Ph.D. Dissertation of City Planning

Essays on Energy Price and Consumer Behavior
: Experimental and Empirical Analyses

에너지 가격과 소비자 행태에 관한
실험 및 실증 연구

August 2023

Graduate School of Environmental Studies
Seoul National University
Department of Environmental Planning

Sungmin Lim

Essays on Energy Price and Consumer Behavior
: Experimental and Empirical Analyses

Advisor: Jong Ho Hong

Submitting a Ph.D. Dissertation of
City Planning

May 2023

Graduate School of Environmental Studies
Seoul National University
Department of Environmental Planning

Sungmin Lim

Confirming the Ph.D. Dissertation written by
Sungmin Lim
June 2023

Chair	Sun Jin Yun	(Seal)
Vice Chair	Booyuel Kim	(Seal)
Examiner	Hyungna Oh	(Seal)
Examiner	Syngjoo Choi	(Seal)
Examiner	Jong Ho Hong	(Seal)

Abstract

This dissertation contains three papers discussing energy pricing policies that reflect the social costs of energy supply and consumer behaviors.

The first paper, titled "Promoting Willingness to Pay for 'Climate Change and Environmental Charge' in Electricity Tariff: Evidence from a Randomized Survey Experiment", analyzes causal effects of various non-price-based information on public support for environmental pricing by conducting a randomized survey experiment on a nationwide sample of over 4,000 electricity consumers in Korea. Based on the previous research on public beliefs about climate change, four informational strategies are developed: (i) Information about environmental external cost of electricity production with an emphasis on how much current payment covers total environmental external cost, (ii) Information about climate policies that are passed with bipartisan support, (iii) Information about successful implementation of environmental policy through collective actions, such as the Montreal protocol, and (iv) Cross-country comparison information of GHG emissions levels and climate change mitigation efforts. This study finds that providing environmental external cost information substantially raises consumers' willingness-to-pay for environmental charge - by 15% compared to the control group receiving no information. The rest of the information show small and insignificant effects. Heterogeneity analysis reveals that respondents' political affiliation may attribute to these overall null-effects by canceling out conservatives' backfiring and neutrals' increase in their willingness-to-pay. Furthermore, this paper provides new empirical evidence that suggests consumers having inaccurate knowledge about environmental charges as a potential driver of this political divide. These findings have important implications for energy policies as they identify key behavioral traits of consumers that influence their support for environmental pricing and explore the mechanisms underlying changes in such support.

The second paper, titled "A Framework for Measuring Electricity Price Literacy: Application to South Korea", develops a comprehensive measure of consumer knowledge of electricity prices, referred to as "Electricity price literacy". Consumers' knowledge of electricity prices and its effect on their consumption behaviors have been widely studied, yet the direct comparison and generalization of these findings are challenging due to variations in definition and survey items used for measurement. To bridge this gap, this study introduces a functional form to represent electricity price systems and systematizes it into three knowledge domains: (i) total bill amount, (ii) rate structure and (iii) rate components to enhance comparability across studies. To demonstrate the practicality, this study applies the proposed framework to South Korea and conducts an online survey on a nationally representative sample of 4,214 electricity consumers. The findings reveal variations in electricity price literacy across different domains and demonstrate that domain-specific knowledge has a differential impact on respondents' electricity-related behaviors. These results emphasize the importance of a comprehensive knowledge scale and suggest that targeted interventions focusing on domain-specific knowledge are necessary to drive desired changes in consumer behavior.

The third paper, titled "Variations in Price Elasticities of Diesel Demand by Relative Prices between Motor Fuels: Evidence from 24 European Countries", analyzes whether and to what extent the own-price elasticities of diesel demand vary with the relative price of diesel to gasoline, which are two main fuels for road transportation and have a close substitution relationship. Using both the Reduced-form and Almost Ideal Demand System (A.I.D.S.) models based on panel data from 24 European countries for the period 1990 to 2020, this study finds different responses to changes in price contingent upon different relative price levels. Specifically, the price elasticity value reaches its peak when the relative price approaches one, and then experiences a significant decline. These findings identify the relative price as a key determinant of the own-price elasticities of diesel demand, which has been largely overlooked in the literature.

They also suggest that policy-makers can improve the accuracy of predicting outcomes of diesel taxation policies by taking account of relative price.

Within the context of the global transition towards sustainable energy systems, which prioritizes energy demand management and energy price system reforms as effective policy instruments, the collective findings of these papers offer valuable insights for the design and implementation of energy price policies that appropriately reflect social costs.

Keyword : Energy pricing policies, Non-price information, Price knowledge, Relative price, Consumer behavior
Student Number : 2019-37476

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

The depletion of energy resources, supply insecurity, environmental concerns including climate change, and social conflicts over the siting of large-scale power plants have reshaped energy policies from a supply-centric to a demand-centric approach. One important policy measure that is pushing energy demand management forward is the reform of the energy pricing system. At present, many countries worldwide fail to fully internalize both private and social costs of energy production into energy prices, mainly due to securing domestic economy and competitiveness. This underpricing of energy has resulted in excessive production and use of energy beyond the socially optimal level (Shi and Sun, 2017; Coady et al., 2018; Parry et al., 2021). The largest gap between current and efficient prices can be found in coal, followed by natural gas, diesel, and gasoline (Parry et al., 2021). Electricity price also falls short of cost-recovery levels in general, even when environmental costs are attributed to primary fuel inputs (Hall et al., 2016; Hobman et al., 2016; Parry et al., 2021).

With a growing importance of demand-side management, efforts to align energy prices with the marginal social cost of energy production are gaining momentum. This principle, commonly referred to as "Getting energy prices right," has been shown to incentivize both energy conservation and investment in energy efficiency (Hobman et al., 2016; Harding and Sexton, 2017; Coady et al., 2018; Parry et al., 2021). By internalizing the true costs of energy production, correct price signals are sent to both energy producers and consumers, encouraging them to make more sustainable choices. This is particularly vital for addressing climate change, as raising fuel prices to their efficient levels can significantly reduce greenhouse gas emissions and help to achieve the Paris Agreement's goal of limiting global temperature increase to 1.5-2℃ (Parry et al., 2021).

Although the concept of getting energy prices right may seem simple, putting it into practice can be complex and challenging, as the acceptance and effectiveness of pricing policies are critically dependent on consumers' perception and reaction to them. For example, energy pricing policies that involve price increases, such as internalization of social costs, are politically difficult to implement due to a lack of broad public support. Recent experiments show that public support for environmental charges decreases as the size of price increases (Stokes and Warshaw, 2017; Andor et al., 2018). Previous literature has identified various factors that affect policy support, with recent studies focusing on psychological factors and behavioral biases, such as rational inattention, risk and loss aversion, status-quo bias, and normative social influence (Drews and Van den Bergh, 2016; Hobman et al., 2016).

Even when the efficient price is introduced, it may not achieve its intended policy goal as consumers often deviate from the predictions of standard microeconomic theory. For instance, consumers tend to respond to average, rather than marginal, price when deciding their electricity consumption (Borenstein, 2009; Ito, 2014; Shaffer, 2020; Labandeira et al., 2022). Similarly, price salience, which is not expected to influence decision-making according to standard theory, is found to significantly undermine consumers' response to price signals (Jessoe and Rapson, 2014; Sexton, 2015; Frondel and Kussel, 2019; Prest, 2020). These sub-optimizing behaviors are mainly explained by rational inattention resulting from the high information cost of knowing the price and consumption. Recent studies have identified energy literacy as a crucial factor in moderating these sub-optimal behaviors. Energy literacy encompasses a range of knowledge and understanding of energy, including affective and behavioral aspects (DeWaters and Powers, 2011; 2013). Therefore, it is important to explore the extent of consumers' knowledge of prices and how this knowledge affects their behavior.

Moreover, accurately predicting consumer response to price changes is crucial for designing more efficient prices and evaluating policy efficacy, yet it poses a significant challenge. Despite a large volume of literature reporting empirical estimates for demand elasticities for energy, the variability of demand elasticities requires further investigation. There is an ongoing investigation into the factors that drive changes in elasticities, such as different contexts or population segments, including fuel price volatility, income levels, tax vs. tax-exclusive price, and economy status (Hughes et al., 2008; Wadud et al., 2009; Lin and Prince, 2013; Li et al., 2014; Bakhat et al., 2017).

This dissertation, consisting of three papers, contributes to the literature on energy pricing and demand-side management by providing a better understanding of consumer behavior. Chapter 2 presents a randomized survey experiment that analyzes the causal effects of non-price information interventions on public support for environmental pricing and investigates the mechanisms underlying changes in support. In Chapter 3, a comprehensive measure of consumer knowledge of electricity prices is developed and its effect on consumers' electricity-related behaviors is empirically analyzed. Chapter 4 analyzes the variability of own-price elasticities of diesel demand by the relative price of diesel to gasoline, improving the accuracy of predicting outcomes of diesel taxation policies.

Finally, the importance of studying both the electricity and transport sectors cannot be overstated, as they are two of the largest contributors to greenhouse gas (GHG) emissions, accounting for a combined share of 61.5% of global CO2 emissions (IEA, 2023a; IEA, 2023b). These sectors have a heavy reliance on fossil fuels, which are typically underpriced, and also the usage of electricity and transport fuels is known as price-inelastic. Therefore, investigating the factors that make prices right and salient, and thus affect consumer behavior in these sectors can help achieve the enormous potential for energy reduction and mitigate negative environmental impact. This dissertation aims to contribute to this important area of research by studying the effects of price and non-price information on consumer behavior in both the electricity and transport sectors.

Chapter 2. Promoting Willingness to Pay for 'Climate Change and Environmental Charge' in Electricity Tariff: Evidence from a Randomized Survey Experiment[1]

2.1. Introduction

Pricing environmental externalities has long been recommended by economists as a key strategy for addressing climate change, which is particularly relevant in the power sector given its largest share in global greenhouse gas (GHG) emissions – 40% in 2022 (IEA, 2023a; IEA, 2023b). Many countries have introduced environmental taxes, levies or charges to internalize the externalities caused by electricity production and to promote clean energy transition. There are many examples, such as environmental charges in Australia, EEG (Erneuerbare−Energien−Gesetz in German) levy in Germany, Environmental/social obligation costs in the UK, RPS (Renewable Portfolio Standard) compliance cost in the US, to name a few. Following this trend, since 2020 South Korea (hereafter, Korea) has begun to impose consumers a fixed surcharge, called the Climate Change & Environmental Charge (hereafter, CCEC) as a separate electricity price component. CCEC was 0.45 cents[2] per kilowatt hour (kWh) in 2020, accounting for 3.5% of an electric bill of average Korean household consuming 350kWh per month.

Despite the recent increase of CCEC to 0.62 cents/kWh in 2022, the current level of CCEC falls short of the total environmental external costs − covering less than one−quarter.[3] A governmental decision to keep the residential electricity prices low − the 4th lowest among OECD countries in 2021 (IEA, 2022a) − has created a large gap between the current and the socially optimal level of CCEC.

[1] This essay represents joint work with Jong Ho Hong, Syngjoo Choi, Booyuel Kim, Jinwook Shin, and Heerae Lee of the Seoul National University.
[2] The exchange rate was 1,176.55 KRW per USD at the time of the survey.
[3] According to local economists in Korea, total environmental external cost under the latest energy mix is estimated as 2.8−3.8 cents/kWh (Kim et al., 2015; Lee, 2017; Lee et al., 2018).

However, it has been well-documented that policies accompanying price increase are difficult to implement due to a lack of public support (Drews and Van den Bergh, 2016). Recent experiments have provided evidence that the level of support for environmental charges considerably decreases with the size of price increases (Stokes and Warshaw, 2017; Andor et al., 2018).

Against this backdrop, this paper explores non-price information interventions that can potentially increase individuals' willingness-to-pay (hereafter, WTP) for CCEC based on a randomized survey experiment administered to a nationally representative sample of 4,214 electricity consumers in Korea. Building on the previous research on public beliefs about climate change – its existence and causes, and a subsequent support around mitigation efforts, four informational strategies are developed: (i) *Environmental external cost information* provides information about environmental external cost of electricity production with an emphasis on how much current CCEC payment covers total environmental external cost – both of which are often elusive to electricity consumers. This information can increase WTP for CCEC by appealing not only to private and social motives as suggested by Delmas and Lessem (2014); Asensio and Delmas (2015), but also to fairness motives for the setting of price by giving consumers a standard to evaluate the fairness of their current payment (Kahneman et al., 1986; Urbany et al., 1989; Bolton et al., 2003; Xia et al., 2004). (ii) *Partisan-free policy information* provides information about climate policies that are passed with bipartisan support (e.g., Green Growth Strategy in Korea). Since climate change beliefs are strongly tied to political identity (Johnson, 2017; Benegal and Scruggs, 2018; Gustafson et al., 2019), a highlight on bipartisan support may increase WTP for CCEC by aligning both parties with their ingroup beliefs. (iii) *International cooperation information* provides information about successful implementation of environmental policy through collective actions, such as the Montreal protocol, which contributes to restoration of the ozone layer. This information may attenuate individuals' uncertainty or skepticism on the effectiveness of climate policy (Akter et al., 2012; Drews and

Van den Bergh, 2016; Bergquist et al., 2022), or their concern for free-riders (Fischbacher et al., 2001; Fischbacher and Gächter, 2010), which play a decisive role in shaping public support. (iv) *Cross-country comparison information* provides social comparison information of GHG emissions levels and climate change mitigation efforts across 57 countries, which together emit more than 90% of global GHGs. As individuals show a tendency to make social comparison and follow social norms or the actions of their neighbors (Frey and Meier, 2004; Allcott, 2011b; Hobman et al., 2016), this information can lead to the increase in WTP for CCEC.

This study uses a between-subjects design and randomly assigned respondents into one of the five groups: one control and four treatment groups, each with a sample size over 800. The control group received no information, while each treatment group received one of the aforementioned information. After receiving randomized information, respondents were asked to report their WTP for CCEC, measured by the following question: 'How much are you willing to pay for Climate Change & Environmental Charge?' They were required to select the exact amount in a specified range: from 0 to 10,000 KRW with a 100 KRW interval. The control group's mean WTP for CCEC is reported as 2,268 KRW (or 1.93 in USD) with standard deviation of 1,902 KRW (or 1.62 USD). While this amount represents a modest increase over an actual payment level, at a factor of 1.2,[4] it still covers only 14-19% of total environmental external cost in Korea, calling for substantial efforts to increase WTP. Treatment effects are primarily shown as percentage change relative to the mean WTP of the control group by transforming the WTP variable (in USD) with inverse hyperbolic sine (IHS) function (Burbidge et al., 1988).[5] The regression results using WTP in an

[4] CCEC was charged at 5.3 KRW (or 0.45 cents) per kWh or equivalently 1,855 KRW (or 1.58 USD) for a four-person household consuming 350 kWh per month at the time of the survey.

[5] The IHS transformation has an advantage of facilitating the interpretation of the estimates as percent change similar to log transformation, while allowing for retaining zero-valued observations. In the sample, a total of 140 observations (3.3%) reported zero-WTP.

absolute value (i.e., USD) as a dependent variable is provided in parentheses, where necessary.[6]

Besides average effects of information provision, this paper further addresses whether there are differential gains in knowledge and resulting policy support within a population, and if so, what factors drives these differences. Recent literature highlights two key predictors: individual differences in cognitive abilities and information processing, as measured by educational attainment or prior knowledge, and political ideology (Nisbet et al., 2015; Bolsen and Druckman, 2018; Ehret et al., 2018). Specifically, political ideology is suggested as a more apt predictor for politically controversial issues like climate change due to ideologically-based motivated reasoning. Building on this line of research, the present study explores the heterogeneous effects of prior knowledge and political ideology and finds that differential reactions to information are primarily rooted in political ideology. Furthermore, this paper investigates the role of prior knowledge (or education) in moderating the effects of partisan identity on policy evaluation. The findings suggest clear evidence of an interaction between two factors, whereby only individuals lacking accurate knowledge about CCEC engage in ideologically-based motivated reasoning, which drives partisan gaps in public support.[7]

---

[6] The full regression results are provided in Table A-1 through A-3 in Appendix A.

[7] Heterogeneity analysis by prior knowledge is presented in Appendix A, as no knowledge-based differences in treatment effects were observed. In addition, heterogeneity analysis by other socioeconomic characteristics (i.e., gender, age, education, and household income), dwelling characteristics (i.e., household size, house type, and home ownership status) and electricity consumption are included in Appendix A. Respondents with higher education, higher income and larger household tend to respond more positively to the information.

2.2. Data[8]

2.2.1. Data Collection

Data of this study were collected through an online survey implemented to 4,214 nationally representative sample of Korean electricity consumers (19 and over) in October 2021 by a Korean survey agency, Hankook research.[9] Gender, age, education and region of residence were used as quota variables and the sample did not significantly differ from the population with respect to them. Table 2-1 compares the sample with the population from national census, which indicates that the sample closely matches the census targets. On average, the sample has a slightly lower income and is more likely to hold neutral political views than the general population.

Table 2-1. Comparison of the Sample with the Population

Variables	(1)	(2)	(3)
	This survey	2021 KSIS	Difference (SE)
Female	0.50 (0.50)	0.50 (0.50)	−0.001 (0.01)
Age			
20s	0.16 (0.36)	0.16 (0.37)	−0.007 (0.01)
30s	0.16 (0.37)	0.15 (0.36)	0.006 (0.01)
40s	0.19 (0.39)	0.19 (0.39)	0.004 (0.01)
50s	0.20 (0.40)	0.20 (0.40)	0.002 (0.01)
60s and above	0.29 (0.45)	0.30 (0.46)	−0.005 (0.01)
Education			
Bachelor or more	0.32 (0.47)	0.33 (0.47)	−0.01 (0.01)
Monthly HH Income			
< KRW 2 million	0.13 (0.34)	0.12 (0.33)	0.008 (0.01)
KRW 2-3 million	0.15 (0.36)	0.12 (0.32)	0.03*** (0.01)

8 This study was approved by the Seoul National University Institutional Review Board (IRB) (IRB No. 2109/003-012) on 27 September 2021 and registered in the AEA RCT Registry on 15 October 2021 (DOI: "10.1257/rct.8366-1.0").

9 The survey was conducted over 10 days from 12 October 2021 to 22 October 2021.

KRW 3–4 million	0.19 (0.39)	0.14 (0.35)	0.04*** (0.01)
KRW 4–5 million	0.16 (0.36)	0.15 (0.36)	0.002 (0.01)
≥ KRW 5 million	0.38 (0.48)	0.46 (0.50)	−0.09*** (0.01)
% of population living in capital area	0.51 (0.50)	0.50 (0.50)	0.004 (0.01)
Political view	3.01 (0.83)	2.91 (0.85)	0.10*** (0.02)
Observations	4,214	8,077	

Notes: Data for the population of Korea – the column (2) – is drawn from 2021 Korea Social Integration Survey (KSIS), which is produced by the Korea Institute of Public Administration (KIPA), and has been authorized for use according to KIPA's regulations on the ownership and use of said research material; Standard deviations are reported in parentheses in columns (1) and (2), while standard errors are reported in parentheses in column (3); The results of mean comparison tests are presented with asterisks; *** p<0.01, ** p<0.05, * p<0.1; Political view is measured on a 5-point Likert scale, 1= very conservative, 2 = conservative, 3 = neutral, 4 = liberal, 5 = very liberal

2.2.2. Survey Design

This survey aims to assess the overall consumer perception of the electricity rate system, covering the entire process of electricity rate making. Applying the “Energy Literacy” framework proposed by DeWaters and Powers (2011, 2013), the survey includes three domains: content knowledge, affective, and behavioral aspects. The survey comprises four parts, along with the survey experiment. Part I focuses on measuring respondents' sociodemographic (e.g., gender, age, education, household income and political view) and dwelling characteristics (e.g., dwelling type, home-ownership status, regions and years of residence). In Part II, respondents' knowledge about the electricity rate system is assessed, including their understanding of both residential and overall electricity rate system in detail. This section also includes the question about CCEC used in this paper. Following the knowledge domain, an information provision experiment is conducted. Then, in Part III, respondents are asked to express their preferences and support for various electricity pricing schemes, such as CCEC and green pricing. Lastly, Part IV encompasses affective and behavioral domains, prompting respondents to share their attitudes and behaviors concerning electricity−related issues, including electricity pricing fairness, trust in rate making bodies, as well as broader energy and environment−related matters.

2.2.3. Experimental Design

The survey experiment was designed to evaluate what kind of information can increase respondents' WTP for CCEC. This paper used a between subjects design and randomly assigned respondents into one of the five groups: one control and four treatment groups, each with a sample size over 800.[10]

The control group received no information, while each treatment group received one of the following information: (i) Environmental external cost information, which informs the presence of environmental external cost during electricity generation and the coverage of current payment by electricity consumers to total environmental external cost; (ii) Partisan−free policy information, which emphasizes the persistency of climate policy in Korea regardless of partisanship of past and present governments; (iii) International cooperation information, which communicates the successful implementation of the Montreal protocol that mitigates the ozone depletion problem through international cooperation; (iv) Cross−country comparison information, which provides social comparison information of GHG emissions levels and climate change mitigation efforts across 57 countries, which together emit more than 90% of global GHGs.

After receiving randomized information, respondents were asked to report their WTP for CCEC, measured by the following question: 'How much are you willing to pay for Climate change & Environmental charge?' They were required to select the exact amount in a specified

[10] This study aimed to recruit 900 participants for each group, resulting in a total sample size of 4,500 participants as outlined in the pre−analysis plan registered in the AEA RCT Registry. The final enrollment in the actual survey yielded 4,214 participants, with each group having a sample size of over 800 individuals.

range: from 0 to 10,000 KRW with a 100 KRW interval.

Figure 2−1 presents a schematic illustrating the survey flow and the experimental design, while Figure 2−2 shows the actual information provided to the respondents in each treatment group during the experiment.

Figure 2−1. Survey Flow and Experimental Design

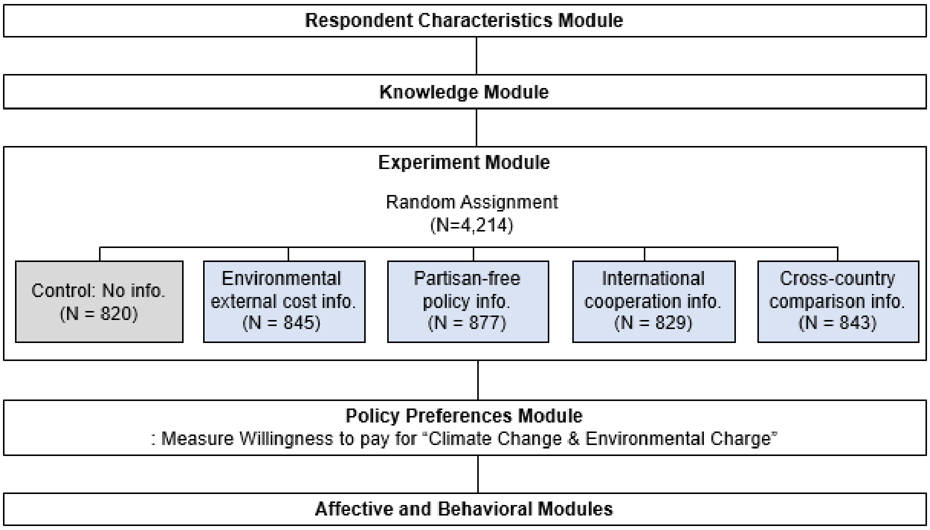


Figure 2–2. Information Provision Treatments

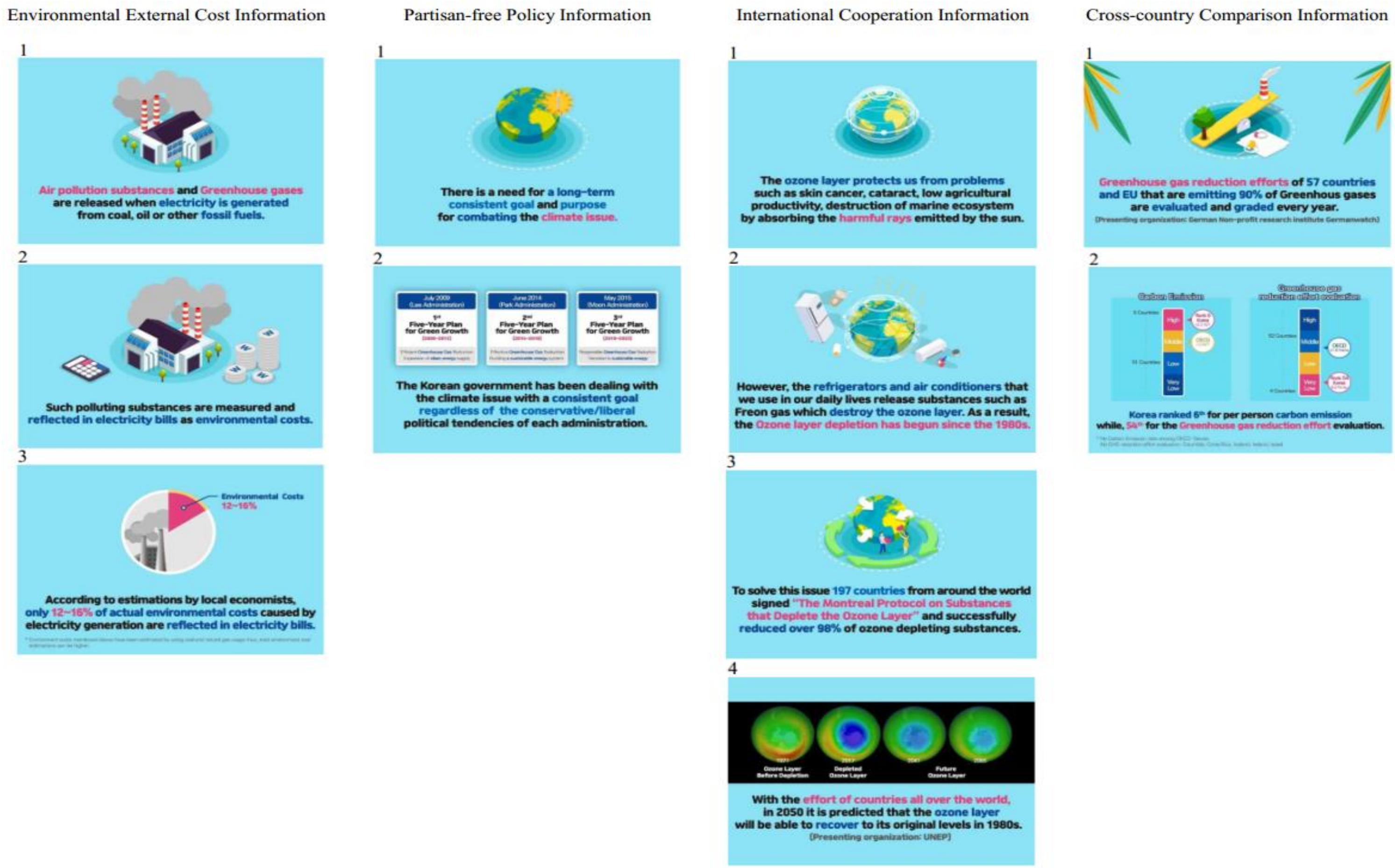


Table 2–2 presents mean differences in several socioeconomic variables between the control group and the treatment groups. The results largely confirm that randomization was well–implemented.

