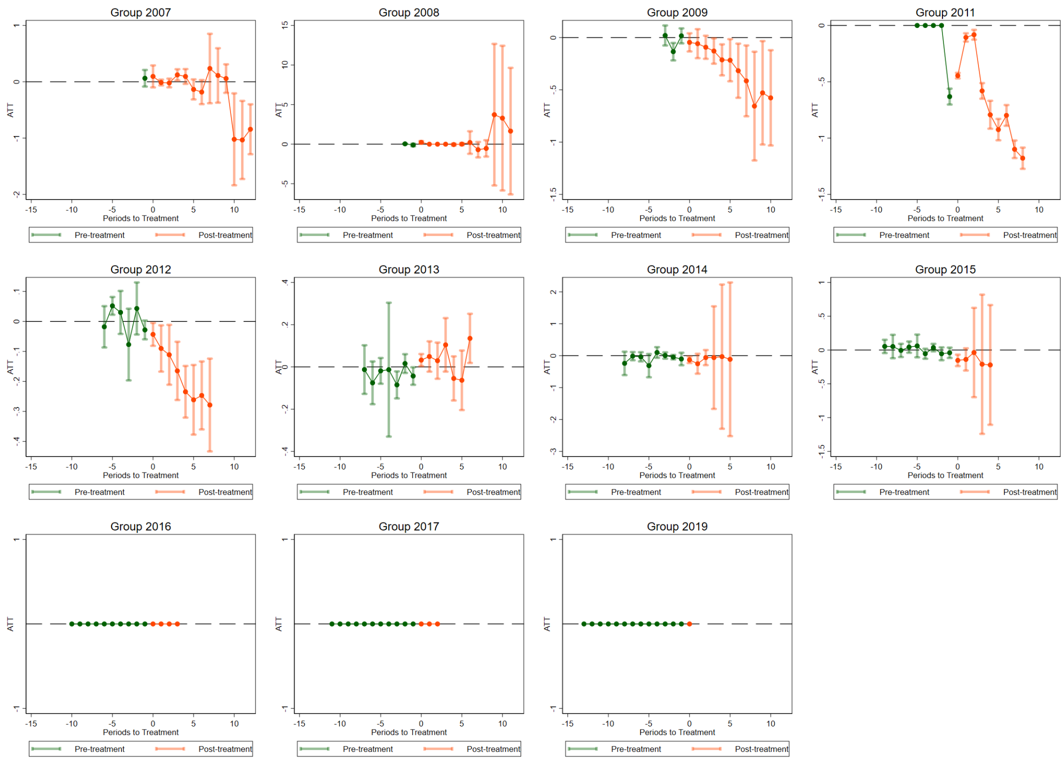


Figure 3.9 county-time ATE of both ICLEI membership - conditional parallel trends