Consumers’ Evaluation of Japan’s Resource Policies

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Consumers' Evaluation of Japan's Resource Policies

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Consumers' Evaluation of Japan's Resource Policies

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By
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CERTIFICATE

The undersigned hereby certify that they have read and recommended to the Graduate School of Engineering for the acceptance of this thesis entitled, "***Consumers' Evaluation of Japan's Resource Policies***" by **Tamaki MORITA** in partial fulfillment of the requirements for the degree of **Doctor of Engineering**.

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Abstract

Japan’s economic growth has been low for approximately thirty years, since the beginning of the 1990s, when the bubble economy burst. In the coming age of a declining birthrate and an aging population, when the size of the labor force will decrease profoundly, Japan needs to improve its factors of production to maintain sustainable growth. In a previous study, the author insisted on the urgency of utilizing physical capital (produced capital and natural capital) to make the efficiency of that capital positive and on the need for investments in education and training to improve the efficiency of human capital. The policies to improve productivity and economic growth are multifold and are typically discussed from the supply side of the economy. Nevertheless, the author focused on the demand side, believing that the policies should be welcomed by consumers to make a real improvement in the economy. A policy to improve productivity should accompany consumers’ quality of life and happiness.

With the above background, the author selected consumer evaluation of policies of three resources, energy, technology, and human resources, as the theme of this thesis. These resources all relate to “inclusive wealth”, which consists of the social values of natural capital, produced capital, and human capital. To measure the consumer evaluation of policies from the demand side, the author conducted internet surveys and analyzed the responses with various econometric methods.

This thesis consists of five chapters. Chapter 1 gives the background of the study and emphasizes the need to measure consumer acceptance of government policies.

Chapter 2 is on energy policy. This chapter presents the results of both discrete choice experiments and choice probability experiments to determine citizens’ willingness to pay (WTP) for residential electricity produced by solar, wind, and nuclear power and by natural gas to evaluate the three energy-mix scenarios presented by the government of Japan. Additionally, the author measures the effects of positive or negative information about nuclear energy, and it is shown that the information affects citizens’ recognition of energy resources. The results indicate that, on average, consumers in Japan had a negative WTP for electricity produced by nuclear power, petroleum, or coal, regardless of the

information they read. Consumers had the highest WTP for the highest renewable energy scenario among the presented scenarios, but the level of WTP for such an energy-mix change was far less than the actual cost of the change.

Chapter 3 is on policies for new technologies. This chapter is intended to predict a future with driverless vehicles. Using choice experiments, the author first elicits potential users' WTP for autonomous driving systems in Japan and determines that WTP is insufficient for the merchandising of highly autonomous vehicles (AVs). Second, compared with a previous US study, the author discusses two expected social dilemmas. One dilemma is that respondents in both countries tend to not purchase items that they think are moral. The other social dilemma is that respondents may not agree with government regulations on AVs, although the regulations match their morality. The author observed this dilemma solely in the US. In Japan, however, the author did not observe the second dilemma because such regulations do not affect consumer behavior. We then estimated the factors influencing these dilemmas, and the credibility of AVs was found to be a critical factor.

Chapter 4 concerns the fact that due to macroeconomic factors, young people in Japan are increasingly opting not to participate in the labor force. The government has tried to institute specific career education programs to encourage young people to find suitable jobs. The author explored the effects of career policies in school settings by identifying graduates' earning capacity (annual income) through an online survey, followed by a quantitative analysis of the results. The author reports the evaluation of career policies by respondents and then measures the effects of these policies on both labor participation and income. Although the specific program the author focused on did not show apparent effects, career education policies, in general, and daily activities in elementary and middle schools, in particular, affected graduates' incomes. We also identify other key attributes in school-age persons that would later increase their postgraduate income.