Table 2–2. Randomization Balance

Variables	Control	Env.Ext info.	Part.Free info.	Int.Coop info.	Cross.Ctry info.
Female	0.49 (0.02)	0.49 (0.02)	0.51 (0.02)	0.51 (0.02)	0.52 (0.02)
Age	48.18 (0.48)	48.19 (0.48)	46.83** (0.48)	46.56** (0.50)	46.67** (0.48)
Bachelor or more	0.29 (0.02)	0.31 (0.02)	0.37*** (0.02)	0.31 (0.02)	0.33* (0.02)
HH Income (1M KRW)	4.34 (0.08)	4.46 (0.08)	4.47 (0.08)	4.33 (0.08)	4.28 (0.08)
% of population living in capital area	0.50 (0.02)	0.52 (0.02)	0.49 (0.02)	0.52 (0.02)	0.51 (0.02)
Political view	3.05 (0.03)	3.02 (0.03)	2.96** (0.03)	3.02 (0.03)	3.00 (0.03)
Observations	820	845	877	829	843

Notes: Env.Ext, Part.Free, Int.Coop, and Cross.Ctry represent the groups that received Environmental external cost, Partisan–free policy, International cooperation and Cross–country comparison information, respectively; Means of each treatment group were compared with those of control groups; Standard errors are in parentheses;*** p<0.01, ** p<0.05, * p<0.1.

2.3. Empirical Strategy

To estimate the average treatment effects, a regression analysis is conducted using the following equation.

$$\mathrm{y_i} = \beta_0 + \beta_1 EnvExt_i + \beta_2 PartFree_i + \beta_3 IntCoop_i + \beta_4 CrossCtry_i + X_i\gamma + \epsilon_i \quad (1)$$

The dependent variable, $\mathrm{y_i}$ is CCEC WTP (in USD) transformed using inverse hyperbolic sine function. $EnvExt_i, PartFree_i, IntCoop_i$ and $CrossCtry_i$ denote dummy variables corresponding to the groups receiving Environmental external cost, Partisan−free policy, International cooperation and Cross−country comparison information, respectively. X_i is the vector of socioeconomic characteristics, including gender, age, education, household income, political view and regions of residence.[11] ϵ_i represents the error term.

To estimate heterogeneous treatment effects among different socioeconomic groups, interaction terms between dummy variables representing the groups of interest and the four treatment groups are included in Equation (1). Table 2−3 presents the survey items used to measure the variables included in regression analysis.

Table 2−3. Summary of Variables

Variables		Survey items
Dependent variable	CCEC WTP	A monthly average electricity consumption of a four−person household in Korea is approximately 350kWh and a corresponding electricity bill is about KRW 54,000. How much are you willing to pay for Climate Change & Environmental Charge? Please select your maximum amount.
Socioeconomic variables	Gender	What is your gender? 1. Male, 2. Female
	Age	How old are you? ( ) years old
	Education	Which of the following best describes your final education level? From none to Doctoral graduate
	Household income	What is your average monthly gross household income (before tax) for the year 2020? Please enter the total income of all household members that are engaged in economic activities.
	Political view	What is your political view? 1. Very conservative, 2. Conservative, 3. Neutral, 4. Progressive, 5. Very progressive

11 This study effectively controls for major socioeconomic variables as outlined in the pre-analysis plan. Given that the randomization ensures group balance, including a subset of a full list of variables stated in the pre-analysis plan does not affect the results.

	Regions of residence	Please select the region you are residing in up to Eup/Myeon/Dong-level.
Knowledge variable	CCEC	Climate Change & Environmental Charge, which is a charge for external cost of greenhouse gas and air pollutants emitted from electricity generation, is applied in the residential electricity rate system in Korea. How much of the electricity bill do you think is charged for Climate Change & Environmental Charge? Please select the amount of this charge from KRW 54,000, which is the average monthly electricity bill for a four-person household in Korea.

2.4. Results

2.4.1. Average Treatment Effects

Figure 2-3 shows average effects of each of the four information interventions on respondents' WTP for CCEC.[12] Providing information about environmental external cost has a significant positive effect on the average WTP for CCEC. This information raises respondents' WTP by 15% relative to the control group who receives no information (or 0.36 USD in an absolute value) ($p<0.01$), which is equivalent to 2.7%-3.6% additional coverage of the total environmental external cost. This effect size is nearly double that of the 8% reduction in household energy usage reported by Asensio and Delmas (2015), which is one of the first studies investigating the role of environmental externalities information disclosure. The result

[12] The stated-preference approach used in this study may introduce biases, such as hypothetical bias and experimenter demand effects. While direct identification of these effects is not available, the use of randomization can help to partially offset them. If the effects are driven by the treatment itself, however, they may not cancel out (de Quidt et al., 2018). To test for these effects, treatment effects are analyzed for other outcome variables subject to social desirability (e.g., the concern for the environment, the willingness to engage in pro-environmental behaviors). No similar treatment effect patterns were found for these outcome variables, indicating that the impact of hypothetical bias and/or experimenter demand effects is likely to be small. This is consistent with prior research, which has found that these effects are typically small and statistically insignificant in various economic experiments (de Quidt et al., 2018).

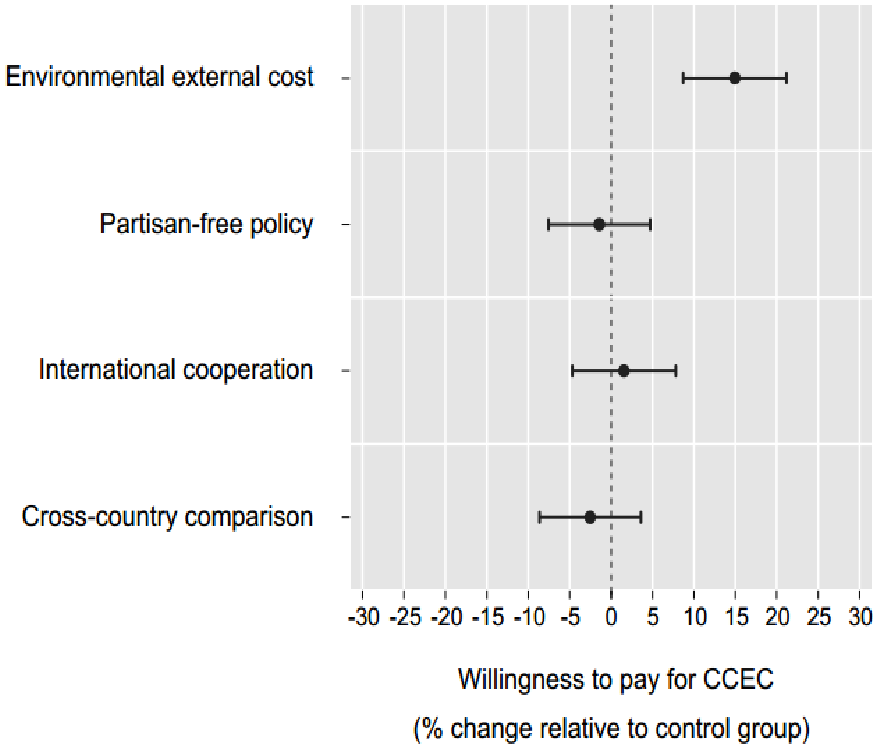
suggests that emphasizing the degree of internalization when communicating environmental externalities may result in a greater response by additionally appealing to consumers' perception of fair price (Kahneman et al., 1986; Campbell, 1999; Homburg et al., 2005; Gielissen et al., 2008).

By contrast, the rest of the interventions appeared not to alter the respondents' WTP on average. The null effect returned by Partisan-free policy information was somewhat anticipated, given the highly politicized nature of climate change and electricity pricing reform in Korea. Previous literature has posited that political polarization stems from motivated reasoning, whereby individuals reject information that contradicts their pre-existing beliefs (Johnson, 2017; Druckman and McGrath, 2019). It is therefore plausible that contrasting effects based on political affiliation account for the absence of a significant effect.

The lack of significant effects with information aimed at resolving skepticism towards the effectiveness of climate change measures (i.e., International cooperation information) and leveraging social norms (i.e., Cross-country comparison information) was rather surprising as they are recognized as the prominent non-price interventions in energy-related contexts (Schultz et al., 2007; Nolan et al., 2008; Allcott, 2011b; Akter et al., 2012; Allcott and Rogers, 2014; Drews and Van den Bergh, 2016; Šćepanović et al., 2017; Gillingham and Tsvetanov, 2018; Bergquist et al., 2022). Various contextual factors (e.g., country-level framing, a potential lack of ingroup identification) may prevent the observation of treatment effects (Šćepanović et al., 2017; Farhidi and Khiabani, 2021). Heterogeneous responses may also occur, particularly by political and environmental ideologies with regard to these types of interventions, as documented in prior studies (Whitmarsh, 2011; Costa and Kahn, 2013).

In light of these observations, this paper proceeds to undertake heterogeneity analyses to delve deeper into the underlying factors that shape individuals' decision-making regarding their WTP for CCEC.

Figure 2-3. Average Treatment Effects on WTP for CCEC



Notes: Treatment effects are reported as percent changes relative to the control group. Error bars indicate 95% confidence intervals around the mean. A mean WTP of the control group is 1.93 USD. All regression estimates include statistical controls for respondents' socioeconomic variables (gender, age, education, household income, political ideology, and region of residence).

2.4.2. Heterogeneous Treatment Effects by Political View

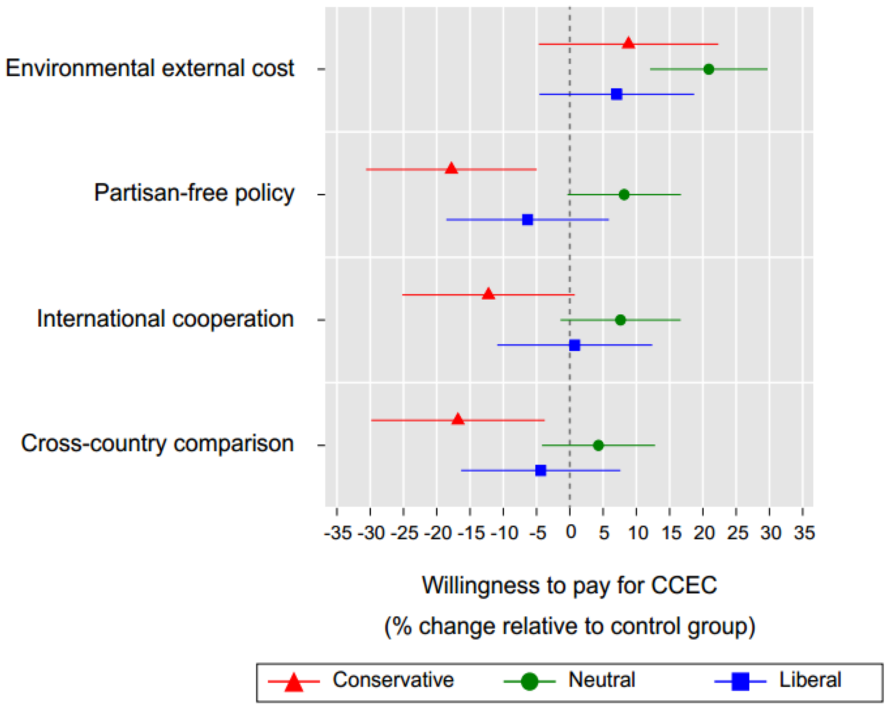
A primary source of heterogeneity found in this study is linked to political identity. As shown in Figure 2-4, respondents who self-identified as political conservative (N=1,038) experienced significant backlash after receiving all information except for Environmental external cost information (-18%, p<0.01; -12%, p<0.1; -17%, p<0.05). Conversely, those who self-identified as political liberal (N=1,082) did not exhibit significant reactions to any of the information, resulting in an increased partisan gap. Recent empirical studies have produced similar results, indicating that the partisan gap over climate change becomes wider with increased education or information provision, due to weak or negative impact of education on conservatives, especially where climate change has become a highly politicized issue (Kahan et al., 2012; Costa and Kahn, 2013; Drummond and Fischhoff, 2017; Johnson, 2017; Czarnek et al., 2021).

The absence of backlash to the Environmental external cost information by political conservatives, who are typically resistant to climate-related information, may be due to the information appealing to consumers' sense of fair pricing. Conservatives are known to endorse corporate rights as a matter of promoting fairness (Frimer et al., 2017). The limited size of the treatment effects among liberals may, in part, be explained by a potential ceiling effect, whereby liberals may have already invested substantial time and resources into voluntary environmental efforts (Costa and Kahn, 2013; Gustafson et al., 2022).[13]

The strong conservative backfire in the latter three treatments is offset by positive reactions from neutral respondents (N=2,094), leading to near-zero average effects. For neutrals, environmental external cost information induces by far the largest increase in WTP by 21% ($p<0.01$), followed by partisan-free policy and international cooperation information both raising 8% relative to the WTP of the control group ($p<0.1$). Cross-country comparison information is also shown to increase the WTP, but its effect was small and statistically insignificant.

[13] The data suggests that within the control group, liberals (N=208, 2.16 USD) report a higher mean WTP than conservatives (N=171, 2.14 USD) and neutrals (N=441, 1.74 USD), although the difference between liberals and conservatives is statistically insignificant.

Figure 2-4. Treatment Effects by Political View



Notes: Treatment effects are reported as percent changes relative to the control group in each political group. Error bars indicate 95% confidence intervals around the mean. Mean WTPs of each political group within the control group are 2.14 USD for conservative, 1.74 USD for neutral, and 2.16 USD for liberal. All regression estimates include statistical controls for respondents' socioeconomic variables (gender, age, education, household income, and region of residence).

2.4.3. Heterogeneous Treatment Effects: Interactions between Political View and Prior Knowledge

To explore possible channels driving the partisan gap observed in Figure 2-4, this study further examines the role of respondents' pre-existing knowledge in shaping political differences in treatment effects. Using the question that measures the respondents' prior knowledge about the current level of CCEC included in the electric bills, this study calculates the deviation from the correct answer and divided the entire sample into accurate and inaccurate groups on the basis of whether their deviations fall into the range of 0.3 SD around

0 (Accurate, N = 1,743; Inaccurate, N = 2,471) (see Figure 2-5).[14]

Figure 2-5. Knowledge Distribution and Grouping

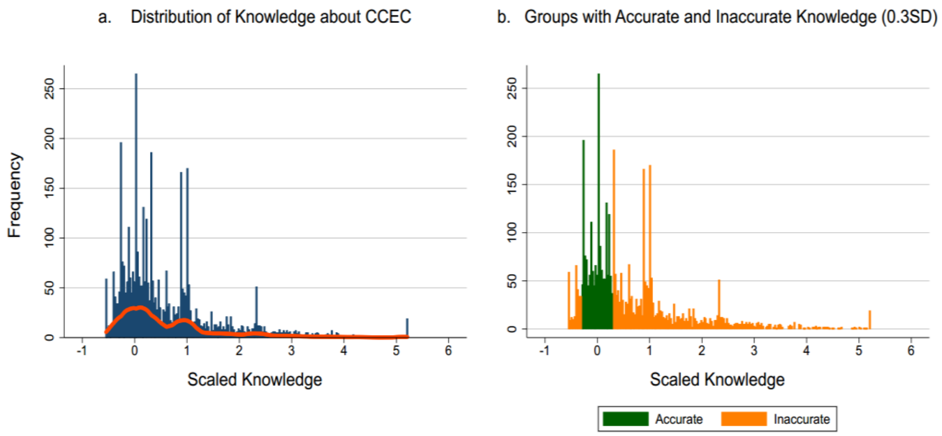
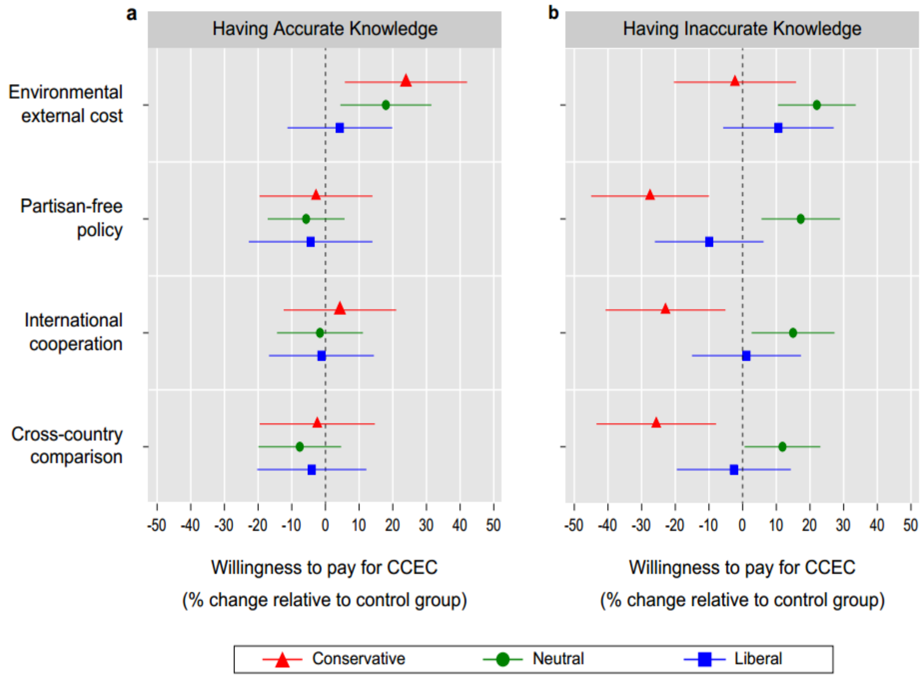


Figure 2-6 illustrates heterogeneous treatment effects of each political group by knowledge level. Importantly, this paper finds the result indicative of the partisan gap stemming from individuals' prior knowledge. While the group having accurate knowledge tends to exhibit a similar pattern in the treatment effects irrespective of their political view – only environmental external cost information is proven effective in increasing the respondents' WTP (Conservatives: 24%, $p<0.01$; Neutrals: 18%, $p<0.01$) (see Panel a of Figure 2-6), the reaction of the group having relatively inaccurate knowledge highly resembles the pattern observed in Figure 2-4 with larger effect sizes (see Panel b of Figure 2-6). Within this group, the conservatives show backfiring effects to all but environmental external cost information (-27%, $p<0.01$; -23%, $p<0.05$; -26%, $p<0.01$). The neutrals in all treatment groups report a significant increase in their WTP after receiving information compared to their corresponding control group (22%, $p<0.01$; 17%, $p<0.01$; 15%, $p<0.05$; 12%, $p<0.05$). The liberals are no different from the

[14] For concerns that the range set is arbitrary, the robustness test using other standards, 0.1 SD and 0.5 SD, is provided in Appendix A. The results of all the specifications are consistent with Figure 2-6.

accurate-liberals, showing no net effect to any of the information treatments.

Figure 2-6. Treatment Effects by Political View and Prior Knowledge



Notes: Treatment effects are reported as percent changes relative to each corresponding control group (by political view and prior knowledge). Error bars indicate 95% confidence intervals around the mean. Mean WTPs of the control group having accurate knowledge are 1.48 USD for conservative, 1.53 USD for neutral, and 1.78 USD for liberal. Mean WTPs of the control group having inaccurate knowledge are 2.61 USD for conservative, 1.88 USD for neutral, and 2.46 USD for liberal. For accurate knowledge group, N=445 for conservative, N=818 for neutral, and N=480 for liberal. For inaccurate knowledge group, N=593 for conservative, N=1,276 for neutral, and N=602 for liberal. All regression estimates include statistical controls for respondents' socioeconomic variables (gender, age, education, household income, and region of residence).

In the existing literature, the role of prior knowledge on moderating the effects of partisan identity on policy evaluation has been examined through two contrasting theories: the information-deficit theory and the ideological-consistency theory. The former suggests that more knowledgeable individuals rely less on partisan identity and more on their own knowledge in policy evaluation, while the latter posits that greater knowledge may reinforce ideological biases and increase reliance on partisan cues. While prior studies focusing primarily on climate change and environment-related policies in the US have supported the ideological-consistency theory (Hamilton, 2011; Nisbet et al., 2015; Bolsen and Druckman, 2018; Ehret et al., 2018), the present paper provides new empirical evidence from Korea, aligning with the information-deficit theory and thus highlighting the context-dependent nature of this finding.[15]

2.5. Conclusion

This paper examines the effects of information tackling commonly held public beliefs about climate policies: (i) Environmental external cost information, (ii) Partisan-free policy information, (iii) International cooperation information, and (iv) Cross-country comparison information on WTP for CCEC. Among the four types of information, providing environmental external cost information was the most effective at increasing individuals' WTP for CCEC, by 15% compared to the control group on average. The other information provision had small and statistically insignificant average effects. Subgroup analysis revealed that these average effects can be attributed to respondents' political ideology. The information motivated political neutrals to significantly increase their WTP; however, there was a strong negative response from political conservatives, nullifying the positive effects. Interestingly, this backlash was not observed in the group receiving environmental external cost information, leading to a net positive effect. In the case

[15] In the context of more general policies such as national security and economics, research conducted in Korea has produced varying results, with certain studies favoring one theory over the other. For instance, Ryu (2012) discovered a notable disparity in policy preferences based on political ideology solely among highly knowledgeable voters. Conversely, Oh et al. (2017) observed that as political knowledge increases, voters' party support and voting choices tend to shift towards class betrayal. These combined findings suggest that the implications of our findings may extend beyond country-specific factors.

of political liberals, all treatments showed nearly zero effect, possibly due to the ceiling effect.

The overall positive effect of environmental external cost information may be related to consumers' perception of fair price. According to the dual entitlement theory proposed by Kahneman et al. (1986), a firm's decision to increase price following cost increase or a firm's pursuit for a positive amount of profit is considered fair. Also, a price increase driven by pro-social motives is considered more fair (Campbell, 1999; Homburg et al., 2005; Gielissen et al., 2008). Therefore, the fact that electricity producers are not meeting ends may make consumers think that their current payment is unfair and report a higher WTP accordingly. Political conservatives who are generally resistant to climate-related information, are more likely to accept this information due to their inclination towards endorsing corporate rights as a means of promoting fairness (Frimer et al., 2017).

This study provides further evidence that respondents' prior knowledge can significantly contribute to political differences in treatment effects. Specifically, these findings demonstrate that respondents with relatively accurate knowledge exhibit consistent treatment effects regardless of their political views. However, respondents with inaccurate knowledge primarily drive the differential reactions by political views, with conservatives backfiring, neutrals reacting positively, and liberals remaining unaffected. These results, favoring the information-deficit theory over the ideological-consistency one, emphasize the need for caution when generalizing US-centric theories to other contexts. The observed inconsistencies in results can be attributed to various factors, including the types of prior knowledge, targeted policy domains, and cultural contexts, among others. Future research aimed at identifying the mechanisms that explain the interaction between knowledge and partisan identity in policy evaluation will greatly contribute to our understanding of this phenomenon.

Finally, this paper provides several important implications to energy policies. Firstly, disclosing environmental externality information, with a particular emphasis on the extent of internalization is a promising communication strategy in promoting public support for environmental pricing. The information is particularly useful in politically divided societies over climate change, as it helps to mitigate political divisions. Secondly, the differential reactions of political groups to the information suggest the potential for political identity-based targeting. The study demonstrates that most of the information presented is useful to political neutrals, who constitute the majority of the population. The advancement of online media enables the feasible implementation of political microtargeting, facilitating the ability to reach the targeted audience and provide tailored information (Baviera et al., 2023). Lastly, the finding that political divisions stem from inaccurate knowledge suggests that addressing ignorance and misperceptions held by individuals can be a potential solution to mitigate ideologically-based motivated reasoning, which poses a significant obstacle to effective intervention. Conducting experimental research to analyze the causal effects of correcting such ignorance and misperceptions is necessary to substantiate this claim. Additionally, given that the information provided does not significantly impact the WTP of respondents with accurate knowledge, it is crucial for future research to explore a broader range of information that can effectively influence these individuals.

Chapter 3. A Framework for Measuring Electricity Price Literacy: Application to South Korea[16]

3.1. Introduction

With a growing demand for residential electricity, contributing to over a quarter of global electricity consumption and related CO2 emissions (IEA, 2022b), changing household energy consumption behavior is more pressing issue than ever. Price measures have been widely used as one of the promising instruments that significantly influence household electricity demand (Zhou and Yang, 2016; Wang et al., 2018; Frondel and Kussel, 2019). For example, the most prevalent increasing block tariff (IBT) has been utilized to induce energy conservation in the residential sector by imposing higher marginal prices for high-consuming households (Foster and Witte, 2020). More recently, cost-reflective tariffs that better reflect temporal, seasonal and regional variation in electricity generation and supply cost are actively being discussed as a means to incentivize a change in consumption patterns by sending correct price signals to consumers (Faruqui and Bourbonnais, 2020).

The effectiveness of these price instruments critically depends not only on their design, but also on consumers' understanding of them. Previous literature found that consumers who are aware of electricity price tend to consume less electricity and are more responsive to price changes than those who are unaware (Jessoe and Rapson, 2014; Blasch et al., 2017; Pon, 2017; Frondel and Kussel, 2019; Trotta, 2021). In addition, consumer understanding of price structure has been identified as a crucial factor in increasing the attractiveness and engagement of demand response programs (Trotta, 2021). For instance, Reis et al. (2021) found that a thorough understanding of tariff structures increases consumers' willingness to adopt time-differentiated tariffs. According to Prest (2020),

[16] This essay represents joint work with Jong Ho Hong, Syngjoo Choi, Booyuel Kim, Jinwook Shin, and Heerae Lee of the Seoul National University.

consumer awareness of pricing mechanism is the most important source for consumer response to time−varying pricing.

However, the prior literature established their own definition for measuring consumers' understanding of price schemes[17] and named them differently, such as price knowledge, price awareness, price perception, or price literacy (Heberlein and Warriner, 1983; Brounen et al., 2013; Ameli and Brandt, 2015; McRae and Meeks, 2015; Blasch et al., 2017; Frondel and Kussel, 2019; Reis et al., 2021; Trotta, 2021; Werthschulte and Löschel, 2021). These differences in definitions and measurement tools make it difficult to conduct meta−analyses, cross−country comparisons, or intertemporal comparisons of the findings, undermining the implications of existing studies (van den Broek, 2019; Martins et al., 2020).

The aim of this paper is to develop a comprehensive measure of electricity price knowledge, which is referred to as "Electricity price literacy" following the concept of price literacy used in financial literacy literature. To achieve this, a functional form is introduced to represent electricity pricing systems, which is flexible enough to accommodate a wide range of pricing schemes available in the market. The functional form is further divided into three separate domains: (i) total bill amount, (ii) rate structure, and (iii) rate components. This structured approach allows for a comprehensive understanding of consumer knowledge and facilitates comparability across studies conducted with different price schemes. Based on the functional form customized to the specific pricing system, survey questions can be

---

[17] Several indicators have been used in the literature to measure electricity price knowledge, including total bill amount (Brounen et al., 2013; Ameli and Brandt, 2015; McRae and Meeks, 2015; Trotta, 2021), average price per kWh (Blasch et al., 2017; Trotta, 2021), and marginal price per kWh (Frondel and Kussel, 2019; Werthschulte and Löschel, 2021). Some of these studies also assess more detailed knowledge of tariff structure, such as block cutoffs and marginal prices of each block under increasing block tariffs (McRae and Meeks, 2015), as well as electricity distribution charge (Trotta, 2021). Other research on time-differentiated pricing has primarily focused on measuring knowledge of the tariff structure, including peak and off-peak time periods, fixed and variable rates, and the peak to off-peak price ratio (Heberlein and Warriner, 1983; Reis et al., 2021) (See Table 3-1).

generated for each knowledge domain.

To demonstrate the practicability of the proposed framework, electricity price literacy in South Korea (hereafter, Korea), which adopts the popular IBT is measured. By representing Korea's electricity price system as a functional structure, a total of 10 questions were generated: 1 question for the total bill amount and rate structure domains each and 8 questions for the rate components domain. The survey was then conducted online with a representative sample of Korean electricity consumers aged 19 and over (N=4,214).

The survey results show substantial variations in knowledge levels across different domains. Concerning total bill amounts, only a quarter of respondents estimated the amount correctly. On the other hand, a higher proportion of respondents − over 50% on average − demonstrated understanding on how their electricity rate is structured (i.e., what price components are included in bills). This understanding was particularly pronounced for long−standing price components (e.g., over 80% for IBT). However, when it came to the specific details of each price component, such as block cutoffs in IBT or the proportions of price components in the total bill, their level of understanding was significantly lower (12%).

