Ph. D. Dissertation in Economics

Factors Affecting the Adoption of Innovative Durable Household Goods: Cases of EV and PV in Korea

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Abstract

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Electric vehicles (EV) and residential photovoltaic (PV) panels are both decentralized energy resources and innovative durable household goods that can induce structural changes in the process of production and consumption of energy—that is, moving from a supplier-oriented system to a consumer-oriented system—as well as fulfilling the need for a low-carbon future due to climate change. The widespread adoption of these innovative technologies is a prerequisite for this transition of the energy system, which will open the doors to possible new business models and successful innovations in the energy industry.

Recognizing the importance of consumers' adoption of these technologies, economic incentive-oriented innovation diffusion policies have been implemented in Korea during the last couple of decades, and studies have attempted to elucidate what drives consumers to decide to adopt them.

Previous studies mainly investigated stated preferences through surveys due to the characteristics of emerging markets. A study analyzing revealed preferences is significant in that such research enables the discovery of new findings that go beyond those of stated preference-based research through comparisons and contrasts with survey-based studies. Therefore, in this study, actual adoption data of EVs and the veranda-type solar mini power plant (mini-solar PV) were analyzed. In addition, the demand for these two innovative durable goods is highly influenced by the characteristics of consumers in a certain country, domestic market conditions, electricity rate structure, and policies regarding diffusion, so international comparative analyses face inherent limitations.

Since the adoption of EVs and mini-solar PV yields count data consisting of consumer choices, the analysis was conducted using a Poisson regression model and negative binomial regression model. Chapter 2 analyzes the factors that encouraged consumers' EV adoption from 2013 to 2017 in each first-tier administrative division. Whereas academia and the media have mainly focused on subsidies and charging infrastructure construction, the analysis showed that the technological excellence, as represented by the range per full charge, had a strong positive impact on EV adoption.

As charging takes a long time relative to refueling an internal combustion engine vehicle, the number of chargers divided by the number of EVs registered in each first-tier administrative division was used as a proxy variable representing public charging infrastructure, but negative and insignificant results were found. Meanwhile, the robustness test using the number of chargers divided by the area of the first-tier administrative division as a proxy variable showed positive and significant results. Since public fast chargers were not frequently used in practice by EV owners and there was a generous amount of non-public level 2 chargers during the study period, we can conclude that the presence of public fast chargers in the vicinity relieved the range anxiety of potential adopters of EVs and induced them to purchase an EV.

In Chapter 3, the factors affecting mini-solar PV adoption in Seoul Metropolitan City from 2014 to 2018 were analyzed. Mini-solar PV units are much smaller than typical residential solar PV units, but can be mounted on the veranda even when living in an apartment without a roof upon which solar panels could be installed, making them suitable for residential sectors in dense cities such as Seoul. The efficiency of PV panels had a strong positive effect on citizens' adoption of mini-solar PV, confirming that technical excellence was the most important factor in adoption, as in the case of EVs. This can also be found in surveys of the adopters of mini-solar PV, where the need for improved panel efficiency was identified as the highest-priority need for future improvements to facilitate the widespread adoption of mini-solar PV.

In contrast to previous studies, however, income-related variables did not explain the adoption of mini-solar PV. This can be interpreted in light of the finding that owner-occupancy was a more important factor; this is because a solar panel, once installed, is not easy to transfer to another residence. This tendency also reflects residence patterns in Korea. Eco-friendliness had a significant positive effect on the adoption of mini-solar PV, but no significant effect on the adoption of EVs. This can likely be explained by the relatively low price of mini-solar PV

compared to EVs and the tendency for consumers to be less sensitive to operating costs than to the initial purchase cost.

This study is of considerable academic significance in that actual data for EVs and PVs were analyzed. However, this also is a weak point of this study, because the limitations of the data prevented us from conducting more sophisticated analyses. The results of this study can provide insights into how to explain consumers’ decisions to adopt innovative household durable goods as the EV and PV markets mature in the future.

Keywords: innovative durable household goods, electric vehicles, residential solar photovoltaics, innovation adoption factors

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Chapter 1. Introduction

1.1 Background and Motivation

The complete technology lifecycle should be considered when evaluating the success of an innovation [IRENA, 2017]. Of the enormous amount of technology innovations that have occurred in the energy sector since the 2000s, it is indisputable that electric vehicles and photovoltaics (PV), especially residential solar PV, are two of the most notable and game-changing innovations. As increasingly many consumers adopt each innovation and reach a “critical mass,” the diffusion of innovations will become self-sustaining [Rogers, 1962] and the transition of the energy system will take place.

Several agencies and companies are touting rosy prospects (Figure 1) [IEA, 2018; OPEC, 2017; BNEF, 2018; BP, 2018; ExxonMobil, 2018], but despite solid governmental support, the proportion of electric vehicles worldwide remains only at around 2.2% [IHS Markit, 2019], and the proportion of electric vehicles in Korea is only 0.24%. Some progress has been made on utility-scale solar PV. The levelized cost of electricity of solar PV has reached grid parity in certain countries, and solar PV also accounts for a significant proportion of installed capacity and generation. However, residential solar PV has not progressed to the same extent. It has been relatively successfully deployed in some countries, such as Australia, Germany, the United States, and Japan, but utility-oriented solar PV still predominates in most countries, including Korea.

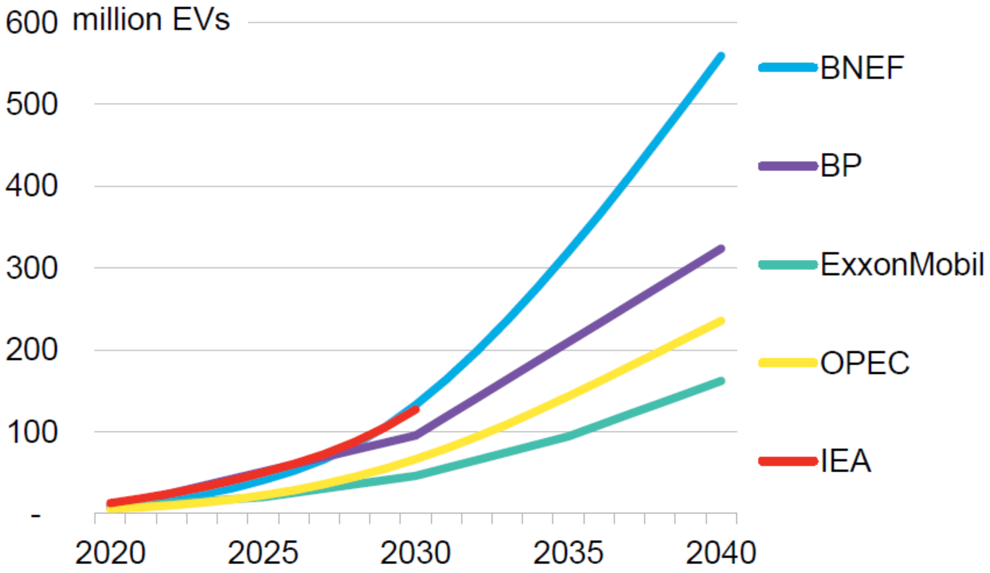

Figure 1. Electric vehicles outlook by 2040[1]

[1] Source: Bloomberg NEF

Residential solar PV is a decentralized energy resource (DER) that enables consumers to generate and consume electricity in the same place, thereby opening the doors to possible new business models and successive innovations in the energy industry, along with smart meters and battery storage. Recently, in countries such as Australia, battery companies such as Tesla and Sonnen have started to operate virtual power plants by connecting hundreds of thousands of residential solar PV installations and batteries. Electric vehicles also belong to DER in the broad sense, and although they are still in incubation, various ideas based on bi-directional power transfer such as V2G using electric vehicle batteries have been proposed by high-tech startups. The widespread adoption of innovative consumer technologies is a prerequisite to induce fundamental changes in the energy industry—that is, from a supplier-oriented system to a consumer-oriented system—as well as to fulfill the need for a low-carbon future due to climate change.

As mentioned earlier, several demand-side innovations have occurred in the past decades, especially in the residential sector. The efficiency of home appliances has improved tremendously, LEDs have shown superior performance in terms of performance and energy efficiency in the lighting field, and batteries have changed electricity, from a “use-it-or-lose-it” good into a storable good.

However, although they reduce energy use in the residential sector by a significant amount, it is difficult to say that high-efficiency home appliances and LEDs are game-changing innovations and that their adoption will lead to further changes in the energy industry. Batteries are a key technology in energy transition, but due to the stable power supply in Korea, battery installation in the domestic sector has not been feasible, and there has not been government support for battery installation in households (Table 1).

Therefore, this study investigated the factors associated with consumer adoption of electric vehicles and residential solar PV in Korea. From a methodological standpoint, this study is significant in that it used actual consumer adoption data. Several previous studies have analyzed factors associated with electric vehicles and residential solar PV adoption, but extensive research on this topic has not yet been conducted in Korea. Since the market has been only established within the last few years and is still in its infancy, there are no readily available data; therefore, most studies have analyzed stated preferences based on surveys or used simulations to make predictions about the future.

Table 1. Demand-side innovations in energy technologies in Korea

	Electric Vehicles	Residential Solar Photovoltaic	High-Efficiency Home Appliances	LED	Battery
Game-changing Technology	●	●	○	○	●
Available in Korea	●	●	●	●	x
Government support	●	●	◐	◐	x
Data availability	◐	◐	x	x	x

x No capability ○ Poorly suited ◐ Capable with limitation ● Well suited

However, setting aside the limitations of specific surveys themselves, there is a tremendous gap between people's intention to adopt and actual adoption; therefore, research based on revealed preferences is essential. For example, according to a survey of the Korea Consumer Agency regarding residential solar PV, 60.6% of 1,000 non-residential PV households said they were willing to install residential solar PV systems. However, as of 2017, the share of households with installed residential solar PV is only 0.23%. As the most prominent piece of evidence regarding this point, the proportion of detached houses in Korea in which it is possible to install residential solar PV with a size of 3 kW or higher was only 23.1% as of 2017, and the ratio is gradually decreasing over time throughout the nation. Therefore, this study analyzed revealed preferences to review whether the stated preferences of consumers actually lead them to decide to purchase the products, and if not, why.

Second, it is significant that this dissertation analyzes these issues in Korea. Of course, several cross-country analyses have been published in the previous literature. However, it must be kept in mind that each country has unique characteristics in terms of both electric vehicles and residential solar PV adoption, including both consumer characteristics and policy differences that affect the market. Therefore, a meaningful comparison between countries must consider these country-specific characteristics.

The automobile market is an excellent example of a market with very different characteristics across countries. Even in a comparison of Korea to China and Japan, which are its closest neighbors, there are considerable differences in the models, brands, size, and body type of cars that consumers prefer. These differences are even more evident when a comparison is made to other major countries around the world.

Each country also has unique circumstances regarding residential solar PV. In addition to variation in solar irradiance according to geographic conditions, the compensation that consumers receive from residential solar PV installations depends on electricity prices and schemes. In countries with low irradiance, such as those in northern Europe, because there is not much excessive generation, the main compensation mechanism is only to save on bills through self-consumption; therefore, unless the system price is low enough and retail rates are high enough, consumers do not have an economic incentive to install the system. In contrast, in Spain, there is excessive generation due to high irradiance, and the profits obtained by retrieving it are high; therefore, the payback period is sufficiently shortened without much governmental support. In Spain, after installation, consumers showed a pattern of selling electricity when the retail rate was high and using electricity from the grid when the retail rate was low.

Considering these two points, this study is significant as a starting point for analyzing what actually drives consumers to adopt electric vehicles and residential solar PV in Korea. Based on these findings, it will be possible to analyze the effects of relevant policies.

1.2 Research Frameworks and Thesis Outline

In this study, I investigate the factors associated with adoption of electric vehicles and mini-solar PV in households, which are consumer durable innovations in the energy industry. Due to the difficulty of acquiring data about the diffusion of technological innovations, the existing studies have mainly focused on surveys, and limited research has been based on actual data. However, survey-based research faces the limitation that consumers' purchasing intentions do not necessarily lead to purchase decisions. Thus, the aim of this study is to evaluate real-world conditions more accurately by analyzing actual decision-making factors using actual adoption data.

1.2.1 Innovation Adoption and Adopter Categories

The diffusion of a technological innovation is ultimately a question of whether consumers will adopt the innovation. Therefore, diffusion and adoption can be viewed as different perspectives on a single problem.

Research into the diffusion of technological innovations can be broadly divided into macro and micro perspectives. In the macro perspective, research focuses on when and how much innovations diffuse, with a consequent emphasis on forecasting the demand for new technologies [Massiani & Gohs, 2015; Chien et al., 2010; Guidolin & Mortarino, 2010], or the diffusion of technology at the country or firm level [Sierzchula et al., 2014; Marques et al., 2010; Lee et al., 2006; van Everdingen et al., 2005; Ganesh & Kumar, 1997].

In the micro perspective, research focuses on who adopts an innovation and why they do so. Because of its usefulness from the marketing point of view, the micro perspective has been extensively studied in the business literature. Within the field of innovation-diffusion studies, micro-perspective research at the individual or household level is relatively underrepresented compared to macro-perspective research. Micro-perspective studies are mainly based on surveys because it is difficult to obtain actual purchase status and related data. However, the importance of research based on actual purchasing data is being increasingly recognized because consumers' purchasing intentions do not necessarily lead to purchasing decisions.

Categorizing adopters according to the timing of adoption has frequently been addressed in the theoretical literature on diffusion. Although several classification methods have been proposed [Zhu and He, 2002; Valente, 1993; Mahajan et al., 1990; Rogers, 1983], a consistent finding is the existence of innovators/early adopters who embrace innovation in the early stages of technology diffusion and play a very important role in the subsequent diffusion process [Martinez et al., 1998].

Adopters can be grouped into categories, in such a way that a given category reflects individuals that are homogeneous with each other and heterogeneous with respect to all the other categories [Martinez et al., 1998]. Demographic and socio-economic variables have most frequently been examined in existing research [Cheng et al., 2004; Martinez et al., 1998; Martinez & Polo, 1996; Greco & Fields, 1991; Mahajan et al., 1990; Dickerson & Gentry, 1983; Ostlund, 1974]. While a few of these studies [Martinez & Polo, 1996; Ostlund, 1974] could not confirm that these variables significantly distinguished adopter categories, most of these studies [Cheng et al., 2004; Martinez et al., 1998; Greco & Fields, 1991; Mahajan et al., 1990; Dickerson

& Gentry, 1983] confirmed that demographic and socio-economic variables are significantly related to adoption behavior [Martinez et al., 1998]. In general, innovators are 1) financially stable, 2) capable of understanding and applying complex technologies, 3) capable of coping with uncertainties in new technologies, and 4) adventurous.

Independent adoption is vital in the early stages of the life cycle of a new product, simply because someone must initiate word-of-mouth communication. To reach a broad spectrum of the market within a reasonable time frame, more than just a handful of individuals are needed. To initiate market adoption, marketing planners need to be able to identify those people most likely to access the product or service independently (in the absence of word of mouth, presumably on the basis of mass-media input) and tailor appeals to them, so as to ensure that they hear about it, adopt it, and spread the word to others [McDonald & Alpert, 2007].

1.2.2 Consumer Durables Innovation and Households' Purchase Decision

It is important to identify which consumers buy the innovative consumer durable goods in the early stages of diffusion, innovators or early-adopters, in order to study whether those innovations will become dominant products that will spread to the entire population. Traditionally, neo-classical and ecological economists saw consumer demand as coming from private preferences and simply considered it as 'revealed' through their actual choice behavior. This view made it possible to analyze the economic system without considering preference formation or preference change. As a result, policies aimed at changing consumption patterns of people have become heavily relied on price instruments such as tax exemptions and subsidies rather than on policies that may affect people's preferences [Faber & Frenken, 2009].

Consumer durables are characterized by 1) high price, 2) long replacement cycles, and 3) time-consuming in information exploration. In marketing literature, it is sometimes said that the product involvement is high. The electric vehicles and mini solar power plant on veranda (hereinafter, mini-solar PV) analyzed in this thesis also share the same characteristics as these consumer durable goods. Moreover, purchase of the electric vehicle or mini-solar PV require high upfront cost, but continuous operation cost saving occurs over a long period of time.

1.3 Methodology

Two main points must be considered when analyzing count data. The first question is which probability mass function best describes the event occurrence probability, and the other is how to estimate the model to derive a consistent and optimally efficient estimator.

The standard model used as a starting point in count data analysis is the Poisson maximum likelihood estimation (MLE) model, which is explained in the next section in detail. The Poisson regression model contains the assumption of equidispersion, and is the most efficient estimator for MLE. However, the estimation is inconsistent if the probability mass function is not specified correctly.

In most cases where the equidispersion assumption is violated, overdispersion occurs rather than underdispersion. The main reason for overdispersion is that unobserved heterogeneity is not controlled properly. To overcome this problem, an unobserved heterogeneity term (ν) can be incorporated into the single parameter μ in a Poisson regression model.

1.3.1 Poisson Regression Model

A Poisson regression model is regarded as the fundamental starting point for the analysis of count data [Greene et al., 2012]. The Poisson distribution is exponential family of distributions. When the number of trials is very large and the probability of occurrence is very small in a binomial distribution, it can converge to a Poisson distribution. The basic Poisson regression model assumes that y given $\mathbb{x} \equiv (x_1, \cdots, x_K)$ has a Poisson distribution. The binomial distribution converges in Poisson regression model with increasing number of trials [Hilbe, 2011]. The probability mass function (pmf) of a Poisson distribution is as follows.

$$\mathrm{Prob}(\mathrm{Y} = y_i | X_i) = \frac{\mu^y e^{-\mu}}{y_i!}, y_i = 0, 1, 2, \cdots \qquad \text{Equation 1-1}$$

y_i: the number of events per unit of time or space

X_i: the regressors (explanatory variables)

μ: mean parameter

$$\mathrm{E}[y_i | X_i] = \exp(X_i' \beta) = \mu_i \qquad \text{Equation 1-2}$$

$$\mathrm{var}[y_i | X_i] = \omega_i \qquad \text{Equation 1-3}$$

$$\mu_i = \omega_i \qquad \text{Equation 1-4}$$

μ_i is the single parameter in Poisson regression model and represents the mean and the variance of y_i.

The standard estimator for the Poisson regression model is the MLE. The log-likelihood function is shown below.

$$\mathcal{L}(\beta) = \sum_{i=1}^{n} \{y_i X_i'\beta - \exp(X_i{}'\beta) - \ln y_i!\} \qquad \text{Equation 1-5}$$

Poisson regression models are generally used to model count data, but sometimes it is more appropriate to model for the rate of count instead of count data themselves, especially when the variable to be modeled is not in the same dimension. For example, it is not appropriate to model the same occurrence six events in one year and six events in 10 years. Similarly, taking the electric vehicles case as an example, modeling by setting the dependent variable equally to 100 adoptions out of 10,000 households and those out of 20,000 households for one year is not appropriate, it is needed to control the total number of households. Therefore, in this study, we designed a Poisson regression model with dependent number of households/year·household as a dependent variable.

In Equation 1-2 above, when y_i is the probability of electric vehicle adoption by i first-tier administrative division and X_i is the explanatory variable vector that affects electric vehicle adoption by i first-tier administrative division, y_i can be expressed as follows.

$$y_i = \frac{N_i}{HH_i} \quad \text{Equation 1-6}$$

N_i: the number of households which adopts EVs in i first-tier administrative division
HH_i: total number of households in i first-tier administrative division

$$y_i = \frac{N_i}{HH_i} = \exp(X_i'\beta) \quad \text{Equation 1-7}$$

$$N_i = HH_i * \exp(X_i'\beta) = \exp(\ln(HH_i) + X_i'\beta) \quad \text{Equation 1-8}$$

In statistics, the variable such as the total number of households in the first-tier administrative division is called as an exposure variable. The exposure variable was included in the model in the form of $\ln(HH_i)$ where the natural logarithm was taken as the coefficient was restricted to 1 as above.

1.3.2 Overdispersion

Equality of the mean and variance is called equidispersion and this property is frequently violated in real-life data [Cameron & Trivedi, 2013]. In most cases where the equidispersion assumption is violated, overdispersion occurs rather than underdispersion. The main reason for overdispersion is that unobserved heterogeneity is not controlled properly. If one uses a basic Poisson regression model despite overdispersion, the standard error is underestimated and an insignificant explanatory variable is incorrectly shown as a significant predictor in the analysis results. Thus, it is important to set up the correct model. The first step in doing so is to check whether the data are overdispersed.

The simplest method to check for overdispersion is to compare the variance of the sample mean and the dependent count variable. If the sample variance is more than twice as large as the sample mean, the data is likely to be overdispersed even after an analysis including the regressors. This is especially true for cross-sectional data, where regressors usually account for less than half of the variation [Cameron & Trivedi, 2013].

Overdispersion can also be determined by statistical calculations. If dividing the Pearson statistic by the degrees of freedom yields a value exceeding 1.25, overdispersion is present. If the number of observations is large, overdispersion is considered to be present if this ratio even exceeds 1.05 [Hilbe, 2011].

When the maximum likelihood method is used for estimation, overdispersion can be determined by comparing restricted and unrestricted models through the Log-likelihood Ratio, Wald, and Lagrange Multiplier tests. The restricted model is the Poisson model, the unrestricted model is the negative binomial model, and the null hypothesis is equidispersion.

1.3.3 Negative Binomial Regression Model

Negative binomial regression is a count data regression model that allows additional dispersion by alleviating the assumptions of Equation 1-4. Let us assume the variance function shown below.

$$\omega_i = \omega(\mu_i, \alpha) \qquad \text{Equation 1-9}$$

ω_i: the conditional variance

ω: some specified function $\omega(\cdot)$

α: a scalar parameter

The general variance function is

$$\omega_i = \mu_i + \alpha\mu_i^p \qquad \text{Equation 1-10}$$

where the constant p is specified. The Poisson regression model is the special case of this with $\alpha = 0$. In the NB1 variance function by Cameron and Trivedi (1986), p is set as 1, which is why the model is named NB "1". Similarly, the NB2 variance function sets $p = 2$.

NB1: $\omega_i = \mu_i + \alpha\mu_i$ Equation 1-11

NB2: $\omega_i = \mu_i + \alpha\mu_i^2$ Equation 1-12

The probability mass function of a standard negative binomial model [Hausman, Hall, Griliches, 1984] is shown below.

$$\Pr(Y_{it} = y_{it}|\mathbb{x}_{it}, \delta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)}\left(\frac{1}{1+\delta_i}\right)^{\lambda_i}\left(\frac{\delta_i}{1+\delta_i}\right)^{y_{it}}$$ Equation 1-13

For panel data, fixed- and random-effect models can be considered. A fixed-effect model considers only variation within each individual, and has the advantage of controlling for the heterogeneity of each individual. A random-effect model considers between-variation and within-variation, and has the advantage of resulting in less information loss than a fixed-effect model. Moreover, since each individual's time-invariant variables cannot be identified in a fixed-effect model, it is advantageous to use a random-effect model when there are time-invariant explanatory variables and estimating the coefficients of these variables is important for the purpose of the analysis.

Fixed-effects enter additively in linear models and multiplicatively in nonlinear models. Estimating a consistent β in a small panel is challenging because it is necessary to control for the infinite number of fixed effects due to the assumption of the asymptotic theory that $n \to \infty$. In a linear model, this is possible. For a Poisson model, this is also possible because it has no incidental parameters problem (IPP) [Lancaster, 2002; Blundell et al., 1999]. However, for some nonlinear fixed-effect panel data models, this is not possible because of the IPP and doing so may yield an inconsistent β_{ML}. Hsiao (2003) demonstrated the inconsistency of the MLE for β in this case, though it disappears as $T \rightarrow \infty$. However, Greene (2004) suggested that for $T \geq 5$, the bias may not be too severe.

Hausman, Hall, and Griliches (1984) proposed a negative binomial fixed-effect model. The mean (μ_i) (dispersion parameter) follows the negative hypergeometric distribution. The parameters are estimated by conditional MLE. Allison & Waterman (2002) argued that the HHG (1984) model is, strictly speaking, not a true fixed-effect model. In other words, it is not a fixed-effect analog of a random-effect negative binomial regression model. For more details, please refer to Allison & Waterman (2002).

Many researchers have suggested various alternatives [Allison & Waterman, 2002; Guimaraes, 2008; Greene, 2007]. Among those, two simple approaches are preferred. One is the simplest approach, suggested by Cameron and Trivedi (2013), is to jointly estimate the coefficients of explanatory variables and individual-specific fixed effects. Due to a full set of individual-specific dummy variables incorporated, this method is computationally demanding especially the number of individuals is large. The other is to estimate a random effects negative binomial model with all the time-varying covariates expressed as deviations from the individual-specific means. This alternative is advantageous in respect that it does not require individual-specific dummy variables so that the estimated results would not suffer from IPP and that it is not computationally demanding.

The datasets used in this study are short panels (large N, small T) that cover only five years for both electric vehicles (EV) and PV cases. According to Greene (2004), the bias from the IPP of a fixed-effect negative binomial model in this analysis seems not to be too severe. Hence, two model were applied separately. Firstly, a fixed-effect Poisson model (FEP model) was used to guarantees the consistency of estimates. After that, to consider overdispersion characteristics of datasets, I ran the random-effect negative binomial model with a full set of individual-specific dummy variables (RENBD model) as a true fixed-effect negative binomial model and compared the results with that of the prior one. In the case of PV case, because N is too large compared to T (N=25), the iteration process did not converge. In that case, I applied the "hybrid method" suggested by Allison (2012) of which applies random effect negative binomial model with all the time-varying covariates de-meaned from the individual-specific means (RENBM). By using modified version of RENB model which in fact are fixed effect models, I was able to get the increased efficiency and the ability to model the effects of constant-within-group variables.

1.3.4 Models Comparison

In the process of choosing the best model, there is a tradeoff between fit, parsimony, and ease of interpretation [Cameron & Trivedi, 2010]. Adding more parameters usually results in a good model fit for the data. The purpose of the goodness-of-fit test is to test whether the data follow the distribution set in the study, that is, to test whether the model is suitable or not. For that reason, improving the goodness-of-fit by increasing the number of parameters that are not very relevant for describing the data makes no sense, and also makes it difficult and unclear to interpret the results. Therefore, a researcher needs to find out the balance among these components, which gives optimal parsimony. Reviewing many previous studies, related data, and domestic market conditions, the author selected convincing variables that are considered to have an important influence on each innovation adoption. After limiting the explanatory variables to those that were crucial, the best model was selected through the goodness-of-fit test of each model.

Poisson model is nested in a negative binomial model, so a likelihood ratio (LR) test is possible. As mentioned in 1.3.3, the Poisson model can be seen as a case where $\alpha = 0$ in Equation 1-10. To test whether α is 0—that is, whether a Poisson model is suitable—the LR test can be performed using $\alpha = 0$ as a restricted model which is a Poisson model, and as an unrestricted model which is a negative binomial model [Cameron & Trivedi, 2013].

$$T_{LR} = -2[\mathcal{L}(\tilde{\theta}_r) - \mathcal{L}(\hat{\theta}_u)] \qquad \text{Equation 1-14}$$

T_{LR}: LR test statistics

$\tilde{\theta}_r$: the restricted MLE

$\hat{\theta}_u$: the unrestricted MLE

The LR statistics is distributed asymptotically as $\chi^2(h)$, where h refers to nonredundant constraints. If there is a high chi -square value, the null hypothesis that α is zero is rejected, and therefore a negative binomial regression model would seems to be appropriate.

The standard method for making comparisons between non-nested ML models is to use information criteria, the most commonly used of which are the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). They are also useful in comparing the models with different number of parameters each other. Each is calculated as follows.

$$\text{AIC} = -2\ln L + 2k \qquad \text{Equation 1-15}$$

$$\text{BIC} = -2\ln L + (\ln n)k \qquad \text{Equation 1-16}$$

L: the maximized value of the likelihood function of the model

k: the number of parameters in the model

(that is, the number of explanatory variables including the constant term)

n: the number of observations

The larger the log-likelihood, the better. The smaller the AIC and BIC, the better. Adding one more explanatory variable to the same model increases the likelihood. This follows the same logic as increasing the R-squared value by adding an explanatory variable in linear regression. However, if the added regressor is not an important variable that explains the characteristics of the data well, although the goodness-of-fit may be slightly improved, we cannot tell whether the model has improved in terms of parsimony and ease of interpretation. Therefore, by adding a penalty term of $2k$ to the AIC and $(\ln n)k$ to the BIC, it is possible to balance the model selection criteria of goodness of fit, simplicity, and ease of analysis. As n and k increase, the penalty increases, and the penalty of the BIC is greater than that of the AIC when n is 8 or higher.

1.3.5 Issues Regarding Multicollinearity

This section discusses the multicollinearity problem resulting from probable correlation between explanatory variables. By definition, multicollinearity is the existence of one or more linear relations among the explanatory variables and the sampling distributions of the coefficient estimators may have such large variances by the problem [Judge et al., 1988]. In my model, two decisive explanatory variables are the price of the innovative durable goods and technical attributes of the product. Due to the properties of the innovative durable goods, technological excellence is one of the key attributes of those products so that there is a chance of having linkage between the price and the technical attributes variables.