Chapter 5 summarizes the findings of this thesis and presents conclusions. Regarding natural resource policies, the Japanese government's energy-mix scenarios do not reflect consumers' preferences. Regarding natural resource policies, the Japanese government's energy-mix scenarios do not reflect consumers' preferences. A majority of consumers have a higher willingness to pay for a renewable-energy-oriented scenario. Regarding adopting new technologies such as autonomous driving vehicles, besides subsidizing the technology, the government and the makers of the AVs better recognize that consumers' morality alters their purchasing behavior. Government regulations for reflecting the morality of the public may not be affected in Japan; nevertheless, they may not work in the US. Regarding human resource policies, the effects of providing specific career education are not yet apparent. We show that government policies that let students enjoy their daily classroom activities in elementary and junior high schools, rather than specific career education, help students appreciate their future jobs.

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Chapter 1 Introduction

Japan's economic growth has been low for approximately thirty years, since the beginning of the 1990s, when the bubble economy burst. The ten-year-average growth rates of Japan's real GDP for the 1950s, 60s, 70s, 80s, 90s, and 2000s were approximately 8.6%, 10.5%, 5.2%, 4.4%, 1.6% and 0.5%, respectively.[1] The Great East Japan Earthquake in 2011 deterred the recovery, and the average growth rate in 2010-2018 was still 1.5%. In the coming age of a declining birthrate and an aging population, when we expect a decrease in the size of the labor force, Japan needs to improve its factors of production to maintain sustainable growth. In a previous study by the author (Sato and Morita, 2010[2]), we compared the productivity of Japan and the US and found that Japan's recent slow growth originated from a negative capital efficiency, but a positive labor efficiency partly compensated for it. We insisted on the urgency of utilizing overinvested physical capital (produced capital and natural capital) to make that the efficiency of that capital positive and on the need for investments in education and training to improve the efficiency of human capital.

The policies to improve productivity and economic growth are multifold and are typically discussed from the supply side of the economy. Nevertheless, the author focused on the demand side, believing that the policies should be welcomed by consumers to make a real improvement in the economy. A policy to improve

[1] National Accounts of Japan, Cabinet Office

productivity should accompany consumers' higher utility: better quality of life and happiness.

The author selected consumer evaluation of policies of three resources, energy, technology, and human resources. These resources all relate to "inclusive wealth", which consists of the social values of natural capital, produced capital, and human capital. To measure consumer evaluation of policies from the demand side, she conducted internet surveys and analyzed the responses with various econometric methods.

In Chapter 2, the author measures Japan's electricity demand and evaluates the policy direction using discrete choice experiments and choice probability experiments. In Chapter 3, the author estimates the value of a brand-new technology—autonomous driving cars that equip artificial intelligence (AI)—using discrete choice experiments. Here, the moral influence of AI technology and the required policy are discussed. In Chapter 4, the author surveys the effectiveness of career education policy, using the difference-in-difference method. Chapter 5 summarizes and concludes.

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[2] Sato, Ryuzo, and Tamaki Morita. 2009. "Quantity or quality: the impact of labour saving innovation on US and Japanese growth rates, 1960-2004." *Japanese Economic Review* 60 (4): 407–34.

Chapter 2　Evaluation of Energy Policy

― Consumer Willingness to Pay for Electricity after the Great East Japan Earthquake ―

2.1 Introduction

The Great East Japan Earthquake on March 11, 2011 (hereafter, the 3.11), severely damaged the Fukushima Daiichi nuclear power plants and reminded people of the potential risks of an electricity supply shortage and the effects of radiation.[3] Consumers began to think again about alternative sources of electricity. Although nuclear power had been a crucial source of clean and stable energy before the 3.11, the spread of radioactive materials from the Fukushima plants made citizens disapprove of nuclear power energy. For example, according to the 89,124 public comments on Japan's future energy mix scenarios collected by the government in August 2011, more than 80% of the respondents favored a scenario involving 0% nuclear electricity in 2030.[4]

This study applies both choice probability experiments and discrete choice experiments to determine citizens' willingness to pay (WTP) for residential electricity produced from different energy sources. Further, we hypothetically evaluate the three energy-mix scenarios proposed by the Japanese government. Additionally, we measure the effects of conveying positive and negative information regarding nuclear energy on WTP.

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[3] Applying conjoint analysis, Tanaka and Ida (2013) observed awareness of voluntary electricity conservation among households after the Great East Japan Earthquake.