Furthermore, a correlation analysis reveals differential effects of domain−specific knowledge on electricity−related behaviors, such as electricity consumption and support for cost−reflective pricing. Specifically, knowledge about the total bill amount is more closely linked to the electricity saving behavior, whereas knowledge of the rate structure and components is more relevant in shaping support for cost−reflective pricing. These findings, collectively, underscore the necessity of a comprehensive knowledge scale encompassing various domains of knowledge.

This research contributes to two strands of literature. First, it contributes to the literature on financial energy literacy, which encompasses knowledge of energy prices and the ability to perform investment analysis for energy−related financial decision−making. As this paper proposes a framework that integrates various indicators commonly used in the literature and organizes them in a systematic way, it will enhance the comprehensibility and comparability of price knowledge across studies. Secondly, this research adds to the literature investigating the impact of price knowledge on consumers' electricity−related behaviors (Brounen et al., 2013; McRae and Meeks, 2015; Blasch et al., 2017). While the previous studies have generally found positive effects of price knowledge on consumer behavior using their single aggregated index, none of them have analyzed price knowledge at a more disaggregated level and explored the heterogeneity within price knowledge. This study uncovers the differential effects of the sub−dimensions of knowledge on consumer behavior regarding electricity.

The remainder of this paper proceeds as follows. Section 3.2 introduces a framework for constructing a measure of electricity price literacy and provides examples of three widely used electricity tariff designs. Section 3.3 provides a detailed application of the framework within the context of Korea's electricity price system. This includes representing the electricity price scheme as a functional structure, constructing a survey questionnaire based on this functional form, and discussing survey results. Section 3.4 concludes with some recommendations for future research.

3.2. Developing a Measure of Electricity Price Literacy

3.2.1. The Framework

This study proposes a framework to measure "Electricity price literacy", that is, overall and detailed knowledge on the electricity pricing system that residential customers must possess to calculate their electricity bills and adjust their behaviors accordingly. Considering the heterogeneity of pricing systems across countries and throughout time spans, this paper introduces a structured approach that encapsulates an electricity pricing system into a single function which can be easily altered to reflect various electricity tariff structures available in the electricity market (Labandeira et al., 2022).

The functional form is given as follows:

$$b_T = \left[p_f(X) + \{p_v(X) \times q\}\right] \times (1 + tax\ \ rate),\ \text{where}\ \ X = \{q, t, e\}. \qquad (1)$$

The electricity bill in the residential sector for period T, denoted as b_T, is determined by a fixed cost, $p_f(X)$, a variable cost, $p_v(X) \times q$, and related taxes. Both fixed and variable costs may vary by the vector of electricity consumption q (in kWh), time t (in hour) and other components e, such as voltage, energy sources, and household characteristics. Various taxes and charges are multiplied to the sum of the fixed and variable costs.

The functional form can be divided into three knowledge domains: the total bill amount (i.e., b_T), the rate structure (i.e., the functional form) and the rate components (i.e., $p_f(X), p_v(X), tax\ \ rate$). The three domains incorporate knowledge measures used in the previous literature (see Table 3-1). For example, the total bill amount domain encompasses knowledge on the level of electricity bill and average price per kWh (Brounen et al., 2013; Ameli and Brandt, 2015; McRae and Meeks, 2015; Blasch et al., 2017; Trotta, 2021). Rate structure and components domains include more detailed knowledge of tariff structure, such as block cutoffs and marginal prices of each block (McRae and Meeks, 2015; Frondel and Kussel, 2019; Werthschulte and Löschel, 2021). This division into three domains further enhances comparability across studies, as these three domains are commonly present in electricity price schemes.

Table 3-1. Electricity Price Knowledge Measures in the Literature

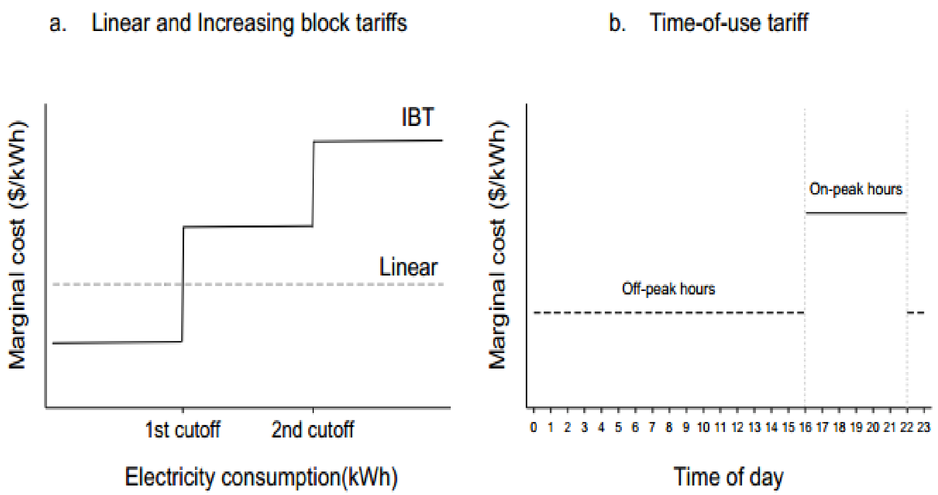
Literature	Price knowledge			Other knowledge	Dependent variables	Impact of price knowledge
	Total amount	Rate structure	Rate components			
Brounen et al. (2013)	Monthly electricity bill			An ability to make a trade-off between long-term savings and short-term benefits	Electricity consumption (Self-reported)	None
Kahn and Wolak (2014)		How its electricity bill is determined from IBT	Marginal prices	How the customer's appliance-using actions translate into dollars on its monthly electricity bill	Electricity consumption (Actual)	Decrease
Ameli and Brandt (2015)	Electricity bill and use				Propensity to invest in energy efficient appliances	Increase
McRae and Meeks (2015)	Total amount of electricity bill for four consumption quantities		IBT block cutoffs, Marginal prices of each block	Usage cost of appliances	Electricity consumption (Actual)	Decrease
Blasch et al. (2017)	Average price per 1kWh			Usage cost of appliances, Electricity consumption of appliances, Compound interest rate calculation	Electricity consumption (Actual)	Decrease

Frondel and Kussel (2019)			Marginal price		Price elasticity of electricity demand	Increase
Prest (2020)		Aware of the change in their tariff structure			% change in energy consumption during peak periods	Decrease
Broberg and Kazukaukas (2021)	Average price per 1kWh	Contract type		Annual electricity consumption	Cost perceptions Willingness to receive information	Lower cost perceptions / More willing
Trotta (2021)	Electricity bills (Summer & Winter) Average price		Electrical energy cost Electricity distribution charge	Electricity operating costs (Dishwasher, Oven)	Electricity consumption (Actual) Willingness to receive information	Decrease / More willing
Reis et al. (2021)			Numeracy and graphical literacy on time-differentiated tariffs	General knowledge on energy issues	Willingness to adopt time-differentiated tariffs	Increase

3.2.2. Examples

To show how to customize this framework, this subsection provides examples for three widely used tariff designs in electricity markets, namely, a linear tariff, an increasing block tariff (IBT), and a time-of-use tariff (TOU). The graphical illustration of these tariff structures is provided in Figure 3-1.

Figure 3-1. Illustration of Three Tariffs



Note: IBT and TOU shown in this figure are simplified examples, with three consumption blocks for IBT and two time blocks for TOU.

First, the linear tariff (also called flat-rate, simple, or single rate tariffs) takes the simplest form of volumetric charging that charges a constant rate on every unit of electricity consumed. Several countries including Australia, Austria, Germany, Guatemala, Malawi, Nigeria, etc. are practicing the linear tariff due to its simplicity and relatively low service costs.[18] A conventional linear tariff applied on residential customers is structured as a two-part tariff with a fixed charge and a flat-rate variable charge (Simshauser and Downer, 2016). This can be represented as the following:

[18] Some countries provide optional flat tariffs as a premium plan with no limits on capacity (Lo et al., 2019).

$$b_T = \{p_f + p_v \times q\} \times (1 + tax\ \ rate).$$

The functional form can be subdivided into three knowledge domains: the total amount of bill (b_T), the rate structure (functional form) and the details of each bill component ($p_f, p_v,$ and $tax\ \ rate$). Under this tariff structure, knowledge about the items included in the bill and their unit prices is critical for consumer responses to electricity prices.

Another popular tariff is the IBT, where the volumetric price increases across successive blocks of electricity consumption. This is the most widely adopted tariff structure for residential customers spanning in both developed and developing countries (Foster and Witte, 2020). Under the IBT with n consumption blocks, Equation (1) is transformed to

$$b_T = \begin{bmatrix} I_{q \le \overline{q_1}}\{p_{f_1} + p_{v_1} \times q\} \\ +I_{\overline{q_1} < q \le \overline{q_2}}\{p_{f_2} + p_{v_1} \times \overline{q_1} + p_{v_2} \times (q - \overline{q_1})\} \\ \vdots \\ +\ I_{q > \overline{q_{n-1}}}\{p_{f_n} + p_{v_1} \times \overline{q_1} + p_{v_2} \times (\overline{q_2} - \overline{q_1}) + \cdots + p_{v_n} \times (q - \overline{q_{n-1}})\} \end{bmatrix} \times (1 + tax\ \ rate),$$

where I represents an indicator function that assigns a value of 1 if a specified condition (the subscript) holds, and a value of 0 otherwise. For $i \in \{1, \ldots, n-1\}$, $\overline{q_\iota}$ denotes the block cutoff. For $j \in \{1, \ldots, n\}$, p_{f_j} and p_{v_j} indicate fixed and variable costs on the j−th block, where $p_{f_1} \le \cdots \le p_{f_n}$ and $p_{v_1} < \cdots < p_{v_n}$. In this representation, the three knowledge domains are the total amount of bill (b_T), the rate structure (functional form) and the details of each bill component (n, $\overline{q_\iota}$, p_{f_j}, p_{v_j} and $tax\ \ rate$). Under the IBT, the number of blocks, the block cutoffs, and the unit price of each block are the pieces of information required to respond to this nonlinear price schedule.

Finally, the TOU is an increasingly popular tariff in the residential sector, where the volumetric price is differentiated according to the time of day. Countries currently offering the TOU tariff to residential customers include Iran, Mongolia, Pakistan, Thailand, UK, and several states in the US (e.g., Arizona, California, Georgia, Michigan, New York). Under the typical TOU tariff that operates with two−time blocks (on−peak and off−peak), Equation (1) can be represented as follows.

$$b_T = \left[p_f + (p_{v_{on}} \times q_{on}) + (p_{v_{off}} \times q_{off})\right] \times (1 + tax\ \ rate),$$

where $p_{\mathrm{v_{on}}}$ and $p_{v_{off}}$ denote on−peak and off−peak prices, respectively, with $p_{v_{on}} > p_{v_{off}}$. Additionally, q_{on} and q_{off} denote the quantities consumed during on−peak and off−peak periods. The three knowledge domains under this tariff are the total amount of bill (b_T), the rate structure (functional form) and the details of each bill component (p_{f}, $p_{\mathrm{v_{on}}}$, $p_{v_{off}}$ and $tax\ \ rate$). As can be seen from the equation, consumers must know when time period changes, what unit prices are to accurately calculate their total bill amount and adjust their consumption under this tariff structure. Real−time pricing (also known as dynamic pricing), where variable price varies each hour based on the utility’ s real−time production cost can also be represented by transforming the equation to a 24 hour basis.

The sample survey questions corresponding to each tariff design are presented in Table B−1 in Appendix B.[19]

3.3. Application: Electricity Price Literacy in Korea

3.3.1. Constructing Electricity Price Literacy Questionnaire

To demonstrate the practicality of the proposed framework, it is applied to the context of Korea as a case study. As a first step to construct the measure of electricity price literacy, the residential electricity pricing system in Korea as of September 2021 (at the time of the survey) is represented as a functional structure using Equation (1).

---

[19] Sample questions for rate components domain is provided in Table B-1 in Appendix B. Refer to Table 3-2 for the questions for the total bill amount and rate structure domains.

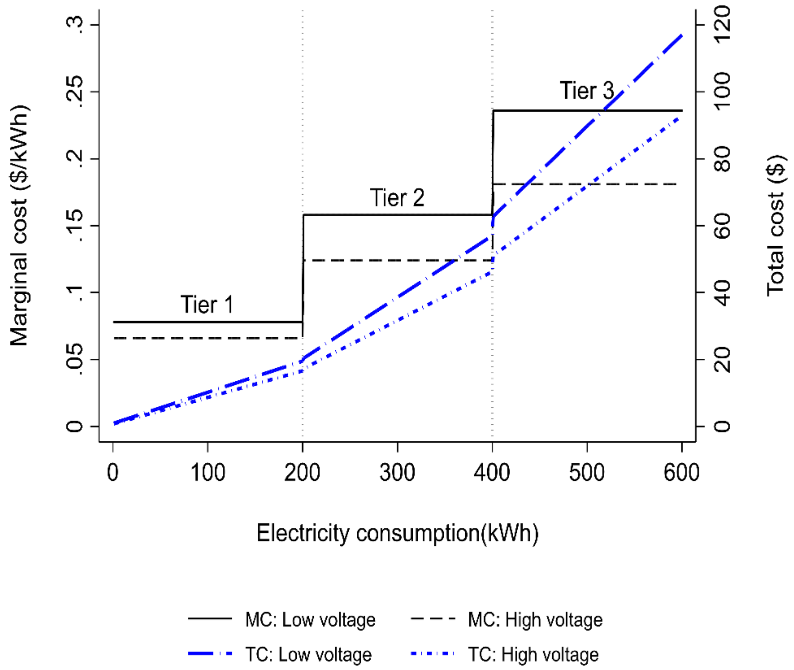
Residential Electricity Pricing System in Korea:

$$b^{\text{Korea}}_{\text{Monthly}} = \Bigg[I_{Voltage=Low} \left\{ \begin{array}{c} I_{q\leq 200}(p^{L}_{f,q\leq 200} + p^{L}_{v,q\leq 200} \times q) \\ + I_{200<q\leq 400}(p^{L}_{f,200<q\leq 400} + p^{L}_{v,q\leq 200} \times 200 + p^{L}_{v,200<q\leq 400} \times (q-200)) \\ + I_{q>400}(p^{L}_{f,q>400} + p^{L}_{v,q\leq 200} \times 200 + p^{L}_{v,200<q\leq 400} \times (400-200) + p^{L}_{v,q>400} \times (q-400)) \end{array} \right\}$$
$$+ I_{Voltage=High} \left\{ \begin{array}{c} I_{q\leq 200}(p^{H}_{f,q\leq 200} + p^{H}_{v,q\leq 200} \times q) \\ + I_{200<q\leq 400}(p^{H}_{f,200<q\leq 400} + p^{H}_{v,q\leq 200} \times 200 + p^{H}_{v,200<q\leq 400} \times (q-200)) \\ + I_{q>400}(p^{H}_{f,q>400} + p^{H}_{v,q\leq 200} \times 200 + p^{H}_{v,200<q\leq 400} \times (400-200) + p^{H}_{v,q>400} \times (q-400)) \end{array} \right\}$$
$$+ \{(FCAR + CCEC) \times q\} - I_{\text{Eligible cases}}\{\text{Discount}\} \Bigg] \times (1 + E - Fund + VAT) \quad (2)$$

The residential electricity pricing system in Korea is structured as a combination of the two−part tariff and the IBT. There exist a fixed rate, p_f, and a variable rate, p_v, both vary by the level of voltage (Low, High) and by the electricity consumption block (a total of three blocks with 200kWh and 400kWh as block cutoffs).[20] In addition, two types of charges are being imposed. Those are the Fuel Cost pass−through Adjustment Rate (hereafter, FCAR) that reflects the changes in fuel costs and the Climate Change & Environmental Charge (hereafter, CCEC), which internalizes the environmental externality costs. Also, a discount is offered to the eligible households including the disabled, low−income, and large households either by a fixed rate or a fixed amount. Finally, two types of taxes − a tax of 3.7% aiming to raise funds for sustainable development of the electric industry (hereafter, E−Fund) and a Value−Added Tax (hereafter, VAT) of 10% − are imposed. Figure 3−2 shows an illustration of the residential electricity pricing system in Korea.

[20] For summer season (July and August), the block cutoffs go up to 300kWh and 450kWh, respectively.

Figure 3-2. Illustration of Residential Electricity Pricing System in Korea



Notes: MC = Marginal cost, TC= Total cost; the exchange rate was 1187.43KRW per dollar as of September 30, 2021.

Based on this monthly electricity bill structure, a total of 10 questions are elicited to measure three domains of electricity price literacy: the total bill amount, rate structure and details of each electric bill component. To measure the knowledge of total bill amount, respondents were asked to estimate total bill amounts at five different electricity usage levels along the price schedule (100, 300, 500, 700, 900kWh) (A1 in Table 3-2). To measure knowledge about rate structure, a question that asks whether respondents know which electric bill components are included in their electric bill is developed (A2 in Table 3-2).[21] Finally, a series of questions that ask details of each bill components are included in rate structure domain (A3-A10

[21] Both price components currently in place and those soon to be implemented are included.

in Table 3-2).[22,23]

Table 3-2. Electricity Price Literacy Questionnaire for Korea

Domain I. Total bill amount

A1. Suppose your monthly electricity usage is [100kWh / 300kWh / 500kWh / 700kWh / 900kWh]. Please indicate the corresponding amount for your monthly electricity bill. For reference, the average monthly electricity consumption for a four-person household in Korea is about 350 kWh.

Domain II. Rate Structure

A2. Please select the items that are included in the calculation of electricity bill for households in Korea.

1. Increasing block tariff: A rate per unit of electricity that increases across successive blocks of electricity consumption
2. Climate change & Environmental charge: A charge for external cost of greenhouse gas and air pollutants emitted from electricity generation
3. Seasonal Time-Of-Use (TOU) tariff: A rate that charges a higher unit price for electricity at times (peak load) and seasons (summer/winter) of high electricity demand and a lower unit price at times (off-peak, mid-peak load) and seasons (spring/fall) of low electricity demand.
4. Fuel cost pass-through adjustment rate: A rate which permits changes in rates as a result of changes in the fuel cost
5. Welfare discount: Discount on an electric bill offered to socially vulnerable classes (e.g., low-income, disabled, etc.)
6. Electric power industry infrastructure fund: Ad-valorem contribution levied on electricity consumed to support sustainable development of electric power industry
7. Value-added tax: A tax levied in the process of trading goods or providing services

Domain III. Rate Components

[Increasing Block Tariffs]

A3. Increasing block tariff, which is a rate per unit of electricity that increases

---

[22] Among 7 price components in A2, no further questions for TOU and VAT are included in rate component domain. This is because, TOU has only been introduced to one specific region of the country (i.e., Jeju Island) at the time of the survey that no details are available to most respondents. VAT is excluded since 10% VAT is levied on all the goods, not for electricity price only.

[23] Each domain appears to be internally consistent, as indicated by Cronbach's alpha, which is 0.95 (total bill amount), 0.79 (rate structure), and 0.88 (rate component), all satisfying generally accepted criteria for internal reliability which is 0.7.

across successive blocks of electricity consumption, is applied in the residential electricity rate system in Korea. How many blocks do you think the increasing block tariff in residential sector is divided into?

A4. Increasing block tariff is divided into three blocks for households in Korea. When your electricity usage exceeds a certain threshold, a rate per unit of electricity increases. What is the threshold usage (kWh/month) at each block? For reference, the average monthly electricity usage for a four-person household in Korea is approximately 350 kWh.

[Climate Change & Environmental Charges]

A5. Climate change & Environmental charge, which is a charge for external cost of greenhouse gas and air pollutants emitted from electricity generation, is applied in the residential electricity rate system in Korea. How much of the electricity bill do you think is charged for Climate change & Environmental charge? Please select the amount of this charge from KRW 54,000, which is the average monthly electricity bill for a four-person household in Korea.

A6. Please select whether the costs listed below are included in the calculation of the Climate change & Environmental charge.

1. Renewable Portfolio Standards (RPS) compliance cost: Electricity generators are obligated to produce a specified fraction of their electricity from renewable energy sources. RPS compliance cost is the cost that incurs in this process.
2. Emissions Trading System (ETS) compliance cost: Electricity generators are obligated to reduce their carbon emissions. ETS compliance cost is the cost that incurs in this process.
3. Coal-powered generation reduction cost: The cost for reducing coal-powered generation to minimize damage caused by fine dust.

[Fuel Cost pass-through Adjustment Rate]

A7. Fuel cost pass-through adjustment rate, which is a rate which permits changes in rates as a result of changes in the fuel cost, is applied in the residential electricity rate system in Korea. Please select all of the energy sources listed below to be considered in calculating Fuel cost pass-through adjustment rate. [Coal / Nuclear / Hydro / Oil / Natural gas / Wind / Solar]

A8. If the fuel cost pass-through adjustment rate is applied, electricity bills may fluctuate drastically due to the fluctuation of fuel cost. In order to prevent such drastic fluctuation of electricity bills, fuel cost pass through adjustment rate has upper and lower limits so that the bill cannot rise/fall beyond a certain level when the fuel cost rises/falls. Is this statement correct?

[Welfare Discount]

A9. The electricity rate system in Korea has a welfare discount system for the socially disadvantaged. Please answer whether the following groups in the list are eligible for the welfare discount system. [Handicapped persons / National independence merit receivers / Jobseekers / Large households with 5 or more family members / Families with 3 or more children / North Korean defectors / Households with children less than 3 years old / Basic life program recipients / Households that use life support equipment]

[Electric Power Industry Infrastructure Fund]
A10. Electric Power Industry Infrastructure Fund is levied as part of the electricity bill for households in Korea to support the sustainable development of electric power industry. How much of the electricity bill do you think is charged for the Electric Power Industry Infrastructure Fund? Please select the amount of this fund from KRW 54,000, which is the average monthly electricity bill for a four−person household in Korea.

3.3.2. The survey

Using the survey questionnaire, an online survey was administered to a nationwide sample of 4,214 electricity consumers aged 19 and above in Korea. The survey was conducted by a survey company, Hankook Research in October 2021. Table 3−3 provides descriptive statistics of sociodemographic characteristics of the sample and mean comparison test results with the population from national census data. Among the characteristics, only the income turns out to be slightly underrepresented.

Table 3−3. Descriptive Statistics and Comparison with the Population

Variables	(1)	(2)	(3)
	This survey	2021 KSIS	Difference(SE)
Female	0.50 (0.50)	0.50 (0.50)	−0.001 (0.01)
Age			
20s	0.16 (0.36)	0.16 (0.37)	−0.001 (0.01)
30s	0.16 (0.37)	0.15 (0.36)	0.006 (0.01)
40s	0.19 (0.39)	0.19 (0.39)	0.004 (0.01)
50s	0.20 (0.40)	0.20 (0.40)	0.002 (0.01)
60s and above	0.29 (0.45)	0.30 (0.46)	−0.005 (0.01)
Education			

Bachelor or more	0.32 (0.47)	0.33 (0.47)	−0.01 (0.01)
Monthly HH Income			
< KRW 2 million	0.13 (0.34)	0.12 (0.33)	0.008 (0.01)
KRW 2−3 million	0.15 (0.36)	0.12 (0.32)	0.03*** (0.01)
KRW 3−4 million	0.19 (0.40)	0.14 (0.35)	0.04*** (0.01)
KRW 4−5 million	0.16 (0.36)	0.15 (0.36)	0.002 (0.01)
≥ KRW 5 million	0.38 (0.48)	0.46 (0.50)	−0.09***(0.01)
Observations	4,214	8,077	

Notes: Data for the population of Korea − the column (2) − is drawn from 2021 Korea Social Integration Survey(KSIS), which is produced by the Korea Institute of Public Administration (KIPA), and has been authorized for use according to KIPA's regulations on the ownership and use of said research material; Standard deviations are reported in parentheses in columns (1) and (2), while standard errors are reported in parentheses in column (3); The results of mean comparison tests are presented with asterisks; *** p<0.01, ** p<0.05, * p<0.1.

3.3.3. Results

3.3.3.1. Levels of Electricity Price Literacy

Using the survey results, levels of electricity price literacy of each domain is measured by calculating the proportion of correct answers. First, each answer was translated into binary variables, assigning a value of 1 for correct answers and 0 for incorrect answers.[24] Then, at the individual level, the binary variables in each domain are averaged to get individual electricity price literacy of each domain. Overall individual electricity price literacy is defined as the average of the three domains' literacy. To get the overall and three domains' electricity price literacy of the entire survey participants, individual literacy is averaged out.

Figure 3−3 presents the overall and each domain's electricity price literacy in Korea. As for total bill amount, an average of 26% of respondents correctly answered about electricity bill amounts at five different electricity usage levels (100, 300, 500, 700, 900kWh). This

[24] The detailed procedure for generating binary variables is described in Appendix B.

result confirms the previous findings that a large proportion of households are not literate about the cost of their monthly electricity use (Brounen et al., 2013; Ameli and Brandt, 2015; McRae and Meeks, 2015; Blasch et al., 2017; Trotta, 2021).[25] In addition, a declining pattern in knowledge levels is identified as electricity usage levels increase, ranging from 45% for 100kWh to 13% for 900kWh. Given that over half of the respondents reported consuming less than 300 kWh per month, this pattern indicates a strong association between the accuracy of knowledge and individuals' prior experiences, as discussed by Kahn and Wolak (2013) and McRae and Meeks (2015).

With regard to how electricity rate is structured, respondents exhibit a higher level of awareness, 52% on average, with greater knowledge on long-standing price components (e.g., 83% for IBT, 76% for discount, 67% for VAT). Relatively low scores were observed for several charges that were recently introduced at the time of the survey, such as FCAR (38%) and CCEC (36%). Similarly, the lowest score recorded for TOU (19%) can be attributed to the fact that TOU tariff was only offered as an optional tariff in a specific region of Korea (Jeju Island) shortly before the survey was conducted.

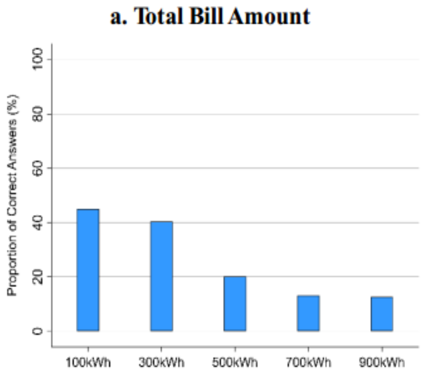
In contrast, respondents exhibit significantly lower levels of knowledge regarding the specific details of each component. Among those who correctly answered the existence of each component within the rate structure, only about 12%, on average, demonstrate knowledge of the component details. For example, when it comes to the IBT, less than one-fifth of the respondents correctly answered key features, such as the number of blocks and the block cutoffs. Likewise, only a small portion of respondents accurately estimated the bill amount, with only 10% for CCEC and 14% for E-Fund. These findings align with Hall et al. (2016) that also observed lower scores

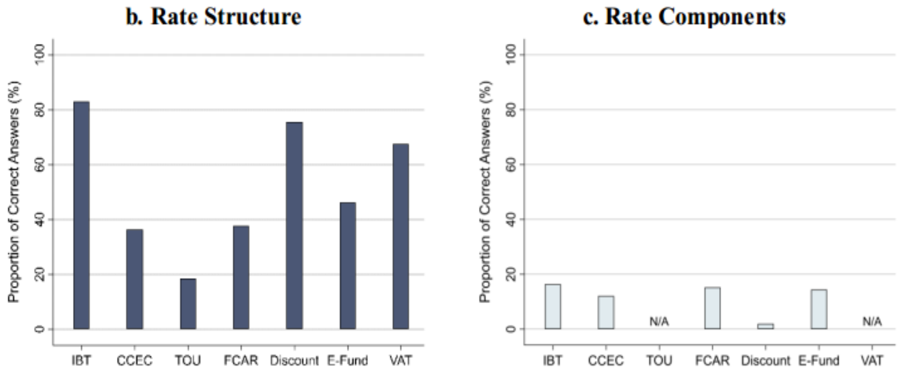
[25] Low level of knowledge regarding electricity bill amounts has been reported in the literature: 56% correct in Brounen et al.(2013); 55% correct in Ameli and Brandt(2015); On average, 44% correct in McRae and Meeks(2015); 27% percent correct in Blasch et al.(2017); 37% correct in Trotta(2021).

as questions become more complex.