Multicollinearity is a common problem in empirical econometrics. In fact, it is very strong constraint to assume that all independent variables are completely independent of each other.

This is due to the fact that the data are generated by the functioning of the economic system, and the collinearities reflect merely the nature of that system [Johnston, 1984].

In general, the following cases do not concern the correlation between explanatory variables: 1) in cases where the variables with high VIFs are control variables, and the variables of interest do not have high VIFs, 2) in cases where the high VIFs are caused by the inclusion of powers or products of other variables, and 3) in cases where the variables with high VIFs are indicator (dummy) variables that represent a categorical variable with three or more categories [Allison, 2012]. In this study, price and range are the variables of interest, so they are not included in the above three cases.

However, even if the variables with collinearity are the specific focus of the research, as in the case of this study, many scholars explain that there is no need to pay much attention to this [Clyde, 2015; Silva, 2015; Giles, 2011; Goldberg, 1991]. This is because multicollinearity is a property of the dataset itself, and we have nothing to do resolve the problem.

In case of multicollinearity having been found, there is no special remedy, so in many cases, the problem is solved by dropping the less important variable among the set of explanatory variables detected as having correlation with other variables. However, there is no theoretical rationale to remove one variable arbitrarily due to the data showing multicollinearity in the model, which has already been theoretically set. Although solutions such as Principal Component Analysis (PCA) are also being proposed [Kendall, 1957], as this methodology artificially orthogonal transforms high-dimensional data to low-dimensional ones, the meaning of explanatory variables is not clear, so it is very abstruse to interpret the results.

There are even scholars who are skeptical about testing whether multicollinearity exists and how severe it is [Judge et al., 1988; Goldberg, 1991]. In Judge et al. (1988), this issue is discussed in more detail. In general, if the simple correlation between two variables is 0.8 or 0.9 or higher, there is a probability that multicollinearity may occur, but these cutoff points themselves are arbitrary. He also pointed out that pairwise correlation does not give any insight when more complex interrelationships exist between the two variables. In using other methods, such as variance inflation factors, Theil's multicollinearity effect, and matrix decomposition, there is no rationale for fixing a cutoff point to see if it is okay or not. They are defined by just a rule of thumb. Therefore, he emphasizes that any of these methods are completely safe to test multicollinearity. Another multicollinearity testing methodology [Farrar & Glauber, 1967] is based on a strong assumption away from reality (multivariate normality of regressors), so its effectiveness may be suspected [Giles, 2011].

Goldberg insisted that the problem due to multicollinearity is just similar level as the problem arisen from small sample size in empirical analysis and also that the reason why people concern it unnecessarily is merely because the term multicollinearity is “an exotic polysyllabic” so that using the term makes them feel erudite themselves. Allison also mentioned that if the model is correctly specified (with the right covariates and the right functional form) then the issue is, in fact, “primarily a matter of statistical power” [Allison, 2012]. He insisted that since the point is the variance of the estimated coefficient and the multicollinearity is possible sources of high variance, the preferred thing to estimate the coefficient is not low collinearity per se. In addition, the larger the sample, the less likely multicollinearity will actually be problematic.

These threads of discussions show why other problems in the empirical econometric analyses such as heteroskedasticity or endogeneity have exact tests to test its existence and typical solutions for it while multicollinearity has not been reached on consensus whether we would be able to test multicollinearity by which methods and even the problem actually matters itself.

Nevertheless, still some researchers concern about that issue, I tried testing multicollinearity for my two datasets in each case to figure out the existence and the severity of it. In the next step, I dropped the variable with multicollinearity, if any, from the model and analyzed again. The comparison of the results from before and after dropping the explanatory variables will be shown in each chapter.

To test multicollinearity, I choose variance inflation factors (VIF) method because of its simplicity and clarity. VIFs are divided into centered VIFs and uncentered VIFs. In the case of centered VIFs, it may be fail to discover collinearity by a constant term [Belsley, 1991]. To solve this problem, uncentered VIFs can be used. Uncentered VIFs treat constants as a legitimate explanatory variable in a regression model, allowing constant terms to have VIF values. The formula for each centered and uncentered VIFs is as follows.

$$VIF_c(x_j) = \frac{1}{1 - \hat{R}_j^2} \quad \text{Equation 1-17}$$

$\hat{R}_j^2$: the square of the centered multiple correlation coefficient that results when x_j is regressed with intercept against all the other explanatory variables

$$VIF_{uc}(x_j) = \frac{1}{1 - \tilde{R}_j^2} \quad \text{Equation 1-18}$$

$\tilde{R}_j^2$: the square of the uncentered multiple correlation coefficient that results when x_j is regressed with intercept against all the other explanatory variables including the constant term

Since there is no strict guideline that multicollinearity exists when VIFs are within a certain range, most analysts rely on the rules of thumb to determine the value of VIFs [Chatterjee & Hadi, 2006]. According to this rule of thumb, multicollinearity may exist when the value of VIFs exceeds 10 [Jansson et al., 2010; Hair et al., 2006]. In the case of conservative scoping, the threshold is sometimes set to 30. More clearly, if VIFs have a high value as described above and significant changes in estimated coefficients occur when the explanatory variable suspected of multicollinearity is removed, this can be considered as strong evidence of multicollinearity. Of course, there is still no theoretically established rule on how significant a significant change should be.

1.4 Organization of the Thesis

The organization of the thesis is as follows. Chapter 2 presents an analysis of the determinants of electric vehicle adoption by domestic consumers based on the research framework and methodology described in Chapter 1. It further examines policies to promote electric vehicle adoption in Korea and the specificity of the domestic market, and reviews the findings of existing studies to obtain useful lessons from them. The next step is to conduct an empirical analysis using the selected variables and acquired data, and to identify the determinants of electric vehicle adoption by domestic consumers based on the results of the analysis. Policy implications are derived as well.

In Chapter 3, in the same manner as Chapter 2, I investigate what drives people in Seoul to install veranda-type mini-solar PV (hereafter, mini-solar PV). After reviewing the background, progress, and status of the introduction of the mini-solar PV diffusion policy in Seoul, ways to fill the gap are identified by reviewing prior research. The next step is to conduct an empirical analysis using the selected variables and acquired data, and to identify the determinants of mini-solar PV adoption by residents of Seoul based on the results of the analysis. Policy implications are also derived.

Chapter 4 summarizes these two analyses and draws overall conclusions. Similarities and differences between the two cases of electric vehicles and PV are discussed. Directions for further research as well as the contributions and significance of the dissertation, are also presented in this chapter.

Chapter 2. Electric Vehicle Adoption by South Korean Households

2.1 Background

The electric vehicle[2] (EV) market in the Republic of Korea formed somewhat later than those in most developed countries, but the domestic market is nonetheless rapidly increasing. Apart from the late formation of the EV market, Korea has already enacted the “Act on the Promotion of Development and Distribution of Environment-friendly Automobiles” in 2004, predicting the era of EVs. Through this act, the government tried to establish an institutional foundation for the development and dissemination of environment-friendly vehicles and secure future advanced technologies.

The specific policy for the activation of the EV industry and diffusion of EVs began as the Lee Myung-bak government announced “Low Carbon Green Growth” as a slogan for National growth strategy. In 2009, the “Activation Plan for the Electric Vehicle Industry” was announced, which included tasks such as technological development, demonstration projects, and phased promotion of EV diffusion. Ministry of Knowledge Economy (currently Ministry of Trade, Industry and Energy) mainly has been responsible for technology development, and Ministry of

[2] Electric vehicles (EVs) refers to battery electric vehicles (BEVs), excluding plug-in hybrid electric vehicles (PHEVs) and hybrid electric vehicles (HEVs) in this study.

Environment has been in charge of the overall diffusion of EVs. Investigating R&D data for EV technology acquired through information disclosure, it does not appear that there has been a control tower that manages overall research and development programs regarding EVs. Rather, several organizations have been involved in R&D for EVs such as Korea Evaluation Institute of Industrial Technology (under Ministry of Trade, Industry and Energy), Korea Agency for Infrastructure Technology Advancement (under Ministry of Land, Infrastructure and Transport), and Center for Environmentally Friendly Vehicle (under Ministry of Environment). Examining the list of tasks which are in progress or were completed, we cannot say that R&D has been extensively conducted in terms of R&D scale and core technology development, compared to the early established legislation and policy roadmap for supporting technology development and diffusion of EVs.

Ministry of Environment began providing subsidies for purchasing EVs to local governments and public institutions in 2011. After supporting the public sector for two years as a demonstration, a full-scale EV diffusion policy was implemented for the private sector from 2013. Consumers who purchase EVs were provided with subsidies to purchase EVs and subsidies to install non-public[3] level 2[4] chargers, and tax benefits such as individual

[3] Non-public chargers refer to not-freely-accessible chargers that are not registered on the Ministry of Environment Electric Vehicle Charging Stations website, a comprehensive system providing the location of all public charging stations in Korea. Public chargers can be searched for on the website and are publicly accessible.

[4] Generally, level 2 chargers are known as “slow chargers” in Korea, but in this study, it is labeled “level 2 chargers” to avoid any confusion.

consumption tax and acquisition tax were also given. The total amount of these financial aids is significantly high compared to other countries, and as of 2017, Norway and South Korea are the only countries with a purchase subsidy of more than $10,000 [Ministry of Trade, Industry and Energy Korea Trade Commission & P&P Patent & Law Firm, 2017]. The total number and the share of registered EVs in Korea from 2011 to 2019 are shown in Figure 2.

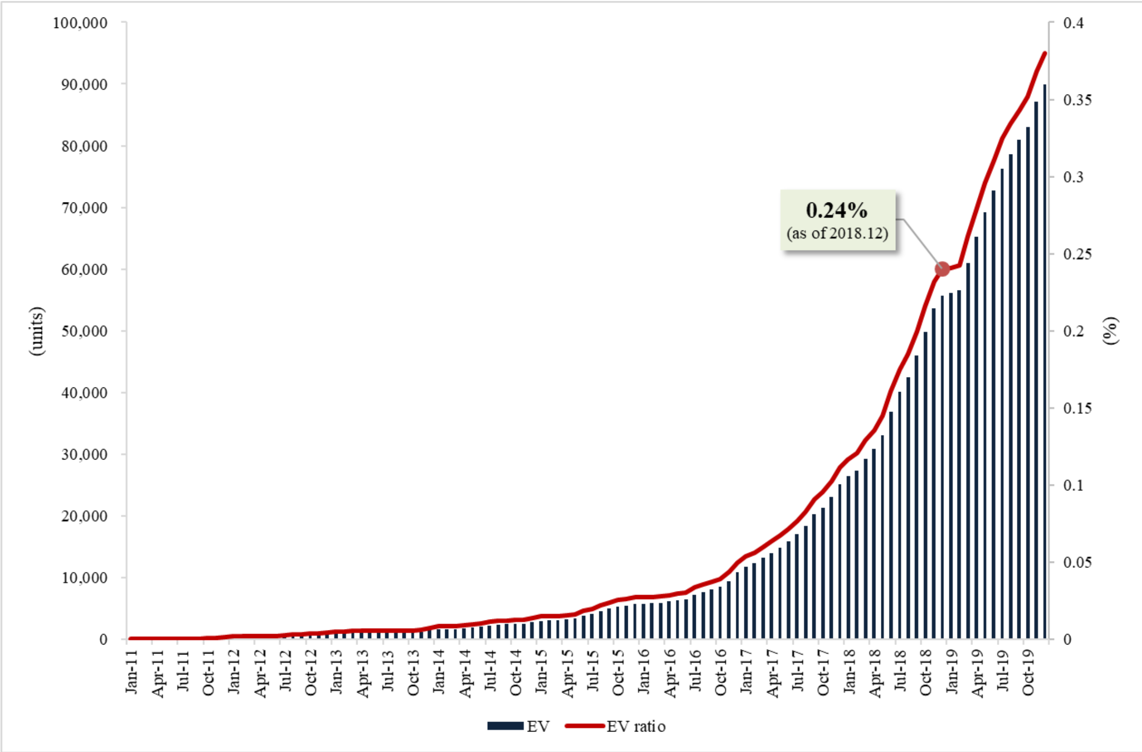

Figure 2. Total registered electric vehicles (2011-2019)[5]

[5] Source: Ministry of Land, Infrastructure and Transport

Of particular note, in 2017, the annual sales of EVs increased twofold compared to the figures in 2016, with over 13,800 vehicles sold. Experts have stated that the announcement that the Ministry of Environment would reduce EV purchase subsidies in 2018 compared to 2017 encouraged consumers who wanted to benefit more from the subsidy to buy EVs ahead of schedule, leading to the surge of EV demand in 2017 [MOTIE & KEA, 2017]. Concerns about the possibility of pouring cold water on the growth of the EV market were raised. As the Korean EV market was still in the early stages of market development, it seemed to be a bad decision for the government to cut EV subsidies. However, this dire prediction has not materialized, as 11,866 EVs were sold in only the first half of 2018, close to the total number of EVs sold in 2017, and many anticipate that the EV sales volume in 2018 will exceed 20,000 vehicles. This means that the market has responded unexpectedly to the curtailment, although many studies have pointed out that purchasing subsidies are among the most critical factors driving EV adoption [Hardman et al., 2017; She et al., 2017; Vassileva & Campillo, 2017; Mersky et al., 2016; Sang & Bekhet, 2015; Zhang et al., 2013; Zhang et al., 2011].

EVs need charging stations to fill up their batteries. However, the behavior of the EV owners regarding “refilling” must be significantly different from that of international combustion engine vehicle (ICEV) owners, since the current technology of charging an EV still requires from 30 minutes to several hours to reach a full charge. At the early stages of EV market formation, considerable uncertainty surrounding market circumstances has made private operators reluctant to enter the EV charging market. Accordingly, there is a growing demand from the automobile industry, the media, and academia for the government to expand the charging infrastructure.

However, the question arises of whether providing sufficient charging infrastructure would lead to a dramatic increase in the adoption of EVs. As mentioned above, although the subsidy was reduced in 2018 compared to 2017, the sales volume of EVs nearly doubled. Thus, the decrease in the subsidy did not decrease the annual sales of EVs. Furthermore, 19,304 non-public level 2 chargers have been installed supported by local governments through the Korea Environment Corporation as of 2017, yielding a total of 21,914 combined with the public fast chargers installed by the Ministry of Environment and other public institutions. The cumulative number of registered EVs through 2017 is 25,593. Therefore, it would seem that the charging infrastructure is not actually in short supply.

The Korean government is aiming to boost the EV market share to 6.3% of new car sales by 2025. To achieve this goal, it is imperative to analyze the factors that determine EV adoption with actual data, and the results of this study can provide policy implications for other countries where the EV market has not yet formed. Therefore, this study aims to analyze the determinants of EV adoption based on actual data starting in 2013, the year of the EV adoption policy implemented for the public in Korea.

I would like to clarify the contribution of this chapter that it analyzed actual sales data (i.e., revealed preference). As the EV market is emerging, the amount of publicly available data is somewhat lacking. For this reason, existing studies in the literature mostly carried out surveys regarding the specific circumstances in which consumers would buy EVs. However, there is an "attitude-action gap" among consumers in emerging markets, especially for green innovation products [Lane & Potter, 2007; Kollmuss & Agyeman, 2002]. Even if consumers have a tendency to purchase eco-friendly products based on environmental protection or economic feasibility, there is a large gap between the intent to purchase and the actual purchase. For instance, according to a recent survey of 500 adult men and women in Korea, 94% of respondents responded "yes" when asked whether they would be willing to buy an EV in the future. Meanwhile, the share of EVs among all registered non-commercial vehicles as of 2018 in Korea was only 0.3% [MOLIT, 2019]. This huge gap between the two figures is an example of the "attitude-action gap." Therefore, when examining the key drivers of EV adoption, it is more appropriate to use revealed preferences—that is, actual sales data—not stated preferences. Although the observations do not represent a significant number, the data used herein are the best figures that are publicly available, since EV adoption by general consumers in Korea started in 2013 and the minimal unit of data from the National Statistical Office is at the municipality level. Moreover, it is worthwhile to review the key drivers of EV adoption in Korea in the early stages of the introduction of EVs.

2.2 Literature Review

Due to the nature of this emerging market, there is an obvious limit to the data regarding the EV that can be obtained. Therefore, the majority of previous studies have analyzed the stated preference of consumers through surveys, mainly in countries in which EVs are relatively more deployed than others. For example, the US [Lane et al., 2018; Carley et al., 2013; Egbue & Long, 2012; Hidrue et al., 2011; Brownstone et al., 2000], China [Wang et al., 2018; Wang et al., 2017; Zhang et al., 2013], Norway [Bjerkan et al., 2016], Sweden [Vassileva & Campillo, 2017; Langbroek et al., 2016], Netherlands [Hoen & Koetse, 2014], the UK [Schuitema et al., 2013], Germany [Plötz et al., 2014], and Spain [Junquera et al., 2016] were studied and some research has been conducted from a global perspective [Hardman et al., 2016; Lieven, 2015]. In the eco-car market, the consumer's "attitude-action gap" is significant [Lane & Potter, 2007; Kollmuss & Agyeman, 2002], so research based on stated preferences has limitations in that these preferences are often far from what is actually happening in the actual market [Sierzchula et al., 2014; Brownstone et al., 2000]. Thus, there is a growing need for research based on revealed preferences.

Several studies presenting empirical analyses of revealed preferences can be found [Wang et al., 2019; Kim et al., 2017; Sierzchula et al., 2014]. However, as the characteristics of the automobile market vary from country to country, it is more appropriate to analyze one country during a certain period than to compare many countries at once. A few studies have examined revealed preferences in Norway and the US [Wee et al., 2018; Mersky et al., 2016]. As these two countries are the leading EV markets, the likelihood of obtaining comprehensive data is strong.

By and large, EV adoption in Korea has not been studied comprehensively, because little time has passed since EVs have been sold in earnest and the relevant policies have been implemented. Even so, it is relatively difficult to find any existing studies that analyzed the factors related with adoption of EVs. In recent studies, EV diffusion was reviewed based on stated preferences [Byun et al., 2018; Kim et al., 2018; Kwon et al., 2018].

A conjoint analysis has dealt with consumers' preferences for EVs and fuel-cell vehicles with regard to their adoption potential [Byun et al., 2018]. The questionnaire was administered to a driver group and a non-driver group. For both groups, the vehicle purchase price was the most crucial factor for vehicle selection. The second most important factor was the number of charging stations in the driver group and CO_2 emissions in the non-driver group. However, on the basis of their analysis, the authors calculated the market share of EVs in 2016 as 13.52%, which is far from the actual value of 0.72%.

In [Kwon et al., 2018], consumers' perceptions of EV policies were analyzed among actual EV users residing in Jeju Special Self-Governing Province (hereafter, Jeju) in Korea. In contrast with the existing literature on the survey of potential users [Jensen et al., 2013; Hidrue et al., 2011], the marginal willingness-to-pay for charging time reduction was very high, indicating that actual users felt very uncomfortable about charging EVs.

Using revealed preference data from Korea has two main advantages. First, the amount of the purchase subsidy and the vehicle tax exemption for EVs in Korea does not depend on the purchaser's income level. Therefore, it is possible to examine the effect of financial incentives on EV adoption more clearly than is possible when using data from countries that give financial incentives depending on the recipient's income. Secondly, revealed preference data capture what is actually happening in the market better than stated preference data because consumers' stated willingness to pay does not always match their actual purchases.

The order of this study is as follows. In Chapter 2.3, data and variables are explained, and then results are presented in 2.4. Finally, I suggested the summary and discussions in 2.5.

2.3 Data and Variables

In this study, I analyze factors influencing EV diffusion based on data from 17 first-tier administrative divisions in Korea. Korea's EV diffusion policy focused on a strategy to create an initial market through demonstration projects and public sector-oriented pilot distribution from 2010 to 2012. Since the policy that was implemented for the public started, practically speaking, in 2013, the analysis period was set to run from 2013 to 2017.

Seven explanatory variables were selected because they showed a statistically significant influence on EV diffusion in previous studies (Table 2). These explanatory variables can be classified into EV-intrinsic factors and EV-extrinsic factors. EV-intrinsic factors are classified into user-intrinsic and user-extrinsic attributes, while EV-extrinsic factors are categorized into technical and non-technical attributes (Figure 3). In addition to the variables discussed in this study, other factors might affect EV diffusion. However, the analysis was limited to these seven variables because including a large number of less critical variables could dilute the results as explained in chapter 1.3.4. The descriptive statistics of the explanatory variables are presented in Chapter 2.4 (Table 4).

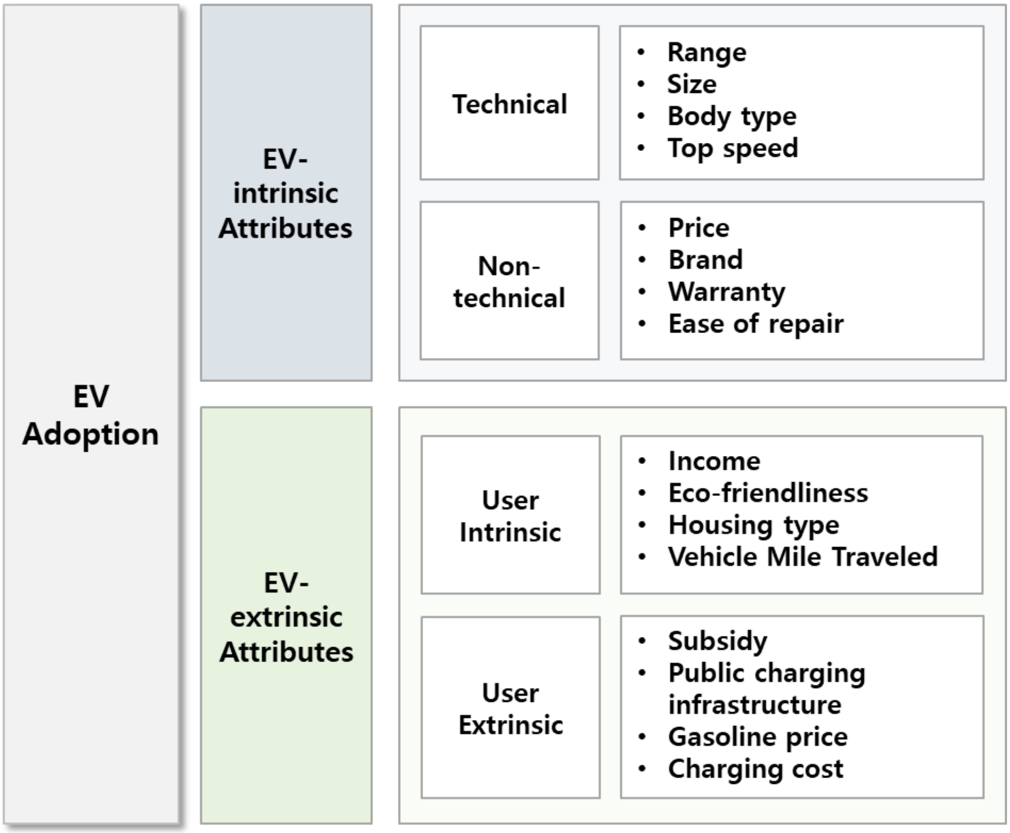

Figure 3. Conceptual framework of key attributes in EV adoption

Table 2. Explanatory variables for EV adoption

Group	Attributes	Variables	Literature
EV-intrinsic factors	Technical	Range	She et al. (2017), Hardman et al. (2016), Langbroek et al. (2016), Junquera et al. (2016), Sang & Bekhet (2015), Krupa et al. (2014), Carley et al. (2013), Jensen et al. (2013), Schuitema et al. (2013), Christensen et al. (2012), Egbue & Long (2012), Hidrue et al. (2011)
	Non-technical	Price	Hardman et al. (2016), Junquera et al. (2016), Langbroek et al. (2016), Carley et al. (2013), Zhang et al. (2013), Christensen et al. (2012), Hidrue et al. (2011),
EV-extrinsic factors	User-intrinsic	Income	Mersky et al. (2016), Sang & Bekhet (2015), Zhang et al. (2013), Zhang et al. (2011)
		Eco-friendliness	Vasilleva & Campillo, (2018), Hardman et al. (2016), Hidrue et al. (2011)
	User-extrinsic	Subsidy	Hardman et al. (2017), She et al. (2017), Vassileva & Campillo (2017), Mersky et al. (2016), Sang & Bekhet (2015), Zhang et al. (2013), Zhang et al. (2011)
		Public charging infrastructure	She et al. (2017), Vassileva & Campillo (2017), Hardman et al. (2016), Junquera et al. (2016), Langbroek et al.(2016), Mersky et al. (2016), Sang & Bekhet (2015), Krupa et al. (2014), Carley et al. (2013), Jensen et al. (2013), Hidrue et al. (2011)
		Gasoline price	Vassileva & Campillo (2017), Hardman et al. (2016), Sang & Bekhet (2015), Plötz et al. (2014), Carley et al. (2013), Schuitema et al. (2013), Zhang et al. (2013), Christensen et al. (2012), Hidrue et al. (2011), Zhang et al. (2011)

2.3.1 EV-intrinsic Variables

2.3.1.1 Range

Technical attributes refer to the technologically innovative attributes of EVs themselves. The commonly analyzed technical attributes of EVs are the possible driving distance per single charge, electricity efficiency (km/kWh), and the available number of models. First, the possible driving distance per single charge is an important factor that is always considered at the first stage when discussing the adoption of EVs [Kim & Heo, 2019; Jensen et al., 2013]. Because of the short driving distance per full charge, preparations need to be made for refueling EVs. Furthermore, although EVs were first invented more than 30 years before ICEVs, they have not played a remarkable role in the market, although the release of the Nissan Leaf in 2009 drew considerable attention.

Secondly, electricity efficiency (km/kWh) is a concept that corresponds to the fuel efficiency of ICEVs. Fuel efficiency is measured with reference to the distance traveled using the same amount of fuel, while electricity efficiency is measured based on the distance that can be traveled using a certain amount of electricity. Lastly, it is reasonable to assume that the presence of a greater variety of products on the market will increase the likelihood of consumers finding a satisfactory car. Needless to say, extensive efforts into R&D are needed to diversify the product line. In [Higgins et al., 2017], the authors divided Canadian consumers into groups according to the vehicle body type they anticipated buying for their next vehicle (economy, intermediate-size sedan, full-size sedan, luxury sedan, minivan/crossover, sport utility vehicle (SUV), and pickup truck), and unlike the HEVs, each group showed different preferences for PHEVs and BEVs. I expect that it will be easier for consumers to find the cars that meet their needs if there is sufficient variety in the body type of available EVs.

Among three candidates, the average of driving range of each EV model available in a given year was used to represent this technical attribute variable in consideration of representativeness and data availability. The driving range is based on the distance traveled at room temperature (20–30℃) with a full charge. The driving range increased by approximately 85% during the analysis period, from 120 km per full charge to 223 km. Of particular note, in 2017, EV models with an extended range such as the BMW i3 (200 km), GM Bolt (383 km) and Tesla Model S 90D (470 km) were launched, substantially increasing the average driving range of EV models (Table 3).

Table 3. Electric vehicles in Korea: models, prices, and specifications[6]

Year	Model	Driving range[7] (km)	Battery capacity (kWh)	Price (10K KRW)	Battery efficiency (km/kWh)
2013	KIA RAY EV	91	16.4	3500	5.0
	Renault-Samsung SM3 Z.E. EV	135	24	4250	4.4
	GM SPARK EV	135	21.4	3990	5.6
2014	KIA RAY EV	91	16.4	3500	5.0
	Renault-Samsung SM3 Z.E. EV	135	26.6	4250	4.4
	GM SPARK EV	135	21.4	3990	5.6
	KIA SOUL EV	148	27	4250	5.0
	BMW i3	132	21.3	6320	5.9
	Nissan LEAF	132	24	5480	5.4
2015	KIA RAY EV	91	16.4	3500	5.0
	Renault-Samsung SM3 Z.E. EV	135	26.6	4190	4.4
	GM SPARK EV	135	21.4	3990	6.0
	BMW i3	132	21.3	6320	5.9
	KIA SOUL EV	148	27	4150	5.0
	Nissan LEAF	132	24	5480	5.2

[6] Source: Ministry of Environment, Naver Auto

[7] Driving range refers to the distance traveled at room temperature (20–30℃) with a full charge by the model EV.