We find that, on average, consumers have a negative WTP for electricity produced by nuclear power, regardless of the information they read, and that their WTP for an energy-mix change is less than the price increase already planned by electrical companies, which do not have any prospects for an actual change in their energy mix.

There is a large body of literature measuring WTP for residential electricity in various countries. In the US, Roe et al. (2001) analyzed US consumer demand for environmental attributes of deregulated residential electricity services. They combined a survey designed to elicit consumers' WTP for such attributes and a hedonic analysis of actual price premiums charged for green electricity in several deregulated markets. From 835 valid responses obtained from eight US cities, they found that only specific population segments were willing to pay larger premiums for emission reductions. A hedonic approach also indicates that a 1% increase in renewable sources increases the premium for a household using 1,000 kWh per month by approximately $6 per annum. Borchers et al. (2007) estimated WTP for voluntary participation in green energy electricity programs with 128 completed interview surveys. Their model estimated WTP for a generic green energy source and compared this estimate to WTP for green energy from specific energy sources, including wind, solar, farm methane, and biomass. They found that there exists a positive WTP for green energy electricity in general but that biomass and farm methane provided less utility than did the other three green sources.

Narrowing the topics, Soskin and Squires (2013) investigated WTP for solar water heating systems, photovoltaic (PV) rooftop systems, and a green pricing (GP) control

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[4] The expected price change for each scenario was not provided by the government.

group. Collaborating with a city-run public utility in Florida to mail field surveys to nearly 25,000 electricity customers, the authors found that homeowner home rooftop solar (HRS) and GP participation rates were comparable. Among respondents' attributes included in the analysis, education, income, and environmental support displayed the expected direct impact on WTP for HRS and GP.

In Europe, Willis et al. (2011) focused on respondents' age attributes. They investigated whether households made up of older people were less inclined to adopt new technologies and whether those households had different behavioral responses to energy efficiency compared with the rest of society. Through a computer-assisted personal interview (CAPI) in late 2007, they obtained 1,279 questionnaires from households in Britain. Households with members aged 65 and above were considerably less likely to adopt microgeneration renewable energy technologies (solar thermal, solar voltaic, or wind power) compared with the rest of the population. Zorić and Hrovatin (2012) analyzed the WTP for electricity generated from renewable energy sources in Slovenia. In 2008, they conducted a household survey, which was a combination of an Internet and a field survey, to obtain 450 responses. The results imply that the decisions regarding "whether to participate in green electricity programs" and "how much to pay for green electricity" were influenced by different factors. While age had a negative influence on both decisions, education and environmental awareness exhibited a positive influence on the decision of whether to contribute. The decision of how much to contribute primarily depended

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Therefore, the expected price change might not have been considered clearly by the public.

on household income. These researchers also provided a concise literature survey of the estimated WTP for green electricity (Zorić and Hrovatin, 2012, Table 1, p. 18.)

In Asia, Nomura and Akai (2004) reported the results of a survey using the contingent valuation method (CVM) of the willingness of Japanese households to pay more, in the form of a flat monthly surcharge, for renewable energy. The median value of WTP for renewable energy for Japanese households was approximately ¥2,000 per month per household (US$16.7 at an exchange rate of ¥120 per US$). Yoo and Kwak (2009) used CVM to obtain estimates of the WTP values for raising the ratio of green electricity in Korea. They used 800 face-to-face interviews to derive a positive WTP for green electricity. Zhang and Wu (2012) identified market segments and estimated the residents' WTP for green electricity in China. Applying a CVM with the payment card method to an e-mail survey, they received 1,139 replies from respondents in Jiangsu province; they found that those with high income and higher education had a higher WTP and that a Veblen effect existed in certain Chinese market segments.