Figure 3-3. Electricity Price Literacy Score in Korea

Electricity Price Literacy	
Total Bill Amount	26%
Rate Structure	52%
Rate Components	12%
Overall	30%





Notes: IBT = Increasing Block Tariff, CCEC = Climate Change & Environmental Charge, TOU = Time-Of-Use tariff, FCAR = Fuel Cost pass-through Adjustment Rate, E-Fund = Electric power industry infrastructure Fund, VAT = Value-Added Tax, N/A = Not Applicable. Among 7 price components in A2, no further questions for TOU and VAT are included in rate component domain. This is because, TOU has only been introduced to one specific region of the country (i.e., Jeju Island) at the time of the survey that no details are available to most respondents. VAT is excluded since 10% VAT is levied on all the goods, not for electricity price only.

3.3.3.2. Correlations between Electricity Price Literacy and Electricity-related Behaviors

Moreover, this study conducts a correlation analysis between electricity price literacy measure and electricity-related behaviors. Two important behaviors commonly used in literature are employed.

The first behavior is the respondents' electricity consumption, which has been a key behavioral outcome of interest in previous studies (Brounen et al., 2013; Kahn and Wolak, 2013; McRae and Meeks, 2015; Blasch et al., 2017; Prest, 2020; Trotta, 2021; Werthschulte and Löschel, 2021).[26] The second behavior is respondents' willingness to support cost-reflective pricing, an important consideration given the increasing need to align utility costs and electricity rates, as well as the desire to induce changes in consumption patterns (Hobman et al., 2016; Faruqui and Bourbonnais, 2020). Three types of cost-reflective pricing are explored: i.e., fuel cost pass-through adjustment rate, regionally-differentiated tariff, and time differentiated tariff, which have just been introduced or will soon be implemented in Korea, as of October in 2021.[27] The level of support for cost-reflective pricing is measured by the following question: "Do you think applying [cost-reflective pricing] in the residential electricity rate is necessary?" The scale ranged from 1 "Highly necessary" to 5 "Highly unnecessary".

These behavioral outcomes are regressed on the electricity price literacy, along with sociodemographic and dwelling characteristics, reported attitudes, and behavioral characteristics variables. Equation (3) presents the model with an overall electricity price literacy measure, following the approach used in previous studies that employed a single composite index to assess price knowledge. On the other hand, Equation (4) introduces the extended model, which incorporates the three distinct domains of price literacy.

$$E_i = \alpha_0 + \alpha_1 Lit_i + X_i\gamma + AB_i\delta + \epsilon_i. \qquad (3)$$

[26] This paper uses electricity consumption data self-reported by respondents as in Brounen et al. (2013).

[27] The Fuel cost pass-through adjustment rate reflects changes in international fuel costs in bills, reducing the financial risks for providers while encouraging flexible consumption by consumers (KEPCO, 2020). The Regionally-differentiated tariff determines electricity prices based on varying electricity distribution conditions at the regional level (Mentel et al., 2018). Finally, the Time-differentiated rate imposes varying charges at different times to provide better signals of changes in utility costs to consumers (Faruqui and Bourbonnais, 2020).

$$E_i = \beta_0 + \beta_1 PLit_{1,i} + \beta_2 PLit_{2,i} + \beta_3 PLit_{3,i} + X_i\gamma + AB_i\delta + \epsilon_i. \quad (4)$$

The dependent variable, denoted as E_i, represents either the respondent's (self-reported) electricity consumption (kWh) or their support for various cost-reflective pricing, which is a binary variable assigning 1 if the respondent chooses positive response options, such as "Highly necessary" and "Necessary". Lit_i in Equation (3) represents overall electricity price literacy score, while $PLit_{1.i}$, $PLit_{2.i}$, $PLit_{3.i}$ in Equation (4) correspond to the scores for total bill amount, rate structure and rate component domains, respectively. The overall literacy is calculated as an unweighted average of the scores from the three domains, each ranging from 0 to 1. The vectors X_i and AB_i are control variables commonly used in previous literature. Specifically, X_i represents sociodemographic variables (e.g. gender, age, education, household income and political view), housing types (e.g., apartment, detached house), home-ownership status (e.g., landlord, tenant), regions, and years of residence. AB_i is a vector capturing respondents' attitudes and behaviors towards environment, measured on a 5-point Likert scale. Finally, ϵ_i denotes the error term.[28] Table 3-4 presents the survey items used to measure the variables included in Equation (3)-(4).

Table 3-4. Summary of Variables

Variables	Survey items
Dependent variables	
Electricity consumption	Do you know your monthly electricity usage (kWh) for the previous month? If you do, please enter your monthly electricity usage.

[28] This survey includes survey experiments, where participants were randomly assigned to either treatment or control groups and exposed to electricity-related information. In order to account for any potential influence of the experiments on the results, the variables for the control/ treatment group assignment are controlled.

Support for various cost-reflective pricing	Fuel cost adjustment rate is a rate which permits changes in rates as a result of changes in the fuel cost. The rate per unit of electricity increases when fuel cost increases and vice versa. Do you think applying fuel cost adjustment rate in the residential electricity rate is necessary? (1: Highly necessary, 5: Highly unnecessary) Regional differential pricing is a tariff which charges different prices for electricity by regions considering region-varying costs of transmission and distribution. Do you think applying regional differential pricing in the residential electricity rate is necessary? (1: Highly necessary, 5: Highly unnecessary) Seasonal Time-of-use tariff is a tariff which charges a higher unit price for electricity at times (peak load) and seasons (summer/winter) of high electricity demand and a lower unit price at times (off-peak, mid-peak load) and seasons (spring/fall) of low electricity demand. Do you think applying seasonal Time-of-use tariff in the residential electricity rate is necessary? (1: Highly necessary, 5: Highly unnecessary)
Sociodemographic characteristics	
Gender	What is your gender? 1. Male, 2. Female
Age	How old are you? ( ) years old
Education	Which of the following best describes your final education level? From none to Doctoral graduate
Household income	What is your average monthly gross household income (before tax) for the year 2020? Please enter the total income of all household members that are engaged in economic activities.
Political view	What is your political view? 1: Very conservative, 2: Conservative, 3: Neutral, 4: Progressive, 5: Very progressive
Dwelling characteristics	
Household size	How many people, including yourself, live in your residence? Please exclude the household members if they currently do not live in your residence and enter the actual number of members currently living in your residence (including yourself).
Dwelling type	What type of house do you currently live in? 1. Apartment 2. Detached house 3. Townhouse/ Multiplex Housing 4. Studio apartment/dual-purpose buildings used for commercial and residential purposes 5. Homes in non-residential buildings

	6. Other ( )
Home ownership status	What is the status of occupancy of the current house? 1. Owned 2. Jeonse – Housing Rental (Year unit contract) 3. Monthly rent with deposit 4. Monthly rent without deposit 5. Other ( )
Regions of residence	Please select the region you are residing in up to Eup/Myeon/Dong-level.
Years of residence	How many years have you lived in the region you currently reside?
Attitudes and Behaviors	
Energy saving	Please read the following statements and indicate your level of agreement: (1: Strongly agree, 5: Strongly disagree) My individual actions would make a contribution to solving environmental problems like global warming if I were to conserve electricity in home appliances, such as refrigerator, air conditioner, etc.
Concern on environment	Please read the following statements and indicate your level of agreement: (1: Strongly agree, 5: Strongly disagree) 1) Greenhouse gases and fine dust emitted during the process of power generation using fossil fuel exacerbate air pollution and climate change. 2) The earth is experiencing serious environmental, ecological and climate crisis at this time. 3) The earth has exceeded its capacity to recover by itself.
Pro-environmental behaviors	Please read the following statements and indicate how you think about each statement: (1: Very willing, 5: Very unwilling) 1) I am willing to adapt my consumption habit and lifestyle in ways that contribute to solving environmental problems. 2) I am willing to exert efforts, such as joining consumer organization, conducting campaigns, and presenting petitions to solve environmental problems 3) I am willing to pay taxes, which will be used to solve environmental problems. 4) I am willing to actively engage in political activities to solve environmental problems.

Table 3-5 shows OLS results for the respondents' self-reported monthly electricity consumption (kWh). Column (1) and (2) correspond to the estimation result using Equation (3) and (4), respectively.

According to column (1), electricity price literacy does not seem to affect electricity consumption. However, this conclusion may be misleading. The analysis shown in column (2) reveals that among three domains of electricity price literacy, knowledge about total bill amount is negative and significantly correlated with electricity consumption. The estimated coefficient implies that respondents scoring 1 (i.e., all correct) in total bill amount domain consume, on average, 20kWh less electricity per month compared to those scoring 0 (i.e., all wrong). Knowledge on rate structure and components, on the other hand, is unlikely to have a significant relation with electricity use, implying that respondents may not rely much on the exact knowledge of how electricity bills are structured and calculated when making consumption decisions.

These results are closely related to the earlier findings that consumers tend to respond to average price due to cognitive difficulty in understanding the nonlinear structure of electricity pricing (Borenstein, 2009; Ito, 2014; Shaffer, 2020; Labandeira et al., 2022).

Table 3-5. OLS Results on Electricity Consumption (kWh)

	Electricity consumption (kWh)	
Variables	(1)	(2)
Electricity price literacy (0-1)	11.88	
	(16.27)	
Total bill amount		−20.41**
		(10.06)
Rate structure		10.28
		(12.66)
Rate components		26.92
		(17.95)
Constant	169.61***	177.43***
	(22.34)	(22.70)
Controls		
X_i	Yes	Yes
AB_i	Yes	Yes
N	4,214	4,214

R−squared	0.150	0.151

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; X_i includes gender, age, education, political view, household income, household size, housing type, home−ownership status, regions and years of residence. AB_i includes reported attitudes and behaviors towards environment.

Subgroup analyses based on household income levels and electricity usage patterns presented in Table 3−6 reinforce the main results that knowledge of total bill amount is the most relevant factor in promoting electricity conservation, and also suggests that these conservation effects are primarily driven by respondents with higher incomes and intensive electricity use, who presumably have greater potential to modify their behaviors (Asensio and Delmas, 2015; Labandeira et al., 2022). Interestingly, the results also revealed that knowledge of the total bill amount tends to increase electricity consumption among respondents with below−average electricity usage. This group may have overestimated their electricity price compared to their counterparts[29] and have already achieved more efficient energy use. Thus, more accurate knowledge may trigger a rebound effect. For this group, knowledge of tariff structure and components appears to be also essential in increasing consumption.

Table 3−6. OLS Results on Electricity Consumption (kWh) by Household Income and Electricity Use Patterns

Variables	Household income		Electricity consumption	
	Above mean	Below mean	Above mean	Below mean
Electricity price literacy (0−1)				
Total bill amount	−27.94*	−13.47	−57.60***	24.58***
	(14.94)	(13.62)	(10.74)	(8.13)
Rate structure	2.25	19.50	4.27	18.71**
	(20.02)	(16.14)	(14.82)	(9.40)
Rate components	30.63	11.79	−12.62	26.82*

29 The data suggests that at the 1% significance level, an average price of electricity per kWh perceived by respondents with below-average electricity consumption (0.14 USD) is higher than that perceived by respondents with above-average electricity consumption (0.13 USD).

	(26.68)	(23.94)	(20.39)	(14.45)
Constant	228.67***	139.75***	442.26***	90.92***
	(38.14)	(29.51)	(27.74)	(16.00)
Controls				
X_i	Yes	Yes	Yes	Yes
AB_i	Yes	Yes	Yes	Yes
N	1,919	2,295	2,058	2,156
R-squared	0.097	0.150	0.082	0.090

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; X_i includes gender, age, education, political view, household income, household size, housing type, home-ownership status, regions and years of residence. AB_i includes reported attitudes and behaviors towards environment

Next, Table 3-7 shows the influence of electricity price literacy on respondents' support for cost-reflective pricing schemes.[30] Unlike the case of electricity consumption, the results show that participants' support for cost-reflective pricing is more closely related to knowledge on rate structure and components than knowledge on total bill amount. Specifically, respondents scoring 1 (i.e., fully informed) in rate structure domain, on average, have more probability to support for cost-reflective pricing - by 10%p for fuel cost pass-through adjustment rate, 12%p for regionally differentiated pricing and 8%p for time differentiated pricing compared to those scoring 0 (i.e., uninformed). Similarly, those scoring 1 in rate components domain are 10%p more likely to support for fuel cost pass through adjustment rate and 14%p for time differentiated pricing compared to those scoring 0 on average. It should be noted that respondents who answer correctly in the rate component domain also possess correct knowledge in the rate structure domain by construct. Thus, the coefficient of the rate component domain has an additive effect on the likelihood of supporting cost-reflective pricing. Specifically, the level of support among respondents with more detailed tariff knowledge is 2 to 2.75

[30] Since the dependent variable is binary, the OLS regression in this case can be regarded as a linear probability model. Logit regression provides qualitatively similar results (see Table B-2 in Appendix B).

times higher than those with knowledge limited to the basic rate structure.[31]

These findings are supported by recent studies about consumer engagement in cost−reflective pricing, which suggest that uptake and efficient usage of such pricing depends on consumer understanding and familiarity with complex tariff structures (Hall et al., 2016; Hobman et al., 2016; Prest, 2020; Reis et al., 2021; Trotta, 2021).[32]

Table 3−7. OLS Results on Support for Cost−reflective Pricing

Variables	Fuel cost pass−through adjustment rate		Regionally−differentiated pricing		Time−differentiated pricing	
	(1)	(2)	(3)	(4)	(5)	(6)
Electricity price literacy (0−1)	0.18***		0.11**		0.24***	
	(0.05)		(0.05)		(0.05)	
Total bill amount		−0.02		−0.06*		0.04
		(0.03)		(0.03)		(0.03)
Rate structure		0.10***		0.12***		0.08**
		(0.04)		(0.04)		(0.04)
Rate components		0.10*		0.03		0.14**
		(0.06)		(0.06)		(0.06)
Constant	−0.48***	−0.46***	−0.18***	−0.16**	−0.40***	−0.39***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)
Controls						
X_i	Yes	Yes	Yes	Yes	Yes	Yes
AB_i	Yes	Yes	Yes	Yes	Yes	Yes
N	4,214	4,214	4,214	4,214	4,214	4,214
R−squared	0.155	0.157	0.076	0.079	0.110	0.110

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; X_i

[31] In case of support for cost-reflective pricing, no statistically significant differences are detected across two groups differing by household income level and electricity use patterns.

[32] For example, Reis et al. (2021) showed that numerical/graphical literacy about energy tariffs – the ability to understand and calculate electricity bills under time-differentiated pricing – is a key factor in promoting willingness to adopt time-differentiated tariffs. Prest (2020) also found that consumers who are aware of time-differentiated tariff structures have more potential for demand-side flexibility.

includes gender, age, education, political view, household income, household size, housing type, home−ownership status, regions and years of residence. AB_i includes reported attitudes and behaviors towards environment

To summarize, these findings emphasize the importance of addressing specific knowledge gaps in order to effectively influence targeted consumer behavior. This is a crucial aspect that previous studies, which relied on aggregated unidimensional measures, failed to capture.[33]

3.4. Conclusion

This paper proposes a comprehensive framework for measuring consumers' electricity price literacy, which refers to the knowledge necessary to understand electricity pricing mechanisms. The framework introduces a flexible functional form to represent electricity pricing systems, enabling customization to various electricity tariffs and encompassing the essential components required for calculating electricity bills. This functional form is further divided into three knowledge domains: total bill amount, rate structure and rate components. This division into three domains not only allows for the incorporation of knowledge measures used in previous literature, but also provides a basis for comparing literacy across different studies, as these domains are present in every electricity price scheme. Specific survey questions for electricity price literacy are generated based on the functional representation.

To demonstrate the practicability of the framework, this study applies the proposed framework to South Korea as a case study. The application involves representing Korea's electricity price scheme using a functional form, developing a survey questionnaire, conducting the survey on a sample of 4,214 electricity consumers aged 19 and above nationwide, and calculating electricity price literacy scores. Additionally, this study performs a correlation

[33] Shi et al. (2016) similarly argued that improving public knowledge about climate change should be approached in a multidimensional way.

analysis between electricity price literacy measures and electricity-related behaviors.

The survey results clearly show that consumers' price knowledge varies significantly across three domains. Consumers tend to have a better understanding of price contents more familiar to them. For instance, they show higher levels of awareness about the existence of long-standing price components included in electricity bills. However, about the details of such contents, their awareness is low. Moreover, this study reveals differential effects of domain-specific knowledge on electricity-related behaviors. Specifically, a negative link is found between knowledge on electricity bill amounts and electricity use, implying that consumers knowledgeable about total bill amounts are likely to consume less. On the other hand, awareness of the rate structure and rate components is closely related to the support for complex cost-reflective pricing. Taken together, these findings underscore a necessity of a comprehensive approach in evaluating electricity price knowledge. Neglecting such heterogeneity could hinder the capacity to accurately identify knowledge gaps and formulate precise interventions aimed at fostering the desired behavioral changes.

This paper has some limitations. According to the literature on choice behavior, individuals' decision making could be affected by the details of question forms, which is called a frame or ancillary condition of a choice (Masatlioglu and Ok, 2005; Salant and Rubinstein, 2008; Frederick et al., 2011). Thus, for the results of the questionnaire to be compared more consistently across studies, a consensus on details of the questionnaire such as the composition of various question types (e.g., true-false, multiple-choice, open-ended) and the number of choice options for multiple-choice questions should be reached.[34] Also, this study deals with self-reported data when examining the impact of electricity price literacy

[34] While there has been no consensus on the details of questions, the questionnaire in this paper was constructed using some set of standards. The standards applied for each question and the underlying reasons are described in Appendix B.

on consumer behavior. Future research could benefit from using actual electricity consumption and/or tariff uptake data in order to more accurately assess the relationship between price literacy and electricity−related behaviors.

Despite its limitations, the framework proposed in this study has the potential to become a standard for measuring consumers' electricity price literacy. The structured approach enables researchers to generate comparable measures of electricity price literacy across various contexts. Furthermore, the practicality of the framework is demonstrated through its application in the case of Korea. By providing a comprehensive perspective, the framework has the capacity to enhance energy policies by delivering customized information to pertinent stakeholders.

Chapter 4. Variations in Price Elasticities of Diesel Demand by Relative Prices between Motor Fuels: Evidence from 24 European Countries

4.1. Introduction

The heavy reliance on petroleum products in road transportation has led to serious concerns regarding climate change and air pollution. Gasoline and diesel are two most widely used fuels, together accounting for 98.6% and 99.4% of energy consumption for passenger and freight cars, respectively, in 2019 (IEA, 2021). Despite diesel having a greater environmental external cost compared to gasoline,[35] a preferential tax treatment for diesel in a number of OECD countries has resulted in a rapid dieselization in the passenger fleet, contributing to heightened air pollution (Harding, 2014).[36]

Acknowledging such environmental impact diesel consumption poses, tax reforms aimed at reducing diesel usage are being actively implemented, particularly in European countries where diesel passenger fleets are prevalent (Mayeres and Proost, 2001; Burguillo−Cuesta et al., 2011; Harding, 2014). Similarly, in Korea, there was a surge in dieselization following the legalization of commercial sales of diesel passenger cars in 2005. This prompted an increase in the diesel excise tax as part of the second energy tax reform, aimed at mitigating air pollution (Park and Ma, 2007; Kang et al., 2008). In light of the recent high levels of fine dust concentration

---

[35] Although diesel emits approximately 15.5% more greenhouse gases (CO_2, CH_4, and N_2O) per liter than gasoline, its emissions per kilometer are comparable to those of gasoline, when accounting for the fuel efficiency of diesel cars (diesel: 174.7 CO_2/km vs. gasoline: 174.6 CO_2/km). However, in terms of air pollutants, diesel emits more NOx and PM than gasoline, by factors of 1.3 and 32.6, respectively (Schipper and Fulton, 2009; Harding, 2014).

[36] Data from 24 OECD member countries indicate that the share of diesel vehicles in total passenger cars increased from 14.2% in 2000 to 37.1% in 2019 (Eurostat, 2023).

in Seoul, which have exceeded twice the World Health Organization's (WHO) standard, there are ongoing proposals for additional reforms to the diesel tax rate as part of the “Special Measures for Fine Dust Control” initiative (Lee, 2017; OECD, 2020).

The success of these tax reforms critically hinges on an accurate prediction of changes in diesel consumption resulting from increased diesel prices. To achieve this, efforts have been made to understand the factors affecting the price elasticity of demand for transportation fuel. Previous studies have identified fuel price levels, price volatility, and income levels as crucial factors in determining the changes in price elasticity (Hanly et al., 2002; Hughes et al., 2008; Wadud et al., 2009; Jung et al., 2012).

This paper aims to shed light on the impact of the relative price between diesel and gasoline on the own-price elasticity of demand for diesel. Despite diesel and gasoline being close substitutes, accounting for the majority of fuel consumption in the road transport sector, many empirical studies estimating the price elasticity of diesel demand often neglect the effect of relative prices between these substitutes (e.g., Liu, 2004; Pock, 2007; Zimmer and Koch, 2017). Microeconomic theory suggests that the price elasticity of each fuel is highly sensitive to the price of other fuels, making it crucial to consider the substitution relationship when determining the own-price elasticity of demand for diesel.

This study uses panel data of 24 European countries for the period 1990 to 2020 to analyze whether and to what extent own-price elasticity of diesel demand varies with the relative price of diesel to gasoline. The sample is divided into quintiles by relative price, and both the reduced form demand model and the Almost Ideal Demand System (A.I.D.S.) model are estimated for each quintile. Results from both specifications show different responses to changes in price, contingent upon different relative price levels. Specifically, it identifies that the value of elasticity reaches its peak when the relative price approaches one, and significantly declines thereafter.

These findings suggest that relative prices must be considered when designing diesel pricing policies aimed at reducing diesel consumption. For instance, if the relative price falls within the 4th quintile, where diesel price approaches gasoline price, the own−price elasticity of diesel demand exceeds the average price elasticity that does not account for relative price. In this case, raising the price higher than necessary to achieve the reduction target will impose an unnecessary burden on diesel car users. On the other hand, if the relative price falls within the 5th quintile, where diesel price exceeds gasoline price, the own−price elasticity of diesel demand is less elastic than the average estimate, and the actual policy effect may be insignificant compared to the prediction.

The remainder of this paper is structured as follows. Section 4.2 provides an overview of literature estimating demand elasticities for diesel. Section 4.3 describes the data, while Section 4.4 explains the empirical models. Section 4.5 presents the results of the empirical analysis, and finally, Section 4.6 concludes with some policy implications.

4.2. Literature Review

There has been a large body of empirical studies on estimating demand elasticities for road transport fuels. While a significant portion of these studies has centered on gasoline, which has been a primary fuel for passenger cars, recent studies have begun to focus on diesel consumption (Dahl, 2012; Wadud, 2016; Aklilu, 2020). Table 4−1 presents an overview of the literature that has estimated the demand elasticities of diesel fuel, including the data used, the empirical models employed and the resulting estimates.

Following the conventional approach for modeling gasoline demand, the most commonly used method for modeling diesel demand has also been the reduced−form demand model that use aggregate data (Basso and Oum, 2007). Previous studies have often relied on these reduced−form demand models to examine the demand for diesel in various countries, with a particular focus on European nations where there has been a significant shift from gasoline to diesel vehicles. The basic diesel demand function is comprised of only fuel price and income (Liu, 2004; Ramli and Graham, 2014; Liddle and Huntington, 2020). However, there have been criticisms that these studies may suffer from bias in their estimation results, as they do not control for other potential variables that could impact diesel demand (Wadud, 2016). To address these concerns, subsequent studies have included additional controls, such as vehicle stock, public transportation, and temperature variables.[37]

As shown in Table 4−1, previous studies based on the reduced−form model for European countries, which is the focus of this study, have reported short−term price elasticities ranging from −0.09 to −0.72 and long−term price elasticities from −0.26 to –1.13 (Liu, 2004; Pock, 2007; Burguillo−Cuesta et al., 2011; Zimmer and Koch, 2017; Liddle and Huntington, 2020).

Alternatively, there has been an increasing interest in the estimation of road transport fuel demand using the Almost Ideal Demand System (A.I.D.S.) model, proposed by Deaton and Muellbauer (1980). Given the solid foundation of the A.I.D.S. model in microeconomic theory and the fact that consumer decisions regarding automobile fuel consumption are typically made within households, using the A.I.D.S. model with household−level data offers advantages in analyzing households' fuel consumption decisions and understanding the factors that drive heterogeneity (Basso and Oum, 2007; Romero−Jordán et al., 2010; Wang et al., 2012). Within this line of literature, researchers have developed various demand systems for road transport fuels. These models have encompassed different fuel types, such as automotive fuel as a whole (Romero−Jordán et al., 2010), gasoline and diesel (Sheng and Ling−Yun, 2016), gasoline, diesel, and ethanol (Tenkorang et al., 2015), or gasoline, diesel, and LPG (Kim et al., 2010). The estimated price elasticity of diesel demand from the A.I.D.S. model ranges from –0.25

---

[37] References for the inclusion of vehicle stock variable can be found in Polemis (2006), Pock (2007), and Burguillo-Cuesta et al. (2011), while Shin (2015), and Lim and Cho (2020) include public transportation-related variables. The role of temperature variable has been discussed in Na (2001), Kang et al. (2008), and Oh et al. (2015).

to –0.5 (Kim et al., 2010; Tenkorang et al., 2015).

However, the aforementioned studies only provide an average estimate of the price elasticity for the country or region during the entire period analyzed. Although this is a useful indicator for predicting the overall effect of diesel pricing policies, it does not capture the possibility that consumers may have different responses to price changes of the same magnitude based on their characteristics or the environment they are exposed to. Hence, subsequent studies have attempted to identify factors that drive changes in price elasticity of transportation fuel demand, such as fuel price levels, price volatility, demand levels, income levels, geographical location, fuel economy and age of vehicles, and economic fluctuations (Hughes et al., 2008; Wadud et al., 2009; Jung et al., 2012; Lin and Prince, 2013; Kwon and Lee 2014; Gillingham et al., 2015; Bakhat et al., 2017).

As noted in the introduction, despite the close substitution relationship between diesel and gasoline, many studies on the price elasticity of diesel demand often overlook the effect of relative prices between these fuels. Considering that the preference for diesel is primarily driven by its economic benefits compared to gasoline, such as lower fuel prices and higher fuel efficiency, the price differential between diesel and gasoline can influence consumer decisions and impact the own-price elasticity of diesel demand (Burguillo-Cuesta et al., 2011; Anderson, 2012; Harding, 2014). This study aims to contribute to the existing literature by empirically analyzing the impact of relative prices on the own-price elasticity of diesel demand.