Table 3. Electric vehicles in Korea: models, prices, and specifications (continued)

Year	Model	Driving range (km)	Battery capacity (kWh)	Price (10K KRW)	Battery efficiency (km/kWh)
2016	KIA RAY EV	91	16.4	3500	5.0
	Renault-Samsung SM3 Z.E.	135	26.6	4000	4.4
	GM SPARK EV	128	18.3	3990	6.0
	BMW i3	132	21.3	6000	5.9
	KIA SOUL EV	148	27	4275	5.0
	Nissan Leaf	132	24	4885	5.2
	Hyundai Ioniq EV	169	28	4150	6.3
2017	KIA RAY EV	91	16.4	3500	5.0
	Renault-Samsung SM3 Z.E. EV	135	22	4050	4.5
	BMW i3	200	33	6060	5.4
	KIA SOUL EV	180	30	4140	5.2
	Nissan Leaf	132	21.3	4885	5.2
	Hyundai Ioniq EV	191	28	4150	6.3
	Chevrolet Bolt	383	60	4779	5.5
	Tesla Model S 90D	470	87.5	11570	4.3

2.3.1.1 Price of EVs

The price of EVs was also used as an explanatory variable. Fundamental principles of economics predict that higher EV prices reduce the likelihood of EV adoption. EVs have not yet achieved price competitiveness compared to ICEVs, as they cost approximately 20 million KRW more than the equivalent model of ICEVs. For example, the price of the KIA SOUL EV in 2017 was 41,400k KRW and that of the KIA SOUL (gasoline) in 2017 was 19,960k KRW, meaning that the price gap between the two models was 21,440k KRW. This price gap is gradually narrowing with technological developments. Table 3 shows the types and prices of EVs that consumers could purchase with subsidies during the analysis period (2013 to 2017).

2.3.2 EV-extrinsic Variables

2.3.2.1 User-intrinsic Variables

The first user-intrinsic variable is local gross income per capita. Higher levels of consumer income increase the probability of the consumer purchasing an EV, considering the relatively high price of EVs. Many studies have found that high income increases the probability of adopting innovative products [Diaz-Rainey & Ashton, 2011; Dobre et al., 2009; Im et al., 2003; Eastlick & Lotz, 1999; Martinez et al., 1998].

Many demographic factors, such as the consumer's age and education level, were included as explanatory variables in previous studies, but were not included in this study. This is because those demographic factors—such as age, education level and marital status—are recognized as important factors affecting income level in the microeconomic literature. Including these demographic factors and analyzing them together with income would pose a risk of multicollinearity. To avoid this problem, I did not include those variables.

The other user-intrinsic variable is the eco-friendliness of consumers. Electric vehicles have a positive impact on the environment in terms of climate change and air quality because the tailpipe emissions emitted during vehicle operation are zero, larger power generation leads to an increase in efficiency, and pollutant treatment is easy. For this reason, several previous studies have determined that consumers' eco-friendliness had a positive effect on EV adoption and included it as an explanatory variable [Vasilleva & Campillo, 2018]. Nonetheless, pro-environmental tendencies are often less important to consumers than vehicle cost and performance attributes such as range and charge time [Sierzchula et al., 2014; Egbue & Long, 2012; Lane & Potter, 2007]. In this study, I included and analyzed eco-friendliness as an explanatory variable to confirm whether pro-environmental tendencies affected EV adoption by consumers.

Measuring eco-friendliness is quite challenging, because it is a highly subjective and individual characteristic, and there is no absolute standard to measure it quantitatively. Previous studies on consumer adoption of EVs have included Sierra Club membership [Gallagher & Muehlegger, 2011], Environmental Performance Index [Sierzchula et al., 2014], and self-statements [White & Sintov, 2017; Hardman et al., 2016; Carley et al., 2013; Hidrue et al., 2011; Turrentine et al., 2011] as proxy variables for representing eco-friendliness. In this study, considering data availability and multicollinearity, the ratio of Green Party votes in the election for the 20th National Assembly in the middle of 2016 was used as a proxy variable for eco-friendliness.

2.3.2.2 User-extrinsic Variables

The first and the most important user-extrinsic variable is the economic incentive from central and local governments that alleviates consumers' financial burden. Subsidies and tax exemptions are critical drivers of EV adoption. Due to the low price-competitiveness of EVs compared to ICEVs, governments provide a subsidy and a tax benefit for EVs, thereby making them cost-competitive. Subsidies consist of both central and local government expenditures. Central government expenditures provide a uniform level of support nationwide, whereas the level of local governments' support differs according to each locality, with corresponding impacts on the annual sales of EVs by region. As of 2017, an EV buyer in Korea will enjoy various tax benefits of 4.6 million KRW (approximately 4066 USD according to the exchange rate as of November 26, 2018 (1131 KRW= 1 USD)), including an individual consumption tax of KRW 2 million, an education tax of KRW 600,000, and an acquisition tax of KRW 2 million, and the annual vehicle tax for EVs is KRW 130,000 regardless of the engine displacement. Tax benefits such as an individual consumption tax occur once at the time of purchase, while exemption from the vehicle tax is an annual benefit. For example, the owner of a standard medium-sized passenger car (2000 cc) with an internal combustion engine is required to pay a vehicle tax of KRW 520,000 per year, whereas EV owners can save KWR 390,000 per year. In this study, the sum of all tax benefits and subsidies was used as an explanatory variable relating to the economic incentives for EV adoption.

Another key factor in decision of EV adoption is public charging infrastructure, which has been consistently mentioned as a main barrier in discussions of widespread EV adoption. Many previous studies have used charging station infrastructure as an explanatory variable [She et al., 2017; Vassileva & Campillo, 2017; Hardman et al., 2016; Junquera et al., 2016; Langbroek et al., 2016; Mersky et al., 2016; Sang & Bekhet, 2015; Krupa et al., 2014; Carley et al., 2013; Jensen et al., 2013; Christensen et al., 2012; Hidrue et al., 2011]. The reason for this is "range anxiety," an issue that has been always discussed with regard to the spread of EVs. This term refers to the psychological anxiety that arises from the relatively short possible driving distance of EVs compared to ICEVs and the lack of sufficient charging infrastructure compared to gasoline station. In addition, the development of space- and time-free charging infrastructure, which is not limited to fixed places such as residential or working areas, can reduce anxiety. By doing so, such infrastructure can make it more likely that consumers will accept EVs.

The average daily driving distance by domestic passenger car drivers is 33.6 km as of 2017; the Kia RAY EV has the shortest driving range of the EVs that are available to be purchased by consumers, with 90 km per single charge in 2013. This means that the current technical level of all EVs can cover daily trips. However, anxiety about scenarios such as having to travel long distances or dealing with an emergency situation can be a barrier to EV adoption.

In this study, the cumulative number of fast chargers installed by the Ministry of Environment was used as a proxy variable for public charging infrastructure. Charging takes at least 30 minutes, so charging availability is limited when there are far more cars to charge than available chargers. To consider this issue of competition for charging infrastructure, the number of chargers was divided by total number of EVs registered in the region.

The last, but not least, user-extrinsic explanatory variable is the retail gasoline price. EVs can achieve higher economic benefits over their life through reduced fuel costs relative to ICEVs.

Therefore, the lower fuel costs of EVs likely increase consumers' preference for the purchase of EVs, a conclusion that has been drawn in several previous studies [Vassileva & Campillo, 2017; Hardman et al., 2016; Link et al., 2012; Hidrue et al., 2011], although their analyses were based on stated preferences. However, other views also exist. Several studies have shown that consumers tend to incorrectly gauge the magnitude of fuel economy benefits [Sierzchula et al., 2014; Sovacool & Hirsh, 2009; Heffner et al., 2007; Turrentine & Kurani, 2007], to such an extent that they are unaware of the potential cost savings [She et al., 2017; Carley et al., 2013; Zhang et al., 2013], and in most cases the fuel cost savings are not the primary attribute governing the vehicle purchase decision [Carley et al., 2013; Egbue & Long, 2012]. During the analysis period, oil prices had stabilized around the world, and domestic gasoline prices steadily decreased; therefore, it is possible to investigate how declining retail gasoline prices influenced EV adoption in Korea.

The descriptive statistics of explanatory variables are presented in Chapter 2.4 (Table 4).

2.4 Empirical Results

The number of registered EVs by year was very overdispersed. The reason for high within-variation is that EVs were just entering the market in Korea during 2013 to 2017. As the market was expanding very rapidly, within-variation was naturally high. High between-variation occurred because this study used data from 17 first-tier administrative divisions in Korea, with differences in area, population, income level, and regional characteristics that influenced the frequency of EV adoption.

Table 4. Descriptive statistics of dependent and independent variables (EV)

Variable		Mean	Std. Dev.	Min	Max	Observation
EV	Overall	288.26	716.02	1	4112	N = 85
	Between[8]		468.18	12.6	1795.4	n = 17
	Within[9]		551.29	-1347.14	3288.06	T = 5
Price	Overall	4588.40	480.24	3913	5392	N = 85
	Between		0	4588.40	4588.40	n = 17
	Within		480.24	3913	5392	T = 5
Income	Overall	4195.82	563.03	3187	5548	N = 85
	Between		505.53	3570.6	5248	n = 17
	Within		322.21	3111.78	5331.58	T = 5
Range	Overall	147	38.49	120	223	N = 85
	Between		0	147	147	n = 17
	Within		38.49	120	223	T = 5
Grant	Overall	2399.24	329.00	1849	3369	N = 85
	Between		222.32	2133	2845	n = 17
	Within		247.32	1815.24	3155.24	T = 5
Gasoline price	Overall	1632.75	207.11	1382.69	2002.96	N = 85
	Between		27.07	1607.34	1720.80	n = 17
	Within		205.42	1400.55	1930.85	T = 5

[8] 'Between' refers to the values of $\overline{x_i}$, or individual means.

[9] 'Within' refers to the values of $x_{it} - \overline{x_i} + \bar{\bar{x}}$, where $\bar{\bar{x}}$ denotes the global mean.

Table 4. Descriptive statistics of dependent and independent variables (EV) (continued)

Variable		Mean	Std. Dev.	Min	Max	Observation
Eco-friendliness	Overall	.65	.17	.45	1.11	N = 85
	Between		.18	.45	1.11	n = 17
	Within		0	.65	.65	T = 5
Public charging infrastructure	Overall	.16	.16	0	.79	N = 85
	Between		.11	.05	.41	n = 17
	Within		.11	-.14	.57	T = 5

First, the variance inflation factor (VIF) was calculated to check for multicollinearity for each variable. The results of the test are shown below (Table 5). Since the test values of all variables did not exceed 10, the problem of multicollinearity between variables can be considered negligible.

Table 5. VIF test results of EVs

Variable	VIF	1/VIF
Range	5.28	0.1896
Price	4.88	0.2047
Subsidy	1.46	0.6863
Public charging infrastructure	1.15	0.8679
Gasoline price	1.47	0.6808
Income	1.25	0.7969
Eco-friendliness	1.11	0.8998
Mean VIF	2.37	

As described in 1.3.3, I applied an FE Poisson (hereafter, FEP) model and RE negative binomial model with individual-specific dummies (hereafter, RENBD), and compared the results from each.

The fit of the model cannot be judged solely by the significance of the regressors. Even if the coefficients of the key variables show very low p-values, a test for goodness-of-fit is necessary because the model may not properly describe the data. Strictly speaking, a model without a fit test can be said to be statistically useless [Hilbe, 2011].

First, comparing the AIC and BIC values of the FEP model and the RENBD model, the goodness-of-fit was significantly improved by using the RENBD model compared to using the FEP model (Table 6). This indicates that the negative binomial regression model was more appropriate than the Poisson regression model because the data were overdispersed. The eco-friendliness variable was dropped from the FE Poisson model because it was time-invariant.

Table 6. Summary of Results from Poisson and negative binomial models (EV)

Model	FEP	RENBD
Range	1.0199*** (0.0006)	1.0195*** (0.0042)
Price	0.9991*** (0.0001)	0.9997 (0.0004)
Subsidy	1.0022*** (0.0001)	1.0013** (0.0003)
Income	1.0012*** (0.0000)	1.0003* (0.0002)
Gasoline price	0.9955*** (0.0001)	0.9979*** (0.0005)
Public charging infrastructure	0.0484*** (0.0097)	0.3763 (0.2641)
Eco-friendliness	-	2.1871 (5.7015)
AIC	3565.878	937.871
BIC	3580.534	998.937

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

In order to facilitate the interpretation of the results of the regression analysis, the IRR value obtained by converting the regression coefficient value into the e^{β} form is displayed. The IRR represents the relative change in the incidence rate according to a change in the value of an explanatory variable. The estimated IRR is interpreted as the rate of increase (%) of the dependent variable as the explanatory variable increases by one unit. It is encouraged to use the IRR rather than the estimated coefficient itself in order to facilitate a more precise interpretation for explaining the relative change of the dependent variable due to changes in the explanatory variables [Cameron & Trivedi, 2013].

$$\mathrm{IRR} = \frac{e^{\ln(exposure)+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_i(x_i+1)+\cdots+\beta_k x_k}}{e^{\ln(exposure)+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_i x_i+\cdots+\beta_k x_k}} = \mathrm{e}^{\beta_i} \qquad \text{Equation 2-1}$$

An analysis using the FEP model (Table 7) showed that range had a statistically significant positive effect on EV adoption in all models. Unsurprisingly, price had a negative effect on EV adoption and income had the opposite effect. Overall, the significance of all variables was high, which can be interpreted as reflecting the fact that the standard error tends to be underestimated when overdispersed data are analyzed by a Poisson model. This can be seen by comparing the results of the RENBD model to those of the FENB model.

Table 7. Summary of Results (FEP - EV)

FEP	Model 1	Model 2
Range	1.0199*** (0.0006)	1.0204*** (0.00062)
Price	0.9991*** (0.0001	0.9992*** (5.79E-05)
Subsidy	1.0022*** (0.0001)	1.0022*** (0.000056)
Income	1.0012*** (0.0000)	1.0013*** (.0000372)
Gasoline price	0.9955*** (0.0001)	0.9950*** (.0000727)
Public charging infrastructure	0.0484*** (0.0097)	-
AIC	3565.878	3801.769
BIC	3580.534	3813.982

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

Table 8 presents the results of the analysis using the RENBD model. The AIC and BIC show that the RENBD model was considerably improved in terms of goodness-of-fit compared to the FEP model presented earlier. The direction of the estimated IRR coefficient of each variable was generally consistent with the results of the FEP model. For price, the estimated IRR coefficient was less than 1, as in the FEP model, but statistical significance was lost. Public charging infrastructure and eco-friendliness variable did not have statistically significant IRRs. The estimated IRR of the gasoline price was below 1, corresponding to a negative impact on EV adoption.

Table 8. Summary of Results (RENBD - EV)

RENBD	Model 1	Model 2	Model 3
Range	1.0195*** (0.0042)	1.0195*** (0.0042)	1.0187*** (0.0043)
Price	0.9997 (0.0004)	0.9997 (0.0004)	0.9999 (0.0004)
Subsidy	1.0013*** (0.0003)	1.0013*** (0.0003)	1.0013*** (0.0003)
Income	1.0003* (0.0002)	1.0003* (0.0002)	1.0003 (0.0002)
Gasoline price	0.9979*** (0.0005)	0.9979*** (0.0005)	0.9980*** (0.0004)
Public charging infrastructure	0.3763 (0.2641)	0.3763 (0.2641)	-
Eco-friendliness	2.1871 (5.7015)	-	-
AIC	937.810	937.871	937.870
BIC	998.937	998.937	996.494

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

Figure 4 shows the number of EV adoptions divided by the number of households in each first-tier administrative division. As can be seen from the bar graph displayed in red, Jeju had a significantly higher number than other first-tier administrative divisions, so it can be considered to be an outlier. Including the outlier in the analysis could lead to inconsistencies in the overall results; therefore, I removed the observations on Jeju from the entire dataset and conducted the same analysis as above on a total of 16 first-tier administrative divisions.

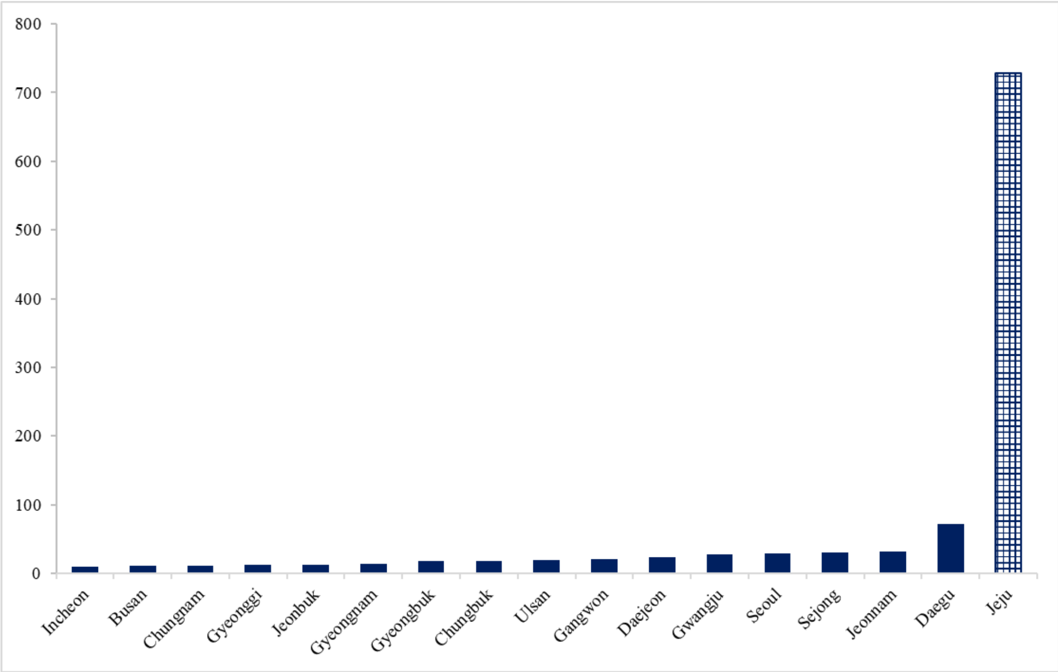

Figure 4. The number of registered EVs per 10,000 households by region[10]

[10] Source: Ministry of Environment, KOSIS

Table 9 shows the descriptive statistics of the dataset excluding Jeju. Before excluding the observations from Jeju, the average number of registered EVs was 288 and the standard deviation was 716. After excluding the observations of Jeju, the average number of registered EVs was 194 with a standard deviation of 516. Overdispersion was still present, because the between-variation of EV adoption among first-tier administrative divisions was large, but the within-variation was also large.

Table 9. Descriptive statistics of dependent and independent variables (EV) (without Jeju)

Variable		Mean	Std. Dev.	Min	Max	Observation
EV	Overall	194.06	516.1947	1	4112	N = 80
	Between[11]		270.0186	12.6	1112.2	n = 16
	Within[12]		444.1154	-706.1375	3193.863	T = 5
Price	Overall	4588.4	480.4237	3913	5392	N = 80
	Between		0	4588.4	4588.4	n = 17
	Within		480.4237	3913	5392	T = 5
Income	Overall	4347.262	576.7065	3187	5548	N = 80
	Between		484.5081	3665.8	5248	n = 17
	Within		331.2527	3157.462	5377.262	T = 5
Range	Overall	147	38.5089	120	223	N = 80
	Between		0	147	147	n = 17
	Within		38.5089	120	223	T = 5
Grant	Overall	2378.375	326.3273	1849	3369	N = 80
	Between		211.729	2133	2845	n = 17
	Within		252.8441	1794.375	3134.375	T = 5
Gasoline price	Overall	1630.372	208.0023	1382.69	2002.96	N = 80
	Between		26.0655	1607.336	1720.798	n = 17
	Within		206.446	1398.172	1928.472	T = 5

[11] 'Between' refers to the value of $\bar{x_i}$, or the individual mean.

[12] 'Within' refers to the value of $x_{it} - \bar{x_i} + \bar{\bar{x}}$, where $\bar{\bar{x}}$ denotes the global mean.

Table 9. Descriptive statistics of dependent and independent variables (EV) (without Jeju) (continued)

Variable		Mean	Std. Dev.	Min	Max	Observation
Eco-friendliness	Overall	0.6314	0.1554	0.4518	1.1124	N = 80
	Between		0.1595	0.4518	1.1124	n = 17
	Within		0	0.6314	0.6314	T = 5
Public charging infrastructure	Overall	0.17	0.1580	0	0.79	N = 80
	Between		0.1094	0.054	0.412	n = 17
	Within		0.1167	-0.134	0.576	T = 5

According to the results of the FEP model excluding the observations from Jeju, the goodness-of-fit in the model based on AIC and BIC significantly improved (Table 10). Although the model described the data well, the estimated IRR coefficient of each variable did not change significantly compared to the results of the FEP model that included the observations from Jeju. The results indicate that public charging infrastructure and retail gasoline price still showed negative effects on EV adoption, although the estimated coefficient of retail gasoline price was not statistically significant. Thus, the reason for these unexpected results may not have been the inclusion of the observations from Jeju. I conducted a further analysis with the RENBD model in consideration of overdispersion of data and interpreted the results.

Table 10. Summary of results from Poisson regression models (EV) (without Jeju)

FEP	With Jeju	Without Jeju
Range	1.0199^{***} (0.0006)	1.0212^{***} (0.0008)
Price	0.9991^{***} (0.0001)	0.9996^{***} (0.0001)
Subsidy	1.0022^{***} (0.0001)	1.0013^{***} (0.0001)
Income	1.0012^{***} (0.0000)	1.0005^{***} (0.0000)
Gasoline price	0.9955^{***} (0.0001)	0.9973^{***} (0.0001)
Public charging infrastructure	0.0484^{***} (0.0097)	0.2685^{***} (0.0573)
Eco-friendliness	-	-
AIC	3565.878	2369.780
BIC	3580.534	2384.072

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

Table 11. Summary of results from Poisson and negative binomial models (EV) (without Jeju)

Model	FEP	RENBD
Range	1.0212^{***} (0.0008)	1.0212^{***} (0.0038)
Price	0.9996^{***} (0.0001)	0.9997 (0.0003)
Subsidy	0.0013^{***} (0.0001)	1.0010^{***} (0.0003
Income	1.0005^{***} (0.0000)	1.0003 (0.0002)
Gasoline price	0.9973^{***} (0.0001)	0.9981^{***} (0.0004)
Public charging infrastructure	0.2685^{***} (0.0573)	0.3402 (0.2584)
Eco-friendliness	-	1.4654 (7.7546)
AIC	2369.780	841.266
BIC	2384.072	898.435

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

The results of the RENBD model show that the goodness-of-fit was greatly improved compared to the FEP model, as in the previous results including the observations from Jeju (Table 11). This likely reflects overdispersal of the data.

The range and subsidy variables had statistically significant and positive impacts on EV adoption in all models (Table 12). The range variable showed robust, strong, and positive effect on EV adoption. Higher prices were associated with worse EV adoption, but this relationship was not statistically significant. Income had a positive effect on EV adoption, but also lost statistical significance. Below, the results for each variable are interpreted and the robustness of each variable is checked.

Table 12. Summary of results (RENBD without Jeju - EV)

RENBD	Model 1	Model 2	Model 3
Range	1.0212^{***} (0.0038)	1.0212^{***} (0.0038)	1.0206^{***} (0.0040)
Price	0.9997 (0.0003)	0.9997 (0.0003)	0.9998 (0.0003)
Subsidy	1.0010^{***} (0.0003)	1.0010^{***} (0.0003)	1.0011^{***} (0.0003)
Income	1.0003 (0.0002)	1.0003 (0.0002)	1.0002 (0.0002)
Gasoline price	0.9981^{***} (0.0004)	0.9981^{***} (0.0004)	0.9982^{***} (0.0004)
Public charging infrastructure	0.3402 (0.2584)	0.3402 (0.2584)	-
Eco-friendliness	1.4654 (7.7546)	-	-
AIC	841.266	841.266	841.408
BIC	898.435	898.435	896.194

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

The average EV price from each year was used as the price variable. EVs with good performance and popularity are likely to have high prices, and to be sold more than other models. Due to data accessibility issues, the average value of the price of the EVs available in each year was used, but averaging may cause bias. To overcome this limitation, I sought to confirm the result by changing the price variable to the maximum value of the EV price for each year.

In the robustness analysis, increasing prices had a negative relationship with EV adoption, which is consistent with the results for the original price, though statistically insignificant, as was the case when the average values were used (Table 13). Since consumers recognize the amount actually paid as the actual price of the product, not the list price, the subsidy was subtracted from the original price and an analysis was performed using the price to be paid as the price variable. This analysis confirmed that the paid price had a negative and significant impact on EV adoption.

Table 13. Robustness test for the price variable (RENBD without Jeju - EV)

RENBD	Model 1	Price_av → Price_max	Price_av → Paid price (price - subsidy)
Range	1.0212*** (0.0038)	1.0254*** (0.0086)	1.0265*** (0.0019)
Price	0.9997 (0.0003)	0.9999 (0.0001)	0.9993*** (0.0002)
Subsidy	1.0010*** (0.0003)	1.0010*** (0.0003)	-
Income	1.0003 (0.0002)	1.0003 (0.0002)	1.0002 (0.0002)
Gasoline price	0.9981*** (0.0004)	0.9981*** (0.0004)	0.9980*** (0.0004)
Public charging infrastructure	0.3402 (0.2584)	0.3402 (0.2582)	0.3166 (0.2260)
Eco-friendliness	1.4654 (7.7546)	1.4545 (7.6997)	0.0702 (0.3768)
AIC	841.266	841.254	864.546
BIC	898.435	898.423	919.333

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

In some previous survey-based studies, fuel cost reduction was the biggest cause of EV adoption, but the results of this study showed the opposite tendency (Table 14). The two largest factors driving fuel cost savings are lower filling prices and longer driving distances. Assuming that the price of fuel is the same, the longer the driving distance, the more the fuel cost is reduced. Therefore, instead of retail gasoline prices, annual travel distance was used to represent the fuel cost savings from using EVs. The annual travel distance appeared to have a positive effect on EV adoption, but it was not statistically significant. The results were the same when the retail gasoline price and the annual mileage were included together. In order to directly investigate the effect of fuel costs, I attempted to conduct an analysis using the retail gasoline price multiplied by the annual travel distance, but the calculation did not reach convergence.

Table 14. Robustness test for the gasoline price variable (RENBD without Jeju - EV)

RENBD	Model 1	Gasprice → Vehicle miles traveled	Gasprice & Vehicle miles traveled	Gasprice → Fuel cost
Range	1.0212*** (0.0038)	1.0210*** (0.0047)	.0207*** (0.0041)	N.A.[13]
Price	0.9997 (0.0003)	1.0000 (0.0004)	0.9998 (0.0003)	N.A.
Subsidy	1.0010*** (0.0003)	1.0007*** (0.0003)	.0011*** (0.0003)	N.A.
Income	1.0003 (0.0002)	1.0001 (0.0002)	1.0002 (0.0002)	N.A.
Gasoline price	0.9981*** (0.0004)	1.0006 (0.0007)	0.9982*** (0.0004)	N.A
Public charging infrastructure	0.3402 (0.2584)	-	1.0002 (0.0006)	N.A.
Eco-friendliness	1.4654 (7.7546)	-	-	-
AIC	841.266	864.546	843.310	-
BIC	898.435	919.333	900.479	-

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

[13] N.A.: Not available due to the inability of convergence

During the analysis period of 2013 to 2017, oil prices steadily decreased (Table 15). However, it is unreasonable to infer that the reduction in oil prices promoted EV adoption. There are three possible interpretations regarding the cause of this outcome.

First, people who have significantly higher mileage per year may have been more likely to buy an EV. When the annual travel distance was included instead of the retail gasoline price, it appeared to have a positive effect, albeit statistically insignificant. As mentioned earlier, higher mileage traveled corresponds to higher fuel costs, meaning that consumers have a strong economic incentive to purchase an EV. For those who travel greater distances than average, it is still beneficial to purchase an EV even if the oil price is low. This is especially true if oil prices are expected to rise in the future. Currently, only aggregated data are available, so it is difficult to verify this possibility directly. If microdata regarding EV adoption and EV adopters becomes available in the future, this conjecture could be confirmed.

Second, as generous financial incentives in Korea significantly alleviated the initial purchase cost and the charging fees of public fast chargers are very low, the economic payback period of EVs might be shortened to a reasonable range. Fuel cost savings are important for EVs because they can offset the high initial cost relative to that of ICEVs. Over time, buying an EV is more economical than buying an ICEV. In 2016, the retail gasoline price was lowest and the charging rates were the highest during the analysis period; therefore, I calculated fuel cost savings and payback periods based on the price and rates in 2016 (Table 16).

Table 15. Yearly retail gasoline price (national average)[14]

Year	2013	2014	2015	2016	2017
KRW/L	1,924.4	1,826.1	1,511.7	1,405.3	1,494.9

Table 16. ICEVs versus EVs: fuel cost saving[15] (2016 Seoul)

<table>
<tr><td rowspan="4">2016
Seoul</td><td rowspan="2">ICEVs</td><td>Retail
gasoline price
(KRW/L)</td><td>Fuel efficiency
(km/L)</td><td rowspan="4">Yearly vehicle
miles traveled
(km)
11205.5</td><td rowspan="2">Fuel cost
(KRW)</td><td rowspan="2">1,165,943</td></tr>
<tr><td>1499.8</td><td>14.4</td></tr>
<tr><td rowspan="2">EVs</td><td>Charging fee
(Public fast)
(KRW/kWh)</td><td>Fuel efficiency
(km/kWh)</td><td rowspan="2">Fuel cost
(KRW)</td><td rowspan="2">601,454</td></tr>
<tr><td>313.1</td><td>5.8</td></tr>
<tr><td colspan="6">Fuel cost saving (KRW)</td><td>564,489</td></tr>
</table>

[14] Source: Petronet

[15] Source: Petronet, Naver Auto, Ministry of Environment, KOSIS (author's calculation)

During the first three years of the analysis period (2013 to 2015), public fast chargers were free to use, and in 2016, it was decided to charge EV owners at 313.1 KRW/kWh; however, in 2017, the charge was again lowered to 173.8 KRW/kWh.