The literature above generally focuses on WTP for natural, renewable energy and does not include electricity generated by nuclear energy. Some literature deals solely with nuclear power electricity and related facilities. Using CVM, Jun et al. (2010) estimated the social value of consumers' WTP for nuclear energy. Using data from 329 face-to-face interviews from four metropolitan areas and four local areas with nuclear power plants in Korea, they suggested that the social value of nuclear energy increased by approximately 68.5% with the provision of adequate information about nuclear energy to the public. Schneider and Zweifel (2013) experimentally measured marginal WTP for increased insurance coverage against the risk of an accident at the nuclear power plant (MWPC) and WTP for solving the nuclear waste disposal problem (WTPW). Using a stated choice experiment in Switzerland, they tested two crucial predictions. First, once they controlled for attitudes influencing the choice of residential location, MWPC values should decrease and then increase with distance from the plants. Second, however, such an effect should be absent from WTPW values. Their results largely confirmed both predictions, lending credence to the estimated MWPC of US$1.20 per year for 1% more coverage and WTPW of US$125 per year for solving the waste disposal problem. Frey et al. (1996) provided an interesting interpretation of the relationship between the political and market behavior of citizens regarding local disamenities. They empirically tested the role of monetary compensation for low- and mid-level radioactive nuclear waste repositories in a small village in Switzerland. Once compensation was introduced, citizens ignored the opportunity costs of rejecting financial rewards and investment opportunities at the polls. Nevertheless, the expected compensation left its mark on their private behavior, and citizens demanded new moral arguments that were consistent with their economic interests, such as highlighting the moral virtues of accepting the facility.

Our research has two novel aspects. First, we measured the impacts of the nuclear-related information by letting respondents answer two sets of conjoint questions, one before reading the information, and the other after reading it, setting an interval. Second, we adopted a choice probability analysis and the usual choice analysis and compared the estimated results. Additionally, we hypothetically calculated a monetary evaluation based on the governments' proposed scenario of the Japanese energy mix. We find that on average, Japanese consumers are willing to pay approximately 6% or more of the electricity fee based on the scenario of raising the ratio of renewable energy.

Section 2.2 explains the method we used, and Section 2.3 shows the results of our surveys. In Section 2.4, by using these WTPs, we calculate Japanese citizens' evaluation of the government's energy mix scenarios for the year 2030.

2.2 Method

We conducted two consecutive web-based surveys from March 9 to 13 and March 23 to 28, 2012. Both are named *Survey on Electric Consumption in Japan*. Before the surveys, we held two focus group discussions and one online pretest with 1,111 samples to improve the questions.[5] The first survey collected 5,318 samples (response rate: 18.19%). One of three types of information was randomly presented to the respondents after they answered the first of the conjoint questions. We conducted the second survey exclusively with respondents to the first survey, where the samples amounted to 3,339 (response rate: 62.83%). During the second survey, respondents reviewed the information from the first survey to recall what they had learned the previous time. Then, they answered the second of the conjoint questions. Thus, the difference between the WTP calculated from the first survey and the second survey reveals the effects of the information. The WTP was measured using the choice probability method and the multinomial logit (MNL) and latent class method. (See Appendix 2.A for details.)

[5] The data were collected with the cooperation of Nikkei Research, Inc.

2.2.1 Design

We designed the conjoint questions to examine people’s demand for four variables: the sources of electric power generation, the stability of the electricity supply, the carbon dioxide emissions from electric power generation, and the monthly electricity fee (see Table 2.1). We did not include the side effects of adopting natural energy, such as wind turbine noise or possible damage to solarpanels, because, in 2012, people in Japan were still not familiar enough with the new energy sources. Since people had not learned enough about the side effects, we thought including these attributes might distract the respondents from making choices.

Giving respondents a choice of electric power source was extremely meaningful in Japan at the time. Japanese consumers were not able to choose the source of home electricity supply due to the regulated electricity market, but the government planned to deregulate that market in 2016. There was no detailed plan for deregulation, but the time that consumers would be able to choose the source of their electricity by choosing their electricity companies had been approaching. We asked respondents to

Table 2.1 Electricity attributes and levels provided in the survey questions

Source of electric power generation (four levels)	Stability of the electricity supply (two levels)	Carbon dioxide emissions from electric power generation (five levels)		Monthly electricity fee (five levels)
		Nuclear, Solar, Wind	Natural gas	
Natural gas	Stable	20% decrease	-	¥1,500 increase
Nuclear	A short blackout could happen	10% decrease	-	¥1,000 increase
Solar		Unchanged	Unchanged	¥500 increase
Wind		-	10% increase	Unchanged
		-	20% increase	¥500 decrease

Source: *Survey on Electric Consumption in Japan*

imagine choosing electric companies that produce electricity from one of the sources in Table 2.1.