Table 4-1. Literature on Estimating Diesel Demand Elasticities

Literature	Data	Method	Variables		Price elasticity	
			Dependent	Explanatory	Short term	Long term
Liu (2004)	1978 −1999 (Annual) OECD−23	PAM (One−step GMM)	Per capita diesel consumption	Diesel price, per capita GDP or income	−0.09	−0.26
Polemis (2006)	1978 −2003 (Annual) Greece	Cointe−gration	Per capita diesel consumption in transport	Gasoline and diesel prices, income, per capita diesel car stock	−0.07	−0.44
Pock (2007)	1990 −2004 (Annual) EU−14	PAM	Diesel consumption per car	Diesel price, per capita GDP, gasoline and diesel car stock per driver	−0.13	−0.29
Kang et al. (2008)	1997 −2007 (Quarter) Korea	ARDL	Diesel demand	Diesel price, income, diesel vehicle stock, temperature, labor hours	−0.24	−0.27
Burguillo−Cuesta et al. (2011)	1990 −2008 (Annual) EU−15	ISUR	Per capita diesel consumption	Per capita income, diesel excise tax, new diesel passenger cars registrations, gasoline price, density, country dummy	−0.27	−0.33
Ramli and Graham (2014)	1980 −2009 (Annual) UK	Cointe−gration	Per capita diesel consumption in road transport	Diesel price, per capita income	−0.11	−0.3
Barla et al. (2014)	1986 −2008 (Annual) Canada	PAM	Per capita diesel demand in road transport	Diesel price, per capita GDP, % of the primary sector in total GDP, trend	−0.43	−0.8

<table>
<tr><td>Cho and Jung (2017)</td><td>2008 −2016 (Month) Korea</td><td>Cointe−gration</td><td>Per capita diesel consumption per day in road passenger</td><td>Income, fuel costs, relative cost of fuels</td><td>−0.67</td><td>−</td></tr>
<tr><td>Zimmer and Koch (2017)</td><td>1990 −2012 (Annual) EU−16</td><td>ADL</td><td>Diesel consumption per car</td><td>Diesel price, per capita GDP, vehicle stock per driver</td><td>−0.17 ~ −0.72</td><td>−1.13</td></tr>
<tr><td rowspan="4">Liddle and Huntington (2020)</td><td rowspan="4">1978 −2016 (Annual) OECD−35 Non−OECD−83</td><td rowspan="4">ADL (1,1,1)</td><td rowspan="4">Per capita diesel consumption in road transport</td><td rowspan="4">Diesel price, per capita GDP</td><td colspan="2">OECD (Europe)</td></tr>
<tr><td>−0.11 (−0.15)</td><td>−0.35 (−0.38)</td></tr>
<tr><td colspan="2">Non−OECD</td></tr>
<tr><td>−0.08</td><td>−0.24</td></tr>
<tr><td>Kim et al. (2010)</td><td>2005 −2009 (Household survey) Korea</td><td>A.I.D.S.</td><td>Gasoline, Diesel, LPG budget share</td><td>Gasoline, Diesel, LPG, Others price index, Household expenditure</td><td colspan="2">−0.45~−0.50</td></tr>
<tr><td>Tenkorang et al. (2015)</td><td>1982 −2012 (Monthly) US</td><td>A.I.D.S.</td><td>Gasoline, Diesel, Ethanol budget share</td><td>Gasoline, Diesel, Ethanol price, Total fuel expenditure</td><td colspan="2">−0.25~−0.42</td></tr>
</table>

4.3. Data

An empirical analysis is conducted using an unbalanced panel data of 24 European countries for the period 1990−2020.[38] The data used in the analysis are summarized in Table 4−2.

Table 4−2. Summary of Data

Variables	Units	Period	Source

[38] Among 27 European countries that are members of the OECD, 3 countries (Iceland, Latvia, Lithuania) are excluded due to data unavailability. The analysis covered the period from 1990 to 2020. The choice of 1990 as the starting year is based on the significant dieselization process initiated since the early 1990s in European countries (Burguillo−cuesta et al., 2011; Zimmer and Koch, 2017). As for the endpoint, 2020 was selected as it is the latest year for which IEA data on diesel consumption in the road transport sector is available.

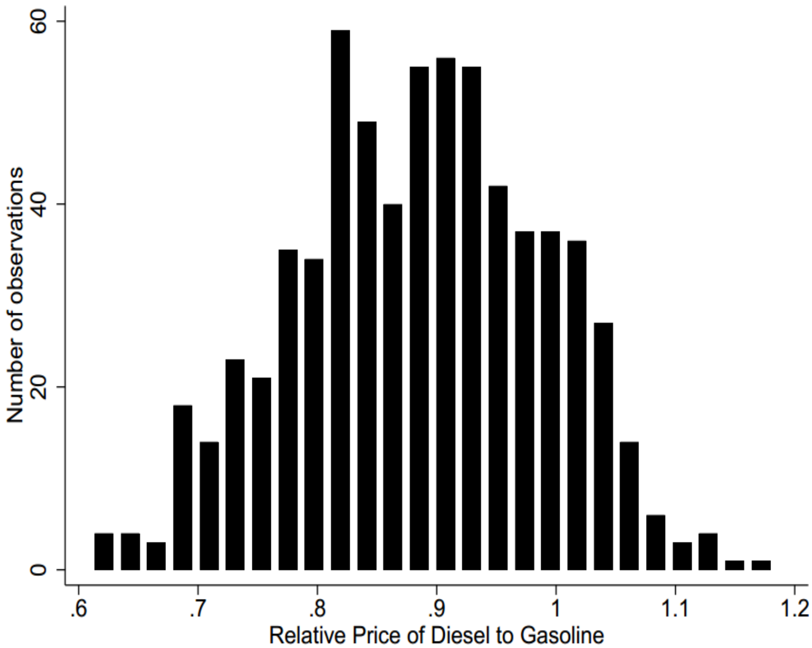
Diesel consumption in road transport sector	Tonnes	1990–2020	IEA Oil Information Statistics
Fuel prices and taxes	USD/liter	1990–2020	IEA Energy Prices and Taxes
Per capita GDP	USD	1990–2020	World Bank
% of urban population	%	1990–2020	World Bank
HDD, CDD	–	1990–2020 (Monthly)	IEA Weather for Energy Tracker
Environmental Policy Stringency Index	0–6 scale	1990–2020	OECD Statistics
Population	Person	1990–2020	OECD Statistics
Consumer price index	2010=100	1990–2020	World Bank

The per capita diesel consumption in the road transport sector (in tonne) is used as the dependent variable in the reduced–form demand model, which is calculated by dividing the diesel consumption in the road transport sector, obtained from the International Energy Agency (IEA), by the total population, obtained from the OECD.

Data on fuel prices and excise taxes (USD/liter), which are used as key explanatory variables, are also taken from the IEA.[39] These variables are converted to real values by using country–specific consumer price index (2010=100). The relative price between diesel and gasoline is calculated by dividing the diesel price by the gasoline price. The distribution of the relative prices is shown in Figure 4–1. The relative price of diesel to gasoline exhibits a nearly normal distribution with a mean of 0.89 and a standard deviation of 0.10.

[39] The price and tax of premium unleaded RON95 for gasoline is used as it is the most common gasoline fuel in Europe (Zimmer and Koch, 2017; IEA, 2022a).

Figure 4-1. Distribution of Relative Prices



In addition, to account for other potential factors that may affect diesel consumption as described in Section 4.2., income, public transportation development, temperature, and stringency of environmental policy are controlled.[40] Real per capita GDP, obtained from the World Bank, is used to control for income. The proportion of the urban population, obtained from the World Bank, is used as a proxy for the degree of public transportation development. To control for temperature, the annual sum of monthly heating and cooling degree days (with a reference temperature of 18℃), obtained from IEA are used. Finally, environmental policy stringency index, developed by OECD, is used.

Table 4-3 shows descriptive statistics of the variables

[40] While previous studies have demonstrated a positive association between diesel vehicle stock and diesel consumption (Polemis, 2006; Burguillo-Cuesta et al., 2011), this study opts to exclude the vehicle stock variable from its reduced-form model. As noted by Dahl and Sterner (1991) and Basso and Oum (2007), incorporating vehicle stock fails to capture the process of response and adaptation that takes place through vehicle replacement over time.

described above. Looking at the key variables, the average per capita diesel consumption in the road transport sector is 0.44 ton. Furthermore, it is evident that the average price and tax of gasoline are higher compared to diesel, indicating the implementation of preferential tax treatment for diesel in European countries.

Table 4−3. Descriptive Statistics

Variables	Obs	Mean	S.D	Min	Max
Per capita diesel consumption	678	0.44	0.52	0.06	3.86
Gasoline price	678	1.52	0.56	0.35	9.12
Diesel price	678	1.34	0.44	0.33	5.67
Gasoline excise tax	677	0.68	0.32	0.01	5.24
Diesel excise tax	678	0.52	0.20	0.13	2.90
Per capita GDP	678	35,668	21,224	3,252	123,613
% of urban population	678	73.6	11.3	47.9	98.1
Heating degree days	678	2,996	933	999	5,502
Cooling degree days	678	229	241	0.01	1077
Environmental policy stringency index	631	2.34	0.98	0.36	4.89

Finally, panel unit root test proposed by Im–Pesaran–Shin (2003) is conducted. The Im–Pesaran–Shin (2003)'s statistics and its associated p−values are reported in Table 4−4. All the variables, except for the proportion of urban population, reject the null hypothesis that all panels contain unit roots. This confirms that there is less concern for spurious regression.

Table 4−4. Panel Unit Root Test Results

Variables	W_{t-bar} statistics	p−value
Per capita diesel consumption	-2.15^{**}	0.02
Gasoline price	-2.48^{***}	0.00
Diesel price	-6.71^{***}	0.00
Gasoline excise tax	-3.24^{***}	0.00

Diesel excise tax	-6.08^{***}	0.00
Relative price	-6.55^{***}	0.00
Per capita GDP	-4.77^{***}	0.00
% of urban population	−0.62	0.27
Heating degree days	-13.12^{***}	0.00
Cooling degree days	-21.53^{***}	0.00
Environmental policy stringency index	-4.23^{***}	0.00

Notes: All the variables are log transformed except for % of urban population. Demean and trend options are applied; Lag(aic) option is applied to allow for the presence of serially correlated errors; *** p<0.01, ** p<0.05, * p<0.1

4.4. Empirical Models

This section presents econometrics models employed for estimating diesel demand elasticities. Given the observed variations in estimated elasticities resulting from different model choices, this study adopts two widely recognized estimation models: the reduced-form demand model and the A.I.D.S. model.

4.4.1. The Reduced-form Demand Model

Firstly, this study employs the static reduced-form demand model, which have been widely preferred in the related literature (Baltagi and Griffin, 1983; Dahl and Sterner, 1991; Basso and Oum, 2007; Wadud et al., 2009; Ramli and Graham, 2014; Aklilu, 2020). The static reduced-form model represents the demand for diesel as a function of price, income, and other control variables. Formally,

$$lnD_{it} = \beta_0 + \beta_1 lnP_{it} + \beta_2 lnY_{it} + X_{it}\gamma + \mu_i + \epsilon_{it}, \qquad (1)$$

where D is per capita diesel consumption in road transport sector, P is real diesel price, and Y is real per capita GDP. X is a vector of control variables that may affect per capita diesel consumption, including the proportion(%) of the population residing in urban area, heating and cooling degree days, environmental policy stringency, a trend variable, and year dummies. Subscript i and t refer to country and year, respectively. All variables are log−transformed except for the proportion of urban population. Finally, μ_i denotes the country−specific fixed effect and ϵ_{it} is an unobserved idiosyncratic error term.

However, it is well−known that a potential endogeneity issue arises due to the joint determination of price and consumption. Therefore, estimating Equation (1) using Ordinary Least Squares (OLS) is likely to yield biased estimates. To address this concern, this study uses an instrumental variable approach with diesel excise tax as an instrument for diesel price, following prior studies by Davis and Kilian (2011) and Zimmer and Koch (2017).[41] Specifically, this study estimates the following equations:

First−stage: $lnP_{it} = \alpha_0 + \alpha_1 lnT_{it} + \alpha_2 lnY_{it} + X_{it}\gamma_1 + \mu_{1i} + \epsilon_{1it,}$ (2)

Second−stage: $lnD_{it} = \delta_0 + \delta_1 \widehat{lnP_{it}} + \delta_2 lnY_{it} + X_{it}\gamma_2 + \mu_{2i} + \epsilon_{2it}$ (3)

where T denotes real diesel excise tax.

This Two Stage Least Squares (2SLS) estimation is performed for the entire sample, serving as a benchmark, as well as for the sub−samples divided based on the relative price level between gasoline and diesel. Specifically, sub−samples divided by quintiles of relative price are defined as follows: the "1st quintile (0−20%, lowest relative price, n=136)" is less than 0.80, the "2nd quintile (20−40%, n=136)"

---

[41] The fuel excise tax is likely satisfying the conditions of relevance($Cov(T_{it}, P_{it}) \neq 0$) and exogeneity ($Cov(T_{it}, \epsilon_{2it}) = 0$). It is relevant as tax change is correlated with price change. Moreover, it is exogenous as many countries primarily impose taxes on road fuels for the purpose of funding transportation infrastructure and services or addressing environmental concerns, which are plausibly exogenous to market conditions. Even if tax legislation may respond to current prices, the implementation of tax changes typically occurs with a time lag, thus allowing us to reasonably assume that changes in tax rates are uncorrelated with unobserved demand changes (Davis and Kilian, 2011). Note that in this study, the tax measure employed excludes the ad−valorem component, such as VAT, as emphasized by Davis and Kilian (2011). This exclusion is necessary due to the functional relationship between VAT and price, which can introduce correlation with the error term.

is between 0.80 and 0.86, the "3rd quintile (40−60%, n=135)" is between 0.86 and 0.91, the "4th quintile (60−80%, n=136)" is between 0.91 and 0.98, and finally, the "5th quintile (80−100%, the highest relative price, n=135)" includes the relative price of 0.98 or higher.[42]

The parameters δ_1, δ_2 and γ_2 represent elasticities of diesel demand with respect to diesel price, income and the other corresponding variables and are to be interpreted as intermediate−term elasticities (Dahl and Sterner, 1991; Basso and Oum, 2007).[43]

4.4.2. The A.I.D.S. Model

This study employs another popular model − the A.I.D.S. model. The A.I.D.S. model is a first order approximation of an arbitrary demand system. Assuming weak separability between road transport fuels and other goods, a demand system for road transport fuel is established, specifically for gasoline and diesel.[44] The A.I.D.S. demand functions in budget share form is given as follows:

---

[42] Group-wise regression is a widely used approach for addressing heterogeneity in energy demand and their elasticities (Wadud et al., 2009; Gilingham et al., 2015). However, dividing the sample by relative price can introduce endogeneity concerns, as unobserved factors determining relative price may also affect price. To explore this issue, this paper considers two main components of fuel price: production costs and taxes. Changes in relative price driven by production costs are not a concern, as the focus is on price variations influenced by exogenously determined excise tax changes. However, if relative price changes due to tax adjustments for environmental goals (Rietveld and van Woudenberg, 2005), using excise tax as an instrument may be problematic. To address this, the study incorporates environmental variables, such as stringency index of environmental policies.

[43] A dynamic panel analysis using the Partial Adjustment Model (PAM) was conducted. However, due to the limited sample size, this analysis is presented as a supplementary analysis and can be found in Appendix C.

[44] In Europe, the combined share of gasoline and diesel accounted for more than 98% of road transport fuel consumption in 2020. The dominance of gasoline and diesel forms a solid foundation for constructing a demand system comprising these two fuels.

$$w_i = \alpha_i + \sum_j \gamma_{ij} lnp_j + \beta_i \, ln\frac{x}{P} + \epsilon_i,$$

where w_i is the share of gasoline or diesel in total fuel expenditure (x), p_j is the real price of gasoline or diesel, and P is a price index expressed as

$$lnP = \alpha_0 + \sum_j \alpha_j lnp_j + \frac{1}{2}\sum_i \sum_j \gamma_{ij} lnp_i lnp_j.$$

As the A.I.D.S. model is non-linear due to the price index, a linear approximation of the A.I.D.S. model (i.e., LA-AIDS, Deaton and Muellbauer, 1980) is used in this study. Under LA-AIDS, the price index is replaced by a stone price index given below:

$$lnP^* = \sum_i w_i lnp_i.$$

Consequently, the share equation becomes

$$w_i = \alpha_i + \textstyle\sum_j \gamma_{ij} lnp_j + \beta_i \, ln\frac{x}{P^*} + \epsilon_i. \qquad (4)$$

As previously mentioned, Equation (4) represents a demand system consisting of two equations, one for diesel and another for gasoline. To address the singularity issue of the error variance-covariance matrix, a uniequational model focusing solely on diesel is estimated for the entire sample and each relative price quintile.

Diesel demand elasticities, including own-price, cross-price and expenditure elasticities are computed based on parameter estimates and sample means of explanatory variables, following Chalfant (1987):

$$\epsilon_{ii} = -1 + \frac{\gamma_{ii}}{w_i} - \beta_i,$$

$$\epsilon_{ij} = \frac{\gamma_{ij}}{w_i} - \beta_i \frac{w_j}{w_i},$$

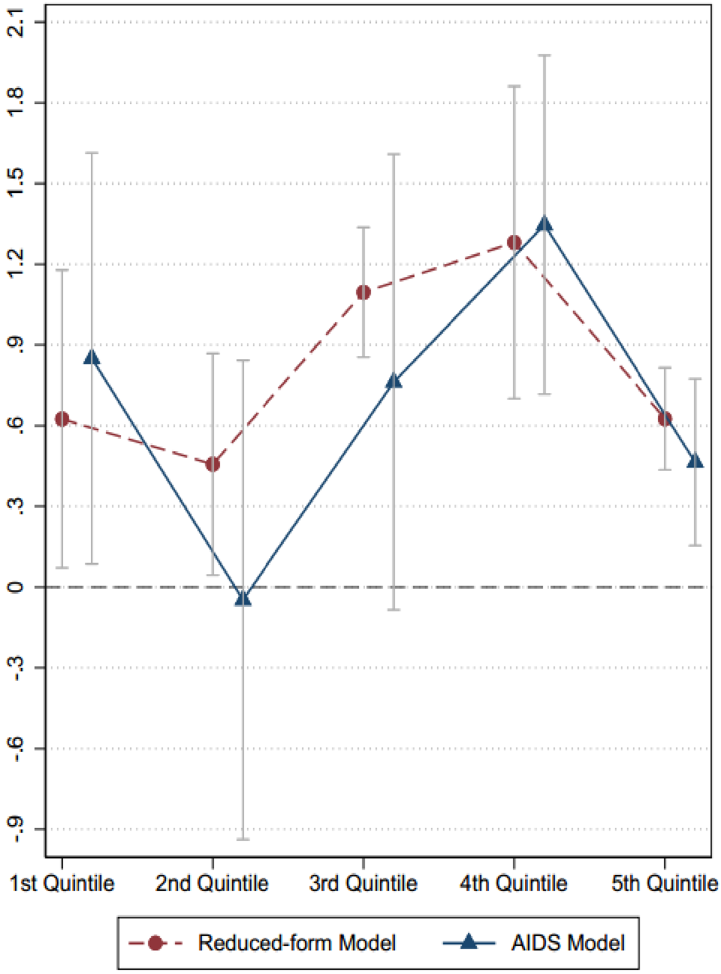
$$\epsilon_x = 1 + \frac{\beta_i}{w_i}.$$

Finally, the estimated own−price elasticity of diesel demand from both reduced form and A.I.D.S. models is compared across relative price quantiles and with the average elasticity estimate obtained from the entire sample by conducting Pairwise Wald tests. This analysis provides insights into the potential variation in the own−price elasticity of diesel demand across different relative price levels and its deviation from the overall average.

4.5. Results

Tables 4−5 and 4−6 present the estimation results for the static reduced−form model and A.I.D.S. model for both the entire sample and sub−samples stratified based on relative price quintiles. Across the different estimation models, a qualitatively consistent pattern emerges in the own−price elasticity of diesel demand. Specifically, as one moves across the relative price quintiles, the price elasticity of diesel demand shows an increasing trend, reaching its peak in the 4th quintile and becoming demand−elastic. Subsequently, the price elasticity experiences a notable decline in the 5th quintile, where diesel prices are, on average, higher than gasoline prices. Figure 4−2 illustrates the changes in own−price elasticity of diesel demand (in absolute terms) for the two models across relative price quintiles.

Figure 4-2. Changes in Price Elasticity of Diesel Demand across Relative Price Quintiles



Note: The graph provided visualizes the price elasticity estimates derived from specification (2) as shown in both Table 4-5 and Table 4-6.

Table 4-5. Static Reduced-form Model Estimation Results

Variables	Sub-samples										Entire sample	
	1st Quintile		2nd Quintile		3rd Quintile		4th Quintile		5th Quintile		Average	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
lnP	−0.397	−0.625**	−0.698***	−0.456**	−0.913***	−1.095***	−1.557***	−1.281***	−0.592***	−0.625***	−0.786***	−0.750***
	(0.427)	(0.282)	(0.264)	(0.210)	(0.263)	(0.123)	(0.416)	(0.296)	(0.217)	(0.097)	(0.097)	(0.096)
lnY	0.233	0.400*	0.273	−0.155	0.468***	0.649***	0.789***	0.621***	0.887***	0.752***	0.637***	0.541***
	(0.304)	(0.221)	(0.322)	(0.213)	(0.130)	(0.100)	(0.192)	(0.147)	(0.192)	(0.062)	(0.108)	(0.089)
Urban		−0.008		−0.025***		0.021*		−0.018		−0.041***		−0.026***
		(0.006)		(0.009)		(0.013)		(0.023)		(0.010)		(0.009)
lnhdd		0.055		0.181		−0.285		−0.304		−0.185		−0.088
		(0.083)		(0.125)		(0.178)		(0.257)		(0.228)		(0.115)
lncdd		−0.017		−0.006		−0.007		0.003		0.005		−0.003
		(0.012)		(0.019)		(0.009)		(0.005)		(0.009)		(0.004)
lneps		0.145		0.069		0.347***		0.379*		−0.256***		0.093
		(0.096)		(0.116)		(0.108)		(0.200)		(0.046)		(0.101)
Constant	−3.860	−5.338**	−4.014	0.416	−6.111***	−6.910***	−8.296***	−3.746	−10.787***	−4.910**	−7.977***	−4.512***
	(3.084)	(2.298)	(3.286)	(2.238)	(1.251)	(1.908)	(1.978)	(3.240)	(1.913)	(1.986)	(1.095)	(1.701)
F-stats[45]	12.08	35.47	71.35	87.67	41.22	95.32	103.22	203.65	48.09	173.16	189.53	204.15
N	136	131	136	120	135	125	136	133	135	122	678	631
No. of countries	16	15	18	17	21	19	21	19	15	14	24	22

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; All specifications include a trend variable and year dummies.

[45] For the entire sample and sub-samples, with the exception of Model (1) in the 1st quintile, the Kleibergen-Paap F statistics surpass the critical values specified by Stock and Yogo (2005). This indicates that there are no significant concerns regarding weak correlation between the instruments and the endogenous regressors for these models.

Table 4−6. A.I.D.S. Model Estimation Results

Variables	Sub−samples										Entire sample	
	1st Quintile		2nd Quintile		3rd Quintile		4th Quintile		5th Quintile		Average	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\ln p_d$	0.094	0.123	0.722***	0.663**	0.281	0.238	−0.161	−0.096	0.307***	0.272***	0.149*	0.152
	(0.177)	(0.150)	(0.234)	(0.233)	(0.339)	(0.254)	(0.254)	(0.215)	(0.073)	(0.079)	(0.086)	(0.095)
$\ln p_g$	−0.153	−0.185	−0.511**	−0.451*	−0.333	−0.232	0.186	0.197	−0.206**	−0.150	−0.153*	−0.169*
	(0.166)	(0.153)	(0.221)	(0.226)	(0.357)	(0.234)	(0.256)	(0.186)	(0.087)	(0.096)	(0.085)	(0.093)
$\ln \frac{x}{P^*}$	0.038	0.126	0.244***	0.256***	0.103	0.155**	0.086	0.194***	−0.039	−0.022	0.093**	0.080*
	(0.107)	(0.084)	(0.037)	(0.027)	(0.087)	(0.071)	(0.089)	(0.061)	(0.030)	(0.040)	(0.042)	(0.040)
lnUrban		−0.594**		−0.511***		1.065*		1.072***		0.287		−0.306
		(0.247)		(0.162)		(0.536)		(0.209)		(0.313)		(0.311)
Constant	−0.261	0.291	−4.700***	−2.852***	−1.703	−7.427**	−1.156	−8.001***	1.726**	0.166	−1.338	0.234
	(2.418)	(2.017)	(0.830)	(0.850)	(2.023)	(3.399)	(2.045)	(1.521)	(0.692)	(2.033)	(0.966)	(1.641)
N	136	136	136	136	135	135	136	136	135	135	678	678
R−squared	0.929	0.940	0.979	0.982	0.974	0.978	0.971	0.977	0.992	0.992	0.930	0.933
Diesel demand elasticities												
Own−price elasticity	−0.826* (0.453)	−0.850** (0.390)	0.175 (0.448)	0.048 (0.454)	−0.639 (0.592)	−0.762* (0.432)	−1.341*** (0.380)	−1.346*** (0.321)	−0.381*** (0.138)	−0.464*** (0.158)	−0.818*** (0.165)	−0.800*** (0.183)
Expenditure elasticity	1.085*** (0.241)	1.286*** (0.190)	1.480*** (0.072)	1.503*** (0.053)	1.171*** (0.144)	1.256*** (0.117)	1.137*** (0.142)	1.308*** (0.097)	0.926*** (0.057)	0.958*** (0.076)	1.172*** (0.077)	1.147*** (0.073)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; All the specifications include country dummies, a trend variable, and year dummies.

Table 4−7 provides statistical significance tests comparing the elasticity estimates across relative price quintiles and with the average elasticity estimate obtained from the entire sample (in absolute terms). The test statistics provide strong support for variations in price elasticity estimates in both the reduced form and A.I.D.S. models. Specifically, the pattern peaks at the 4th quintile and declines at the 5th quintile, which is of particular interest given the current trend of increasing diesel prices compared to gasoline prices around the world. When comparing the estimates of these quintiles with the average, the results indicate statistically significant differences, highlighting the limitation of relying solely on averaged elasticities.

Table 4−7. Pairwise Wald Tests

Panel A: The Static Reduced−form Model						
Ref. \ Comp.	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile	Average
1st Quintile	−	−0.17	0.47	0.66*	0.00	0.13
2nd Quintile		−	0.64***	0.83***	0.17	0.29
3rd Quintile			−	0.19	−0.47***	−0.35***
4th Quintile				−	−0.66***	−0.53*
5th Quintile					−	0.13
Panel B: The A.I.D.S. Model						
Ref. \ Comp.	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile	Average
1st Quintile	−	−0.90**	−0.09	0.52	−0.39	−0.05
2nd Quintile		−	0.81+	1.39***	0.51	0.85***
3rd Quintile			−	0.58+	−0.30	0.04
4th Quintile				−	−0.88***	−0.55*
5th Quintile					−	0.34*

Notes: Wald tests were conducted using the price elasticity estimates derived from specification (2) in Table 4−5 and 4−6. Ref. and Comp. stand for the reference group and comparison group, respectively. Each cell in the table represents the difference in the price elasticity estimates between the reference and comparison groups; ***, ** and * represent 1%, 5% and 10% statistical significance levels, respectively; + represents marginal significance, with p=0.107 and p=0.118.

The variation observed in the diesel price elasticities may be attributed to the shared and distinct characteristics of diesel and gasoline. On the one hand, both fuels serve the common purpose of providing power to automobiles. In particular, several automobile manufacturers offer both diesel-powered models and gasoline-powered models that exhibit similar overall performance, making them near perfect substitutes for consumers considering these models. Previous studies have shown that the lower fuel cost of diesel compared to gasoline is one of the main factors driving the increased demand for diesel vehicles (Greene, 1986; Burguillo-Cuesta et al., 2011; Harding, 2014). This suggests that a significant proportion of consumers emphasize this functional similarity and thus consider diesel and gasoline as near perfect substitutes.