According to Table 16, as of 2016, fuel costs can be reduced by about 560,000 KRW per year when using an EV rather than using an ICEV. The price of a Hyundai Ioniq EV, which was an EV model launched in 2016, was 41,500k KRW, and the difference in price from a Hyundai Avante (19,130k KRW), an ICEV in the same class, was 22,370k KRW. A substantial proportion of this difference can be covered by subsidies (Ministry of Environment 12,000k KRW, Seoul metropolitan government 4,500k KRW) and the tax reduction (4,390k KRW), so the initial cost to be paid in comparison to the comparable ICEV is actually 1,480k KRW.

According to the above calculation, the initial cost paid in addition to the equivalent class of an ICEV can be compensated by reduced fuel costs after approximately two and a half years. Although no official statistics exist on the car replacement cycle in Korea in recent years, EV use would be advantageous even with only a 3-year replacement cycle, which is at the low end of car replacement cycles, which usually range from 3 to 10 years. The incentive for EV adoption is stronger if the owner's annual mileage is much higher than average or if there is an expectation that gasoline prices will rise in the future.

Third, because people are sensitive to price increases and have an asymmetrical tendency toward price perceptions to react insensitively to price declines, they may not have responded specifically to falling gasoline prices during the analysis period. Some previous studies have reported that people tend to incorrectly estimate the magnitude of fuel economy benefits [Cherif et al., 2017; Mersky et al., 2016; Helveston et al., 2015; Sierzchula et al., 2014; Turrentine &

Kurani, 2007]. If longer time series data are obtained and there is a rise and fall in oil prices during the period, it will be possible to analyze whether consumers actually react differently to rises and falls in oil prices by comparing the elasticity between periods of rising and falling gasoline prices.

In the RENBD model, it was found that the number of chargers per number of EVs registered had a negative effect on EV adoption, but it was not statistically significant (Table 17). As a robustness test, the cumulative number of public fast chargers installed by the Ministry of Environment was divided by the area of each first-tier administrative division, and the relative density of chargers was analyzed as a proxy of public charging infrastructures. The cumulative number of public chargers and the relative density of the fast charger in each municipality are shown in Table 18 and 19 respectively.

Table 17. Robustness test for the public charging infrastructure variable (RENBD without Jeju - EV)

	Model 1	Chargers per EV → chargers per area	Chargers per EV → detached houses	Chargers per EV → chargers per area & detached houses
Range	1.0212*** (0.0038)	1.0167*** (0.0048)	1.0241*** (0.0041)	1.0204*** (0.0046)
Price	0.9997 (0.0003)	0.9999 (0.0004)	0.9999 (0.0003)	1.0000 (0.0003)
Subsidy	1.0010*** (0.0003)	1.0011*** (0.0003)	1.0010*** (0.0003)	1.0010*** (0.0003)
Income	1.0003 (0.0002)	1.0000 (0.0002)	1.0002 (0.0002)	1.0001 (0.0002)
Gasoline price	0.9981*** (0.0004)	0.9984*** (0.0003)	0.9974*** (0.0005)	0.9976*** (0.0004)
Public charging infrastructure	0.3402 (0.2584)	1.0464** (0.0210)	-	1.0358** (0.0183)
Detached	1.4654 (7.7546)	-	1.3887*** (0.1415)	1.3432*** (0.1372)
AIC	841.266	838.562	834.663	832.826
BIC	898.435	895.731	891.832	892.377

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

Table 18. The cumulative number of public chargers[16] (units)

Year	Seoul	Busan	Daegu	Incheon	Gwang-ju	Daejeon	Ulsan	Sejong	Gyeong-gi	Gang-won	Chung-buk	Chung-nam	Jeon-buk	Jeon-nam	Gyeong-buk	Gyeong-nam
2013	32	10	1	10	6	2	1	1	27	8	1	9	1	8	8	13
2014	40	15	1	11	9	2	1	1	41	9	2	13	2	11	12	18
2015	40	15	4	11	9	2	4	1	56	13	13	17	15	31	28	29
2016	47	16	11	13	9	3	9	1	65	24	27	42	34	48	47	46
2017	99	29	16	24	9	14	9	1	132	66	62	70	62	71	98	72

Table 19. The cumulative number of public chargers divided by the area of each first-tier administrative division[17] (units per km^2)

Year	Seoul	Busan	Daegu	Incheon	Gwang-ju	Daejeon	Ulsan	Sejong	Gyeong-gi	Gang-won	Chung-buk	Chung-nam	Jeon-buk	Jeon-nam	Gyeong-buk	Gyeong-nam
2013	0.053	0.013	0.001	0.009	0.012	0.004	0.001	0.002	0.003	0.000	0.000	0.001	0.000	0.001	0.000	0.001
2014	0.066	0.019	0.001	0.010	0.018	0.004	0.001	0.002	0.004	0.001	0.000	0.002	0.000	0.001	0.001	0.002
2015	0.066	0.019	0.005	0.010	0.018	0.004	0.004	0.002	0.005	0.001	0.002	0.002	0.002	0.003	0.001	0.003
2016	0.078	0.021	0.012	0.012	0.018	0.006	0.009	0.002	0.006	0.001	0.004	0.005	0.004	0.004	0.002	0.004
2017	0.164	0.038	0.018	0.023	0.018	0.026	0.009	0.002	0.013	0.004	0.008	0.009	0.008	0.006	0.005	0.007

[16] Source: Ministry of Environment

[17] Source: Ministry of Environment, KOSIS

In order to understand the cause of these contradictory results, the current usage pattern of public fast chargers by EV owners was examined. The information is provided by the Ministry of Environment through an information disclosure claim (Table 20). The average number of usages of public fast chargers per registered non-business EV was 0.77 times nationwide. Of the 17 first-tier administrative divisions, the usage count of public fast chargers per EV was below 1 in 11 first-tier administrative divisions (64.7%).

As of 2018, the average battery capacity of EVs that consumers can purchase is 42.5 kWh. The charge amount of fast chargers per EV per month in 10 first-tier administrative divisions was less than 10 kWh, which is approximately less than 25% of the full charge on average. Only four first-tier administrative divisions—Chungcheongbuk-do, Chungcheongnam-do, Gyeongsangbuk-do, and Jeju— showed an average charge amount of about 20 kWh, which is half the average battery capacity. These data show that the public fast chargers were not extensively used by EV owners.

In this study, considering the fact that it takes at least 30 minutes to charge, the total number of public fast chargers was adjusted by the total number of registered EVs in each first-tier administrative division. However, the usage statistics of the public fast chargers indicate that competition with other EVs was very low, because public fast chargers were hardly used. Thus, it seems that adjusting the number of public fast chargers by the number of EVs was indeed meaningless, which may explain why the coefficient of the original variable (cumulative public chargers divided by the number of registered EVs) was statistically insignificant.

Table 20. Statistics of rapid charging use by EV owners[18]

Metropolitan municipalities (as of August 2018)	Monthly average		Number of EVs registered (non-business use)	Number of charges per EV	Charge amount per EV (kWh)
	Number of charges	Charge amount (kWh)			
Seoul	2,835	35,767	3,753	0.76	9.53
Busan	644	8,311	1,114	0.58	7.46
Daegu	951	12,493	4,327	0.22	2.89
Incheon	540	7,262	1,104	0.49	6.58
Gwangju	263	3,530	1,012	0.26	3.49
Daejeon	250	3,861	796	0.31	4.85
Ulsan	286	3,664	581	0.49	6.31
Sejong	28	380	248	0.11	1.53
Gyeonggi	3,659	48,773	4,801	0.76	10.16
Gangwon	954	14,000	881	1.08	15.89
Chungbuk	855	12,478	672	1.27	18.57
Chungnam	1,051	14,959	780	1.35	19.18
Jeonbuk	693	10,030	662	1.05	15.15
Jeonnam	1,047	13,899	1,583	0.66	8.78
Gyeongbuk	2,093	30,140	1,491	1.40	20.21
Gyeongnam	1,201	15,008	1,687	0.71	8.90
Jeju	14,398	175,416	9,232	1.56	19.00

18 Source: Ministry of Environment

Since charger density had a positive effect on EV adoption, it can be assumed that public chargers were actively used where the charger density was high. However, as shown in Table 20, the frequency and the amount of public fast charger usage in Seoul, Busan, Daegu, Incheon, and Gwangju, which are the five areas with the densest distribution of public fast chargers, were quite low. Meanwhile, previous studies based on stated preferences argued that public charging infrastructure is a key factor in EV adoption [She et al., 2017; Vassileva & Campillo, 2017; Junquera et al., 2016; Sang & Bekhet, 2015; Carley et al., 2013].

Based on these points, the fact that the public fast chargers exist at a short distance may have a positive effect on the adoption of EVs by creating a psychological feeling of relief in consumers, who recognize that there is a place to charge at any time, even if the actual usage of these chargers is infrequent.

The next question is then where EV users charge their EVs. According to the "2017 Energy Consumption Survey—Electric Vehicles Owners Survey Report" by the Korea Energy Agency, EV users who answered the questionnaire were found to charge their EVs mainly at public organizations' charging stations (31.0%), homes (27.9%), charging stations of private charging service providers (24.0%), and workplaces (15.3%) (Figure 5).

As of October 25, 2018, there are a total of 4,986 public charging stations that can be searched on the Ministry of Environment's EV charging station website. According to these statistics, chargers installed by public institutions such as the Ministry of Environment are primarily fast chargers, which account for 81.6% of chargers, while 18.4% are level 2 chargers (Table 21). In contrast, the charging stations installed by private operators are mainly level 2 chargers, which account for 94.9%, whereas only 5.1% are fast chargers. Therefore, the charging stations installed by public institutions such as the Ministry of Environment are mainly fast chargers, and charging stations installed by private operators are mainly level 2 chargers. As will be explained again later, considering the convenience of charging, the price of the charger, and governmental support, it is reasonable to assume that all chargers installed in residential areas are level 2 chargers. The same can be said for workplaces. By a rough calculation, the results of the 2017 survey show that EV users utilize fast chargers and level 2 chargers at a ratio of about 7:3.

Table 21. Type of chargers by operating organization[19]

	Fast chargers (%)	Level 2 chargers (%)	Total
Public organization	81.6	18.4	100
Charging service providers	5.1	94.9	100

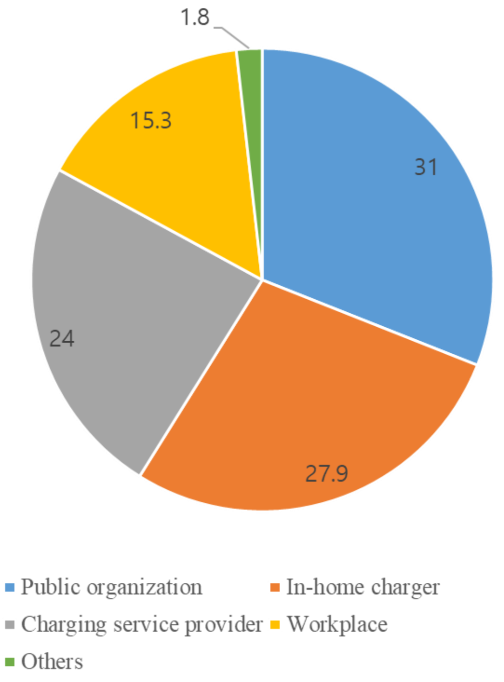

Figure 5. The distribution of charging places used by EV users[20]

[19] Ministry of Environment Electric Vehicle Charging Stations Website. Available online: www.ev.or.kr (accessed on 5 November 2018).

[20] Source: Ministry of Trade, Industry, and Energy & Korea Energy Agency (2017)

In Korea, the Ministry of Environment provides an installation subsidy for one non-public (private use only) level 2 charger for one purchase of an EV from 2013 to 2018 (Table 22). In some first-tier administrative divisions, the subsidy eligibility criterion is "who owns (leases) a parking space to install a level 2 charger" (2013 Jeju, 2015 & 2016 Busan, etc.). In the "Guidelines for Distributing Electric Vehicles and Charging Infrastructures Construction Project Subsidies," it is written that it is necessary to examine whether the recipient of the subsidy has a charger installed for operating the EV. This statement was maintained from 2013 to 2016 and disappeared in 2017. Under these circumstances, it is likely that most EV buyers have non-public level 2 chargers, reducing the need for public fast chargers.

Table 22. Subsidy for non-public level 2 chargers from the Ministry of Environment[21]

Year	2013	2014	2015	2016	2017	2018
1,000 KRW	8,000	7,000	6,000	4,000	3,000	1,500

[21] Source: Ministry of Environment

Since the cost of installing non-public level 2 chargers is mostly covered by governmental subsidies, the main barrier to installation of the charger is the presence or absence of an installation space. If one lives in a detached house, it is much easier to install the charger. People living in multi-dwelling units need to get permission at a residents' meeting to install the charger in the public parking lot. Therefore, a high proportion of detached houses in the area can be considered to favor the adoption of EVs, at least for the installation of non-public level 2 chargers. To verify this conjecture, the same analysis was performed using the ratio of detached houses by region instead of charger density (Table 17, Model 3). The ratio of detached homes was found to have a strong positive effect on the adoption of EVs.

The above discussion can be summarized as follows. First, because EV users did not utilize public fast chargers extensively, competition due to the existence of other EVs was very low, which is presumed to be the cause of the statistically insignificant coefficient of the total of public fast chargers divided by the number of registered EVs. Second, EV adopters did not actually use public fast chargers frequently, but the fact that public fast chargers existed nearby had a positive effect on EV adoption by reducing range anxiety. Third, during the analysis period, the government's support for non-public level 2 chargers favored EV adoption by people living in single-family homes.

Table 23. Robustness test for the eco-friendliness variable (RENBD without Jeju - EV)

RENBD	Model 1	Green Party votes → Democratic Party votes	Eco-friendliness excluded
Range	1.0212*** (0.0038)	1.0212*** (0.0038)	1.0212*** (0.0038)
Price	0.9997 (0.0003)	0.9997 (0.0003)	0.9997 (0.0003)
Subsidy	1.0010*** (0.0003)	1.0010*** (0.0003)	1.0010*** (0.0003)
Income	1.0003 (0.0002)	1.0003$^{\wedge}$ (0.0002)	1.0003$^{\wedge}$ (0.0002)
Gasoline price	0.9981*** (0.0004)	0.9981*** (0.0004)	0.9981*** (0.0004)
Public charging infrastructure	0.3402 (0.2584)	0.3402 (0.2584)	0.3402 (0.2584)
Eco-friendliness	1.4654 (7.7546)	1.0050 (0.0695)	-
AIC	841.266	841.266	841.266
BIC	898.435	898.435	898.435

$^{\wedge}$: p-value < 0.15

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

Eco-friendliness, as represented by Green Party votes, was not statistically significant Table 23). The reason for this result may be that the Green Party is too small of a minority and that Korea's political system is almost bipartisan. To test the robustness of the results, I reanalyzed the data with the ratio of Democratic Party vote instead of Green Party votes. Democratic parties tend to support pro-environmental policies in general [Crago & Chernyakhovskiy, 2017]. However, the results did not change. Several studies have found that consumers' environmental concerns encourage them to adopt vehicle types with less environmental impact [Axsen et al., 2015; Jensen et al., 2013], but this was not the case in this study. It is difficult, however, to conclude that eco-friendliness did not affect EV adoption, because both of these variables were very comprehensive measures of political inclination [Allan & McIntyre, 2017]. However, as mentioned in several previous studies, a pro-environmental tendency does not necessarily lead to the purchase of eco-friendly products [Sierzchula et al., 2014; Egbue & Long, 2012; Lane & Potter, 2007]. From the perspective of widespread diffusion or marketing, care is needed when choosing publicity for eco-friendliness as a principal measure. If a proxy variable can be found that represents eco-friendliness of consumers more accurately, is easily quantifiable, and is suitable for obtaining many observations, a more sophisticated analysis of the effect of eco-friendliness of consumers on EV adoption will be possible.

2.5 Summary and Discussion

In chapter 2, I attempt to identify drivers of EV adoption using actual data on EVs purchased in Korea from 2013 to 2017. The analysis showed that the estimated IRR of each variable had a similar direction, magnitude, and statistical significance in the FEP and RENBD models.

The findings of this study are as follows. As the range with a full charge and total economic incentives from the government appeared to have a robust and positive effect in all models, it can be concluded that these two variables had the most important influence on the adoption of EVs in Korea from 2013 to 2017, and this result is consistent with the literature. Since the price of EVs has a negative effect on EV adoption, automobile manufacturers should make efforts to lower prices through technological innovation and mass production. Consumers' income did not have a statistically significant effect on EV adoption, most likely due to the availability of various financial products and installment programs related to automobile purchases, which minimize the impact of the consumer's ability to pay. In this study, it was found that eco-friendliness, as measured by voter turnout for the Green Party or Democratic Party, was insignificant, in contrast to the previous literature.

EV adoption increased despite a steady decline in oil prices during the analysis period, which does not align with the findings of previous studies based on stated preferences [Vassileva & Campillo, 2017; Hardman et al., 2016; Link et al., 2012; Hidrue et al., 2011]. There are multiple reasons. First, people who have an annual mileage that is significantly higher than average may have been more likely to purchase an EV. For those who travel a greater distance than the average mileage, it is still beneficial to purchase an EV even if the oil price is slightly lower. Second, as generous financial incentives in Korea significantly alleviated the initial purchase cost and the charging fees for public fast chargers were very low, the economic payback period of EVs might have been shortened enough to make the purchase of an EV reasonable. Third, because people are sensitive to price increases, while they have an asymmetrical tendency to react insensitively to price declines, they may not have reacted specifically to falling gasoline prices during the analysis period.

Regarding public charging infrastructure, the number of public fast chargers adjusted by the total number of EVs in the area showed a negative effect, whereas the value adjusted by the area of the municipality showed a positive effect. To interpret this, it should first be noted that the competition due to the presence of other EVs was not significant because the actual use rate of public fast chargers by EV users was very low, which might explain why the estimated coefficient of the variable was insignificant. Second, although EV adopters did not actually utilize public fast chargers frequently, the fact that public fast chargers existed nearby may have had a positive effect on EV adoption by relieving range anxiety. Third, with governmental support for non-public level 2 chargers, EV adoption was favorable for people living in single-family homes.

The following policy implications can be derived from the above findings. First, more efforts should be invested into making EVs themselves competitive. Since range had strong positive effects on EV adoption, R&D efforts should be made by automobile manufacturers to reduce the inconvenience of charging and range anxiety, and to reach a sufficient quality for competition with ICEVs.

Second, although public charging infrastructure has not been used extensively, it is still important for widespread EV adoption. It has regularly been claimed that the lack of public chargers is an obstacle to the spread of EVs. In that regard, the government also provides generous subsidies for the installation of non-public level 2 chargers in addition to efforts to expand the public fast charging infrastructure. Examining the results of the analysis and reviewing the literature, it can be seen that until now, most people who bought EVs were those who can install a level 2 charger or who can charge an EV at their workplace. However, the diffusion of EVs will be inherently limited if only people in such circumstances purchase EVs. It is important to build a sufficient charging infrastructure because public charging infrastructure has a positive impact on people, both practically and psychologically. In particular, considering that people mainly use slow charging at their homes or workplaces, it seems necessary to supplement them systematically, so that “parking is charging.”

This study has some limitations in terms of data due to the emerging market characteristics of EVs and the relatively short history of EV policy implementation in Korea. A more accurate analysis is likely to be available when more comprehensive and extended time-series data are obtained in the near future. However, it should be pointed out that the dataset used in this research is one of the best options so far.

The data used in this study are short panel discrete data. As the unit root test for discrete data has not been well established academically yet [Park, 2015], and time series analysis of panel data assumes a large T [Baltagi, 2013], it was difficult to apply time-series methodologies such as panel cointegration in this study. Trend variables that take into account the effects of time are generally used to capture technological progress [Münzel et al., 2019; Crago & Chernyakhovskiy, 2014]. This study already included a variable for technical attributes, which represent technological improvement over time. It is expected that the panel time series analysis method will become applicable as data accumulate over time and T increases. Some issues could not be analyzed because they have not yet been observed. For instance, examining the asymmetries of EV adoption when gasoline prices rise and fall will yield a better understanding of the impact of operating costs when purchasing innovative durables.

Another point to keep in mind is that the government has a targeted number of EVs to supply each year. Carefully examining the data, it is found that during the analysis period of this study, the target set by the government was unmet each year due to low public interest. When analyzing the data by region and year, the target was exceeded or matched only in a few instances. However, demand for EVs will increase as the performance of EVs improves and the models are diversified. It may be increasingly common that people who want to buy EVs with governmental support have to give up the purchase due to budgetary constraints. The government can draw up revised supplementary budgets to respond to the excess demand, in which case a simultaneous equation model should be used because EV adoption and the budget are determined simultaneously. In this study, this methodology was not applied since those cases are negligible and the benefit of using the complicated methodologies with a small dataset is imperceptible. Nevertheless, these points should be considered in further studies analyzing EV adoption in the mature phase.

As aggregate-level data were used rather than disaggregated data, some aspects remain incompletely understood. For example, the available data did not allow a determination of whether people with higher mileage per year actually bought more EVs than those with a lower annual mileage.

An interesting research topic for the near future is vehicle body type. Koreans have distinct preferences for vehicle body type, as the two most preferred body types are large sedans and small SUVs. During the introductory phase of EV adoption from 2013 to 2017, the EV models available were light, small, and semi-medium sedans, and there was no large sedan segment until the Tesla S 90D became available for purchase in 2017. The release of the KONA EV and NIRO EV in 2018 seems to have attracted a great deal of demand from those who had not bought an EV because they preferred small SUVs. The mileage, needless to say, has also significantly improved, to approximately 400 km per full charge. If more detailed data can be obtained, the effect of the body type of EVs on the adoption of consumers can also be analyzed. I tried to analyze this effect by incorporating the number of selectable models as a variable, but it was not included in the final analysis due to multicollinearity. Therefore, it is expected that when the market is more mature and more data are accumulated, it will be possible to conduct additional studies of the interesting issues mentioned above.

Chapter 3. Residential Photovoltaic Adoption by South Korean Households

3.1 Background

Residential solar photovoltaic (PV) installations have been successfully established in several countries, such as Germany, Australia, and Japan. In comparison, the conditions of Korea are unfavorable, with more than 60% of the population living in multi-dwelling units and the highest population density among OECD countries (approximately 530 people per square kilometer in 2018), followed by Netherlands (approx. 508 people per square kilometer).

Therefore, the next best alternative to emerge onto the market is the veranda-type solar mini-power plant (hereafter, mini-solar PV). The Seoul Metropolitan Government has encouraged the use of renewable energy by citizens since 2014 by implementing the “Reduce One Nuclear Power Plant” policy. The city of Seoul comprises only 0.6% of the total land area of Korea, but is inhabited by about 19% of the country's population. As such, its population density is quite high (15,984 people per square kilometer as of 2018), and it is the densest metropolitan city among any of the 17 first-tier administrative divisions in Korea (with a population density 177 times higher than that of Gangwon-do, the region with the lowest population density) (Figure 6).

The majority (63%) of residents of Seoul live in multi-family houses, and it was the first area in the nation to adopt a mini-solar PV distribution policy. Mini-solar PV units generally have a much smaller capacity (250-500 kW) than typical residential solar PV units (3-10 kW). As the panel is small, it has the advantage of being possible to fix and mount on the balcony railing of an apartment, even if no large area is available, such as the roof of a detached house.

In order to encourage the installation of mini-solar PV units, citizens are provided differential subsidies based on capacity from the Seoul Metropolitan Government since 2014 based on "Energy Ordinance Article 25." Several *gu*[22] governments also provide additional subsidies for mini-solar PV installation.

[22] *Gu* denotes the districts of Seoul.

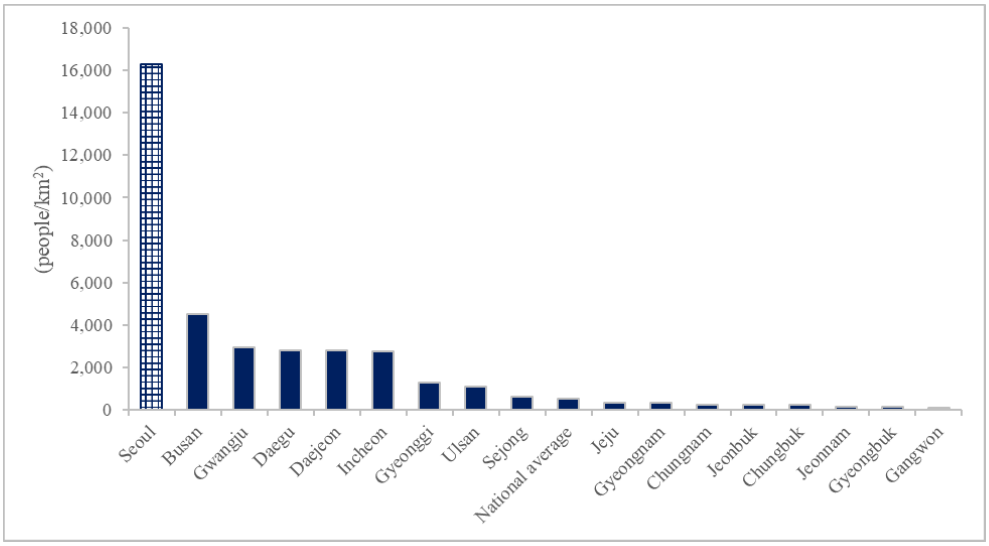

Figure 6. Population density by region[23]

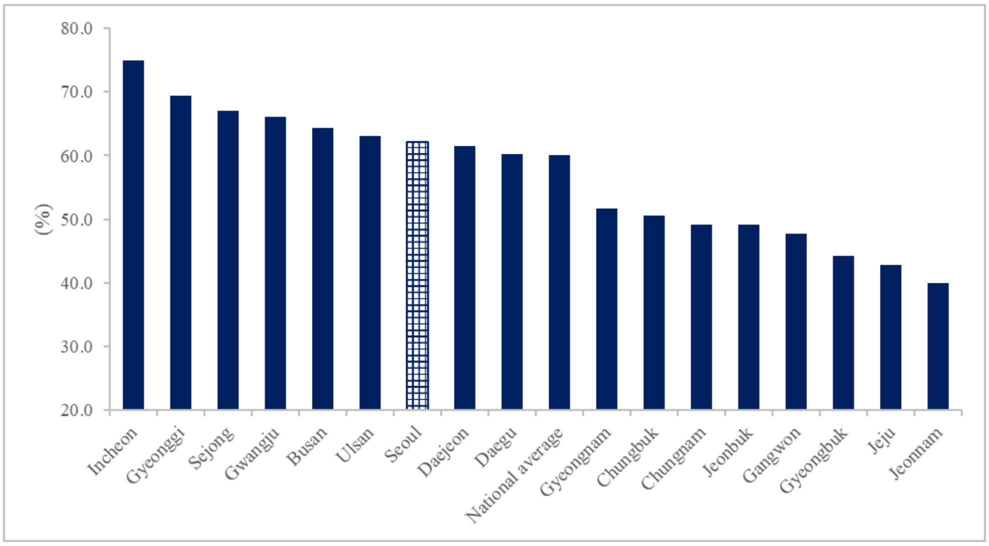

Figure 7. The ratio of multi-dwelling units by region[24]

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[23] Source: KOSIS

[24] Source: KOSIS

Efforts have been made to identify factors contributing to residential solar PV adoption. However, studies have mainly focused on countries where residential solar PV installations are already actively spreading, such as the United States and Germany [Crago & Chernyakhovskiy, 2017; Dharshing, 2017; Rai & McAndrews, 2012]. However, the profitability of residential solar PV is strongly affected by solar irradiation, the electricity rate structure, and the policy support system. Therefore, it is meaningful to analyze factors contributing to residential solar PV adoption in a country-specific manner.

There are also several advantages to limiting the scope of analysis to Seoul, rather than to the national level. It is difficult to analyze the effectiveness of a single policy when multiple policies are implemented simultaneously. In the case of Seoul, the installation of mini-solar PV in a multi-family house is only supported by a subsidy for installation costs during the initial installation. Therefore, these circumstances provide optimal conditions for analyzing the effects of the policy. Furthermore, since retail electricity sales are exclusive to the KEPCO and the household electricity rate system is the same for all households, the analysis is easier than in other countries where multiple utility options are available.