We made the experimental design based on an orthogonal design. To minimize the burden of making many repeated choices, we blocked the design into eight sets, each comprising eight choice occasions. Respondents were randomly assigned to one of the eight blocks and presented with one choice set at a time to minimize any effects of learning or fatigue. We used the same sets of questions in the two survey waves.

Respondents were asked to state their probabilities of choosing each alternative. As Figure 2.1 shows, they chose aspects from combinations of Cards A and B that sum to 100%. This method permits respondents to express uncertainty about their behavior.[6]

	Card A	Card B
Source of electric power generation	Solar	Wind
Stability of the electricity supply	A short blackout could happen	Stable
Carbon dioxide emissions from electric power generation	10% decrease	20% decrease
Monthly electricity fee	Unchanged	¥500 down
	Card A	Card B

25% 75% ▼

Figure 2.1 An example of a pair of cards

Note: The probabilities are chosen from the pull-down menu below the card; the menu lists the probabilities in the form of ranges that increased by 5%.
Source: *Survey on Electric Consumption in Japan*

[6] Manski (1990) explains how researchers can measure respondents' percent chance that they would choose an action by using this setting.

2.2.2 Relationship of Methods

We followed the literature and used several frameworks to analyze the experimental data. Figure 2.2 shows the eight models we used and their classification. The models are classified by the treatment of data collected in the surveys. In Models A1, A2, B1, and B2, we give numerical values to attributes of energy sources according to the average recognition of respondents.

In Models C1, C2, D, and E, each energy source is evaluated separately. Our experiments give the choice probabilities of respondents. To compare these probabilities with the generally used method, we arrange the probabilities as