According to microeconomic theory, in a market of two perfect substitutes, the lower-priced good takes all the demand, and the higher-priced good has zero demand. Therefore, consumers who perceive diesel and gasoline as near perfect substitutes have little incentive to replace diesel cars with gasoline cars in response to an increase in diesel price, if the price of diesel is significantly lower than that of gasoline. However, there is a growing incentive for preference to shift from diesel cars to gasoline cars as the price gap between the two fuels narrows. This explains why diesel price elasticity is increasing and reaches its maximum at the 4th quintile, where the relative price is close to 1.[46]

On the other hand, diesel and gasoline also have distinct characteristics in terms of performance, size, design, and purpose.

[46] In this study, the value of diesel price elasticity is highest at 4th quintile, where the relative price of diesel to gasoline is slightly lower than 1. This may seem inconsistent with the theoretical prediction that substitution occurs when the relative price is 1. However, it is important to note that consumers take into account the total cost of the vehicle, including vehicle price, maintenance cost, and fuel price when making a purchase decision (Verboven, 2002; Allcott, 2011a). Since there is a difference in vehicle price and maintenance cost between the diesel model and the gasoline model even for the same vehicle type, the point at which elasticity greatly increases may be slightly different from the theoretically predicted value of 1.

Since diesel is more expensive than gasoline in the 5th quintile,[47] it is likely that the proportion of diesel consumers whose preference for these differentiated characteristics is strong and thus respond relatively inelastic to diesel price increases will be higher than in other quintiles. For example, SUVs (Sports Utility Vehicles) are dominated by diesel engines, so consumers with a strong preference for SUVs have relatively little incentive to replace diesel vehicles with gasoline vehicles even if diesel prices rise. Similarly, the freight transport sector relies heavily on diesel engines and is unable to replace them with gasoline. Studies have shown that the price elasticity of diesel consumption is particularly low in this sector, as diesel is linked to economic activities for livelihood (Wadud, 2016; Cho and Jung, 2017). This explains why the price elasticity of diesel consumption is relatively low in 5th quintile.

4.6. Conclusion

The own-price elasticity of diesel demand across different quintiles, based on the relative price between gasoline and diesel, is estimated using both the reduced-form and A.I.D.S. models. The results find a substantial variation in the own-price elasticities of diesel demand in relation to the relative price. Specifically, the price elasticity of diesel demand exhibits an increasing trend, reaching its peak in the 4th quintile and subsequently declines in the 5th quintile, where diesel prices, on average, exceed those of gasoline.

These findings underscore the importance of considering relative prices when designing diesel pricing policies aimed at reducing diesel consumption. Relying solely on the average price elasticity estimated across the entire sample may lead to suboptimal outcomes. For instance, if the relative price of diesel to gasoline falls within the 4th quintile, the own-price elasticity of diesel will be

[47] The 5th quintile, where the relative price of diesel to gasoline is the highest, has an average relative price of 1.03. This quintile is primarily composed of observations where the price of diesel is higher than that of gasoline, accounting for 102 out of 135 observations.

underestimated. In this case, raising the price higher than necessary to achieve the reduction target will impose an unnecessary burden on diesel car users. Conversely, if the relative price falls within the 5th quintile, the own−price elasticity of diesel will be overestimated, which render the actual policy effect insignificant compared to the predicted outcomes. Hence, a nuanced approach that accounts for the relative price level is crucial in designing efficient diesel pricing policies.

Applying the findings in the context of Korea provides more practical implications for policy makers. Suppose, for example, that the environmental policy target in Korea is to reduce diesel consumption in the road transport sector by 5%. As of 2020, the relative price of diesel to gasoline in Korea is 0.86, which falls within the 3rd quintile defined in this research. Considering the estimated price elasticity within this quintile to be −1.095 (Model (2) in Table 4−5), the diesel price needs to be increased by 4.57% from the current level to achieve the reduction target (=5% reduction target / elasticity 1.095). Given that the average diesel price in Korea in 2020 was 1,203.63 KRW/liter, this entails a rise of 55 KRW/liter. However, if the average price elasticity (−0.750) is used without considering the change in price elasticity according to the relative price, the diesel price should be increased by 6.67% (= 5% reduction target / elasticity 0.750), which means an increase of 80.3 KRW/liter. This discrepancy in price elasticity estimates would result in an additional fuel cost burden of around 153.4 billion KRW per year for diesel consumers nationwide.[48]

[48] Applying the estimated price elasticity for the 3rd quintile would result in an additional fuel cost of 361.5 billion KRW if the diesel price is raised to achieve the 5% reduction target (= 55 KRW/liter x Annual diesel consumption x (1-0.05)). This cost is calculated based on the annual diesel consumption of private diesel passenger cars in Korea, which was about 6.9 billion liters according to 2017 Energy Consumption Survey. On the other hand, if the average price elasticity estimate across all quintiles is used to raise the diesel price, annual diesel consumption would decrease by 7.30%(= 6.67% price increase x elasticity 1.095), resulting in an additional fuel cost of 514.9 billion KRW(= 80.3 KRW/liter x Annual diesel consumption x (1-0.073)). The difference between these two costs represents the additional fuel cost burden

There are some limitations that should be addressed in future research. Firstly, this study primarily relies on the aggregate measure of diesel consumption within the road transport sector. While this approach represents an important initial step and is indispensable for considering all transportation modes that utilize diesel in practical policy implementation, it introduces challenges when interpreting the results due to the potential confounding effects arising from the varying behaviors exhibited by different transportation modes. To enhance our comprehension of changes in diesel price elasticity in relation to the relative price of fuels, it would be highly advantageous to obtain more disaggregated data, categorizing it by transportation mode and purpose (commercial and non-commercial). Furthermore, the incorporation of disaggregate data at the household level, in conjunction with the A.I.D.S. model, would provide valuable insights into the actual behavioral changes of households in response to price changes. This would allow for the analysis of the specific channels through which changes in diesel consumption occur as a result of a change in diesel prices. Moreover, it is crucial to acknowledge the emergence of alternative vehicles (such as electric and biofuel vehicles) and their increasing popularity in recent times. Therefore, future research should consider the inclusion of these alternative options alongside traditional gasoline and diesel vehicles. Constructing a more sophisticated demand system that accounts for these evolving trends will be necessary. These are left as potential avenues for future research.

---

caused by underestimating the price elasticity.

Chapter 5. Conclusion

This dissertation comprises three papers, each of which has implications for the design and implementation of energy pricing policies.

Chapter 2 explores various non-price informational strategies to encourage consumer support for environmental pricing included in electricity tariffs. A randomized survey experiment was conducted on a nationwide sample of over 4,000 electricity consumers in Korea. The results show that providing information about the environmental external costs of electricity production significantly increases consumers' willingness-to-pay for environmental charges. However, the effectiveness of other informational strategies, such as emphasizing bipartisan support for climate policies, highlighting international cooperation, and comparing climate change mitigation efforts across countries, is highly dependent on respondents' political affiliation, particularly among those with low knowledge of environmental pricing. These findings have important implications for the design and implementation of effective environmental pricing. Policymakers should ensure that consumers understand the presence of environmental external costs and the current payment level, as they are often elusive to them. Additionally, considering the differential effects of non-price information based on political affiliations, policymakers should use targeted information interventions to maximize their effects.

Chapter 3 develops a comprehensive measure of consumer knowledge of electricity prices, referred to as “Electricity price literacy”. By employing a flexible functional form to represent various electricity tariffs and systematizing the function into three domains (total bill amount, rate structure and rate components), this measure allows for a more comprehensive and comparable analysis of electricity price knowledge and its impact on electricity-related behaviors. Specifically, the survey conducted on over 4,000 electricity consumers in Korea reveals variations in electricity price literacy across domains and demonstrates the differential effects of domain−specific knowledge on electricity−related behaviors. This helps identify what consumers actually know about electricity pricing mechanisms in detail and which price information should be targeted to encourage desired electricity−related behaviors.

Chapter 4 examines the dependency of the own−price elasticity of diesel demand on the relative price of diesel to gasoline, the two primary fuels for road transportation with a close substitution relationship. Using panel data from 24 European countries spanning the period 1990 to 2020, this study finds a substantial variation in the own−price elasticities of diesel demand contingent upon relative price level, as estimated from both reduced−form and A.I.D.S. models. These findings suggest that policymakers should consider the relative price when designing diesel taxation policies in order to accurately predict outcomes and ensure policy effectiveness.

In summary, the three essays presented in this dissertation contribute significantly to our understanding of consumer behavior within the context of energy pricing policies. Through rigorous experimental and empirical analyses, these papers offer insights into the factors that influence consumer decision−making and the role of both price and non−price information in shaping their behavior. The findings deepen our understanding of consumer preferences and responses to energy pricing and provide policy implications for promoting sustainable energy practices and enhancing the effectiveness of energy pricing mechanisms. Policymakers and practitioners can leverage these insights to design targeted policies that take into account consumer behavior, encourage informed consumer choices, and support a sustainable energy future.

References

Aklilu, A.Z., 2020. Gasoline and diesel demand in the EU: Implications for the 2030 emission goal. Renewable and Sustainable Energy Reviews 118, 109530.

Akter, S., Bennett, J., Ward, M., 2012. Climate change scepticism and public support for mitigation: Evidence from an australian choice experiment. Global Environmental Change 22(3), 736–745.

Allcott, H., 2011a. Consumers' perceptions and misperceptions of energy costs. American Economic Review 101(3), 98–104.

Allcott, H., 2011b. Social norms and energy conservation. Journal of Public Economics 95(9–10), 1082–1095.

Allcott, H., Rogers, T., 2014. The short–run and long–run effects of behavioral interventions: Experimental evidence from energy conservation. American Economic Review 104(10), 3003–3037.

Ameli, N., Brandt, N., 2015. Determinants of households' investment in energy efficiency and renewables: Evidence from the OECD survey on household environmental behaviour and attitudes. Environmental Research Letters 10(4), 044015.

Anderson, S.T., 2012. The demand for ethanol as a gasoline substitute. Journal of Environmental Economics and Management 63(2), 151–168.

Andor, M., Frondel, M., Sommer, S., 2018. Equity and the willingness to pay for green electricity in germany. Nature Energy 3(10), 876–881.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The Review of Economic Studies 58(2), 277–297.

Asensio, O., Delmas, M., 2015. Nonprice incentives and energy conservation. Proceedings of the National academy of sciences 112(6), E510–E515.

Bakhat, M., Labandeira, X., Labeaga, J.M., López–Otero, X., 2017. Elasticities of transport fuels at times of economic crisis: An empirical analysis for Spain. Energy Economics 68, 66–80.

Baltagi, B.H., Griffin, J.M., 1983. Gasoline demand in the OECD: An

application of pooling and testing procedures. European Economic Review 22(2), 117–137.
Barla, P., Gilbert–Gonthier, M., Kuelah, J.R.T., 2014. The demand for road diesel in Canada. Energy Economics 43, 316–322.
Basso, L.J., Oum, T.H., 2007. Automobile fuel demand: a critical assessment of empirical methodologies. Transport Reviews 27(4), 449–484.
Baviera, T., Cano–Oron, L., Calvo, D., 2023. Tailored messages in the feed? Political microtargeting on Facebook during the 2019 General Elections in Spain. Journal of Political Marketing, 1–20.
Benegal, S., Scruggs, L., 2018. Correcting misinformation about climate change: The impact of partisanship in an experimental setting. Climatic change 148(1), 61–80.
Bergquist, M., Nilsson, A., Harring, N., Jagers, S., 2022. Meta–analyses of fifteen determinants of public opinion about climate change taxes and laws. Nature Climate Change 12(3), 235–240.
Blasch, J., Boogen, N., Filippini, M., Kumar, N., 2017. Explaining electricity demand and the role of energy and investment literacy on end–use efficiency of Swiss households. Energy Economics 68, 89–102.
Bolsen, T., Druckman, J.N., 2018. Do partisanship and politicization undermine the impact of a scientific consensus message about climate change?. Group Processes & Intergroup Relations, 21(3), 389–402.
Bolton, L., Warlop, L., Alba, J., 2003. Consumer perceptions of price (un) fairness. Journal of consumer research 29(4), 474–491.
Borenstein, S., 2009. To what electricity price do consumers respond? Residential demand elasticity under increasing–block pricing. Preliminary Draft April, 30, 95.
Broberg, T., Kazukauskas, A., 2021. Information policies and biased cost perceptions – The case of Swedish residential energy consumption. Energy Policy 149, 112095.
Brounen, D., Kok, N., Quigley, J.M., 2013. Energy literacy, awareness, and conservation behavior of residential households. Energy Economics 38, 42–50.
Burbidge, J., Magee, L., Robb, A., 1988. Alternative transformations

to handle extreme values of the dependent variable. Journal of the American Statistical Association 83(401), 123–127.
Burguillo–Cuesta, M., García–Inés, M.J., Romero–Jordan, D., 2011. Does dieselization favour a cleaner transport? Evidence from EU–15. Transport Reviews 31(5), 571–589.
Campbell, M., 1999. Perceptions of price unfairness: antecedents and consequences. Journal of Marketing Research 36(2), 187–199.
Chalfant, J.A., 1987. A globally flexible, almost ideal demand system. Journal of Business & Economic Statistics, 5(2), 233–242.
Cho, C., Jung, J., 2017. A study on estimating the price and cross–elasticity of demand for domestic transportation fuels. Korea Energy Economics Institute.
Choi, S et al., 2021. A survey experimental study for stimulating individual action to combat climate change. AEA RCT Registry. October 25. https://doi.org/10.1257/rct.8366–1.1
Coady, D., Parry, I.W., Shang, B., 2018. Energy price reform: lessons for policymakers. Review of Environmental Economics and Policy.
Costa, D., Kahn, M., 2013. Energy conservation "nudges" and environmentalist ideology: Evidence from a randomized residential electricity field experiment. Journal of the European Economic Association 11(3), 680–702.
Czarnek, G., Kossowska, M., Szwed, P., 2021. Right–wing ideology reduces the effects of education on climate change beliefs in more developed countries. Nature Climate Change 11(1), 9–13.
Dahl, C.A., 2012. Measuring global gasoline and diesel price and income elasticities. Energy Policy 41, 2–13.
Dahl, C., Sterner, T., 1991. Analysing gasoline demand elasticities: a survey. Energy Economics 13(3), 203–210.
Davis, L.W., Kilian, L., 2011. Estimating the effect of a gasoline tax on carbon emissions. Journal of Applied Econometrics 26(7), 1187–1214.
De Quidt, J., Haushofer, J., Roth, C., 2018. Measuring and bounding experimenter demand. The American Economic Review, 108(11), 3266–3302.
Deaton, A., Muellbauer, J., 1980. An almost ideal demand system.

The American Economic Review 70(3), 312-326.
Delmas, M., Lessem, N., 2014. Saving power to conserve your reputation? the effectiveness of private versus public information. Journal of Environmental Economics and Management 67(3), 353-370.
DeWaters, J.E., Powers, S.E., 2011. Energy literacy of secondary students in New York State (USA): A measure of knowledge, affect, and behavior. Energy Policy, 39(3), 1699-1710.
DeWaters, J., Powers, S., 2013. Establishing measurement criteria for an energy literacy questionnaire. The Journal of Environmental Education, 44(1), 38-55.
Drews, S., Van den Bergh, J., 2016. What explains public support for climate policies? A review of empirical and experimental studies. Climate Policy 16(7), 855-876.
Druckman, J., McGrath, M., 2019. The evidence for motivated reasoning in climate change preference formation. Nature Climate Change 9(2), 111-119.
Drummond, C., Fischhoff, B., 2017. Individuals with greater science literacy and education have more polarized beliefs on controversial science topics. Proceedings of the National Academy of Sciences 114(36), 9587-9592.
Ehret, P.J., Van Boven, L., Sherman, D.K., 2018. Partisan barriers to bipartisanship: Understanding climate policy polarization. Social Psychological and Personality Science, 9(3), 308-318.
Eurostat, 2023. Passenger cars, by type of motor energy. Eurostat, https://ec.europa.eu/eurostat/databrowser/view/ROAD_EQS_CARPDA__custom_4856627/default/table?lang=en.
Farhidi, F., Khiabani, V., 2021. The impact of social norms on cross-state energy regime changes. Energy Policy 154, 112257.
Faruqui, A., Bourbonnais, C., 2020. The tariffs of tomorrow: Innovations in rate designs. IEEE Power and Energy Magazine, 18(3), 18-25.
Feick, L.F., 1989. Latent class analysis of survey questions that include don't know responses. Public Opinion Quarterly, 53(4), 525-547.
Fischbacher, U., Gächter, S., 2010. Social preferences, beliefs, and the dynamics of free riding in public goods experiments. The American Economic Review 100(1), 541-556.

Fischbacher, U., Gächter, S., Fehr, E., 2001. Are people conditionally cooperative? Evidence from a public goods experiment. Economics Letters 71(3), 397-404.

Foster, V., Witte, S. H., 2020. Falling Short: A Global Survey of Electricity Tariff Design. World Bank Policy Research Working Paper(9174).

Frederick, S.W., Meyer, A.B., Mochon, D., 2011. Characterizing perceptions of energy consumption. Proceedings of the National Academy of Sciences, 108(8), E23-E23.

Frey, B., Meier, S., 2004. Social comparisons and pro-social behavior: Testing "conditional cooperation" in a field experiment. The American Economic Review 94(5), 1717-1722.

Frimer, J., Tell, C., Motyl, M., 2017. Sacralizing liberals and fair-minded conservatives: Ideological symmetry in the moral motives in the culture war. Analyses of Social Issues and Public Policy 17(1), 33-59.

Frondel, M., Kussel, G., 2019. Switching on electricity demand response: Evidence for German households. The Energy Journal, 40(5).

Gielissen, R., Dutilh, C., Graafland, J., 2008. Perceptions of price fairness: An empirical research. Business and Society 47(3), 370-389.

Gillingham, K., Jenn, A., Azevedo, I.M., 2015. Heterogeneity in the response to gasoline prices: Evidence from Pennsylvania and implications for the rebound effect. Energy Economics 52, S41-S52.

Gillingham, K., Tsvetanov, T., 2018. Nudging energy efficiency audits: Evidence from a field experiment. Journal of Environmental Economics and Management 90, 303-316.

Greene, D.L., 1986. The market share of diesel cars in the USA, 1979-83. Energy Economics 8(1), 13-21.

Gustafson, A., Goldberg, M., Bergquist, P., Lacroix, K., Rosenthal, S., Leiserowitz, A., 2022. The durable, bipartisan effects of emphasizing the cost savings of renewable energy. Nature Energy, 1-8.

Gustafson, A., Rosenthal, S., Ballew, M., Goldberg, M., Bergquist, P., Kotcher, J., Maibach, E., Leiserowitz, A., 2019. The

development of partisan polarization over the green new deal. Nature Climate Change 9(12), 940–944.
Hall, N. L., Jeanneret, T. D., Rai, A., 2016. Cost–reflective electricity pricing: Consumer preferences and perceptions. Energy Policy 95, 62–72.
Hamilton, L.C., 2011. Education, politics and opinions about climate change evidence for interaction effects. Climatic Change 104(2), 231–242.
Hanly, M., Dargay, J., Goodwin, P., 2002. Review of income and price elasticities in the demand for road traffic, Department for Transport, London. ESRC TSU
Harding, M., 2014. The diesel differential: Differences in the tax treatment of gasoline and diesel for road use, OECD Taxation Working Papers 21, 1–37.
Harding, M., Sexton, S., 2017. Household response to time–varying electricity prices. Annual Review of Resource Economics 9, 337–359.
Heberlein, T.A., Warriner, G.K., 1983. The influence of price and attitude on shifting residential electricity consumption from on–to off–peak periods. Journal of Economic Psychology 4(1–2), 107–130.
Hobman, E., Frederiks, E., Stenner, K., Meikle, S., 2016. Uptake and usage of cost–reflective electricity pricing: Insights from psychology and behavioural economics. Renewable and Sustainable Energy Reviews 57, 455–467.
Homburg, C., Hoyer, W., Koschate, N., 2005. Customers' reactions to price increases: do customer satisfaction and perceived motive fairness matter? Journal of the Academy of Marketing Science 33(1), 36–49.
Hughes, J., Knittel, C.R. Sperling, D., 2008. Evidence of a shift in the short–run price elasticity of gasoline demand. The Energy Journal 29(1), 113–134.
IEA, 2021. Energy consumption in road transport by source, 2000 vs. 2019. https://www.iea.org/data–and–statistics/charts/energy–consumption–in–road–transport–by–source–2000–vs–2019
IEA, 2022a. End–use prices: Energy prices in US dollars (Edition 2021). IEA Energy Prices and Taxes Statistics (database),

http://lps3.doi.org.libproxy.snu.ac.kr/10.1787/78e38fe3-en.
IEA. 2022b. World electricity final consumption by sector, 1974-2019. Retrieved 02-07 from https://www.iea.org/reports/electricity-information-overview/electricity-consumption
IEA, 2023a. CO2 Emissions in 2022. https://www.iea.org/reports/co2-emissions-in-2022.
IEA, 2023b. Global CO2 emissions by sector, 2019-2022. https://www.iea.org/data-and-statistics/charts/global-co2-emissions-by-sector-2019-2022.
IEA, 2023c. OECD product supply and consumption. IEA Oil Information Statistics (database), https://doi.org/10.1787/data-00478-en.
IEA, 2023d. Weather for Energy Tracker, https://www.iea.org/data-and-statistics/data-tools/weather-for-energy-tracker
Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. Journal of econometrics 115(1), 53-74.
Ito, K., 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. The American Economic Review 104(2), 537-563.
Jessoe, K., Rapson, D., 2014. Knowledge is (less) power: Experimental evidence from residential energy use. The American Economic Review 104(4), 1417-1438.
Johnson, D., 2017. Bridging the political divide: Highlighting explanatory power mitigates biased evaluation of climate arguments. Journal of Environmental Psychology 51, 248-255.
Jung., J., Lee, J., Park, S., 2012, Study on the changes in price elasticity of demand for domestic petroleum products in the transportation sector. Korea Energy Economics Institute.
Kahan, D., Peters, E., Wittlin, M., Slovic, P., Ouellette, L., Braman, D., Mandel, G., 2012. The polarizing impact of science literacy and numeracy on perceived climate change risks. Nature climate change 2(10), 732-735.
Kahn, M., Wolak, F., 2013. Using information to improve the effectiveness of nonlinear pricing: Evidence from a field experiment. Unpublished. http://web.stanford.edu/group/fwolak/cgibin/sites/default/fles

/fles/kahn_wolak_July_2_2013.pdf.
Kahneman, D., Knetsch, J., Thaler, R., 1986. Fairness as a constraint on profit seeking: Entitlements in the market. The American Economic Review, 728–741.
Kang, M., Lee, S., Cho, J., 2008. Estimation of the elasticity of energy demand and performance of the second energy tax reform in Korea. Environmental and Resource Economics Review, 17(3), 1–29.
KEPCO, 2020. Fuel Cost Pass-Through Adjustment Rate – Press Release (2020.12.17)
https://www.etrans.or.kr/lib/download.php?no=3044&file_name=1217%28%EB%B3%B4%EB%8F%84%EC%B0%B8%EA%B3%A0%EC%9E%90%EB%A3%8C%29%EC%A0%84%EB%A0%A5%EC%8B%9C%EC%9E%A5%EA%B3%BC%2C+%EC%9B%90%EA%B0%80%EC%97%B0%EA%B3%84%ED%98%95+%EC%9A%94%EA%B8%88%EC%A0%9C+%EB%93%B1+%ED%95%A9%EB%A6%AC%EC%A0%81+%EC%A0%84%EA%B8%B0%EC%9A%94%EA%B8%88+%EC%B2%B4%EA%B3%84%EA%B0%9C%ED%8E%B8%EC%95%88+%ED%99%95%EC%A0%95.pdf&save_file=a_202012231649070.pdf
Kim, H., Gu, H., Won, D., Yang, H., 2010. Study on domestic petroleum products for transportation: Focusing on consumer characteristics, Korea Energy Economics Institute.
Kim, S et al., 2015, Study on alternative energy policy considering environmental and climate change factors, Ministry of Environment
Korea Institute of Public Administration, 2022. Korea social integraion survey 2021. Korea Institute of Public Administration.
https://www.kipa.re.kr/site/kipa/sta/selectBaseView.do?seSubCode=BIZ017A001&seqNo=STAT_000000000001028
Krosnick, J.A., Holbrook, A.L., Berent, M.K., Carson, R.T., Michael Hanemann, W., Kopp, R. J., Cameron Mitchell, R., Presser, S., Ruud, P.A., Kerry Smith, V., 2002. The impact of “no opinion" response options on data quality: non-attitude reduction or an invitation to satisfice? Public Opinion Quarterly, 66(3), 371–403.
Kwon, Y. Lee, J., 2014. Asymmetric responses of highway travel

demand to changes in fuel price: An explanation via fuel price uncertainty. Transportation Research Part A: Policy and Practice, 63, 56−66.

Labandeira, X., Labeaga, J.M., Teixidó, J.J., 2022. Major reforms in electricity pricing: evidence from a quasi−experiment. The Economic Journal 132(644), 1517−1541.

Lee, C., 2017. Evaluating economic and environmental viability of power generation with a focus on thermal power generation. Korea Environment Institute.

Lee, D., 2017. Review of adjusting relative prices between transport fuels, Korea Institute of Public Finance.

Lee, D et al., 2018. Research on reforming the energy tax system for power generation. Korea Institute of Public Finance.

Li, S., Linn, J., Muehlegger, E., 2014. Gasoline taxes and consumer behavior. American Economic Journal: Economic Policy 6(4), 302−342.

Liddle, B. Huntington, H., 2020. 'On the Road Again': A 118 country panel analysis of gasoline and diesel demand. Transportation Research Part A: Policy and Practice 142, 151−167.

Lim, H., Cho, H., 2020. Drivers of carbon decoupling in transportation sector and the effect of energy transition: Panel analysis of 25 OECD countries. Environmental and Resource Economics Review 29(3), 389−418.

Lin, C.Y.C., Prince, L., 2013. Gasoline price volatility and the elasticity of demand for gasoline. Energy Economics 38, 111−117.

Liu, G., 2004. Estimating energy demand elasticities for OECD countries − A dynamic panel data approach. Statistics Norway.

Lo, H., Blumsack, S., Hines, P., .Meyn, S.. 2019. Electricity rates for the zero marginal cost grid. The Electricity Journal 32(3), 39−43.

Martins, A., Madaleno, M., Dias, M.F., 2020. Energy literacy: What is out there to know? Energy Reports 6, 454−459.

Masatlioglu, Y., Ok, E.A., 2005. Rational choice with status quo bias. Journal of Economic Theory 121(1), 1−29.

Mayeres, I. Proost, S., 2001. Should diesel cars in Europe be discouraged? Regional Science and Urban Economics 31(4), 453−470.

McRae, S., Meeks, R., 2015. Price perception and electricity demand with nonlinear tariffs. Unpublished. https://www.sdmcrae.com/publication/price-perception-and-electricity-demand/price-perception-and-electricity-demand.pdf.

Mentel, G., Vasilyeva, T., Samusevych, Y., Pryymenko, S., 2018. Regional differentiation of electricity prices: Social-equitable approach. International Journal of Environmental Technology and Management 21(5-6), 354-372.

Na, I., 2001. Analysis of the effects of domestic fuel price regime changes, with a focus on gasoline prices and demand. Korea Energy Economics Institute.

Nisbet, E. C., Cooper, K. E., Ellithorpe, M., 2015. Ignorance or bias? Evaluating the ideological and informational drivers of communication gaps about climate change. Public Understanding of Science 24(3), 285-301.

Nolan, J., Schultz, P., Cialdini, R.B., Goldstein, N., Griskevicius, V., 2008. Normative social influence is underdetected. Personality and Social Psychology Bulletin 34(7), 913-923.