In particular, the most demanding aspect of empirical analysis is that it is always necessary to control for unobserved heterogeneity, but doing so is very difficult because unobserved heterogeneity is, by definition, unobserved. Therefore, care is taken to select as many models as possible including the major factors affecting the dependent variable, or to exclude the effects of heterogeneity. The social and demographic characteristics of the citizens of Seoul are more homogeneous than those of all residents of Korea, so unobserved heterogeneity can be better controlled. In addition, the city of Seoul has a small area (605 km^2). Since the distance from the north end to the south end of Seoul is only 30.3 km, the solar irradiation in each *gu* can be considered to be almost the same, which can eliminate another source of uncertainty in the analysis. Furthermore, external shocks (e.g., typhoon damage, abnormal temperatures, or legal changes affecting PV adoption) can be assumed to affect mini-solar PV use in Seoul relatively evenly.

3.2 Literature Review

Existing research on innovation diffusion policy for solar photovoltaics was mainly focused on expanding the share of renewable energy at the national level [Kim & Heo, 2016; Li et al., 2015; Smith & Urpelainen, 2014; Zhao et al., 2013; Dong, 2012]. This is because there was a high demand to change the energy mix to cope with climate change, and there was lack of economic benefits for residential buildings to install solar panels due to low price competitiveness compared to the traditional energy resources. However, as technology advances and learning effects occurs within the industry, the PV module cost has reached nearly a tenth from $2 per W (global benchmark) in 2010 to $0.23 per W in the first half of 2019 [Bloomberg NEF, 2019]. Accordingly, through various national support policies, it was possible to obtain economic advantages by installing solar PV in residential sector.

Prior studies on residential solar PV have been conducted mainly in countries where residential solar is most extensively deployed, such as Germany [Candas et al., 2019; Dharshing, 2017; Klein & Deissenroth, 2017; Schaffer & Brun, 2015], United States [Crago & Chernyakhovskiy, 2017; Robinson & Rai, 2015; Chen et al., 2013; Krasko & Doris, 2013], and Australia [Zander et al., 2019; Agnew et al., 2018; Simpson & Clifton, 2017; Chapman et al., 2016; Simpson & Clifton, 2016; Nelson et al., 2011].

In analyzing the adoption factors of residential solar PV, economic factors are generally considered to be the most important factors so that there are many studies related to them. Examples include papers that calculate the payback time of residential solar PV systems through simulation [Hirvonen et al., 2015], that study economic viability of residential solar PV through net present value (NPV) and internal rate of return (IRR) calculations [Klein & Deissenroth, 2017; La Monaca & Ryan, 2017; Hagerman et al., 2016], and that analyze factors which lower installation costs, such as price transparency and soft costs [O'Shaughnessy & Margolis, 2018; Morris et al., 2014; Seel et al., 2014]. In recent years, studies on positive feedback have been published that the demand for electricity from the grid decreased due to the increase in residential solar PV, which increases electricity prices, which in turn leads to more of consumers' residential solar PV adoption [Chesser et al., 2018; Laws et al., 2017; Cai et al., 2013].

The study of factors affecting the adoption of residential solar PV can be largely divided into the studies based on stated preferences and those based on revealed preferences. The policy supporting the dissemination of residential solar PV has a longer history than that for EVs in many countries, so that we can find the studies based on revealed preference more easily [Allan & McIntyre, 2017; Briguglio & Formosa, 2017; Crago & Chernyakhovskiy, 2017; Dharshing, 2017; Kwan, 2012]. Besides, a large number of studies based on stated preferences in the EV literatures have analyzed the intention to purchase EVs for potential adopters, while in the case of residential solar PV, many studies have been conducted a survey to adopters who already installed solar panels [Simpson & Clifton, 2017; Sommerfeld et al., 2017; Rai & McAndrews, 2012].

In Simpson & Clifton (2017), the authors investigated what encourages early majority of adopters to decide to install residential solar panels from 2013 to 2015 in Australia through mail-out survey and in-depth interviews. According to the results, financial incentives are the most priority in the decision-making process for residential solar PV adopters, which makes early majority distinguishable to early adopters who generally cares technical or environmental reasons more than financial incentives. However, a study that conducted in-depth interviews on 22 households with residential solar PV installations between 2008 and 2015 showed that the concern for the environment was the least discussed motivation and economic motivation was the highest installation factor [Sommerfeld et al., 2017]. Nonetheless, comparing those who installed residential solar PV between 2008 and 2012 and those who installed thereafter, larger percentage of former households answered that the concern for the environment had an effect on installation decisions than that of latter households.

Studies based on revealed preference attempted to identify factors affecting adoption using econometric methods including adopters' demographic and socioeconomic factors as well as the policy and institutional factors. Economic factors such as income, subsidies, and electricity prices have largely been found to be important, and some studies have shown that adopters' eco-friendliness have had a positive impact on residential solar adoption [Crago & Chernyakhovskiy, 2017; Bollinger & Gillingham, 2012]. There are studies that pro-government sentiment has a greater impact than eco-friendliness on the adoption of residential solar PV [Briguglio & Formosa, 2017]. Although such various variables were included in the empirical analysis, studies dealing with the properties of the photovoltaic panel itself are very rare excepting Chen et al. (2013), which used machine learning methodology to extract the main attributes of solar panel. Considering the importance of the product's intrinsic technical properties as an innovative durable household goods, they were surprisingly rarely covered in prior studies. This study fills the gap of the existing literature in that module efficiency is used as the most representative technical property of solar panels for one of the explanatory variable.

Studies focusing domestic markets also dealt with residential solar PV on the rooftops of detached houses before Seoul Metropolitan governments launched the diffusion policy for mini solar PV on veranda railing of the multi-dwelling units. There is an early study that analyzed citizens' perceptions on the distribution of solar power in domestic residential sector [Ban & Lee, 2010]. The questionnaire was aimed at general citizens, civil servants, and workers in the solar PV industry, and asked about the general perception of the policy for residential solar PV diffusion. The respondents said that the governments should implement the diffusion policy in consistent manner over the long term and the module efficiency needs to be improved to widespread diffusion of residential solar PV. Also, they expect that residential solar PV would be the solution to environmental problems and the landscape would not be severely destroyed.

There is a study of Green Home residents surveying housing choice factors and residential satisfaction [Park et al., 2014]. According to the results, Green Home residents considered economic benefit as the most important factors for housing choice. Factors affecting residential satisfaction were also found in order of economic benefit, ease of maintenance, and ease of installation. In An & Chung (2018), solar energy acceptability for rural residents was analyzed based on Rogers' theory of innovative diffusion. The authors found that economic benefit as a relative advantage brings the adoption even if the adopter is not aware well regarding complexity and compatibility of the innovative product.

Recently, a small number of studies have been published on mini-solar PV. The authors of Baek & Yun (2015) surveyed the citizens in Nowon-gu of Seoul city, which has implemented a leading diffusion policy for the installation of mini solar PV in multi-dwelling housing. The survey showed that the electricity bill savings, installation subsidies, and the concern for the environment were main factors that affected the installation. 31.9 percent of the respondents said module efficiency should be increased to generate more electricity, indicating that citizens have a high demand for technological improvement. There is also an analysis of the stringency determinants of the mini-solar PV policy of each autonomous Gu-district rather than the consumer's adoption factors [Han & Yun, 2019]. Lee & Shepley (2020) surveyed low-income families living in social housing on the support policy for installing mini solar energy. The results showed that electricity bill reduction and government funding for the system were the most important motivations for installation of mini solar PV.

Thorough reviewing the existing literatures, this study has the following significances. First, this study considers the technical attributes of solar panel as an important explanatory variable in examining factors for mini-solar PV adoption. Although the technical excellence of solar panels is crucial and many respondents who already adopted mini-solar PV answered that increase in module efficiency is needed, few study investigated the effect of technical excellence of solar panels on its adoption. Second, this study utilized the revealed preference for mini-solar PV adoption. There are, of course, limitations due to lack of data availability because it is in the early stages of market introduction. Nonetheless, the results of a study analyzed based on actual adoption data are significant in that they can enable us to find out new facts that were not seen in studies which only deal with stated preferences through comparison and contrast with studies based on surveys.

Third, this study focused on mini-solar PV. There have been many previous studies analyzed on residential solar PV, but mini-solar PV has not yet been fully researched because it is not spurred in many countries yet and the market history is short. Also, in a dense city like Seoul, mini-solar PV can be a good alternative when it is necessary to increase the ratio of renewable energy in energy mix, so that it is meaningful to analyze what encourage consumers' adoption of mini-solar PV.

3.3 Data and Variables

The explanatory variables used in this study are shown below (Table 24). They were selected according to the results of previous studies, data availability, and suitability for residents of Seoul. Explanatory variables can be grouped into PV-intrinsic factors and PV-extrinsic factors. PV-intrinsic factors are classified into user-intrinsic and user-extrinsic attributes, while PV-extrinsic factors are categorized into technical and non-technical attributes (Figure 8).

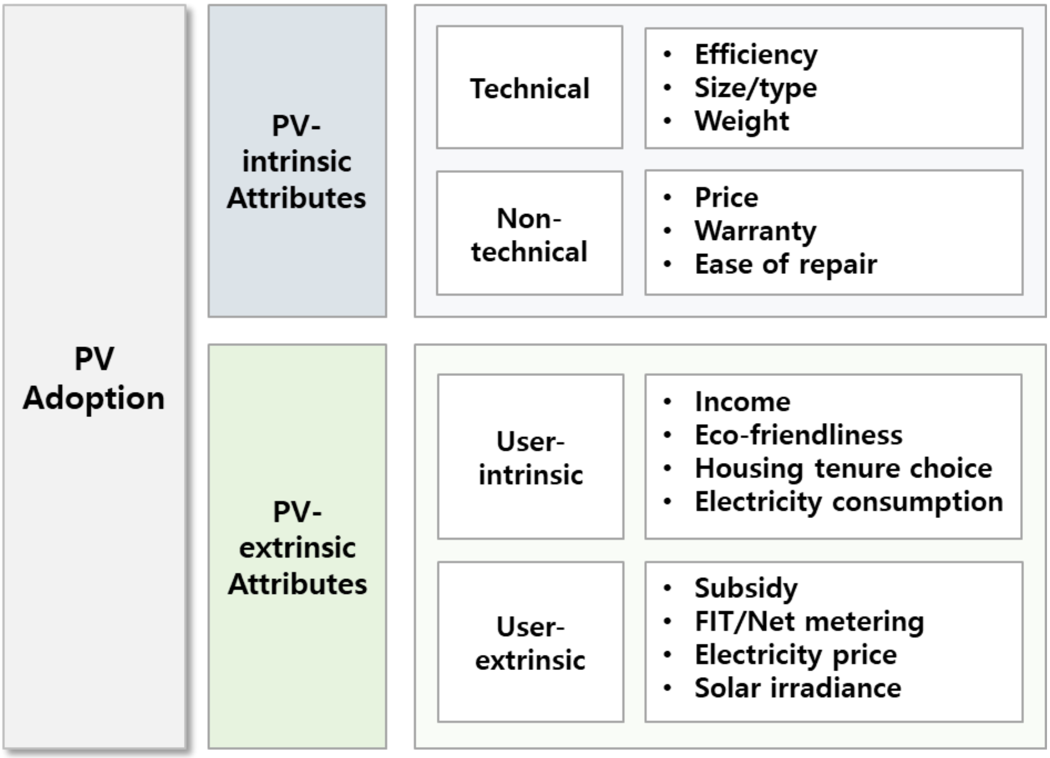

Figure 8. Conceptual framework of key attributes for PV adoption

Table 24. Explanatory variables for EV adoption

Group	Attributes	Variables	Literature
PV-intrinsic Factors	Technical	Efficiency	Hirvonen et al. (2015), Chen et al. (2013), Shih & Chou (2011)
	Non-technical	Price	Candas et al. (2019), Lee et al. (2018), Islam (2014), Shih & Chou (2011)
PV-extrinsic factors	User-intrinsic	Income	Allan & McIntyre (2017), Briguglio & Formosa (2017), Crago & Chernyakhovskiy (2017), Dharshing (2017), Robinson & Rai (2015), Schaffer & Brun (2015), Sardianou & Genoudi (2013), Bollinger and Gillingham (2012), Kwan (2012), Rai & McAndrews (2012)
		Eco-friendliness	Allan & McIntyre (2017), Briguglio & Formosa (2017), Crago & Chernyakhovskiy (2017), Dharshing (2017), Schaffer & Brun (2015), Bollinger and Gillingham (2012), Kwan (2012)
		Housing tenure choice	Candas et al. (2019), Allan & McIntyre (2017), Briguglio & Formosa (2017), Bollinger and Gillingham (2012)
		Electricity consumption	Crago & Chernyakhovskiy (2017), Kwan (2012), Shih & Chou (2011)
	User-extrinsic	Subsidy	Bauner & Crago (2015), Cherrington et al. (2013), Jenner et al. (2013), Krasko & Doris (2013), Kwan (2012), Hsu (2012)

3.3.1 PV-intrinsic Variables

3.3.1.1 Efficiency

A mini-solar power plant consists of modules, inverters, monitoring devices, and other materials. However, despite the importance of technical attributes of solar panels, few papers dealing with solar PV adoption have addressed them. It is not realistic to include variables for all technical attributes in the analysis. In this study, after assessing three key attributes based on the study of Chen et al. (2013), the conversion efficiency of the module was set as a technical attribute variable based on two criteria: representativeness and data availability.

In Chen et al. (2013), data from small-scale PV systems installed from 2007 to 2011 were obtained from the California Solar Initiative database. After selecting the top 140 panels with the highest market share out of a total of 586 panel types, a list of 34 product attributes was constructed by combining the electrical, physical, certification, warranty, and economic properties of these panels. As expected, the expanded list of attributes exhibited a high degree of multicollinearity, meaning that the attributes were highly correlated. This is a problem, as it decreases the accuracy of the model. To reduce parameter correlation between the attributes and to improve the multiple regression model, the redundant attributes were identified using a variance inflation factor (VIF) calculation, which quantifies the severity of multicollinearity in an ordinary least squares regression analysis. This method was chosen because of the ease of comparing multicollinearity between attributes. Eight attributes with a VIF over 20 were removed, resulting in a list with a total of 26 attributes. Using three machine learning methods—

an artificial neural network, random forest decision trees, and gradient boosted regression—for each attribute, three key attributes were identified: power warranty, efficiency, and the length of time that the panel has been on the market. Power warranty is linked to consumer confidence, as well as the reliability of the solar panel. Efficiency is a reflection of the performance of the technology, in this case the panel's ability to convert solar PV into electricity. Weight per watt is a measure of the ease of installation of the panel, and hence points toward the influence of the installation process on the consumer's purchasing decision.

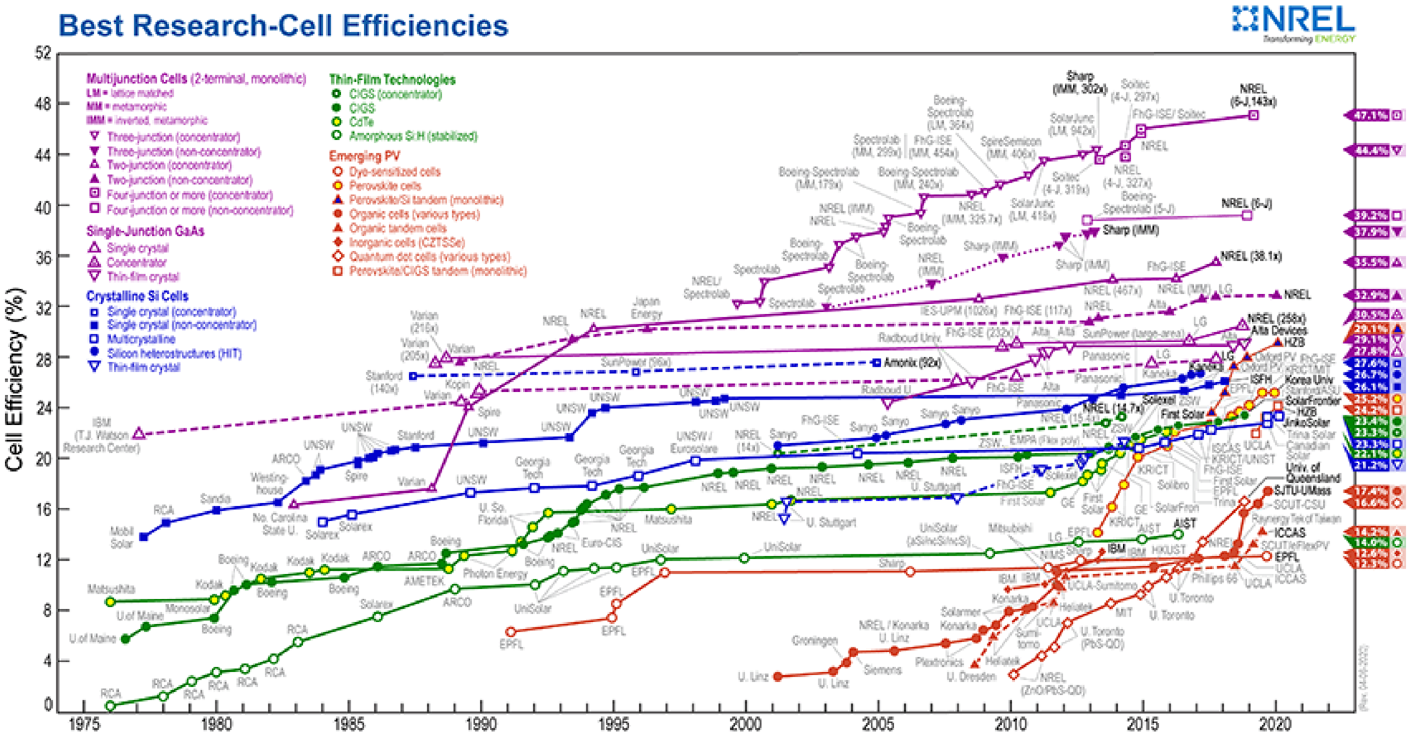

Figure 9. Best research-cell efficiencies of solar module[25]

25 Source: NREL

Silicon solar cells, which are commonly used for residential PV installations, have reached a theoretical power generation efficiency of 26-27% and are known to be a mature technology (Figure 9). However, this figure only reflects the best research-cell efficiencies, and is different from the efficiency of solar panels that consumers can install. In this study, attempts were made to obtain data on the level of efficiency of solar panels actually installed by consumers, but such data could not be obtained. Therefore, the following two variables were used.

If a solar module-related organization provides conversion efficiency for each module type, this information can be used as a representative proxy of the technical attributes of mini-solar PV. However, no domestic institutions have provided conversion efficiency data for each module type in a time series as a unified indicator. In fact, since there are so many efficiency values for each country and each product, it is challenging to find a representative number for each year and time series data. In this study, after a long search, the choice was made to use the monocrystalline and polycrystalline conversion efficiency figures for silicon solar cells provided by Bloomberg New Energy Finance, which were re-quoted and used by the Korea Export-Import Bank (2018) (Figure 10).

A polycrystalline solar panel has a lower conversion efficiency than a monocrystalline solar panel, but has high price competitiveness. According to a report from Energysage, which provides an online estimate service for solar power generation, 96% of US residential PV estimates are for monocrystalline panels [re-quoted by the Korea Institute of Information and Communication Planning and Evaluation (2019)]. In general, polycrystalline panels are preferred for large-scale power generation, and monocrystalline panels are preferred for residential use in small areas. In fact, there are no statistics regarding the types of panels that were used in Seoul for the veranda-type mini-solar PVs. Therefore, in this study, the conversion efficiency of a mono-crystal panel was first analyzed as a variable, and then the conversion efficiency of a polycrystalline panel was checked as a robustness test. According to the BNEF, the efficiency of monocrystalline panels increased from 19.4% to 21.1% and that of polycrystalline panels increased from 17.8% to 19.1% during the analysis period of this study.

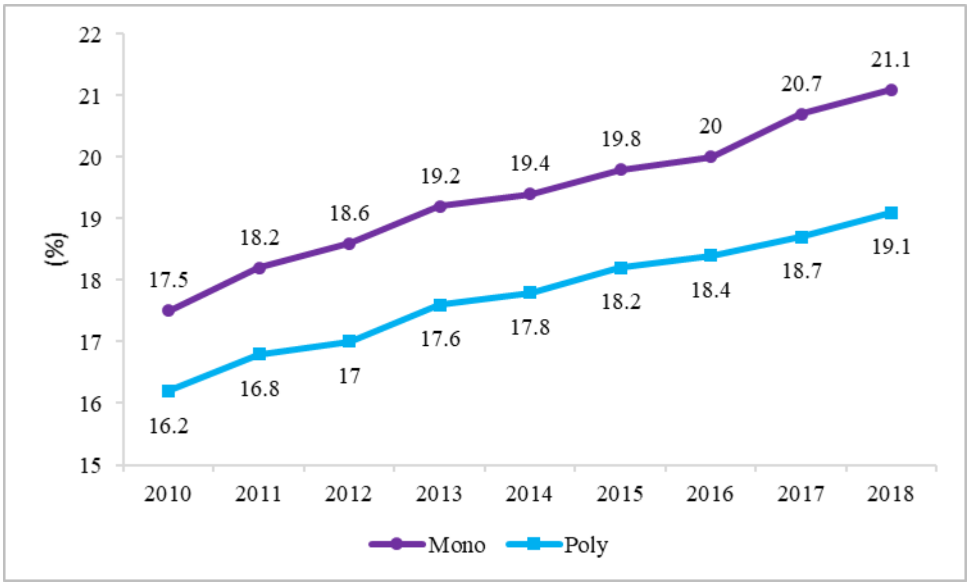

Figure 10. Trends in silicon solar cell efficiency[26]

[26] Source: Bloomberg NEF

3.3.1.2 Installation Cost

Few studies have analyzed the effect of the cost of mini-solar PV as a factor influencing adoption. Studies focusing on the costs of mini-solar PV have mainly analyzed economic viability by calculating the levelized cost of electricity [Say et al., 2018; Hagerman et al., 2016; Holdermann et al., 2014; Reichelstein & Yorston, 2013], soft cost reduction [Morris et al., 2014; Seel et al., 2014], or price transparency [O'Shaughnessy & Margolis, 2018].

The system cost of the mini-solar PV can compensate for the investment by cost-savings during continuous operation, instead of high upfront costs, as is the case for EVs. Islam (2014) used the theory of disruptive innovation to predict the diffusion of solar PV for household level electricity generation, and showed that the cost of installation played an important role in PV diffusion. The total cost for mini-solar PV installation was expressed as the installation cost in this study because the cost for installing a solar panel in Korea, unlike in other countries such as Germany and United States, is expressed as a lump sum cost without discrimination between the system cost and the soft cost.

The installation cost is especially important in the adoption of mini-solar PV in Korea. Unlike general residential solar PV installations, the electricity generated from mini-solar PV installations cannot be fed into the grid, so that the main remuneration mechanism is electricity bill savings resulting from the generated electricity being used as soon as it is generated to avoid consumption from the grid. Of course, in some cases, the cost per kWh may be lowered by reducing costs through the progressive system of electricity pricing due to a decrease in total electricity consumption. As will be further explained in the user-intrinsic variables section below, the amount of electricity that can be produced from a mini-solar PV installation in a month is about 24.3 kWh on average. Therefore, only households with 200-224 kWh or 400-424 kWh of electricity consumption per month can benefit from reduced costs through the progressive system of electricity pricing. For this reason, the cost reduction due to reduced electricity usage is the main benefit; thus, the higher the installation cost, the longer the payback period, hindering mini-solar PV installation.

The Seoul Metropolitan Government discloses the specifications and prices of each mini-solar PV installation company and each product on the Seoul Solarmap website. Citizens can freely access the website and obtain information. In this study, the price information published on this website was used.

3.3.2 PV-extrinsic Variables

3.3.2.1 User-intrinsic Variables

In this study, income, owner-occupancy, electricity consumption, and eco-friendliness were selected as user-intrinsic variables.

First, income level was used as an explanatory variable because higher income is linked to a consciousness of low financial risks. Many studies have found that high income leads to a high probability of adopting innovative products [Diaz-Rainey and Ashton, 2011; Dobre et al., 2009; Im et al., 2003; Eastlick & Lotz, 1999; Martinez et al., 1998], although some researchers have insisted that income is not a proper factor to describe adoption behavior [McDonald et al., 2003; Flynn & Goldsmith, 1993].

Previous studies related to solar PV adoption have also shown that in most cases, income-related variables had a positive effect on PV adoption [Briguglio & Formosa, 2017; Crago & Chernyakhovskiy, 2017; Dharshing, 2017; Schaffer & Brun, 2015; Sardianou & Genoudi, 2013; Kwan, 2012, Rai & McAndrews, 2012], although a few studies have presented different opinions [Allan, McIntyre, 2017].

Median income [Dharshing, 2017; Schaffer & Brun, 2015; Sardianou & Genoudi, 2013; Kwan, 2012, Rai & McAndrews, 2012], median home value [Crago & Chernyakhovskiy, 2017; Kwan, 2012; Rai & McAndrews, 2012], and employment/unemployment rate [Allan & McIntyre, 2017; Briguglio & Formosa, 2017; Dharshing, 2017] have been used as variables representing income in previous studies. However, even when the same variable is used, its meaning may be different. Crago & Chernyakhovskiy (2017) set the median home value as a proxy for median income and stated that the reason for doing so was that median income is highly correlated with other demographic variables. In contrast, Kwan (2012) saw home values as a kind of collateral; in other words, the higher the median home value, the more collateral will be used to procure costs for solar PV projects. In contrast, Briguglio & Formosa (2017) chose to use the unemployment rate.

Allan & McIntyre (2017) analyzed income and assets separately. The employment rate was selected as an income-related variable, while the owned-mortgage ratio was used as a variable for assets. The former had no effect, while the latter had a positive effect. Based on these results, the authors argued that housing wealth is more important for PV uptake than earned income. Although Kwan (2012) did not specify that it a distinction was made between income and assets, as in Allan & McIntyre (2017), Kwan (2012) included both median income and median home values, and showed that both variables had an effect.

In this analysis, the average income per household for each *gu* was set as a proxy for income to facilitate comparisons with previous studies. The Seoul Survey publishes monthly average income data per household by *gu* through annual sample surveys. A limitation is that the data are not panel survey data, but this is the only source of available data for each *gu*.

The second user-intrinsic variable was owner-occupancy. The higher the owner-occupancy rate, the higher the incentive to install mini-solar PV. A veranda-type mini-solar PV is installed on the veranda railing in an apartment complex. Tenants must obtain permission from the owner. From the owner's point of view, all the benefits of installing a mini-solar PV accrue to the tenants, so there is a possibility that the owner will not allow mini-solar PV installation due to concerns about damage to the veranda or typhoons. Moving after installation will make it necessary to relocate the mini-solar PV, incurring separate costs. These factors might collectively have a negative impact of PV adoption by non-homeowners. For these reasons, previous studies also showed that the owner-occupancy rate was an important explanatory variable with a positive effect on PV adoption [Allan & McIntyre, 2017; Bruguglio & Formosa, 2017; Schaffer & Brun, 2015].

In general, the key variables that determine the type of housing occupancy are holding assets, income, and housing cost by housing type. In particular, many previous studies have shown that assets and income are important variables [Jung, 2017; Lee & Jung, 2016; Lee & Lee, 2016; Nam & Kim, 2015; Kim & Yoo, 2013; Kang & Ma, 2009; Lee et al., 2009; Choi et al., 2002]. This is a reasonable result, in that sufficient assets must be accumulated in order to purchase a house that costs several times the annual income, and a stable income for long-term loan repayment is required [Lee & Lee, 2016].

Therefore, there is a risk of multicollinearity when analyzing income and the owner-occupancy rate simultaneously as explanatory variables. As shown in Table 29, the results of the VIF test showed that multicollinearity was not a problem. However, since multicollinearity test—including the VIF test itself—does not have an absolute standard, a rule of thumb determines the presence or absence of multicollinearity. It is difficult to completely rule out this possibility. Therefore, in this study, we first conducted an analysis including both income and owner-occupancy, and then checked the robustness by comparing the results separately.

Since data on the type of occupancy for multi-dwelling units are not released every year, 20% of the 2015 census data provided by the National Statistical Office was used as a time-invariant variable with the results of the sample survey (Table 25).

Table 25. Owner-occupancy ratio of multi-dwelling housing units by *gu*[27]

gu	Self-occupancy	Yearly rentals	Monthly rentals	Others[28]	Total	Owner-occupancy ratio (%)
Jongno	15,233	5,989	5,556	1,273	28,051	54.3
Jung	13,913	8,264	6,180	471	28,828	48.3
Yongsan	21,132	14,406	9,494	2,385	47,417	44.6
Seongdong	35,441	18,264	10,604	1,681	65,990	53.7
Gwangjin	34,749	15,652	8,324	1,117	59,842	58.1
Dongdaemun	45,192	15,158	9,804	1,432	71,586	63.1
Jungnang	49,601	15,125	10,127	710	75,563	65.6
Seongbuk	59,729	23,243	11,407	2,883	97,262	61.4
Gangbuk	40,788	15,086	12,324	1,296	69,494	58.7
Dobong	63,563	15,695	9,308	1,945	90,511	70.2
Nowon	97,240	38,479	34,421	3,567	173,707	56.0
Eunpyeong	70,428	30,134	13,321	2,722	116,605	60.4
Seodaemun	39,152	16,936	10,869	1,837	68,794	56.9
Mapo	44,839	28,201	19,826	2,298	95,164	47.1
Yangcheong	70,387	34,086	14,323	2,211	121,007	58.2
Gangseo	84,866	39,815	32,183	3,622	160,486	52.9
Guro	65,728	22,753	10,679	2,059	101,219	64.9
Geumcheon	30,298	8,113	5,730	1,902	46,043	65.8
Yeongdeungpo	45,220	17,646	9,400	2,611	74,877	60.4
Dongjak	51,892	22,404	12,263	3,038	89,597	57.9
Gwanak	54,368	21,631	16,552	2,751	95,302	57.0
Seocho	55,904	34,787	19,699	2,944	113,334	49.3
Gangnam	63,593	47,177	40,392	3,494	154,656	41.1
Songpa	84,577	49,499	32,870	4,177	171,123	49.4
Gangdong	54,653	31,549	14,211	1,116	101,529	53.8
Total	1,292,486	590,092	379,867	55,542	2,317,987	55.8

27 Source: KOSIS

28 Official residences, company housing, etc. are included.

The third user-intrinsic variable was electricity consumption. The main remuneration scheme of mini-solar PV installations is largely bill-saving due to self-consumption and financial benefits due to additional incentive mechanisms. The greater the benefits of remuneration, the more PV adoption is advantageous to the consumer.

First, the most important factor in calculating the profits from self-consumption is the rate structure of electricity. If one pays a flat rate, the profit from self-consumption is limited to the avoided costs from grid electricity. However, under an increasing block pricing tariff system like that in Korea (referred to as the "progressive system" elsewhere in this chapter), self-consumption can lower total power consumption, thereby accruing a benefit by shifting a household down to a lower pricing block.

In Korea, a progressive system is applied to residential power, in which households with higher levels of power consumption are subject to higher demand charges and energy charges to induce energy-saving behavior. Social demands have been made to restructure the existing six-phase progressive system, which has been maintained for 12 years, due to heat waves in 2016. However, for consumers towards the bottom of pricing blocks, there is a considerable incentive to use mini-solar PV to drop down to the pricing block directly below (Table 26).

Table 26. Residential tariffs in Korea: before and after the reform in 2016[29]

Before reform (until 2016.11.30)		
Stage	Demand charge (KRW/households)	Energy charge (KRW/kWh)
≤ 100 kWh	410	60.7
101 − 200 kWh	910	125.9
201 − 300 kWh	1,600	187.9
301 − 400 kWh	3,850	280.6
401 − 500 kWh	7,300	417.7
≥ 501 kWh	12,940	709.5
After reform (2016.12.1 to the present)		
Stage	Demand charge (KRW/households)	Energy charge (KRW/kWh)
≤ 200 kWh	910	93.3
201 − 400 kWh	1,600	187.9
≥ 401 kWh	7,300	280.6

[29] Source: KEPCO

When using only mini-solar PV without a battery, the generation time and the usage time must match. Even if power generation and usage time coincide, bill-saving due to self-consumption does not occur beyond consumers' consumption. Therefore, the high retail rate of electricity is an important factor in maximizing profits from self-consumption. Several previous studies have shown that electricity price has a positive effect on PV adoption [Crago & Chernyakhovskiy, 2017; Sardianou & Genoudi, 2013; Kwan, 2012]. During the analysis period, retail rate of electricity did not change and it is relatively low compared to that of other countries.

The possibility of gaining additional profits depends on the remuneration scheme. In the region where net metering is implemented, when excessive generation occurs, it can be sold to the grid and compensated at a retail rate [La Monaca & Ryan, 2017; Hagerman et al., 2016; Krasko & Doris, 2013]. In areas where FIT schemes are applied to residential solar energy, tariffs can be received for excessive generation [Allan & McIntyre, 2017; Klein & Deissenroth, 2017; La Monaca & Ryan, 2017; Sommerfeld et al., 2017; Hirvonen et al., 2015; Islam, 2014], where renewable energy credits are available in areas covered by the RPS scheme [Candas et al., 2019; Crago & Chernyakhovskiy, 2017; Krasko & Doris, 2013]. In Seoul, mini-solar PV installations cannot provide power to the grid, so the remuneration scheme described above cannot be applied.

In general, the power consumption of the previous year can be a positive incentive to install PV, but the PV installation amount of the corresponding year can be a negative factor for the power consumption of the next year. Therefore, including this variable in the model raises the possibility of endogeneity.

The problem is that only aggregated data for each *gu* are available. In terms of individual households, the logic above may be plausible. According to the Seoul Metropolitan

Government’s announcement in 2014, a 200–260 W standard module produces 292 kWh per year, which is similar to the annual consumption of a 900-liter double-door refrigerator. Since the average monthly electricity use for residential power in Seoul from 2014 to 2018 was 416.6 kWh per household, the amount of electricity used by a household for one year is 4999.2 kWh. The amount of electricity produced by a 200–260 W standard mini-solar power unit therefore accounts for 5.84% of a household's annual power consumption.

As of 2018, the district in which the largest number of households had installed veranda-type mini-solar PV units was Dobong-gu. Of the total 95,894 multi-dwelling units in Dobong-gu, 4,172 households had installed a mini-solar PV and the percentage of households with mini-solar PV was 4.35%. The total number of households in Dobong-gu was 105,526, and the total amount of electricity used for residential use in Dobong-gu in 2018 was 527,545,579.2 kWh. In 2018, 4,172 households produced 1,218,224 kWh from 260 W panels, corresponding to 0.23% of the total electricity consumption in Dobong-gu. This value calculated for 2018 is expected to be much higher than the value from 2017, as new installations accounted for approximately 43% of the cumulative number of households with mini-solar PV installations in 2018. Therefore, the analysis was conducted in light of the finding that the reduction of power consumption from the grid due to the installation of mini-solar PV units was negligible, and power consumption was therefore regarded as an exogenous variable. Of course, this assumption will need to be changed when households with a mini-solar PV installation eventually become the majority over time and panel efficiency improves, resulting in a mature phase of power generation.

The last user-intrinsic variable is eco-friendliness. In previous studies that conducted surveys on the social characteristics of consumers, it was found that higher eco-friendliness led to a higher probability of adopting mini-solar PV [Crago & Chernyakhovskiy, 2017; Bollinger & Gillingham, 2012]. Since mini-solar PV does not emit greenhouse gases in the process of generating electricity, it is helpful for overcoming climate change; as such, people with eco-friendly tendencies are more likely to adopt mini-solar PV.

Measuring eco-friendliness is quite tricky because it is highly subjectively evaluated on an individual level and there is no absolute standard for quantitatively measuring it. However, for the reasons mentioned above, it is thought that eco-friendliness is likely to affect PV adoption. Several previous studies have attempted to quantitatively measure eco-friendliness, using proxy variables such as hybrid vehicle adoption [Crago & Chernyakhovskiy, 2017; Bollinger & Gillingham, 2012], Green (or Democratic) Party voting [Allan & McIntyre, 2017; Briguglio & Formosa, 2017; Crago & Chernyakhovskiy, 2017; Dharshing, 2017], and recycling rate [Allan & McIntyre, 2017, Briguglio & Formosa, 2017].

In the literature related to hybrid vehicle adoption, it has been found that the adoption of hybrid vehicles is positively influenced not only by economic benefits, but also by pro-environmental preferences [Gallagher & Muehlegger, 2011; Kahn, 2007], which became the basis for using hybrid vehicle adoption as a proxy for eco-friendliness. Crago & Chernyakhovskiy (2017) and Bollinger & Gillingham (2012) used hybrid vehicle adoption as a proxy for environmental preferences. In both studies, eco-friendliness—operationalized as hybrid vehicle adoption—had a large and highly statistically significant effect. However, careful interpretation of these findings is needed, because the analyses included several variables that affect hybrid vehicle adoption (income, education, and long commute). For example, income and age variables were shown to have a significant positive effect on hybrid vehicle adoption by

Gallagher & Muehlegger (2011), and these variables were used along with hybrid vehicle adoption in both studies.

Voting for the Green Party is a fairly comprehensive proxy for representing eco-friendliness. Studies that used the Green Party vote as a proxy for eco-friendliness have also mentioned this point [Allan & McIntyre, 2017], while Crago & Chernyakhovskiy (2017) used Democratic Party votes as a proxy instead of Green Party votes, since the logic was the same as for Green Party votes. In general, the Democratic Party cares about environmental issues and supports legislation to address climate change, so that if someone votes for the Democratic Party, we can consider that she also supports the stance of the party regarding environmental issues.

The recycling rate is a somewhat country-specific proxy. In the UK, since the government does not give financial incentives for households to recycle or levy financial penalties for not recycling, the number of households recycling should directly reflect environmental sentiments [Allan & McIntyre, 2017]. However, in Korea, it is impossible to find households that do not recycle, and if food and recycled products are mixed in a "pay-as-you-go bag," a fine will be imposed according to the Waste Management Act and the bag will not be collected. Therefore, the recycling rate is a variable that does not fit the situation of Korea.

However, eco-friendliness has also been shown not to be a particularly significant variable [Allan & McIntyre, 2017; Dharshing, 2017; Sommerfeld et al., 2017; Schaffer & Brun, 2015]. Allan & McIntyre (2017) sought to determine whether the environmental sentiment of British consumers could help explain variation between local authorities in PV uptake. In their study, three proxies were used. The first was whether the UK Green Party did not field candidates for local authority elections in the region, the second was the recycling rate, and final one was the proportional representative vote rate of the Green Party in the 2009 European Parliament election. Of course, voting entails complex decision-making and making strategic choices, but the authors viewed voting for the Green Party as generally representing environmentalism. An econometric analysis showed insignificant results for all three variables. Sommerfeld et al. (2017) attempted to confirm motivations for installation through in-depth interviews with representatives of 22 households in Australia that had installed and used solar PV. The authors divided motivations into economic, social, and environmental. Economic motivations were the strongest and environmental issues were the least discussed motivation among interviewees.

Several methods could be used to determine the real significance of eco-friendliness, such as conducting a meta-analysis of previous studies focusing on this variable. Doing so would be beyond the scope of this study; however, since there are clearly some research results showing that eco-friendliness has a significant effect, the effect of this variable should be checked (in other words, it would be inappropriate to exclude this variable from the analysis *a priori*).

In this study, in consideration of multiple studies, data availability, and multicollinearity with other variables, the proportion of votes for the Green Party for each *gu* was set as a proxy. The election of the National Assembly of the Republic of Korea adopts a proportional representation system at the national level. Voters vote for one candidate running in a district and one vote for their preferred party. A party with a national proportion of the vote not exceeding 3.0% cannot elect a proportional representative. The Green Party was founded in 2012 and first ran candidates in the 2012 19th National Assembly election. However, the Green Party failed in all districts, with a nationwide share of the vote of 0.48% and a share of the vote of 0.61% in Seoul. Given these precedents, if a voter in the 20th Congressional Election held in 2016 aimed to vote strategically, the likelihood of voting for a Green Party candidate would be quite low, because such votes would be meaningless except as a symbolic gesture. Therefore, the share of votes for the Green Party in the election of the 20th National Assembly was used to represent the eco-friendliness of the local residents. Incorporating this variable into the model can provide clues as to how environmentally friendly propensity plays a role in overcoming barriers to product selection in the absence of sufficient information in the early stages of the proliferation of innovative durable goods or in the absence of user experience. The analysis period of this study was 2014-2018, and the voter turnout rate for each *gu* in the 20th congressional election in 2016 was set as a time-invariant variable for eco-friendliness. As a robustness test, the analysis was also conducted using the turnout rate for the Democratic Party.

3.3.2.2 User-extrinsic Variables

In Seoul, a rebate is provided for the initial installation cost to supply mini-solar PV. The city is focusing on subsidies, and in addition, additional rewards of 50-100k KRW are provided by each *gu* office. The remuneration scheme is only for self-consumption because it is impossible to feed power into the grid using mini-solar PV units. These conditions make it more difficult to compensate for the system cost. This is because, as described above, the time when the consumer uses electricity must match the time when power generation occurs. Even if the power consumption level is high, the benefits due to mini-solar PV are limited since the main usage time is the evening. This is especially true considering the fact that domestic electricity bills in Korea are set at a relatively low level and a fixed price is paid regardless of season or time. Therefore, a rebate program that lowers the initial cost is essential for PV diffusion. La Monaca & Ryan (2017) also pointed out that it is important to sufficiently lower the system cost when additional remuneration due to excessive generation is low.

The process of installing a mini-solar PV unit and receiving subsidies is shown in Figure 11 below. Among households living in multi-family houses, those who wish to install a mini-solar PV unit select the installation company directly and conduct a consultation and installation. When the installation is completed, the company signs a form confirming the installation by the household and submits it to the *gu* office along with the standard installation contract, subsidy application, and on-site inspection table. After confirming the documents, the *gu* office takes the documents to Seoul city office, and after review at Seoul city office, subsidies are paid to the company. Consumers only need to pay the amount of money excluding subsidies, so the subsidy is not provided after the consumer pays the actual price. This is a more convenient system for consumers.

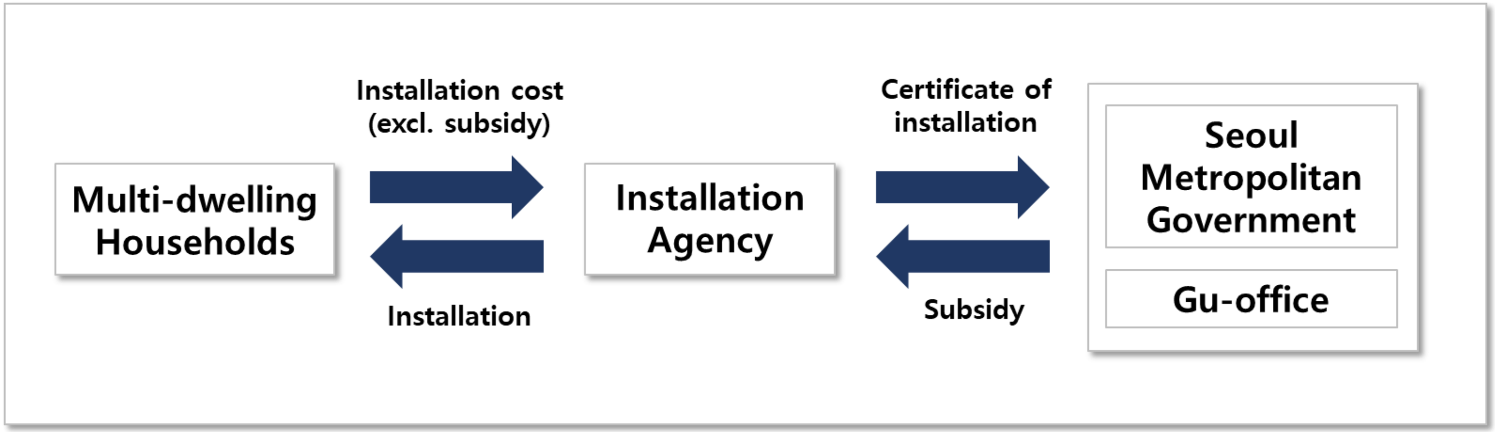

Figure 11. Mini-solar PV installation process by agents

3.4 Empirical Results

Descriptive statistics (Table 27) showed apparent overdispersion in the number of PV adoptions by year. As with EVs, the high within-variation appears to have been due to the fact that veranda-type mini-solar PV units had just been introduced. The high between-variation seems to have been caused by differences in factors such as the population, number of apartments, subsidies, and income in each *gu*.

Table 27. Descriptive statistics of dependent and independent variables (PV)

Variable		Mean	Std. Dev.	Min	Max	Observation
PV	Overall	312.416	368.4912	6	2194	N = 125
	Between[30]		193.0128	56.2	834.4	n = 25
	Within[31]		315.8062	-467.0	1672.0	T = 5
Efficiency	Overall	20.2	0.6189	19.4	21.1	N = 125
	Between		0	20.2	20.2	n = 25
	Within		0.6189	19.4	21.1	T = 5
Installation cost	Overall	683.406	35.5590	636.05	739.64	N = 125
	Between		0	683.41	683.41	n = 25
	Within		35.5590	636.05	739.64	T = 5
Subsidy	Overall	416.4	89.2554	300	542	N = 125
	Between		20.5487	369.6	451.6	n = 25
	Within		86.9362	264.8	548.8	T = 5
Income	Overall	438.5361	74.56525	308.3777	669.5399	N = 125
	Between		37.145	394.4902	535.6031	n = 25
	Within		64.9980	337.2824	671.1760	T = 5
Owner-occupancy	Overall	56.37053	6.984355	41.119	70.2268	N = 125
	Between		7.099807	41.119	70.2268	n = 25
	Within		0	56.3705	56.3705	T = 5

[30] ‘Between’ refers to the value of $\bar{x_i}$, or the individual mean.

[31] ‘Within’ refers to the value of $x_{it} - \bar{x_i} + \bar{\bar{x}}$, where $\bar{\bar{x}}$ denotes the global mean.

Table 27. Descriptive statistics of dependent and independent variables (PV) (continued)

Variable		Mean	Std. Dev.	Min	Max	Observation
Electricity consumption	Overall	430.9884	108.9989	251.8140	693.50	N = 125
	Between		110.2194	261.2203	677.73	n = 25
	Within		11.1507	406.9148	473.39	T = 5
Eco-friendliness	Overall	0.0114	0.0041	0.0073	0.0222	N = 125
	Between		0.0041	0.0073	0.0222	n = 25
	Within		0	0.0114	0.0114	T = 5

Table 28. The number of mini-solar PV installations in Seoul (2014-2018)[32]

	2014	2015	2016	2017	2018	Total	Average	Std. Dev.
Jongno	36	77	75	47	106	341	68	24.65
Jung	10	42	52	74	113	291	58	34.28
Yongsan	25	17	20	13	206	281	56	75.00
Seongdong	40	25	150	196	538	949	190	185.72
Gwangjin	24	39	6	377	422	868	174	185.29
Dongdaemun	79	159	287	666	1,539	2,730	546	535.80
Jungnang	33	58	178	234	866	1,369	274	305.29
Seongbuk	119	237	393	705	1,051	2,505	501	338.05
Gangbuk	41	88	115	177	418	839	168	132.60
Dobong	55	111	425	1,387	2,194	4,172	834	830.93
Nowon	466	208	276	670	1,774	3,394	679	570.74
Eunpyeong	58	102	84	642	1,050	1,936	387	396.45
Seodaemun	28	72	329	647	874	1,950	390	327.47
Mapo	66	110	240	483	690	1,589	318	235.99
Yangcheong	57	426	442	622	1,007	2,554	511	308.69
Gangseo	70	94	106	273	479	1,022	204	154.95
Guro	91	410	316	392	448	1,657	331	127.65
Geumcheon	90	39	325	447	776	1,677	335	266.37
Yeongdeungpo	39	91	177	507	521	1,335	267	206.48
Dongjak	74	54	226	769	726	1,849	370	314.37
Gwanak	50	60	128	549	604	1,391	278	245.65
Seocho	37	29	55	98	251	470	94	82.05
Gangnam	30	29	22	388	242	711	142	148.48
Songpa	53	176	334	375	429	1,367	273	138.76
Gangdong	106	41	340	418	900	1,367	361	303.85
Total	1,777	2,794	5,101	11,156	18,224	39,052	-	
Average	71	112	204	446	729	-		
Std. Dev.	84.87	106.35	133.18	290.77	501.03			

32 Source: Seoul Metropolitan government

First, a VIF test was performed to check for multicollinearity among variables. The results of the test are shown below (Table 29). Since the test values of all variables did not exceed 10, the problem of multicollinearity between variables was considered negligible.

Table 29. VIF test results of PVs

Variable	VIF	1/VIF
Efficiency	6.29	0.1589
Installation cost	2.59	0.3863
Subsidy	5.17	0.1934
Income	2.04	0.4906
Owner-occupancy	1.48	0.6761
Electricity consumption	1.33	0.7508
Eco-friendliness	1.31	0.7617
Mean VIF	2.89	

As described in 1.3.3, due to the limitations of the fixed-effect negative binomial model, a random-effect negative binomial model with individual-specific dummies was applied and analyzed in the EV case of Chapter 2. However, for PVs, it was necessary to target 25 *gu*s, so the calculation to be performed when the RENBD model is applied exceeds the computing capacity of a typical computer.

Therefore, for PVs, the second alternative [Allison, 2012] described in Section 1.3.3, was analyzed; specifically, an RE negative binomial model with demeaned time-varying covariates (hereafter, RENBM) was applied, and the results were compared with those of the FEP model.

After changing from the FEP model to the RENBM model, goodness-of-fit measured by AIC and BIC was significantly improved. It seems more desirable to use the RENBM model in consideration of overdispersion. Owner-occupancy and eco-friendliness were dropped in the FEP model because they are time-invariant variables.

As shown in Table 30, the results were generally consistent between the two models. In both models, efficiency, subsidy, and electricity consumption had positive effects on PV adoption. Both price and income had negative effects on PV adoption. For both variables, the estimated IRR coefficient was statistically significant in the FEP model, but the significance was lost in the RENBM model. This seems to have been due to underestimation of the standard error, because overdispersion is not considered in the FEP model. Owner-occupancy and eco-friendliness were shown to have a positive effect on PV adoption in the RENBM model.

Table 30. Summary of results from the FEP and RENBM models (PV)

Model	FEP	RENBM
Monocrystalline efficiency	2.0249^{***} (0.0628)	1.8203^{***} (0.3549)
Price	0.9989^{***} (0.0004)	0.9975 (0.0022)
Subsidy	1.0041^{***} (0.0002)	1.0042^{***} (0.0012)
Income	0.9988^{***} (0.0001)	0.9994 (0.0009)
Owner-occupancy	-	1.0707^{***} (0.0114)
Electricity consumption	1.0108^{***} (0.0007)	1.0076^{*} (0.0041)
Eco-friendliness	-	1.4827^{**} (0.2612)
AIC	4728.604	1509.507
BIC	4742.745	1537.79

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

As mentioned in Section 3.3.1.1, since no efficiency indicators are currently readily available for Korea, the global module efficiency indicators provided by BNEF were used in this study. First, the conversion efficiency of monocrystalline panel was used in the analysis as the efficiency variable, and then it was replaced with that of the polycrystalline panels to check robustness.

The results of the analyses using the FEP model and RENBM model are as follows (Table 31, 32). In both models, both efficiency variables had a positive effect on PV adoption. In terms of goodness-of-fit, the indicators of polycrystalline modules better described the data. However, it is not possible to infer whether or not polycrystalline modules are mainly installed in Seoul based on these results.

Table 31. Robustness test for the efficiency variable (FEP - PV)

FEP	Monocrystalline efficiency	Polycrystalline efficiency
Efficiency	2.0249*** (0.0628)	2.8094*** (0.1029)
Price	0.9989*** (0.0004)	0.9992** (0.0003)
Subsidy	1.0041*** (0.0002)	1.0042*** (0.0002)
Income	0.9988*** (0.0001)	0.9982*** (0.0001)
Electricity consumption	1.0108*** (0.0007)	1.0078*** (0.0007)
AIC	4728.604	4421.030
BIC	4742.745	4435.172

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

Table 32. Robustness test for the efficiency variable (RENBM - PV)

RENBM	Monocrystalline efficiency	Polycrystalline efficiency
Efficiency	1.8203^{***} (0.3549)	2.4094^{***} (0.5302)
Installation cost	0.9975 (0.0022)	0.9977 (0.0020)
Subsidy	1.0042^{***} (0.0012)	1.0043^{***} (0.0009)
Income	0.9994 (0.0009)	0.9989 (0.0009)
Owner-occupancy	1.0707^{***} (0.0114)	1.0715^{***} (0.0112)
Electricity consumption	1.0076^{*} (0.0041)	1.0052 (0.0041)
Eco-friendliness	1.4827^{**} (0.2612)	1.4746^{**} (0.2595)
AIC	1509.507	1503.523
BIC	1537.790	1531.806

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

The installation cost was found to have a negative effect on PV adoption in both the FEP and RENBM models, but it did not have statistical significance in the RENBM model. In this case, it can be suspected that the standard error was underestimated in the FEP model.

Since consumers respond to the amount actually paid as the actual price of the product, not the original price, the subsidy was subtracted from the original price and an analysis was performed using the price to be paid as the installation cost variable (Table 33). As a result, the actual amount paid obtained statistical significance, which can be interpreted as showing that consumers are reluctant to adopt PV units with a higher installation cost.

Table 33. Robustness test for the price variable (RENBM - PV)

RENBM	Installation cost	Installation cost → paidprice
Efficiency	1.8203*** (0.3549)	1.7484*** (0.3325)
Installation cost	0.9975 (0.0022)	0.9958*** (0.0012)
Subsidy	1.0042*** (0.0012)	-
Income	0.9994 (0.0009)	0.9997 (0.0008)
Owner-occupancy	1.0707*** (0.0114)	1.0686*** (0.0111)
Electricity consumption	1.0076* (0.0041)	1.0056* (0.0033)
Eco-friendliness	1.4827** (0.2612)	1.4581** (0.2560)
AIC	1509.507	1508.283
BIC	1537.790	1533.738

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

The subsidy showed a robust, positive, statistically significant relationship. If there was no subsidy, the price of a 300W mini-solar panel, which is the most widely installed type, was around mid-600,000 KRW as of 2018, and was 850,000 KRW in 2015. When the initial cost is high, the payback period for offsetting the cost with the remuneration scheme becomes very long.

For example, if a 260 W mini-solar panel costing 650,000 KRW is installed with 300,000 KRW of support from the city government, the payback period is 23.3 months, assuming that the gains obtained by self-consumption and price block shifts in the progressive system are about 15,000 KRW per month. In other words, in less than two years, the entire amount invested is recovered and its subsequent use is purely profitable. However, without a subsidy, it would take about 43.3 months (more than three years and seven months) to reach the break-even point, corresponding to almost twice the time needed when the installation is subsidized. Therefore, the subsidy is an important installation incentive for consumers, as shown by both models.

The estimated IRR coefficient of the income variable was less than 1, which is interpreted as showing that the higher the income, the more reluctant consumers were to adopt a mini-solar PV unit. This relationship was statistically significant in the FEP model, but not in the RENBM model. In general, if a consumer's income is high, all else being equal, the probability of purchasing certain goods is the same or higher.

Approximately 1.5% of all multi-dwelling households have mini-solar PV systems installed (39,052 households out of 2,541,982 households as of the end of 2018). According to Rogers' (1965) adopter categories, people who have adopted mini-solar PV by 2018 belong to the innovator group. Innovators are generally known to 1) have substantial financial resources, which can absorb the possible losses from an unprofitable innovation, 2) have the ability to understand and apply complex technologies, 3) be able to cope with the uncertainty of new technologies, and 4) be adventurous. Higher income itself enables consumers to purchase innovative goods, and also tends to raise the probability of 3) and 4).

Table 34. Robustness test for the income variable (RENBM - PV)

RENBM	Income	Assets	Income & assets	Income excluded
Monocrystalline efficiency	1.8203*** (0.3549)	1.7032* (0.5573)	1.7690* (0.5830)	1.7295*** (0.3170)
Installation cost	0.9975 (0.0022)	0.9965** (0.0018)	0.9975 (0.0022)	0.9965** (0.0018)
Subsidy	1.0042*** (0.0012)	1.0046*** (0.0012)	1.0043*** (0.0012)	1.0046*** (0.0011)
Income	0.9994 (0.0009)	-	0.9994 (0.0009)	-
Asset	-	1.0007 (0.0122)	1.0013 (0.0122)	-
Owner-occupancy	1.0707*** (0.0114)	1.0691*** (0.0112)	1.0708*** (0.0114)	1.0691*** (0.0112)
Electricity consumption	1.0076* (0.0041)	1.0067 (0.0049)	1.0073 (0.0050)	1.0068* (0.0039)
Eco-friendliness	1.4827** (0.2612)	1.4686** (0.2590)	1.4840** (0.2618)	1.4678** (0.2584)
AIC	1509.507	1510.037	1511.495	1508.040
BIC	1537.790	1538.320	1542.607	1533.495

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

The author investigated various studies to explore possible reasons for the counterintuitive effects of the income variable. The possibilities that can be drawn from the previous studies reviewed in Section 3.3.2.1 are as follows.

First, assets should be considered in addition to income. Income and assets may both be important for PV adoption [Kwan, 2012], or it may be the case that assets, not income, have a more significant effect on PV adoption [Allan & McIntyre, 2017]. In this study, the apartment sale price index by year was set and analyzed as a proxy for assets. Table 34 summarizes the results of analyzing three types of models that included only income, only assets, and both income and assets. Although it was not statistically significant, it was found that assets had a positive effect on PV adoption.