OECD, 2020. Economic review of Korea. https://www.oecd.org/economy/surveys/ Overview-2020-economic-survey-korea-korean.pdf,

OECD, 2023a. Environmental Policy Stringency Index, https://stats.oecd.org/Index.aspx?DataSetCode=EPS#.

OECD, 2023b. Labour force statistics: Historical population data. OECD Employment and Labour Market Statistics (database), https://doi.org/10.1787/4cf3d106-en.

Oh, S., Choi, G., Heo, E., 2015. A study on the asymmetry and market power in Korean petroleum products market. Korean Energy Economic Review 14(3), 1-25.

Oh, S., Park, S., Lee, J., 2017. Class Betrayal Voting and Political Knowledge in the 20th Korean General Election, Korean Political Science Review 51(1), 153-180.

Park, Y. Ma, Y., 2007. Current situation and reform of taxation system on transportation oil products. Korea Energy Economic Review 6(2), 257-287.

Parry, I., Black, M.S., Vernon, N., 2021. Still not getting energy prices right: a global and country update of fossil fuel subsidies.

International Monetary Fund.
Pock, M., 2007. Gasoline and diesel demand in Europe: new insights, Reihe Ökonomie/ Economics Series, 202, pp.1-30, Vienna, Institute for Advanced Studies(IHS).
Polemis, M.L., 2006. Empirical assessment of the determinants of road energy demand in Greece. Energy Economics 28(3), 385-403.
Pon, S., 2017. The effect of information on TOU electricity use: An irish residential study. The Energy Journal 38(6).
Prest, B.C., 2020. Peaking interest: How awareness drives the effectiveness of time-of-use electricity pricing. Journal of the Association of Environmental and Resource Economists 7(1), 103-143.
Ramli, A.R. Graham, D.J., 2014. The demand for road transport diesel fuel in the UK: Empirical evidence from static and dynamic cointegration techniques. Transportation Research Part D: Transport and Environment, 26, 60-66.
Reis, I.F., Lopes, M.A., Antunes, C.H., 2021. Energy literacy: An overlooked concept to end users' adoption of time-differentiated tariffs. Energy Efficiency 14(4), 1-28.
Rietveld, P., van Woudenberg, S., 2005. Why fuel prices differ. Energy Economics 27(1), 79-92.
Romero-Jordán, D., Del Rio, P., Jorge-García, M., Burguillo, M., 2010. Price and income elasticities of demand for passenger transport fuels in Spain. Implications for public policies. Energy Policy 38(8), 3898-3909.
Ryu, J., 2012. The role of political knowledge through political ideology in formation of policy preferences, Journal of Korean Politics 21(2), 53-86.
Salant, Y., Rubinstein, A., 2008. (A, f): choice with frames. The Review of Economic Studies 75(4), 1287-1296.
Šćepanović, S., Warnier, M., Nurminen, J., 2017. The role of context in residential energy interventions: A meta review. Renewable and Sustainable Energy Reviews 77, 1146-1168.
Schipper, L. Fulton, L., 2009. Disappointed by diesel? Impact of shift to diesels in Europe through 2006. Transportation Research Record 2139(1), 1-10.
Schultz, P., Nolan, J., Cialdini, R., Goldstein, N., Griskevicius, V., 2007.

The constructive, destructive, and reconstructive power of social norms. Psychological Science 18(5), 429−434.

Sexton, S., 2015. Automatic bill payment and salience effects: Evidence from electricity consumption. Review of Economics and Statistics 97(2), 229−241.

Shaffer, B., 2020. Misunderstanding nonlinear prices: Evidence from a natural experiment on residential electricity demand. American Economic Journal: Economic Policy 12(3), 433−461.

Sheng, Y., Ling−Yun, H.E., 2016. Fuel demand, road transport pollution emissions and residents' health losses in the transitional China. Transportation Research Part D: Transport and Environment 42, 45−59.

Shi, J., Visschers, V.H., Siegrist, M., Arvai, J., 2016. Knowledge as a driver of public perceptions about climate change reassessed. Nature Climate Change 6(8), 759−762.

Shi, X., Sun, S., 2017. Energy price, regulatory price distortion and economic growth: A case study of China. Energy Economics 63, 261−271.

Shin, D., 2015. Impacts of volatility, ageing and urbanization on transport sector energy consumption: Evidence from 78 countries. Korean Energy Economic Review 14(2), 127−176.

Simshauser, P., Downer, D., 2016. On the inequity of flat−rate electricity tariffs. The Energy Journal 37(3).

Stock, J., Yogo, M., 2005. "Testing for weak instruments in linear IV regression" in identification and inference for econometric models: Essays in Honor of Thomas Rothenberg, edited by Andrews, D.W. and Stock., J.H. Cambridge: Cambridge University Press, 80–108.

Stokes, L., Warshaw, C., 2017. Renewable energy policy design and framing influence public support in the united states. Nature Energy 2(8), 1−6.

Tenkorang, F., Dority, B. L., Bridges, D., Lam, E., 2015. Relationship between ethanol and gasoline: AIDS approach. Energy Economics 50, 63−69.

Trotta, G., 2021. Electricity awareness and consumer demand for information. International Journal of Consumer Studies 45(1), 65−79.

Urbany, J., Madden, T., Dickson, P., 1989. All's not fair in pricing: an

initial look at the dual entitlement principle. Marketing Letters 1(1), 17–25.
van den Broek, K.L., 2019. Household energy literacy: A critical review and a conceptual typology. Energy Research & Social Science 57, 101256.
Verboven, F., 2002. Quality-based price discrimination and tax incidence: Evidence from gasoline and diesel cars. RAND Journal of Economics 33(2), 275–297.
Wadud, Z., 2016. Diesel demand in the road freight sector in the UK: Estimates for different vehicle types. Applied Energy 165, 849–857.
Wadud, Z., Graham, D.J., Noland, R.B., 2009. Modelling fuel demand for different socio-economic groups. Applied Energy 86(12), 2740–2749.
Wang, H., Zhou, P., Zhou, D.Q., 2012. An empirical study of direct rebound effect for passenger transport in urban China. Energy Economics 34(2), 452–460.
Wang, S., Lin, S., Li, J., 2018. Exploring the effects of non-cognitive and emotional factors on household electricity saving behavior. Energy Policy 115, 171–180.
Werthschulte, M., Löschel, A., 2021. On the role of present bias and biased price beliefs in household energy consumption. Journal of Environmental Economics and Management 109, 102500.
Whitmarsh, L., 2011. Scepticism and uncertainty about climate change: Dimensions, determinants and change over time. Global Environmental Change 21(2), 690–700.
World Bank, 2023a. Consumer price index (2010=100). The World Bank, Data, https://data.worldbank.org/indicator/FP.CPI.TOTL.
World Bank, 2023b. GDP per capita (current US$). The World Bank, Data, https://data.worldbank.org/indicator/NY.GDP.PCAP.CD.
World Bank, 2023c. Urban population (% of total population). The World Bank, Data, https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS.
Xia, L., Monroe, K.B., Cox, J., 2004. The price is unfair! a conceptual framework of price fairness perceptions. Journal of marketing 68(4), 1–15.
Zhou, K., Yang, S., 2016. Understanding household energy consumption behavior: The contribution of energy big data

analytics. Renewable and Sustainable Energy Reviews 56, 810–819.

Zimmer, A., Koch, N., 2017. Fuel consumption dynamics in Europe: Tax reform implications for air pollution and carbon emissions. Transportation Research Part A: Policy and Practice 106, 22–50.

A. Appendix to Chapter 2

A.1. Regression Results

Table A−1. Average Treatment Effects

Variables	Asinh(WTP$) Coeff.	(SE)	WTP($) Coeff.	(SE)
Treatments				
Environmental external cost info.	0.15***	(0.03)	0.36***	(0.08)
Partisan−free policy info.	−0.01	(0.03)	0.01	(0.08)
International cooperation info.	0.02	(0.03)	0.07	(0.08)
Cross−country comparison info.	−0.03	(0.03)	−0.07	(0.08)
Socioeconomic variables				
Female	0.06***	(0.02)	0.07	(0.05)
Age	−0.01***	(0.00)	−0.02***	(0.00)
Education				
None	Ref.		Ref.	
Elementary school dropout	−1.17***	(0.25)	−3.21***	(1.24)
Elementary school graduate	−0.83***	(0.28)	−2.53**	(1.27)
Middle school dropout	−0.73***	(0.27)	−2.49**	(1.27)
Middle school graduate	−0.77***	(0.25)	−2.34*	(1.25)
High school dropout	−0.93***	(0.25)	−2.76**	(1.24)
High school graduate	−0.93***	(0.24)	−2.74**	(1.23)
College (2−year) attending or taking leave of absence	−0.84***	(0.25)	−2.54**	(1.25)
College (2−year) graduate	−1.01***	(0.24)	−2.91**	(1.23)
University (4−year) attending or taking leave of absence	−0.92***	(0.25)	−2.69**	(1.24)
University (4−year) graduate	−0.92***	(0.24)	−2.71**	(1.23)
Master’ s course attending	−1.09***	(0.28)	−3.16**	(1.27)
Master’ s course all but except for dissertation	−0.76***	(0.27)	−2.36*	(1.27)
Master’ s course graduate	−0.86***	(0.24)	−2.59**	(1.24)
Doctoral course attending	−0.74***	(0.28)	−2.63**	(1.28)
Doctoral course all but except for dissertation	−0.89***	(0.27)	−2.77**	(1.26)
Doctoral course graduate	−1.01***	(0.26)	−3.11**	(1.25)
Household income	0.03***	(0.00)	0.07***	(0.01)
Regions of residence				
Seoul	Ref.		Ref.	
Busan	0.03	(0.05)	0.11	(0.12)
Daegu	0.08	(0.05)	0.13	(0.13)

Incheon	0.03	(0.05)	0.09	(0.13)
Gwangju	0.04	(0.06)	0.08	(0.16)
Daejeon	0.01	(0.06)	−0.01	(0.16)
Ulsan	−0.00	(0.07)	−0.07	(0.17)
Gyeonggi	0.00	(0.03)	−0.02	(0.08)
Gangwon	−0.06	(0.06)	−0.19	(0.14)
ChungBuk	−0.09	(0.06)	−0.17	(0.16)
ChungNam	−0.00	(0.05)	0.03	(0.14)
JeonBuk	0.03	(0.06)	0.08	(0.15)
JeonNam	0.05	(0.05)	0.03	(0.13)
KyeongBuk	0.08	(0.05)	0.17	(0.13)
KyeongNam	0.00	(0.05)	0.05	(0.12)
Jeju	0.12	(0.08)	0.23	(0.23)
Sejong	0.24	(0.26)	0.82	(0.84)
Political view				
Conservative	Ref.		Ref.	
Neutral	−0.03	(0.03)	−0.03	(0.06)
Liberal	0.07**	(0.03)	0.18**	(0.07)
Constant	2.34***	(0.25)	5.20***	(1.23)
Observations	4,214		4,214	
R−squared	0.056		0.053	

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A-2. Heterogeneous Treatment Effects by Political View

Variables	Asinh(WTP$) Coeff.	(SE)	WTP($) Coeff.	(SE)
Treatments x Political views				
Environmental external cost info. & Conservative	0.09	(0.07)	0.17	(0.18)
Environmental external cost info.& Neutral	0.21***	(0.05)	0.51***	(0.11)
Environmental external cost info.& Liberal	0.07	(0.06)	0.19	(0.16)
Partisan-free policy info.& Conservative	-0.18***	(0.07)	-0.46***	(0.17)
Partisan-free policy info.& Neutral	0.08*	(0.04)	0.23**	(0.11)
Partisan-free policy info.& Liberal	-0.06	(0.06)	-0.03	(0.17)
International cooperation info.& Conservative	-0.12*	(0.07)	-0.39**	(0.16)
International cooperation info.& Neutral	0.08*	(0.05)	0.28**	(0.12)
International cooperation info.& Liberal	0.01	(0.06)	0.04	(0.16)
Cross-country comparison info.& Conservative	-0.17**	(0.07)	-0.46***	(0.17)
Cross-country comparison info.& Neutral	0.04	(0.04)	0.10	(0.10)
Cross-country comparison info.& Liberal	-0.04	(0.06)	-0.09	(0.16)
Socioeconomic variables				
Female	0.06***	(0.02)	0.06	(0.05)
Age	-0.01***	(0.00)	-0.02***	(0.00)
Education				
None	Ref.		Ref.	
Elementary school dropout	-1.13***	(0.25)	-3.12**	(1.23)
Elementary school graduate	-0.82***	(0.28)	-2.50**	(1.26)
Middle school dropout	-0.74***	(0.28)	-2.50**	(1.26)
Middle school graduate	-0.78***	(0.25)	-2.34*	(1.24)
High school dropout	-0.93***	(0.25)	-2.75**	(1.23)
High school graduate	-0.93***	(0.24)	-2.72**	(1.22)
College (2-year) attending or taking leave of absence	-0.84***	(0.25)	-2.53**	(1.24)

College (2−year) graduate	−1.00***	(0.24)	−2.90**	(1.22)
University (4−year) attending or taking leave of absence	−0.91***	(0.25)	−2.68**	(1.22)
University (4−year) graduate	−0.91***	(0.24)	−2.69**	(1.22)
Master' s course attending	−1.10***	(0.29)	−3.18**	(1.26)
Master' s course all but except for dissertation	−0.75***	(0.27)	−2.33*	(1.26)
Master' s course graduate	−0.85***	(0.24)	−2.57**	(1.23)
Doctoral course attending	−0.72**	(0.29)	−2.57**	(1.27)
Doctoral course all but except for dissertation	−0.89***	(0.27)	−2.76**	(1.25)
Doctoral course graduate	−1.01***	(0.26)	−3.09**	(1.24)
Household income	0.03***	(0.00)	0.07***	(0.01)
Regions of residence				
Seoul	Ref.		Ref.	
Busan	0.03	(0.05)	0.11	(0.12)
Daegu	0.07	(0.05)	0.13	(0.13)
Incheon	0.03	(0.05)	0.09	(0.13)
Gwangju	0.04	(0.06)	0.09	(0.16)
Daejeon	0.01	(0.06)	−0.01	(0.16)
Ulsan	−0.01	(0.07)	−0.08	(0.17)
Gyeonggi	−0.00	(0.03)	−0.03	(0.08)
Gangwon	−0.06	(0.06)	−0.19	(0.14)
ChungBuk	−0.09	(0.06)	−0.18	(0.16)
ChungNam	−0.00	(0.05)	0.02	(0.15)
JeonBuk	0.03	(0.06)	0.08	(0.15)
JeonNam	0.04	(0.05)	0.01	(0.13)
KyeongBuk	0.08	(0.05)	0.17	(0.13)
KyeongNam	0.00	(0.05)	0.04	(0.12)
Jeju	0.12	(0.08)	0.22	(0.23)
Sejong	0.24	(0.26)	0.83	(0.84)
Political view				
Conservative	Ref.		Ref.	
Neutral	−0.19***	(0.06)	−0.50***	(0.15)
Liberal	−0.00	(0.07)	−0.09	(0.18)
Constant	2.44***	(0.25)	5.50***	(1.23)
Observations	4,214		4,214	
R−squared	0.060		0.057	

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A-3. Heterogeneous Treatment Effects by Political View and Prior Knowledge

Variables	Asinh(WTP$) Coeff. (SE)		WTP($) Coeff. (SE)	
Treatments x Political views x Knowledge levels				
Environmental external cost info. & Conservative & Accurate	0.24***	(0.09)	0.49**	(0.22)
Environmental external cost info. & Conservative & Inaccurate	−0.02	(0.09)	−0.06	(0.25)
Environmental external cost info. & Neutral & Accurate	0.18***	(0.07)	0.43**	(0.18)
Environmental external cost info. & Neutral & Inaccurate	0.22***	(0.06)	0.55***	(0.15)
Environmental external cost info. & Liberal & Accurate	0.04	(0.08)	0.07	(0.20)
Environmental external cost info. & Liberal & Inaccurate	0.11	(0.08)	0.33	(0.24)
Partisan-free policy info.& Conservative & Accurate	−0.03	(0.09)	−0.10	(0.19)
Partisan-free policy info.& Conservative & Inaccurate	−0.27***	(0.09)	−0.69***	(0.24)
Partisan-free policy info.& Neutral & Accurate	−0.06	(0.06)	−0.15	(0.13)
Partisan-free policy info.& Neutral & Inaccurate	0.17***	(0.06)	0.47***	(0.16)
Partisan-free policy info.& Liberal & Accurate	−0.04	(0.09)	0.06	(0.24)
Partisan-free policy info. & Liberal & Inaccurate	−0.10	(0.08)	−0.14	(0.23)
International cooperation info. & Conservative & Accurate	0.04	(0.09)	0.01	(0.19)
International cooperation info. & Conservative & Inaccurate	−0.23**	(0.09)	−0.65***	(0.23)
International cooperation info. & Neutral & Accurate	−0.02	(0.07)	0.03	(0.16)
International cooperation info. & Neutral & Inaccurate	0.15**	(0.06)	0.48***	(0.16)
International cooperation info. & Liberal & Accurate	−0.01	(0.08)	−0.11	(0.19)
International cooperation info. & Liberal & Inaccurate	0.01	(0.08)	0.11	(0.24)

Cross−country comparison info. & Conservative & Accurate	−0.02	(0.09)	−0.09	(0.19)
Cross−country comparison info. & Conservative & Inaccurate	−0.26***	(0.09)	−0.69***	(0.24)
Cross−country comparison info. & Neutral & Accurate	−0.08	(0.06)	−0.16	(0.14)
Cross−country comparison info. & Neutral & Inaccurate	0.12**	(0.06)	0.27*	(0.14)
Cross−country comparison info. & Liberal & Accurate	−0.04	(0.08)	−0.09	(0.20)
Cross−country comparison info. & Liberal & Inaccurate	−0.03	(0.09)	−0.04	(0.24)
Political views x Knowledge levels				
Conservative & Accurate	Ref.		Ref.	
Conservative & Inaccurate	0.46***	(0.09)	1.14***	(0.25)
Neutral & Accurate	0.01	(0.08)	−0.00	(0.19)
Neutral & Inaccurate	0.13*	(0.08)	0.31	(0.19)
Liberal & Accurate	0.14	(0.09)	0.24	(0.22)
Liberal & Inaccurate	0.38***	(0.09)	0.87***	(0.23)
Socioeconomic variables				
Female	0.06***	(0.02)	0.06	(0.05)
Age	−0.01***	(0.00)	−0.02***	(0.00)
Education				
None	Ref.		Ref.	
Elementary school dropout	−0.89***	(0.24)	−2.54**	(1.18)
Elementary school graduate	−0.73***	(0.27)	−2.27*	(1.21)
Middle school dropout	−0.58**	(0.26)	−2.10*	(1.21)
Middle school graduate	−0.69***	(0.24)	−2.12*	(1.19)
High school dropout	−0.81***	(0.24)	−2.44**	(1.18)
High school graduate	−0.80***	(0.23)	−2.39**	(1.17)
College (2−year) attending or taking leave of absence	−0.72***	(0.24)	−2.24*	(1.19)
College (2−year) graduate	−0.87***	(0.23)	−2.56**	(1.17)
University(4−year) attending or taking leave of absence	−0.80***	(0.23)	−2.39**	(1.18)
University(4−year) graduate	−0.78***	(0.23)	−2.36**	(1.17)
Master’s course attending	−1.00***	(0.27)	−2.93**	(1.21)
Master’s course all but except for dissertation	−0.65**	(0.25)	−2.07*	(1.22)
Master’s course graduate	−0.69***	(0.23)	−2.15*	(1.18)

Doctoral course attending	−0.53**	(0.26)	−2.08*	(1.21)
Doctoral course all but except for dissertation	−0.80***	(0.26)	−2.51**	(1.21)
Doctoral course graduate	−0.88***	(0.24)	−2.77**	(1.19)
Household income	0.03***	(0.00)	0.07***	(0.01)
Regions of residence				
Seoul	Ref.		Ref.	
Busan	0.03	(0.05)	0.10	(0.12)
Daegu	0.07	(0.05)	0.11	(0.13)
Incheon	0.04	(0.05)	0.11	(0.12)
Gwangju	0.03	(0.06)	0.04	(0.16)
Daejeon	0.01	(0.06)	0.00	(0.16)
Ulsan	−0.01	(0.07)	−0.09	(0.17)
Gyeonggi	0.01	(0.03)	−0.01	(0.08)
Gangwon	−0.06	(0.06)	−0.19	(0.14)
ChungBuk	−0.08	(0.06)	−0.17	(0.15)
ChungNam	0.01	(0.05)	0.07	(0.14)
JeonBuk	0.04	(0.06)	0.10	(0.15)
JeonNam	0.05	(0.05)	0.03	(0.13)
KyeongBuk	0.08*	(0.05)	0.18	(0.13)
KyeongNam	0.01	(0.05)	0.06	(0.12)
Jeju	0.15*	(0.08)	0.30	(0.23)
Sejong	0.22	(0.23)	0.78	(0.79)
Constant	1.99***	(0.24)	4.36***	(1.19)
Observations	4,214		4,214	
R−squared	0.097		0.096	

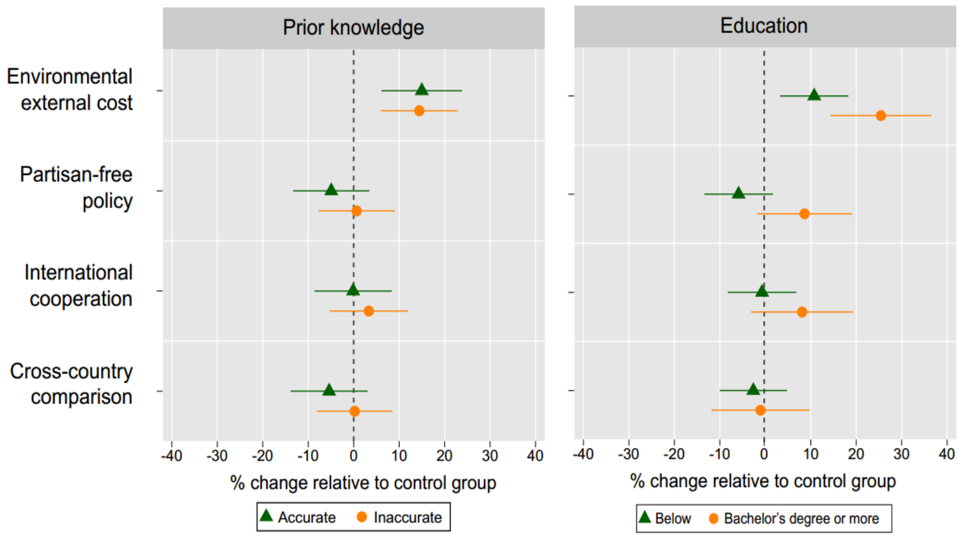
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

A.2. Heterogeneity Analysis

A.2.1. Heterogeneity Analysis by Prior Knowledge and Education

Heterogeneity analysis based on prior knowledge reveals no variation in treatment effects between groups with accurate and inaccurate knowledge about CCEC. When education is used as a proxy for prior knowledge, the analysis indicates that individuals with higher education tend to respond more favorably to information, particularly regarding environmental external costs and partisan-free policy information (see Figure A-1).

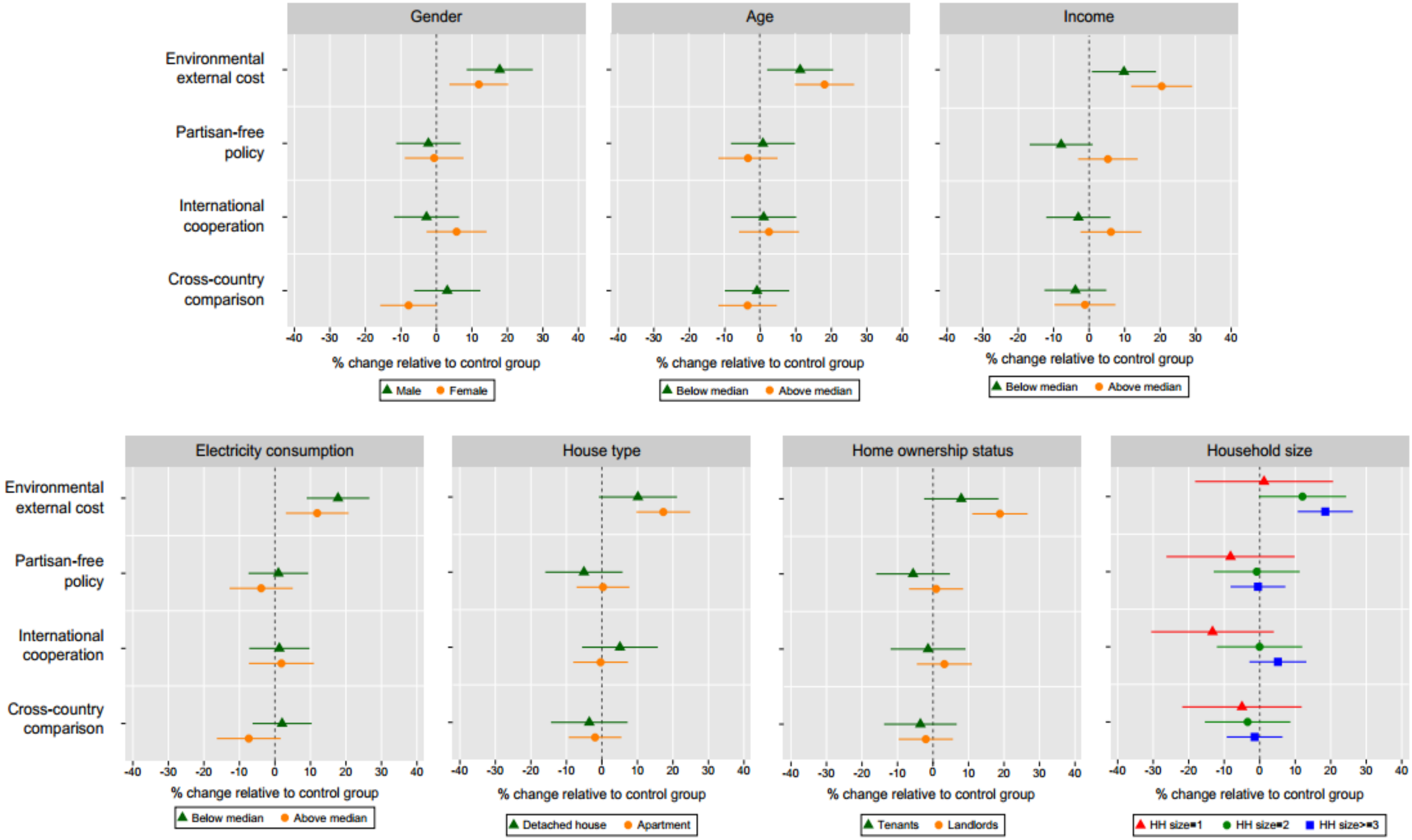
Figure A-1. Heterogeneity Analysis by Prior Knowledge and Education



A.2.2. Heterogeneity Analysis by Other Characteristics

Heterogeneous treatment effects by other socioeconomic and dwelling characteristics are provided in Figure A-2. The results reveal significant differences in treatment effects only regarding household income levels and household size.

Figure A−2. Heterogeneity Analysis by Other Characteristics



A.3. Robustness Checks

A.3.1. Using Different Standards for Grouping by Knowledge

To address concerns regarding the arbitrary nature of the standard used to divide the Accurate and Inaccurate knowledge groups in the main results (0.3 SD), additional regression results using alternative standards, namely 0.1 SD (Accurate, N = 639; Inaccurate, N = 3,575) and 0.5 SD (Accurate, N = 2,387; Inaccurate, N = 1,827), are presented. Figure A−3 illustrates how the accurate and inaccurate groups are determined at each standard, while Figure A−4 displays the results for all the specifications. The findings demonstrate consistency with Figure 2−6.