Second, the multicollinearity between income and other variables was checked [Crago & Chernyakhovskiy, 2017]. According to Table 29, income is unlikely to be multicollinear with other variables. However, as income is replaced by assets, the VIF exceeds 20, and the multicollinearity problem becomes significant (Table 35). When the scope of VIF is set conservatively, a safe value is less than 30. However, Crago & Chernyakhovskiy (2017) stated that income was found to be highly correlated with other demographic variables. In the literature on income and owner-occupancy in Korea, several studies have pointed out that income is the main factor in determining owner-occupancy [Jung, 2017; Lee & Lee, 2016; Lee & Jung, 2016; Nam & Kim, 2015; Kim & Yoo, 2013; Kang & Ma, 2009; Lee et al., 2009; Park et al., 2009].

In consideration of these prior studies' claims and multicollinearity, income variables were dropped (Table 34). As a result, owner-occupancy remains positive and significant, and the goodness-of-fit and the significance of each variable increases.

Table 35. VIF test results of PVs (Income replaced by assets)

Variable	VIF	1/VIF
Efficiency	20.76	0.04817
Installation cost	11.72	0.08533
Subsidy	5.76	0.17355
Asset	1.65	0.60597
Self-occupancy	1.59	0.62849
Electricity consumption	1.32	0.76015
Eco-friendliness	1.27	0.78660
Mean VIF	6.30	

Owner-occupancy had a robust positive association with PV adoption, regardless of whether all models and other dependent variables were included. Previous studies using owner-occupancy as an explanatory variable confirmed that it generally promotes PV adoption. However, Dharshing (2017) did not find a clear relationship between owner-occupancy and residential PV adoption in a study conducted in Germany, which the author explained as reflecting the relatively long housing tenure period in Germany.

According to the Korea Housing Survey released by the Ministry of Land, Infrastructure, and Transport in 2018, the average residence period in rental households was 3.4 years, while that of owner-occupied households was 10.7 years. In other words, the residence period is about three times longer for owner-occupied households. This characteristic can be considered as a very serious obstacle to the installation of veranda-type solar PV units because one has to relocate the solar PV when he or she moves out, which will cost time and effort, constituting a barrier to PV adoption by renters. Therefore, owner-occupancy had a strong positive effect on PV adoption in Korea.

For electricity consumption, as described in Section 3.3.2.4, the financial benefit that offsets the high upfront cost is large, so the higher the electricity usage, the stronger the incentive for PV adoption. Unfortunately, due to data limitations, it was not possible to analyze whether individuals tended to install mini-solar PV to drop down to a lower pricing block in the progressive system. A detailed analysis would have been possible if microdata had been available.

Eco-friendliness had positive effects on PV adoption at statistically significant levels (Table 36). To test the robustness of the result, I conducted a reanalysis with the ratio of Democratic

Party votes instead of that of Green Party votes. This is because Democratic parties tend to support pro-environmental policies in general [Crago & Chernyakhovskiy, 2017]. Using the Democratic Party ratio, the estimated IRR coefficient value showed positive, though it was not statistically insignificant. Taken together, eco-friendliness seems to have a positive impact on PV adoption, as I could not find any other better variable to quantify eco-friendliness.

Table 36. Robustness test for eco-friendliness variable (RENBM - PV)

Model	Income excluded	Green Party votes → Democratic Party votes	Eco-friendliness excluded
Mono-crystalline efficiency	1.7295*** (0.3170)	1.7108*** (0.3130)	1.7270*** (0.3147)
Price	0.9965** (0.0018)	0.9964** (0.0017)	0.9962** (0.0018)
Subsidy	1.0046*** (0.0011)	1.0045*** (0.0011)	1.0045*** (0.0011)
Owner-occupancy	1.0691*** (0.0112)	1.0525*** (0.0138)	1.0596*** (0.0106)
Electricity consumption	1.0068* (0.0039)	1.0068* (0.0039)	1.0065* (0.0039)
Eco-friendliness	1.4678** (0.2584)	1.0404 (0.0495)	-
AIC	1508.040	1511.579	1510.294
BIC	1533.495	1537.033	1532.920

*: p-value < 0.1

**: p-value < 0.05

***: p-value < 0.01

3.5 Summary and Discussion

In Chapter 3, I attempted to identify what encouraged mini-solar PV adoption using actual adoption data in Seoul from 2014 to 2018. The estimated IRR of each variable had a similar direction, magnitude, and statistical significance in the FEP and RENBM models.

The main findings of this study are as follows. Module efficiency had a strong positive and significant effect on PV adoption. The subsidy also showed a positive, and highly statistically significant effect on mini-solar PV adoption. Subsidies promote PV adoption as a mechanism to shorten the payback period by reducing the initial cost. Owner-occupancy had robust, positive effects on PV adoption. As the residence period varies by about three times depending on whether a housing unit is owner-occupied, the lifetime costs of mini-solar PV units are higher for tenants than for owner-occupants. Unlike previous studies, which reported that income was a good predictor of residential PV adoption [Crago & Chernyakhovskiy, 2017; Dharshing, 2017; Schaffer & Brun, 2015, Sardianou, & Genoudi, 2013; Kwan, 2012; Rai & McAndrews, 2012;], owner-occupancy was a better predictor of mini-solar PV adoption in Seoul than income due to the short tenure of residents in Seoul. In the case of electricity consumption, it was found that it is has a positive effect on PV adoption. However, the magnitude and statistical significance were not very strong. This is presumed to be due to the analysis of those who can drop the block of pricing and those who cannot at once, by using aggregate data. Eco-friendliness is likely to have a positive impact as well.

The following policy implications can be derived from the above findings. First, the reduction of subsidies can significantly inhibit mini-solar PV adoption since they had an important effect on PV adoption, and there is no remuneration scheme other than self-consumption or a decrease in the progressive system of electricity pricing due to Korea's electricity rate structure. Second, considering that owner-occupancy had a significant effect on PV adoption, policy measures other than subsidies may be required for widespread diffusion. For tenants, the incentive to install a mini-solar PV is significantly reduced in terms of ease of installation and payback period. Policies such as obliging the installation of solar PV systems in new apartment construction would be helpful. Last but not least, there is still room for improving mini-solar panel efficiency and reducing the system cost, so that more R&D efforts on the supply-side are needed.

Notwithstanding the useful insights, there are some limitations of this study. The data used in this study are short panel discrete data. As the unit root test for discrete data has not been well established academically [Park, 2015], and the time series analysis of panel data assumes a large T [Baltagi, 2013], it was difficult to apply time-series methodologies such as panel cointegration in this study. Trend variables that take into account the effects of time are generally used to capture technological progress [Münzel et al., 2019; Crago & Chernyakhovskiy, 2014]. This study included a variable for technical attributes already, which represented technological improvement over time. It is expected that the panel time series analysis method can be applied as data accumulates over time and T increases.

Chapter 4. Overall Conclusion

4.1 Summary of the Study

This study investigated the factors associated with consumer adoption of EVs and residential solar PV in Korea. These demand-side innovations are game-changing technologies opening the doors to possible new business models and successive innovations in the energy industry. The widespread adoption of innovative consumer technologies is a prerequisite for fundamental changes in the energy industry—that is, to move from a supplier-oriented system to a consumer-oriented system—as well as to fulfill the need for a low-carbon future due to climate change. Therefore, it is necessary to identify the factors of consumer adoption to promote the widespread adoption of EVs and PVs.

In Chapter 2, the drivers of EV adoption in Korea from 2013 to 2017 were analyzed. The range with a full charge had robust and strong positive effects in all models, and can therefore be considered to have the most important influence on the adoption of EVs in Korea from 2013 to 2017. Total economic incentives from the government also showed positive effect on EV adoption. Since the price of EVs had a negative effect on EV adoption, automobile manufacturers should make efforts to lower prices through technological innovation and mass production. The income of the consumers did not have a statistically significant effect on EV adoption, because there are various financial products and installment programs related to automobile purchases, so that the consumer's ability to pay may not be a major obstacle. Eco-friendliness, as measured by the voter turnout for the Green Party or Democratic Party, was found to be insignificant. EV adoption increased despite a steady decline in oil prices during the analysis period. Regarding public charging infrastructure, it was found that EV adopters did not actually utilize public fast chargers frequently, but the fact that public fast chargers existed at a close distance had a positive effect on EV adoption by relieving range anxiety.

In Chapter 3, the factors encouraging mini-solar PV adoption in Seoul from 2014 to 2018 were investigated. Efficiency and the subsidy from the government had positive and significant effects on PV adoption. Owner-occupancy had a robust positive effect on PV adoption. As the residence period varies by about three times depending on owner-occupancy, the lifetime costs of mini-solar PV units are higher for tenants than for owner-occupants. Moreover, owner-occupancy described mini-solar PV adoption in Seoul better than income. Electricity consumption had a positive effect on PV adoption, but its magnitude and statistical significance were not very strong. This is presumed to be due to the use of aggregated data, which cannot separate the consumers who can drop to a lower pricing block by installing a mini-solar PV and those who cannot. Eco-friendliness has a positive impact on mini-solar PV adoption.

4.2 Discussion of Results

4.2.1 Connecting Two Dots: EVs and PVs

The following conclusions can be drawn from the results of the analysis of the factors of EV and mini-solar PV adoption in Chapter 2 and Chapter 3 of this study. First, technical attributes are among the most decisive factors of consumer adoption for both EVs and PVs. According to the results, variables relating to technical attributes were statistically significant and robustly positive in both cases. The media and academia have focused on economic incentives for the widespread adoption of both EVs and PVs, and policies have also been oriented towards financial incentive measures. According to the “2017 Energy Consumption Survey—Electric Vehicles Owners Survey Report” of the Ministry of Trade, Industry, and Energy and Korea Energy Agency, the reason why more than twice as many EVs were sold in 2017 than in the previous year was because consumers moved up their purchases in response to a notice that the subsidies would be reduced in 2018. However, despite the reduction in subsidies in 2018, more than twice the number of EVs were sold as in 2017, so the reduction in subsidies does not necessarily impede the adoption of technological innovation.

Sophisticated users, such as the adopters of EVs or PVs in this study, lead early diffusion, and then less sophisticated users additionally adopt an innovation, leading to mass diffusion [Faber & Franken, 2009]. In order to reach the level of mass diffusion, innovation should go beyond the threshold of quality. For EVs, there is considerable room for improvement in terms of the range per full charge, which is one of the most important technical attributes, and the diversification of size, body type, and brand will also be an important improvement for exceeding the threshold of quality for many members of the general public.

For PVs, although the efficiency of solar panels in laboratories has almost reached the theoretical limit [NREL, 2019], there remains space for improvement by more than 7%p compared to the efficiency of households' PV panels. An increase in efficiency will lead to more electricity production, which in turn will enable greater electricity bill cuts, thereby allowing more households to benefit economically from the installation of solar panels.

In the survey results of mini-solar PV adopters in Seoul, 40.5% of all respondents answered that the efficiency of equipment should be increased to promote PV adoption in the future. This figure is more than twice the number of respondents (19.6%) who replied that the amount of subsidies should be increased. Improvement of the efficiency of solar panels means that one can generate the same power by installing a smaller panel. Improved efficiency would make it possible to reduce the likelihood of conflict with neighbors (e.g., prospect rights and solar rights) and to improve ventilation and aesthetic requirements. All of these factors are thought to help meet the minimal quality requirements of the early majority with diverse needs, as distinct from early innovators. Thus, in summary, a diffusion policy to accelerate diffusion of EVs and PVs with price instruments alone may not be successful if the quality of innovative products is not improved.

Second, income explained the adoption of EVs well, but did not have a clear effect on PV adoption. In general, a higher income is expected to have a positive effect on the purchase of products because it expands the consumer's budget constraints. In particular, high-income households have a higher probability of adoption because they are resilient to potential losses due to the uncertainty of new technologies with innovative durable goods. For this reason, previous studies have shown that income has generally positive effects on each innovation. However, in this study, income showed a positive effect for EVs, but not for PV, for which a statistically insignificant negative effect was observed.

The primary reason for this may relate to the average price and the method of payment that consumers must pay to purchase each good. In 2016, the average monthly income of all households was 3,652,121 KRW, and the average price of EVs for purchase was 44 million KRW. Since the average of subsidies and tax benefits is 22.5 million won, consumers pay about 20 million won on average. This corresponds to approximately 6 months of salary. If there was no financial support, one would need to pay an amount equivalent to a full year of income. As such, initial costs are quite expensive; therefore, when a car is purchased, one generally pays a down payment, followed by a monthly payment for the next few years. While there are no official statistics on the average number of months of car purchase payments in installments, one agency for second-hand cars surveyed car owners and showed that a 36-month duration of payments was most widely preferred. It is possible to accumulate the initial down payment and to pay the remaining installments only when a consumer consistently earns a certain income. In that sense, income is an important explanatory variable to explain the purchase of EVs.

In contrast, for PVs, although the installation cost varies depending on the capacity, a 260 W panel (which is one of the most widely installed) cost an average of 670,000 KRW in total in 2016. Considering the installation subsidies from Seoul Metropolitan City (approximately 310,000 KRW) and the additional subsidies of 50,000 to 100,000 KRW provided by the district governmental office, the actual amount paid will be about 260,000 won. This amount corresponds to about 7% of the average monthly income of all households in 2016. It would be 18.3% of monthly income even without financial support from the government. As with EVs, there are no official statistics on payments of the PVs installation. It would seem to be possible to use the installment program provided by card companies because it is possible to pay the installation cost of PVs by credit card. Nonetheless, it is not common to purchase mini-solar PV units using the same pattern as in an EV purchase. Therefore, the differences between these goods in terms of the average price and method of payment likely resulted in the difference in the explanatory power of the income variable.

Of course, in both cases, aggregated data at the first-tier administrative division- or *gu-* levels were used, rather than microdata from individual consumers, so that we cannot completely rule out the possibility that these factors were not captured in the data, although *gu*s with high household incomes tended to show a high rate of PV installation. However, as can be seen in the figure below, although there is a tendency for owner-occupancy to become more common as household income increases in general, the Housing Database dataset of the OECD pointed out that the share of homeowner households hardly varies with the income quartile in Korea. As examining the effect of income on owner-occupancy is outside the scope of this study, no further analysis was performed. However, this trend may also disrupt the effect of income on the adoption of PVs. Overall, these highly specific characteristics of the housing market and residential patterns in Korea underscore the importance of an analysis limited to Korea, rather than a comparative analysis of various countries.

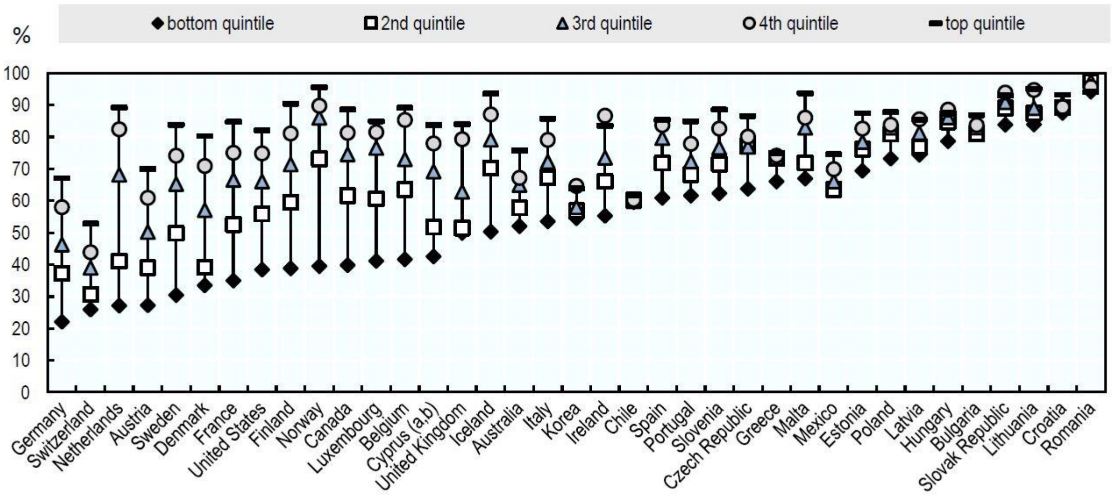

Figure 12. Share of homeowner households (with and without outstanding mortgage) by income quintile[33]

[33] Source: OECD

4.2.2 Revealed Preferences and Stated Preferences

In this study the factors for adopting technological innovation were analyzed based on revealed preferences. Such studies are significant because they can discover new facts that are not seen in the studies only based on stated preferences, through comparisons and contrasts with studies based on stated preferences.

First, the results of the effect of gasoline price on the adoption of EVs are different from those presented in research using stated preferences. EV adoption increased despite a steady decline in oil prices during the analysis period, unlike what has been reported in previous studies based on stated preferences [Vassileva & Campillo, 2017; Hardman et al., 2016; Link et al., 2012; Hidrue et al., 2011]. The reasons for this are as follows. First, people who have an annual mileage that is significantly higher than average may have been more likely to purchase an EV, because under such circumstances, it is still beneficial to purchase an EV even if the oil price is slightly lower. Secondly, as generous financial incentives in Korea significantly alleviated the initial purchase cost and the charging fees of public fast chargers were very low, the economic payback period of EVs might have been shortened to a reasonable range. Third, because people are sensitive to oil price increases, while they have an asymmetrical tendency in terms of price perceptions to react insensitively to price declines, they may not have reacted specifically to falling gasoline prices.

In surveys of domestic consumers regarding their propensity for purchasing eco-friendly vehicles based on price and fuel economy, approximately 85% of respondents said that they valued fuel economy [Woo, 2015]. In the "2017 Energy Consumption Survey—Electric Vehicles Owners Survey Report," 43.6% of EV users chose fuel cost reduction as the most important purchasing decision factor. However, the economic benefits from reducing fuel costs can only be achieved through a long payback period. Numerous studies have shown that people tend to incorrectly estimate the size of fuel economy benefits [Sierzchular et al., 2014; Turrentine & Kurani, 2007], perceive the payback period as very short [Turrentine & Kurani, 2007], and hardly concern themselves with the potential cost savings when making a vehicle purchase decision [Carley et al., 2013]. Altogether, in contrast with survey results, fuel costs did not significantly affect consumers' actual adoption of EVs.

The impact of public charging infrastructure on the adoption of EVs can also be explored in more detail by comparing the results of this study with the results of surveys and actual public charger usage data.

According the consumer survey by Woo (2015), the possibility of early dissemination of public charging infrastructure (35.31%) was the most important factor for consumers to purchase an eco-friendly car, followed by eco-friendliness (26.51%), safety and ease of use (20.57%), and a reasonable price (16.65%). Other survey-based studies in Korea pointed out that drivers perceived the public charging infrastructure as a vital factor in EV adoption [Byun et al., 2018] and that consumers were concerned about the charging time of an EV [Kwon et al., 2018]. Previous studies of countries other than Korea based on stated preferences also reported that public charging infrastructure was a key factor in EV adoption [She et al., 2017; Vassileva & Campillo, 2017; Junquera et al., 2016; Sang & Bekhet, 2015; Carley et al., 2013].

In this study, an analysis was performed using the number of public fast chargers per registered EVs as a public charging infrastructure variable, but it was found that it did not significantly affect the adoption of EVs. An analysis using charger density, defined as the number of public fast chargers divided by the area of the first-tier administrative division, showed a positive effect on the adoption of EVs, but it was not statistically significant. Since charger density had a positive effect on EV adoption, it might be assumed that public chargers were actively used where the charger density was high. However, the frequency and the amount of public fast charger usage were quite low. Instead, it appears that when people have nearby public charging infrastructure, their range anxiety is lowered, making them more likely to adopt EVs, even though they do not actually use public fast chargers frequently since they can charge their EVs at home or workplaces.

The results in Chapter 3 are quite similar to the survey results of people who actually installed mini-solar PVs, but by connecting and interpreting the two sets of findings, it is possible to obtain a more accurate picture of reality.

First, eco-friendliness, which did not have a significant impact on EV adoption, had a significant positive effect on mini-solar PV adoption. As described above, since the mini-solar PV installation costs about 7% of the average monthly income, the eco-friendliness of consumers can drive the installation decision even if the installation does not provide a major economic benefit. The rationale for this interpretation can be found in the results of a survey of people who had installed mini-solar PV units [Seoul Metropolitan Government, 2017; Baek & Yun, 2015]. In the two surveys, the main reasons for the PV installation for consumers were saving electricity bills, which accounted for 81.4% in Seoul Metropolitan Government (2017) and 61% in Baek & Yun (2015), followed by the concern for the environment.

Although economic aspects were considered to be decisive factors for mini-solar PV adoption in both surveys, the proportion of households with less than 8,000 KRW in electricity bill savings after installation reached about 47%, and the proportion of those who said they did not know how much they had saved was about 30%, according to data from the Seoul Metropolitan Government (2017). Baek & Yoon (2015) also found that the correlation between overall satisfaction and the monthly average electricity bills saving was not statistically significant after the installation of mini-solar PV units. In contrast, the analysis of this study found that the power consumption per household had a positive effect on the adoption of mini-solar PV units.

Taken together, it seems that even though consumers are concerned about economic factors such as electricity bill savings when deciding whether to install a mini-solar PV unit, they do not tend to maximize profits through accurate calculations; instead, they tend to be satisfied with the fact that they have installed a mini-solar PV unit, despite not clearly recognizing the amount of savings or the slight amount of the benefit. Thus, a possible interpretation is that consumers respond sensitively to the initial cost, but relatively less sensitively to operating costs, as with fuel costs for EVs. It can therefore be concluded that focusing on reducing the initial cost, rather than operating costs, when designing a technology innovation diffusion policy in the future will be more effective for promoting the widespread diffusion of an innovation.

Bibliography

Agnew, S., Smith, C., & Dargusch, P. (2018). Causal loop modelling of residential solar and battery adoption dynamics: a case study of Queensland, Australia. *Journal of Cleaner Production*, *172*, 2363-2373.

Allan, G. J., & McIntyre, S. G. (2017). Green in the heart or greens in the wallet? The spatial uptake of small-scale renewable technologies. *Energy Policy*, *102*, 108-115.

Allison, P. D., & Waterman, R. P. (2002). Fixed–effects negative binomial regression models. *Sociological methodology*, *32*(1), 247-265.

Allison, P. (2012, June 8). Beware of Software for Fixed Effects Negative Binomial Regression. Message posted to https://statisticalhorizons.com/fe-nbreg

Axsen, J., Bailey, J., & Castro, M. A. (2015). Preference and lifestyle heterogeneity among potential plug-in electric vehicle buyers. *Energy Economics*, *50*, 190-201.

Baltagi, B. H. (2013). *Econometric Analysis of Panel Data* (5th ed.). Chichester: John Wiley & Sons Ltd.

Bauner, C., & Crago, C. L. (2015). Adoption of residential solar power under uncertainty: Implications for renewable energy incentives. *Energy Policy*, *86*, 27-35.

Belsley, D. A. (1991). A guide to using the collinearity diagnostics. *Computer Science in Economics and Management*, *4*(1), 33-50.

Bjerkan, K. Y., Nørbech, T. E., & Nordtømme, M. E. (2016). Incentives for promoting battery electric vehicle (BEV) adoption in Norway. *Transportation Research Part D: Transport and Environment*, *43*, 169-180.

Bloomberg New Energy Finance (BNEF). *Comparison of Long-term Electric Vehicle Outlooks 2018*. Bloomberg New Energy Finance: New York, USA, 2018.

Bloomberg New Energy Finance (BNEF). *1H 2019 LCOE Update*. Bloomberg New Energy Finance: New York, USA, 2019.

Blundell, R., Griffith, R., & Van Reenen, J. (1999). Market share, market value and innovation in a panel of British manufacturing firms. *The review of economic studies*, *66*(3), 529-554.

Bollinger, B., & Gillingham, K. (2012). Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science*, *31*(6), 900-912.

Briguglio, M., & Formosa, G. (2017). When households go solar: Determinants of uptake of a Photovoltaic Scheme and policy insights. *Energy Policy*, *108*, 154-162.

British Petroleum (BP) p.l.c. (2018). *BP Energy Outlook*. BP) p.l.c.: London, United Kingdom.

Brownstone, D., Bunch, D. S., & Train, K. (2000). Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. *Transportation Research Part B: Methodological*, *34*(5), 315-338.

Byun, H., Shin, J., & Lee, C. Y. (2018). Using a discrete choice experiment to predict the penetration possibility of environmentally friendly vehicles. *Energy*, *144*, 312-321.

Cai, D. W., Adlakha, S., Low, S. H., De Martini, P., & Chandy, K. M. (2013). Impact of residential PV adoption on Retail Electricity Rates. *Energy Policy*, *62*, 830-843.

Cameron, A. C., & Trivedi, P. K. (1986). Econometric models based on count data. Comparisons and applications of some estimators and tests. *Journal of applied econometrics*, *1*(1), 29-53.

Cameron, A. C., & Trivedi, P. K. (2010). Microeconometrics using Stata (revised ed.). *Number musr in Stata Press books. StataCorp LP*.

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data* (Vol. 53). Cambridge university press.

Candas, S., Siala, K., & Hamacher, T. (2019). Sociodynamic modeling of small-scale PV adoption and insights on future expansion without feed-in tariffs. *Energy Policy*, *125*, 521-536.

Carley, S., Krause, R. M., Lane, B. W., & Graham, J. D. (2013). Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. *Transportation Research Part D: Transport and Environment*, *18*, 39-45.

Chapman, A. J., McLellan, B., & Tezuka, T. (2016). Residential solar PV policy: An analysis of impacts, successes and failures in the Australian case. *Renewable Energy*, *86*, 1265-1279.

Chatterjee, S., Hadi, A. S., & Price, B. (2006). Analysis of collinear data. *Regression analysis by example*, 143-174.

Chen, H. Q., Honda, T., & Yang, M. C. (2013). Approaches for identifying consumer preferences for the design of technology products: a case study of residential solar panels. *Journal of Mechanical Design*, *135*(6).

Cheng, J. M., Kao, L. L., & Lin, J. Y. C. (2004). An investigation of the diffusion of online games in Taiwan: An application of Rogers' diffusion of innovation theory. *Journal of American Academy of Business*, *5*(1/2), 439-445.

Cherif, R.; Hasanov, F.; Pande, A. *Riding the Energy Transition: Oil Beyond 2040*; International Monetary Fund: Washington, DC, USA, 2017.

Cherrington, R., Goodship, V., Longfield, A., & Kirwan, K. (2013). The feed-in tariff in the UK: A case study focus on domestic photovoltaic systems. *Renewable Energy*, *50*, 421-426.

Chesser, M., Hanly, J., Cassells, D., & Apergis, N. (2018). The positive feedback cycle in the electricity market: Residential solar PV adoption, electricity demand and prices. Energy Policy, 122, 36-44.

Chien, C. F., Chen, Y. J., & Peng, J. T. (2010). Manufacturing intelligence for semiconductor demand forecast based on technology diffusion and product life cycle. International Journal of Production Economics, 128(2), 496-509.

Christensen, L., Kveiborg, O., & Mabit, S. L. (2012). The Market for electric vehicles – what do potential users want. Paper presented at 12th World Conference on Transportation Research, Lisbon, Portugal.

Clyde, S. (2015, June 9). Multicollinearity Panel Data. Message posted to https://www.statalist.org/forums/forum/general-stata-discussion/general/1297526-multicollinearity-panel-data

Crago, C., & Chernyakhovskiy, I. (2014). *Solar PV technology adoption in the United States: An empirical investigation of state policy effectiveness* (No. 329-2016-13292, pp. 1-20).

Crago, C. L., & Chernyakhovskiy, I. (2017). Are policy incentives for solar power effective? Evidence from residential installations in the Northeast. *Journal of Environmental Economics and Management*, *81*, 132-151.

Dharshing, S. (2017). Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. *Energy research & social science*, *23*, 113-124.

Diaz-Rainey, I., & Ashton, J. K. (2011). Profiling potential green electricity tariff adopters: green consumerism as an environmental policy tool?. *Business Strategy and the Environment*, *20*(7), 456-470.

Dee Dickerson, M., & Gentry, J. W. (1983). Characteristics of adopters and non-adopters of home computers. *Journal of Consumer research*, *10*(2), 225-235.

Dobre, C., Dragomir, A., & Preda, G. (2009). Consumer Innovativeness: A Marketing Approach. *Management & Marketing*, *4*(2).

Dong, C., Clarke, D. B., Yan, X., Khattak, A., & Huang, B. (2014). Multivariate random-parameters zero-inflated negative binomial regression model: An application to estimate crash frequencies at intersections. *Accident Analysis & Prevention*, *70*, 320-329.

Eastlick, M. A., & Lotz, S. (1999). Profiling potential adopters and non-adopters of an interactive electronic shopping medium. *International Journal of Retail & Distribution Management*.

Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy policy*, *48*, 717-729.

ExxonMobil. (2018). 2018 Outlook for Energy: A View to 2040. Exxon Mobil Corporation: Texas, United States.

Faber, A., & Frenken, K. (2009). Models in evolutionary economics and environmental policy: Towards an evolutionary environmental economics. *Technological Forecasting and Social Change*, *76*(4), 462-470.

Farrar, D. E., & Glauber, R. R. (1967). Multicollinearity in regression analysis: the problem revisited. *The Review of Economic and Statistics*, 92-107.

Flynn, L. R., & Goldsmith, R. E. (1993). Identifying innovators in consumer service markets. *Service Industries Journal*, *13*(3), 97-109.