Figure A−3. Grouping Using Different Standards

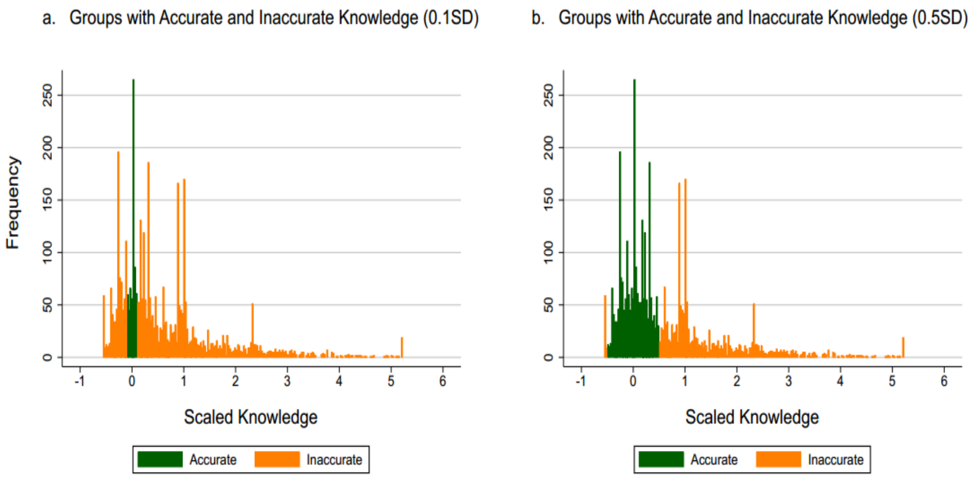
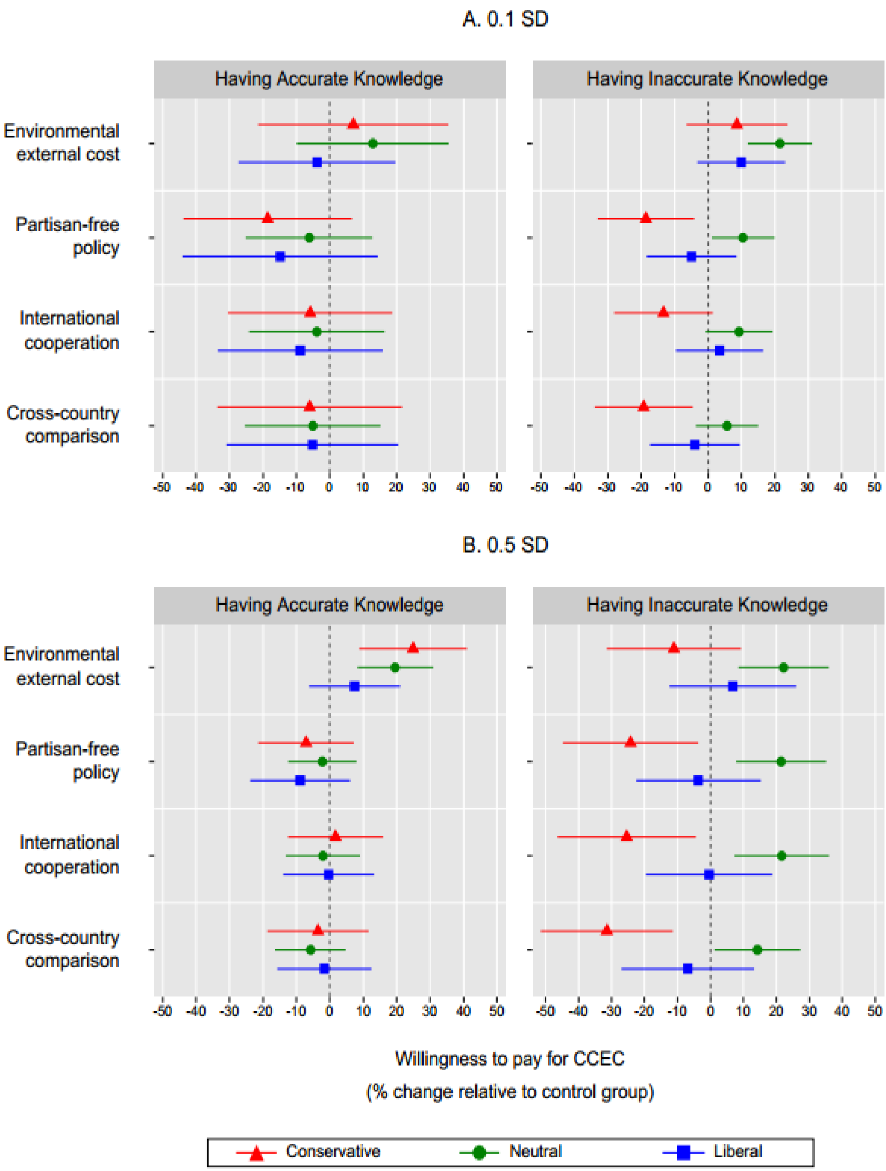


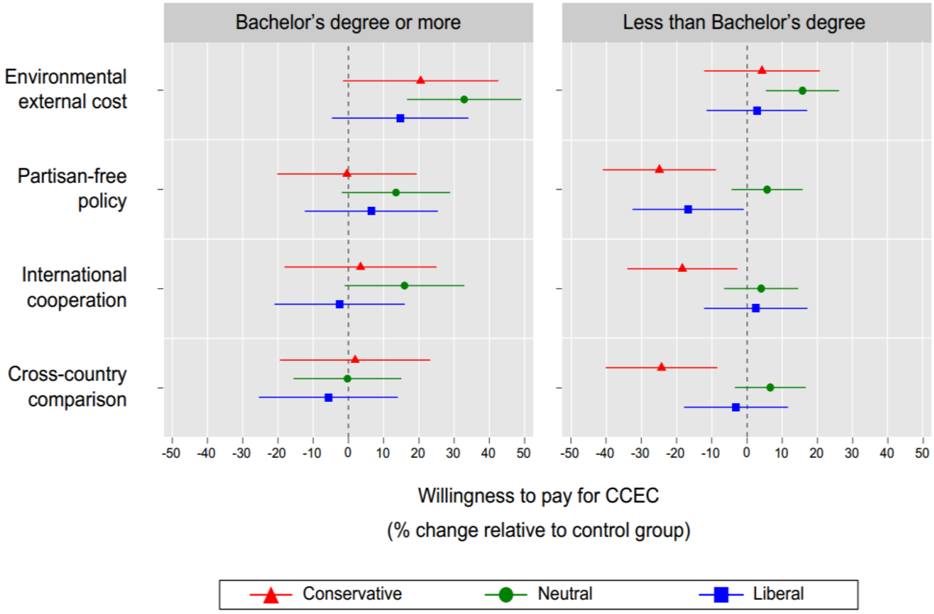
Figure A-4. Heterogeneity Analysis by Political View and Prior Knowledge Using Different Standards



A.3.2. Using Education as a Proxy for Knowledge

Using education as a proxy for knowledge about CCEC produces qualitatively similar results, with respondents having lower levels of education primarily driving the partisan gaps observed when receiving the information.

Figure A-5. Heterogeneity Analysis by Political View and Education



B. Appendix to Chapter 3

B.1. Sample Survey Questions

Table B-1. Sample Questions for Three Tariff Designs

A linear tariff	An increasing block tariff (Three block case)	A Time-of-use tariff (Two period case)
Linear tariff is a rate that charges a constant rate on every unit of electricity consumed. Q1. Which of the items are included in the calculation of a fixed price? [Basic service cost, Grid construction, operation, and maintenance cost, etc.] Q2. Which of the items are included in the calculation of a variable price? [Electricity generation cost, Environmental charges, CHP levy, etc.] Q3. What are fixed and variable prices? Fixed ( ), Variable ( )	Increasing block tariff (IBT) is a rate per unit of electricity that increases as the volume of consumption increases. Q1. How many blocks do you think the increasing block tariff in residential sector is divided into? ( ) blocks Q2. What is the threshold usage (kWh/month) at each block? Block 1 → 2: ( ) kWh Block 2 → 3: ( ) kWh Q3. What are fixed and variable prices at each block? Block 1: Fixed ( ), Variable ( ) Block 2: Fixed ( ), Variable ( ) Block 3: Fixed ( ), Variable ( )	Time-Of-Use (TOU) is a rate that charges a higher unit price for electricity at times of high electricity demand and a lower unit price at times of low electricity demand. Q1. How many periods are there in your TOU tariff? ( ) periods Q2. What are the time periods defined as on-peak and off-peak times? On-peak ( ) - ( ) Off-peak ( ) - ( ) Q3. What is a price ratio between on-peak and off-peak time periods? On-peak : Off-peak= ( ):1 Q4. What are fixed and variable prices at on-peak and off-peak time periods? On-peak: Fixed( ), Variable( ) Off-peak: Fixed( ), Variable( )

B.2. Transformation of Responses into Binary Variables

September 2021 is selected as a reference month for calculating the correct answers, as it is the latest month that respondents could have received their electricity bills before the survey.

As for the total bill amount domain, which contains five open-ended questions (A1 in Table 3-2), respondents were assigned a value of 1 if their answers fall within ±0.2SD around the correct answer and a value of 0 otherwise.[49] With regard to the rate structure domain, the correct responses are directly counted as this domain is composed of a true-false type question (A2 in Table 3-2). For the rate component domain, knowledge about each price component (e.g., IBT, CCEC, etc.) is measured by a combination of various question types (e.g., true-false, multiple-choice, open-ended). For true-false and open-ended questions, a binary variable that equals 1 for each correct answer and 0 for each incorrect response is created. For questions with multiple sub-questions (e.g., A6, A7, A9 in Table 3-2), a value of 1 is assigned only if all the answers to the sub-questions are correct.

When the proportions of correct answers of the rate component domain is calculated, only respondents who possess correct knowledge about whether corresponding price component is included are considered. For example, as for the rate component questions for increasing block tariff (IBT), the answers of the respondents who know that the IBT is included in their electricity bills are only considered.

[49] As a robustness check, additional standards were applied: ±0.1SD and ±0.3SD as correct answer ranges, revealing similar declining patterns with slightly different proportions of correct answers.

B.3. Regression Results

Table B−2. Logit Regression Results

Variables	Fuel cost pass−through adjustment rate	Regionally differentiated pricing	Time−differentiated pricing
Electricity price literacy (0−1)			
Total bill amount	−0.02	−0.06*	0.04
	(0.03)	(0.03)	(0.03)
Rate structure	0.10***	0.12***	0.08**
	(0.04)	(0.04)	(0.04)
Rate component	0.10*	0.02	0.15**
	(0.06)	(0.06)	(0.06)
Controls			
X_i	Yes	Yes	Yes
AB_i	Yes	Yes	Yes
N	4,214	4,214	4,214

Notes: The reported coefficients represent the average marginal effects, which are calculated as the average of all the marginal effects from each observation in the sample; The standard errors are calculated using the Delta method and are reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$; X_i includes gender, age, education, political view, household income, household size, housing type, home−ownership status, regions and years of residence. AB_i includes reported attitudes and behaviors towards environment.

B.4. Standards Used to Construct Individual Questions

As discussed in the conclusion section, the way in which the details of each question are set inevitably influences respondents' answers. To ensure comparisons of survey results across regions and over time, it is necessary to establish suitable standards for constructing individual questions through consensus. While this paper does not propose a comprehensive set of standards in detail, our questionnaire was constructed based on certain criteria. This section outlines the standards employed and provides the rationale behind them.

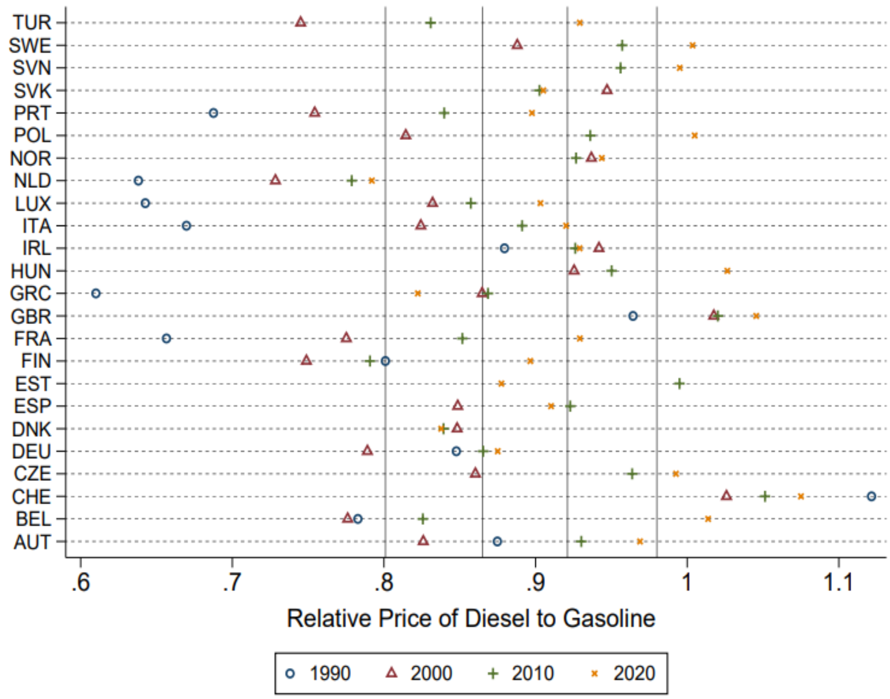
Including an “I don’t know” option in most of the questions is a subject of ongoing debate, with researchers discussing both advantages and disadvantages (Feick, 1989; Krosnick et al., 2002). One of the key benefits of including this option is the reduction of noise in the data. While no definitive conclusion has been reached, it is widely considered appropriate to include this option for factual questions.

The unit used in electricity bills, such as USD per 1kWh, may not be a familiar numeric concept for typical consumers. Therefore, in our questionnaire, the questions inquire about unit prices at a more relatable level – the average monthly consumption level of households in Korea, which is 350kWh per month for a family of four (A1, A4, A5, A10 in Table 3-2).

C. Appendix to Chapter 4

C.1. Distribution of Relative Price by Country

Figure C-1. Relative Price by Country and Year



Note: The data used in this study is an unbalanced panel, and thus some countries may have missing values.

Table C-1. Country Code and Name

Code	Name	Code	Name	Code	Name
AUT	Austria	FIN	Finland	NLD	Netherlands
BEL	Belgium	FRA	France	NOR	Norway
CHE	Switzerland	GBR	United Kingdom	POL	Poland
CZE	Czech Republic	GRC	Greece	PRT	Portugal
DEU	Germany	HUN	Hungary	SVK	Slovak Republic
DNK	Denmark	IRL	Ireland	SVN	Slovenia
ESP	Spain	ITA	Italy	SWE	Sweden
EST	Estonia	LUX	Luxembourg	TUR	Turkey

C.2. First-stage Estimation Results

Table C-2. First-stage Results

Variables	Sub-samples										Entire sample	
	1st Quintile		2nd Quintile		3rd Quintile		4th Quintile		5th Quintile		Average	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
lnT	0.367***	0.369***	0.520***	0.551***	0.649***	0.696***	0.464***	0.467***	0.698***	0.759***	0.675***	0.622***
	0.106	0.062	0.062	0.059	0.101	0.071	0.045	0.033	0.100	0.057	0.049	0.044
lnY	0.492***	0.482***	0.328	0.237	−0.016	−0.103*	0.080*	0.064	0.009	−0.046	0.155**	0.173**
	0.084	0.046	0.217	0.273	0.066	0.050	0.046	0.047	0.093	0.041	0.072	0.072
Urban		−0.010***		−0.013**		−0.025***		−0.006		−0.008		0.001
		0.003		0.005		0.007		0.005		0.008		0.005
lnhdd		−0.024		−0.014		−0.090		−0.072		0.063		−0.017
		0.099		0.146		0.087		0.119		0.105		0.095
lncdd		0.007		0.002		0.002		0.001		0.004		−0.003
		0.011		0.009		0.007		0.002		0.006		0.004
lneps		−0.107*		−0.089		−0.124**		−0.066		−0.115***		0.157***
		0.059		0.055		0.043		0.046		0.017		0.031
Constant	−4.621***	−3.627***	−2.903	−0.873	0.859	4.124***	−0.344	0.869	0.466	1.169	−0.899	−1.051
	0.949	1.089	2.237	2.689	0.646	0.971	0.500	0.609	0.977	0.874	0.744	1.150
N	136	131	136	120	135	125	136	133	135	122	678	631
No. of countries	16	15	18	17	21	19	21	19	15	14	24	22

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; All the specifications include a trend variable and year dummies.

C.3. Dynamic Panel Analysis

This paper also employs the Partial Adjustment Model (PAM) to account for time lags in consumer behavior adjustment, which can be attributed to factors like consumer habits and inertia. The PAM assumes a gradual adjustment of fuel consumption towards desired levels, following a first−order process. The model is presented as follows:

$$lnD_{it} = \beta_0 + \beta_1 lnP_{it} + \beta_2 lnY_{it} + \beta_3 lnD_{it-1} + X_{it}\gamma + \mu_i + \epsilon_{it}. \qquad (C.1)$$

The estimation of Equation (C.1) is conducted using the generalized method of moments (GMM) proposed by Arellano and Bond (1991) for the entire sample and sub−samples based on relative price. For the sub−sample analysis, due to the limited sample size and the requirement of a large number of instruments, the sample is divided into quartiles instead of quintiles. Additionally, the maximum lags of the dependent variable and the endogenous variable (i.e., diesel price) used as instruments are restricted to t−2.

The parameters β_1, β_2 and γ represent short−term elasticities of diesel demand with respect to corresponding variables. Dividing these parameters by $1-\beta_3$, where β_3 is the adjustment rate, gives long−term elasticities.

Table C−3 shows the estimation results from the dynamic PAM model. The inverted−U pattern in the own−price elasticity of diesel demand is also observed, with a more pronounced effect in the long−term with vehicle replacement compared to the short term, where consumers exhibit less price elasticity and appear to be little affected by relative price changes.

Table C-3. Dynamic Reduced-form Model Estimation Results

Variables	Sub-samples								Entire sample	
	1st Quartile		2nd Quartile		3rd Quartile		4th Quartile		Average	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
lnD(t-1)	0.696***	0.662***	0.324***	0.209	0.698***	0.477***	0.486***	0.451***	0.856***	0.826***
	(0.057)	(0.109)	(0.092)	(0.132)	(0.125)	(0.135)	(0.103)	(0.128)	(0.047)	(0.046)
lnP	0.036	0.302	-0.687***	-0.632***	-0.357***	-0.535***	-0.240***	-0.228*	-0.146***	-0.155***
	(0.245)	(0.406)	(0.125)	(0.124)	(0.107)	(0.127)	(0.063)	(0.123)	(0.047)	(0.050)
lnY	0.001	-0.227	0.443***	0.414***	0.207	0.371**	0.266**	0.257	0.131***	0.133***
	(0.205)	(0.338)	(0.146)	(0.124)	(0.138)	(0.173)	(0.103)	(0.147)	(0.042)	(0.039)
Urban		0.021		-0.026		-0.032		-0.024		-0.005*
		(0.017)		(0.025)		(0.021)		(0.020)		(0.002)
lnhdd		0.053		-0.024		-0.166		-0.213*		-0.032
		(0.122)		(0.057)		(0.136)		(0.104)		(0.044)
lncdd		0.016*		-0.003		0.002		-0.006		0.002
		(0.008)		(0.009)		(0.003)		(0.008)		(0.003)
lneps		0.038		-0.007		0.079**		-0.048		0.015
		(0.055)		(0.035)		(0.033)		(0.071)		(0.024)
Long-run price elasticity	0.118	0.894	-1.016***	-0.799***	-1.183***	-1.023***	-0.466***	-0.415**	-1.012***	-0.891***
	(0.808)	(1.344)	(0.208)	(0.255)	(0.439)	(0.191)	(0.118)	(0.218)	(0.205)	(0.197)
N	145	140	158	140	166	159	161	148	630	587
# of countries	16	15	20	18	20	19	16	15	24	22

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; All specifications include a trend variable and year dummies. For Arellano-Bond GMM, one-step efficient GMM with small sample option is applied; The maximum lags of the dependent variable and the endogenous variable (i.e., diesel price) for use as instruments are restricted to t-2 for sub-samples, while no restrictions for entire sample.

Abstract in Korean

임성민

서울대학교 환경대학원 환경계획학과

본 학위논문은 에너지 공급의 사회적 비용을 적절히 반영하는 에너지 가격 합리화 정책의 수용성과 효과성을 결정짓는 소비자 특성과 행태에 관한 세 가지 주제를 다룬다. 구체적으로 합리적인 에너지 가격 정책에 대한 소비자의 지지도를 높일 방안을 모색하고, 에너지 가격에 대한 소비자 지식 수준을 종합적으로 측정하기 위한 체계를 개발하며, 도로 수송에서의 경유 수요의 가격탄력성을 보다 정확히 추정할 수 있는 방법을 제시한다.

첫 번째 연구에서는 전력 생산으로 인한 외부비용의 내부화를 위해 도입된 기후환경요금에 대한 소비자 지불의사를 제고하기 위한 정보전략을 탐구한다. 구체적으로, 한국을 대표하는 전기소비자 총 4,214명을 무작위배정을 통해 1개의 통제집단과 4개의 처치집단으로 구분한 후, 통제집단에는 정보를 제공하지 않고, 각 처치집단에는 기후변화와 관련한 소비자의 행동특성을 고려하여 다음 정보를 제공하였다: (i) 주의 환기, 사회적 동기, 공평성 동기 자극을 위한 환경 외부비용 정보, (ii) 당파성에 의한 의사결정 편향을 완화시키기 위한 기후변화정책과 집권정당 간 무관함에 대한 정보, (iii) 기후변화정책의 효과성에 대한 불확실성을 줄이기 위한 국제적 협력을 통한 환경정책의 성공사례 정보, (iv) 사회 규범의 영향을 이용한 기후변화 대응 노력에 대한 국가간 비교 정보. 이후 기후환경요금에 대한 지불의사를 측정한 결과, 환경 외부비용 정보를 제공받은 집단의 지불의사가 통제집단에 비해 약 15% 높아 해당 정보가 외부비용 내부화에 대한 소비자 인식 개선에 효과적임이 입증되었다. 반면 그 외 정보들은 소비자 지불의사를 통계적으로 유의미하게 변화시키지 않았다. 이질성 분석 결과, 이는 정보 제공이 중도층의 지불의사를 높인 반면 보수층의 지불의사를 낮추고, 진보층의 지불의사에는 유의하지 않은 효과를 미치기 때문임을 발견하였다. 또한, 정치 성향에 따른 이질적인 처치효과는 기후환경요금에 대한 사전 지식이 부족한 집단에 의해 주도된다는 새로운 실증적 증거를 제시하였다. 이 연구는 외부비용

을 반영하는 에너지가격의 지지도에 미치는 소비자의 다양한 행동특성의 인과적 효과를 비교분석하고, 기저의 메커니즘에 대한 설명을 제공했다는 점에서 의의를 지닌다.

두 번째 연구에서는 전기 가격에 대한 소비자의 지식을 측정하는 종합적 지표인 “전기가격 문해력(electricity price literacy)” 개념을 개발한다. 문헌으로부터 에너지 가격에 대한 소비자의 지식은 에너지 가격에 따른 소비 행태 및 사회적 비용 반영 가격정책에 대한 지지도의 주요 결정요인임이 알려져 있다. 그러나 개별 연구마다 소비자 지식의 정의 및 측정 방법이 다르기 때문에 서로 다른 연구 결과를 비교하기 어려우며, 이에 따라 일반적 함의를 이끌어내기도 어렵다. 본 논문에서는 현존하는 다양한 전기요금제도를 포괄할 수 있는 유연한 함수 형태를 통해 전기요금제도를 표현한 후, 이를 (i) 총 요금액, (ii) 요금 구조, (iii) 요금 구성 요소의 세 가지 영역으로 체계화하여 각 영역별 지식을 측정하는 체계를 수립함으로써 연구 간 비교 가능성을 향상시켰다. 또한, 이러한 체계를 한국 사례에 적용하여 전기가격 문해력 측정의 전 과정을 제시하였다. 이 체계에 따라 설문 개발 후, 총 4,214명의 대표 표본을 대상으로 설문 조사 결과, 전기가격 문해력의 영역별로 소비자의 지식수준이 상이하게 나타났으며, 소비자의 전기 관련 행동에서도 차등 효과가 나타났다. 이러한 연구 결과는 전기가격 지식의 측정에 있어 종합적이고 다차원적으로 구성된 지표의 필요성을 함의하며, 또한 목표로 하는 소비자 행동 변화에 따라 특정 영역의 지식이 요구된다는 정책적 시사점을 제공한다.

세 번째 연구에서는 도로 수송 부문에서 대기오염물질 증가의 주요 원인으로 지목되어 온 경유 우대 세제 개편 시 고려해야 할 요인으로, 도로 수송의 대표 연료이자, 밀접한 대체 관계에 있는 휘발유와 경유 간 상대가격 구조에 따른 경유 소비 행태의 변화를 분석하였다. 구체적으로 유럽 24개국의 1990-2020년 패널자료를 이용하여 경유와 휘발유 간 상대가격에 따른 수송용 경유 수요의 자기가격탄력성의 변화를 분석하였다. 분석 결과, 휘발유 대비 경유의 상대가격이 증가할 때, 경유 수요의 자기가격탄력성(절댓값)이 경제적 및 통계적으로 유의하게 증가하다가 감소하는 구간이 존재함을 밝혀내었다. 이는 기존 문헌에서 주목하지 않은 경유와 휘발유 간 대체 관계가 경유 수요의 자기가격탄력성의 중요한 결정요인임을 시사한다. 이러한 결과는 경유 가격 조정을 통해 경유 소비를 줄이는 것을 목표로 하는 환경정책 설계에 있어 대체 연료 간 상대가격을 고려함으로써 정책 효과를 보다 정확하게 예측할 수 있음을 함의

한다.

전 세계적으로 지속가능한 에너지체계로의 전환을 위해 에너지수요 관리가 적극 추진되며, 효과적인 정책수단으로써 에너지 가격체계의 개편이 이루어지는 상황에서, 본 논문은 에너지가격개편의 수용성과 효과성을 높이는 소비자 특성과 행태에 대해, 전통경제학과 행태경제학에 근거하여 실험 및 실증분석을 통해 고찰해 보았다. 본 연구결과는 사회적 비용을 반영하는 에너지 가격 정책 수립과 집행에 있어 주요 자료로 활용될 수 있다는 점에서 의의가 있다고 하겠다.

주요어 : 에너지가격정책, 비가격정보, 가격지식, 상대가격, 소비자행태
학 번 : 2019-37476

Acknowledgments

I would like to express my sincere gratitude to my advisor, Professor Jong Ho Hong, for his continuous guidance and unwavering support throughout my PhD journey. His invaluable mentorship has been instrumental in helping me navigate this intricate process.

I am deeply appreciative of Professors Syngjoo Choi and Booyuel Kim, who introduced me to the world of behavioral and experimental economics. Their sharing of expert knowledge, rich experiences, and consistent support throughout various projects and the dissertation writing process has proven to be remarkably valuable.

I would also like to acknowledge the insightful feedback provided by my dissertation committee members: Professors Sun Jin Yun, Booyuel Kim, Hyungna Oh, and Syngjoo Choi. Their constructive input has greatly improved the quality of this research.

I express my profound appreciation to the Korea Electric Power Corporation for providing the financial support that made this research possible.

Furthermore, I wish to extend my appreciation to my co-authors, friends, and fellow graduate students at the Laboratory for Sustainable Economy and Policy. I consider myself extremely fortunate to have had such remarkable people in my life who have stood by me and supported me throughout this process.

Finally, I dedicate this dissertation to my family. Their love and support have been the cornerstone of my achievements, and I am profoundly grateful for their presence in my life.