Gallagher, K. S., & Muehlegger, E. (2011). Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology. *Journal of Environmental Economics and management*, *61*(1), 1-15.

Ganesh, J., Kumar, V., & Subramaniam, V. (1997). Learning effect in multinational diffusion of consumer durables: An exploratory investigation. *Journal of the Academy of Marketing Science*, *25*(3), 214-228.

Giles, D. (2011, September 15). Micronumerosity. Message posted to https://davegiles.blogspot.com/2011/09/micronumerosity.html

Goldberger, A. S. (1991). *A Course in Econometrics.* Harvard University Press, Cambridge MA.

Greco, A. J., & Fields, D. M. (1991). Profiling early triers of service innovations: A look at interactive home video ordering services. *Journal of Services Marketing*.

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. The Econometrics Journal, 7(1), 98-119.

Greene, W. H. (2007). Fixed and random effects models for count data.

Greene, W. H. (2012). Econometric Analysis (7th ed.). Harlow: Pearson Education Ltd.

Guidolin, M., & Mortarino, C. (2010). Cross-country diffusion of photovoltaic systems: modelling choices and forecasts for national adoption patterns. *Technological forecasting and social change*, *77*(2), 279-296.

Guimaraes, P. (2008). The fixed effects negative binomial model revisited. Economic Letters, *99*(1), 63-66.

Hagerman, S., Jaramillo, P., & Morgan, M. G. (2016). Is rooftop solar PV at socket parity without subsidies?. *Energy Policy*, *89*, 84-94.

Hair, J. F. J., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis*. New Jersey: Pearson Education.

Hardman, S., Shiu, E., & Steinberger-Wilckens, R. (2016). Comparing high-end and low-end early adopters of battery electric vehicles. *Transportation Research Part A: Policy and Practice*, *88*, 40-57.

Hardman, S., Chandan, A., Tal, G., & Turrentine, T. (2017). The effectiveness of financial purchase incentives for battery electric vehicles–A review of the evidence. *Renewable and Sustainable Energy Reviews*, *80*, 1100-1111.

Hausman, J. A., Hall, B. H., & Griliches, Z. (1984). *Econometric models for count data with an application to the patents-R&D relationship* (No. t0017). national bureau of economic research.

Heffner, R. R., Kurani, K. S., & Turrentine, T. S. (2007). Symbolism in California's early market for hybrid electric vehicles. *Transportation Research Part D: Transport and Environment*, *12*(6), 396-413.

Helveston, J. P., Liu, Y., Feit, E. M., Fuchs, E., Klampfl, E., & Michalek, J. J. (2015). Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the US and China. *Transportation Research Part A: Policy and Practice*, *73*, 96-112.

Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. (2011). Willingness to pay for electric vehicles and their attributes. *Resource and energy economics*, *33*(3), 686-705.

Higgins, C. D., Mohamed, M., & Ferguson, M. R. (2017). Size matters: How vehicle body type affects consumer preferences for electric vehicles. *Transportation Research Part A: Policy and Practice*, *100*, 182-201.

Hilbe, J. M. (2011). *Negative binomial regression (2nd ed.)*. New York: Cambridge University Press.

Hirvonen, J., Kayo, G., Cao, S., Hasan, A., & Sirén, K. (2015). Renewable energy production support schemes for residential-scale solar photovoltaic systems in Nordic conditions. *Energy Policy*, *79*, 72-86.

Hoen, A., & Koetse, M. J. (2014). A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. *Transportation Research Part A: Policy and Practice*, *61*, 199-215.

Holdermann, C., Kissel, J., & Beigel, J. (2014). Distributed photovoltaic generation in Brazil: An economic viability analysis of small-scale photovoltaic systems in the residential and commercial sectors. *Energy Policy*, *67*, 612-617.

Hsiao, C., 2003. Analysis of Panel Data, 2nd Edition. Cambridge University Press, Cambridge.

Hsu, C. W. (2012). Using a system dynamics model to assess the effects of capital subsidies and feed-in tariffs on solar PV installations. *Applied energy*, *100*, 205-217.

IHS Markit. (2019). New vehicle registration data. Retrieved from https://ihsmarkit.com/

Im, S., Bayus, B. L., & Mason, C. H. (2003). An empirical study of innate consumer innovativeness, personal characteristics, and new-product adoption behavior. *Journal of the academy of marketing science*, *31*(1), 61-73.

International Energy Agency (IEA). *Global EV Outlook 2018*. IEA: Paris, France, 2018.

International Renewable Energy Agency (IRENA). *Accelerating the Energy Transition through Innovation*. International Renewable Energy Agency: Abu Dhabi, UAE, 2017.

Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy*, *65*, 340-350.

Jansson, J., Marell, A., & Nordlund, A. (2010). Green consumer behavior: determinants of curtailment and eco-innovation adoption. *Journal of consumer marketing*, *27*(4), 358-370.

Jenner, S., Groba, F., & Indvik, J. (2013). Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries. *Energy Policy*, *52*, 385-401.

Jensen, A. F., Cherchi, E., & Mabit, S. L. (2013). On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment*, *25*, 24-32.

Johnston, J., & DiNardo, J. E. (1984). Econometric Methods McGraw Hill. *New York*.

Judge, G. G., Hill, R. C., Griffiths, W. E., Lütkepohl, H., & Lee, T. C. (1988). *Introduction to the Theory and Practice of Econometrics* (No. 330.015195 I61 1988). J. Wiley.

Junquera, B., Moreno, B., & Álvarez, R. (2016). Analyzing consumer attitudes towards electric vehicle purchasing intentions in Spain: Technological limitations and vehicle confidence. *Technological Forecasting and Social Change*, *109*, 6-14.

Kahn, M. E. (2007). Do greens drive Hummers or hybrids? Environmental ideology as a determinant of consumer choice. *Journal of Environmental Economics and Management*, *54*(2), 129-145.

Kendall, M. G. (1957). A course in multivariate analysis: London. *Charles Griffin & Co*.

Kim, E., & Heo, E. (2019). Key drivers behind the adoption of electric vehicle in Korea: An analysis of the revealed preferences. *Sustainability*, *11*(23), 6854.

Kim, S., Lee, J., & Lee, C. (2017). Does driving range of electric vehicles influence electric vehicle adoption?. *Sustainability*, *9*(10), 1783.

Kim, M. K., Oh, J., Park, J. H., & Joo, C. (2018). Perceived value and adoption intention for electric vehicles in Korea: Moderating effects of environmental traits and government supports. *Energy*, *159*, 799-809.

Klein, M., & Deissenroth, M. (2017). When do households invest in solar photovoltaics? An application of prospect theory. *Energy Policy*, *109*, 270-278.

Kollmuss, A., & Agyeman, J. (2002). Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior?. *Environmental education research*, *8*(3), 239-260.

Krasko, V. A., & Doris, E. (2013). State distributed PV policies: Can low cost (to government) policies have a market impact?. *Energy Policy*, *59*, 172-181.

Krupa, J. S., Rizzo, D. M., Eppstein, M. J., Lanute, D. B., Gaalema, D. E., Lakkaraju, K., & Warrender, C. E. (2014). Analysis of a consumer survey on plug-in hybrid electric vehicles. *Transportation Research Part A: Policy and Practice*, *64*, 14-31.

Kwan, C. L. (2012). Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States. *Energy Policy*, *47*, 332-344.

Kwon, Y., Son, S., & Jang, K. (2018). Evaluation of incentive policies for electric vehicles: An experimental study on Jeju Island. *Transportation Research Part A: Policy and Practice*, *116*, 404-412.

La Monaca, S., & Ryan, L. (2017). Solar PV where the sun doesn't shine: Estimating the economic impacts of support schemes for residential PV with detailed net demand profiling. *Energy Policy*, *108*, 731-741.

Lancaster, T. (2002). Orthogonal parameters and panel data. *The Review of Economic Studies*, *69*(3), 647-666.

Lane, B., & Potter, S. (2007). The adoption of cleaner vehicles in the UK: exploring the consumer attitude–action gap. *Journal of cleaner production*, *15*(11-12), 1085-1092.

Lane, B. W., Dumortier, J., Carley, S., Siddiki, S., Clark-Sutton, K., & Graham, J. D. (2018). All plug-in electric vehicles are not the same: Predictors of preference for a plug-in hybrid versus a battery-electric vehicle. *Transportation Research Part D: Transport and Environment*, *65*, 1-13.

Langbroek, J. H., Franklin, J. P., & Susilo, Y. O. (2016). The effect of policy incentives on electric vehicle adoption. *Energy Policy*, *94*, 94-103.

Laws, N. D., Epps, B. P., Peterson, S. O., Laser, M. S., & Wanjiru, G. K. (2017). On the utility death spiral and the impact of utility rate structures on the adoption of residential solar photovoltaics and energy storage. *Applied energy*, *185*, 627-641.

Lee, J., Cho, Y., Lee, J. D., & Lee, C. Y. (2006). Forecasting future demand for large-screen television sets using conjoint analysis with diffusion model. *Technological Forecasting and Social Change*, *73*(4), 362-376.

Lee, H. J., Huh, S. Y., & Yoo, S. H. (2018). Social preferences for small-scale solar photovoltaic power plants in South Korea: A choice experiment study. *Sustainability*, *10*(10), 3589.

Lee, J., & Shepley, M. M. (2020). Benefits of solar photovoltaic systems for low-income families in social housing of Korea: Renewable energy applications as solutions to energy poverty. *Journal of Building Engineering*, *28*, 101016.

Li, S., Yoo, H. K., Macauley, M., Palmer, K., & Shih, J. S. (2015). Assessing the role of renewable energy policies in landfill gas to energy projects. *Energy Economics*, *49*, 687-697.

Lieven, T. (2015). Policy measures to promote electric mobility–A global perspective. *Transportation Research Part A: Policy and Practice*, *82*, 78-93.

Mahajan, V., Muller, E., & Srivastava, R. K. (1990). Determination of adopter categories by using innovation diffusion models. *Journal of Marketing Research*, *27*(1), 37-50.

Marques, A. C., Fuinhas, J. A., & Manso, J. P. (2010). Motivations driving renewable energy in European countries: A panel data approach. *Energy policy*, *38*(11), 6877-6885.

Martínez, E., & Polo, Y. (1996). Adopter categories in the acceptance process for consumer durables. *Journal of Product & Brand Management*.

Martinez, E., Polo, Y., & Flavian, C. (1998). The acceptance and diffusion of new consumer durables: differences between first and last adopters. *Journal of Consumer Marketing*.

Massiani, J., & Gohs, A. (2015). The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. *Research in Transportation Economics*, *50*, 17-28.

McDonald, H., & Alpert, F. (2007). Who are "innovators" and do they matter?. *Marketing Intelligence & Planning*.

McDonald, H., Corkindale, D., & Sharp, B. (2003). Behavioral versus demographic predictors of early adoption: a critical analysis and comparative test. *Journal of Marketing Theory and Practice*, *11*(3), 84-95.

Mersky, A. C., Sprei, F., Samaras, C., & Qian, Z. S. (2016). Effectiveness of incentives on electric vehicle adoption in Norway. *Transportation Research Part D: Transport and Environment*, *46*, 56-68.

Morris, J., Calhoun, K., Goodman, J., & Seif, D. (2014, June). Reducing solar PV soft costs: A focus on installation labor. In *2014 IEEE 40th Photovoltaic Specialist Conference (PVSC)* (pp. 3356-3361). IEEE.

Münzel, C., Plötz, P., Sprei, F., & Gnann, T. (2019). How large is the effect of financial incentives on electric vehicle sales?–A global review and European analysis. *Energy Economics*, *84*, 104493.

Nelson, T., Simshauser, P., & Kelley, S. (2011). Australian residential solar feed-in tariffs: industry stimulus or regressive form of taxation?. *Economic Analysis and Policy*, *41*(2), 113-129.

Organization of the Petroleum Exporting Countries (OPEC). (2017). *2017 OPEC World Oil Outlook*. Organization of the Petroleum Exporting Countries: Vienna, Austria.

Organization for Economic Cooperation and Development (OECD). (2019). *HM1.3 HOUSING TENURES*. OECD Affordable Housing Database. Accessed July 7,2020 (https://www.oecd.org/els/family/HM1-3-Housing-tenures.pdf).

O'Shaughnessy, E., & Margolis, R. (2018). The value of price transparency in residential solar photovoltaic markets. *Energy Policy*, *117*, 406-412.

Ostlund, L. E. (1974). Perceived innovation attributes as predictors of innovativeness. *Journal of consumer research*, *1*(2), 23-29.

Plötz, P., Schneider, U., Globisch, J., & Dütschke, E. (2014). Who will buy electric vehicles? Identifying early adopters in Germany. *Transportation Research Part A: Policy and Practice*, *67*, 96-109.

Rai, V., & McAndrews, K. (2012, May). Decision-making and behavior change in residential adopters of solar PV. In *Proceedings of the World Renewable Energy Forum*.

Reichelstein, S., & Yorston, M. (2013). The prospects for cost competitive solar PV power. *Energy Policy*, *55*, 117-127.

Robinson, S. A., & Rai, V. (2015). Determinants of spatio-temporal patterns of energy technology adoption: An agent-based modeling approach. *Applied Energy*, *151*, 273-284.

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). New York: Free Press.

Sang, Y. N., & Bekhet, H. A. (2015). Modelling electric vehicle usage intentions: an empirical study in Malaysia. *Journal of Cleaner Production*, *92*, 75-83.

Sardianou, E., & Genoudi, P. (2013). Which factors affect the willingness of consumers to adopt renewable energies?. *Renewable energy*, *57*, 1-4.

Say, K., John, M., Dargaville, R., & Wills, R. T. (2018). The coming disruption: The movement towards the customer renewable energy transition. *Energy Policy*, *123*, 737-748.

Schaffer, A. J., & Brun, S. (2015). Beyond the sun—socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. *Energy Research & Social Science*, *10*, 220-227.

Schuitema, G., Anable, J., Skippon, S., & Kinnear, N. (2013). The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. *Transportation Research Part A: Policy and Practice*, *48*, 39-49.

Seel, J., Barbose, G. L., & Wiser, R. H. (2014). An analysis of residential PV system price differences between the United States and Germany. *Energy Policy*, *69*, 216-226.

She, Z. Y., Sun, Q., Ma, J. J., & Xie, B. C. (2017). What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China. *Transport Policy*, *56*, 29-40.

Shih, L. H., & Chou, T. Y. (2011). Customer concerns about uncertainty and willingness to pay in leasing solar power systems. *International Journal of Environmental Science & Technology*, *8*(3), 523-532.

Sierzchula, W., Bakker, S., Maat, K., & Van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183-194.

Simpson, G., & Clifton, J. (2016). Subsidies for residential solar photovoltaic energy systems in Western Australia: Distributional, procedural and outcome justice. *Renewable and Sustainable Energy Reviews*, *65*, 262-273.

Simpson, G., & Clifton, J. (2017). Testing diffusion of innovations theory with data: financial incentives, early adopters, and distributed solar energy in Australia. *Energy Research & Social Science*, *29*, 12-22.

Silva, J. S. (2015, June 9). Multicollinearity Panel Data. Message posted to https://www.statalist.org/forums/forum/general-stata-discussion/general/1297526-multicollinearity-panel-data

Smith, M. G., & Urpelainen, J. (2014). The effect of feed-in tariffs on renewable electricity generation: An instrumental variables approach. *Environmental and resource economics*, *57*(3), 367-392.

Sommerfeld, J., Buys, L., & Vine, D. (2017). Residential consumers' experiences in the adoption and use of solar PV. *Energy Policy*, *105*, 10-16.

Sovacool, B. K., & Hirsh, R. F. (2009). Beyond batteries: An examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition. *Energy Policy*, *37*(3), 1095-1103.

The National Renewable Energy Laboratory, U.S. DOE. Retrieved Jun 29, 2020 (https://www.nrel.gov/pv/cell-efficiency.html).

Turrentine, T. S., & Kurani, K. S. (2007). Car buyers and fuel economy?. *Energy policy*, *35*(2), 1213-1223.

Turrentine, T., Garas, D., Lentz, A., & Woodjack, J. (2011). The UC davis MINI E consumer study.

Valente, T. W. (1993). Diffusion of innovations and policy decision-making. *Journal of Communication*, *43*(1), 30-45.

Van Everdingen, Y. M., Aghina, W. B., & Fok, D. (2005). Forecasting cross-population innovation diffusion: A Bayesian approach. *International Journal of Research in Marketing*, *22*(3), 293-308.

Vassileva, I., & Campillo, J. (2017). Adoption barriers for electric vehicles: Experiences from early adopters in Sweden. *Energy*, *120*, 632-641.

Wang, S., Li, J., & Zhao, D. (2017). The impact of policy measures on consumer intention to adopt electric vehicles: Evidence from China. *Transportation Research Part A: Policy and Practice*, *105*, 14-26.

Wang, S., Wang, J., Li, J., Wang, J., & Liang, L. (2018). Policy implications for promoting the adoption of electric vehicles: Do consumer's knowledge, perceived risk and financial incentive policy matter?. *Transportation Research Part A: Policy and Practice*, *117*, 58-69.

Wang, N., Tang, L., & Pan, H. (2019). A global comparison and assessment of incentive policy on electric vehicle promotion. *Sustainable Cities and Society*, *44*, 597-603.

Wee, S., Coffman, M., & La Croix, S. (2018). Do electric vehicle incentives matter? Evidence from the 50 US states. *Research Policy*, *47*(9), 1601-1610.

White, L. V., & Sintov, N. D. (2017). You are what you drive: Environmentalist and social innovator symbolism drives electric vehicle adoption intentions. *Transportation Research Part A: Policy and Practice*, *99*, 94-113.

Zander, K. K., Simpson, G., Mathew, S., Nepal, R., & Garnett, S. T. (2019). Preferences for and potential impacts of financial incentives to install residential rooftop solar photovoltaic systems in Australia. *Journal of Cleaner Production*, *230*, 328-338.

Zhang, Y., Yu, Y., & Zou, B. (2011). Analyzing public awareness and acceptance of alternative fuel vehicles in China: The case of EV. *Energy Policy*, *39*(11), 7015-7024.

Zhang, X., Wang, K., Hao, Y., Fan, J. L., & Wei, Y. M. (2013). The impact of government policy on preference for NEVs: The evidence from China. *Energy Policy*, *61*, 382-393.

Zhao, Y., Tang, K. K., & Wang, L. L. (2013). Do renewable electricity policies promote renewable electricity generation? Evidence from panel data. *Energy policy*, *62*, 887-897.

Zhu, J. J., & He, Z. (2002). Perceived characteristics, perceived needs, and perceived popularity: Adoption and use of the Internet in China. *Communication research*, *29*(4), 466-495.

강은택, & 마강래. (2009). 주택점유 및 보유형태선택의 요인분석에 관한 연구. *주택연구*, *17*(1), 5-22.

강정화. (2019). *2018 년 4 분기 태양광산업 동향*. 한국수출입은행 해외경제연구소 2019 분기보고서 Vol. 2019-02 호 (2019.02.01)

국토교통부 통계누리. (2020). *자동차등록현황보고* (Total Registered Moter Vehicles). Retrieved Jul 18, 2020 (http://stat.molit.go.kr/portal/cate/statFileView.do?hRsId=58&hFormId=5).

김은성, & 허은녕. (2016). 동적 패널 모형을 이용한 재생에너지 정책의 OECD 국가 재생에너지 보급 효과 분석. *자원· 환경경제연구*, *25*(2), 229-253.

김주영, & 유승동. (2013). 가구특성이 주택점유형태와 주택유형 선택에 미치는 영향 분석-생애주기상 가구원수 변화와 가구의 경제적 특성을 중심으로. *주택연구*, *21*(4), 65-89.

남진, & 김진하. (2015). 서울시 소득계층별 주택유형과 점유형태 선택요인 분석. *도시행정학보*, *28*(2), 199-222.

박종훈. (2019). *미국 주택용 태양광 시장, 독점 판매·시공업체 네트워크 확보가 관건*. 정보통신기획평가원 주간기술동향 (2019.05.01).

박준용. (2015). 확산모형의 평균회귀와 단위근 성질. 한국연구재단 연구결과보고서.

박창주, 박세운, & 신철. (2014). 그린홈 주거선택요인에 관한 연구: 창원시 그린홈 거주자를 중심으로. *산업경제연구*, *27*(2), 915-940.

반영운, & 이태호. (2010). 국내 주택부문 태양광 보급정책에 대한 시민 인식분석. *한국태양에너지학회 논문집*, *30*(2), 1-9.

백종학, & 윤순진. (2015). 서울시원전 하나 줄이기를 위한 전략적 틈새로서 미니태양광사업과 에너지 시민성의 변화: 서울시 노원구 주민 인식조사를 바탕으로. *서울도시연구*, *16*(3), 91-111.

산업통상자원부 무역위원회 & 피앤피특허법인. (2017). *2017 년 전기차산업 경쟁력 조사* (2017. 11).

산업통상자원부 & 한국에너지공단. (2017). *2017 에너지총조사 전기자동차 조사 결과보고서* (2017. 11).

서울특별시. (2018). *서울시 미니태양광 설치 만족도 및 시민인식조사 자료 제공*. (2018.02.06) (https://opengov.seoul.go.kr/sanction/14583849?fileIdx=0#pdfview)

안주형, & 정서용. (2018). 혁신확산이론을 기반으로 한 농촌 주민들의 태양광 에너지 수용성 연구. *한국태양광발전학회지*, *4*(2), 54-61.

에너지경제연구원. (2016). 네트워크 기반의 전기자동차 충전인프라 구축방안 연구. 기본연구보고서 16-08

에너지경제연구원. (2017). 전기자동차 구매 보조금 제도 개선 방안 연구. 기본연구보고서 17-26

에너지경제연구원. (2019). 에너지총조사 가정부문 자료를 활용한 신재생에너지 설비 설치 요인과 에너지 소비 특성 분석. 기본연구보고서 19-01

우경봉. (2015). 친환경 자동차 선택요인에 관한 연구. *한일경상논집*, *66*, 47-66.

이용래, & 정의철. (2016). 가구소득의 변동성이 주택점유형태 및 자가 주택수요에 미치는 영향 연구. *부동산학연구*, *22*(1), 41-55.

이주형, 임종현, & 이천기. (2009). 가구특성에 따른 주택의 점유형태 및 유형 선택에 관한 연구. *국토계획*, *44*(3), 79-93.

이현진, & 이용만. (2016). 소득계층별 자가 소유 결정요인과 제약요인에 대한 연구. *부동산분석학회 학술발표논문집*, *2016*, 133-154.

정영훈. (2019). 태양광 에너지 시장의 소비자문제 개선방안 연구. 한국소비자원 정책연구보고서 19-01 (2019.12.13)

정의철. (2017). 주택점유형태의 동태적 결정요인에 관한 연구. 주택연구, 25(4), 181-209.

최막중, 지규현, & 조정래. (2002). 주택금융 제약이 주택소비규모와 점유형태 선택에 미치는 영향에 관한 실증분석. 주택연구, 10(1), 33-48.

한진이, & 윤순진. (2019). 시 자치구 미니태양광 보조금 확산과 정책 효과 분석. 서울도시연구, 20(3), 61-77.

Abstract (Korean)

전기자동차와 가정용 태양광 발전은 대표적인 분산형 에너지 자원 (decentralized energy resources, DER)이자 소비자들이 직접 채택할 수 있는 가정용 혁신 내구재이다. 이 제품들을 소비자가 직접 시장에서 구매할 수 있게 되면서, 친환경기기의 공급 확대는 물론, 기존 공급자 중심의 에너지 시스템이 상당부분 수요자 위주의 에너지 시스템으로 전환시킬 수 있는 전기를 마련하였다. 또한 이 기술들이 널리 채택되면 새로운 비즈니스 모델과 추가적인 기술혁신이 가능하다. 이에, 이 두 제품의 시장에서의 선택 여부에 대한 연구는 향후 에너지 관련 산업의 변화를 촉진할 기술혁신에 대한 연구라고 할 수 있다.

우리나라 정부 역시 이들 기기의 보급이 가지는 이러한 중요성을 인식하고 20세기 말부터 경제적 인센티브 중심의 보급 정책을 시행하였으며, 학계에서도 소비자의 채택 요인에 대해 규명하려는 연구가 시도되었다. 선행연구에서는 초기 시장의 특성상 설문조사 기반의 연구가 주로 이루어졌는데, 실제 데이터를 바탕으로 분석한 한 연구의 결과는 설문조사를 기반으로 한 연구와의 비교·대조를 통해 한 측면만으로 보지 못했던 새로운 사실을 확인할 수 있다는 점에서 의의를 가진다. 따라서 본 연구에서는 전기자동차와 베란다형 미니 태양광 실제 채택 데이터를 바탕으로 분석을 수행하였다. 또한 이 두 혁신 내구재의 수요는 해당 국가 소비자의

특성이나 시장 여건, 전기요금 체계 및 정책 등에 영향을 많이 받기 때문에 국제 비교분석으로는 규명하기 어려운 부분이 존재한다. 이러한 점에서 특정 한 국가를 대상으로 분석하는 것에 의의가 있다고 할 수 있다.

본 연구에서는 국내 소비자의 전기자동차와 베란다형 미니 태양광 채택 요인에 대해 각각 분석을 수행하였다. 기술혁신의 채택은 소비자들의 선택으로 이루어지는 가산 자료이기 때문에 포아송 회귀 모형과 음이항 회귀 모형을 사용하여 분석하였다. 먼저 첫 번째 에세이에서는 2013년부터 2017년까지 국내 각 지방자치단체별 전기자동차 채택 요인 분석을 수행하였다. 현재까지 전기자동차의 보급 확산에 대해 학계 및 언론의 관심이 주로 보조금과 충전 인프라 구축에 초점이 맞춰져 있던 것에 비해, 분석 결과 1회 충전 시 주행 가능 거리로 대표되는 기술적 우수성이 강건한 긍정적인 영향을 미친다고 나타났다. 이는 2015년 대비 2016년, 그리고 2017년 대비 2018년 전기자동차 한 대당 지급되는 보조금의 금액이 감소했음에도 불구하고 각각 전년대비 두 배 이상 판매량이 증가했다는 점에서도 알 수 있다. 충전 인프라의 경우 충전에 많은 시간이 소요되는 바, 지자체별 전기차 등록대수로 조정된 충전기 대수를 변수로 사용하였으나 부정적이면서 유의하지 않은 결과가 나타났다. 반면 지자체 면적으로 조정한 충전기 밀도 변수로 강건성 검정을 한 결과 긍정적인 영향을 나타냈다고 나타났다. 이는 실제 지자체별 공공 급속충전기의 낮은 사용 현황과 분석 기간 동안 지급된 비공용 완속충전기 설치 보조금을 고려했을 때, 전기자동차 채택자들은 실제로 공공 급속충전기를 잘 이용하지는 않았

으나 가까운 거리에 공공 급속충전기가 존재한다는 사실이 주행거리불안(range anxiety)을 경감시켜 전기자동차 채택에 긍정적인 영향을 미친 것으로 해석할 수 있다.

두 번째 에세이에서는 2014년부터 2018년까지 서울시 베란다형 미니 태양광 채택 요인 분석을 수행하였다. 분석 결과 태양광 패널의 효율이 시민들의 베란다형 미니 태양광 채택에 강한 긍정적인 영향을 미친다고 나타나, 전기자동차의 경우와 마찬가지로 기술적 우수성이 채택의 중요한 요인이라는 점을 확인하였다. 이는 베란다형 미니 태양광 설치 가구를 대상으로 한 설문조사에서도 추후 개선점에 대해 패널 효율성의 향상이 가장 높은 비율의 응답을 얻은 데에서도 찾아볼 수 있다. 소득 변수는 기존 선행연구에서와는 다르게 베란다형 미니 태양광의 채택에 대해 잘 설명해주지 못하는데, 한번 설치하면 이동에 제약이 있는 태양광 패널의 특성상 소득 보다는 자가 점유 상태가 더 중요한 영향을 미치기 때문인 것으로 판단된다. 이는 자가 소유가 아닌 경우 다른 국가에 비해 상대적으로 거주 기간이 짧은 국내 거주 특성을 반영한 결과라고 할 수 있다. 친환경성의 경우 전기자동차의 경우와는 달리 혁신 채택에 유의한 긍정적인 영향을 미쳤다고 나타났다. 이는 전기자동차에 비해 상대적으로 낮은 가격과, 소비자들이 초기 구매 비용에 비해 운영비용에 덜 민감한 특성으로 인해 나타나는 현상으로 해석할 수 있다.

이 연구는 아직 시장 도입 초기 단계인 전기자동차와 베란다형 미니 태양광을 대상으로 실제 데이터로 분석을 수행하였다는 점에서 의의를 가지나, 그렇기 때문

에 데이터의 한계로 인해 보다 정교한 분석에 대해 한계가 존재한다. 향후 두 혁신 내구재의 시장이 성숙기로 들어서고 소비자 선택에 대한 미시적 데이터의 확보가 가능해질 때 본 분석의 결과가 시사점을 제공할 수 있을 것으로 기대한다.

주요어 : 혁신 내구재, 전기자동차, 베란다형 미니 태양광, 기술혁신 채택 요인

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