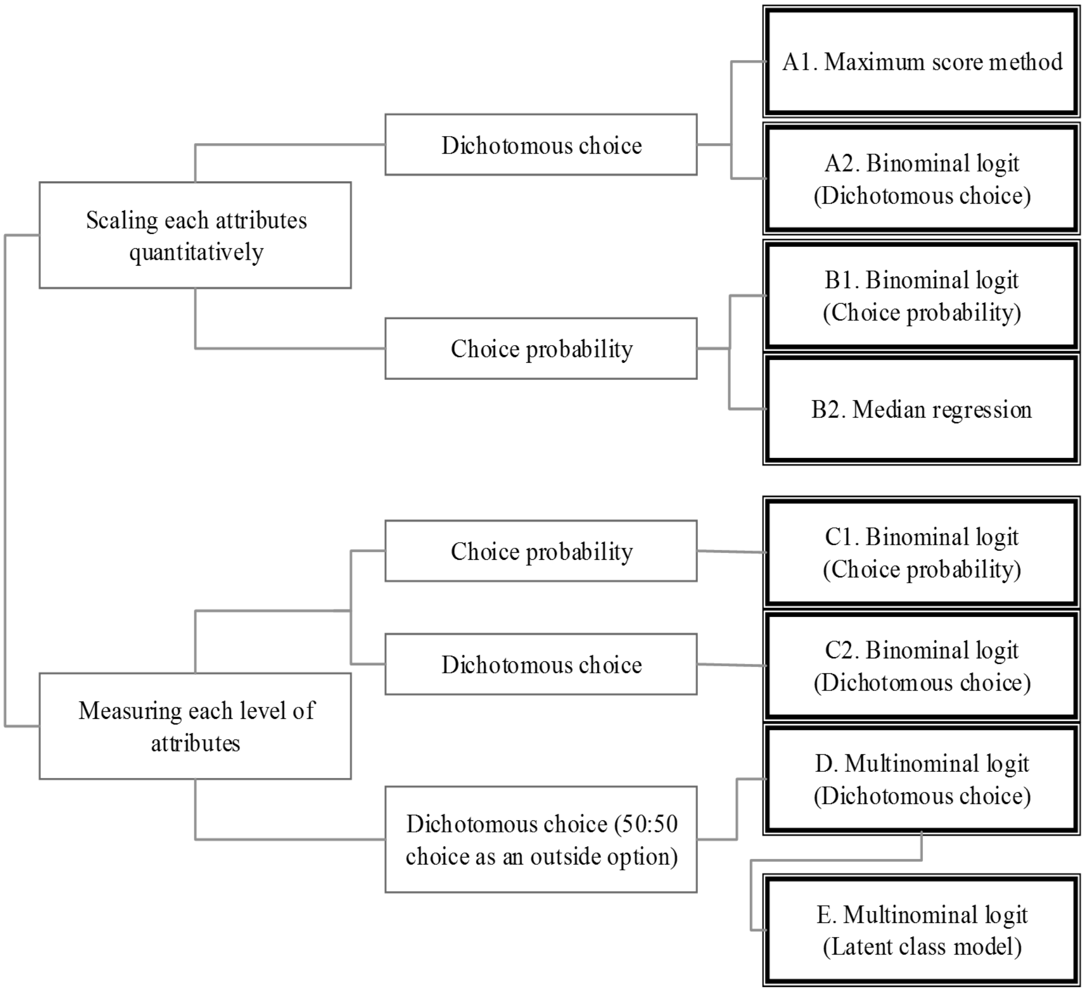

Figure 2.2 Methods

Source: Authors

dichotomous choices by converting a chosen probability of less than 50% to zero and a chosen probability of greater than 50% to one. In Models C1 and C2, responses of 50% are randomly assigned either zero or one. In Models D and E, responses of 50% are interpreted as an outside option, and the choices are converted to a choice among Card A, Card B, and No Buy.

Fundamental theories of these models are demonstrated in Appendix 2.A.

2.3 Results

2.3.1 Data

Attributes of the respondents are outlined in Table 2.2. The male to female ratio in Survey 2 is slightly greater than that of the national population because men tended to remain in the second survey. The age distribution did not change much between the first and second surveys; only those under the age of 30 years had significantly lower participation in Survey 2. The area distribution indicates that there was lower participation from those in Tohoku prefecture due to the effects of the 3.11 earthquake. We asked annual income and education in the second survey to balance the burden of respondents to answer these fundamental questions.

We found in the focus group sessions that even energy-conscious citizens are not aware of the actual mix of Japanese energy. Therefore, in the first survey, we showed a figure for Japan’s energy sources before the quake (thermal 61.7% comprised coal 24.7%, liquefied natural gas 29.4% and petroleum 7.6%; nuclear 29.2%, hydro 8.1%, and new energy-renewables except hydro 1.1%) and asked the respondents how much renewable energy they want by 2020 and 2050 (Figure 2.3). This question indicates how citizens evaluate former Prime Minister Naoto Kan’s intention to

Table 2.2 Selected attributes of respondents

		Survey 1		Survey 2		National
		Count	Ratio	Count	Ratio	Ratio
Sex	Male	2,808	52.8	1,866	55.9	49.9 [a]
	Female	2,510	47.2	1,473	44.1	50.1
Age	< 30	795	14.9	452	13.5	16.3 [b]
	30–39	1,064	20.0	646	19.3	21.3
	40–49	936	17.6	603	18.1	21.0
	50–59	1,171	22.0	758	22.7	19.1
	60–69	1,352	25.4	880	26.4	22.3
Area	Hokkaido	302	5.7	185	5.5	4.3 [c]
	Tohoku	288	5.4	179	5.4	7.3
	Kanto	1,769	33.3	1,110	33.2	33.0
	Chubu	1,003	18.9	634	19.0	17.1
	Kinki	957	18.0	609	18.2	17.8
	Chugoku	317	6.0	189	5.7	5.9
	Shikoku	151	2.8	100	3.0	3.1
	Kyushu	531	10.0	333	10.0	11.4
Annual Income	$I < 2$			233	7.0	18.5 [d]
	$2 \leq I < 3$			188	5.6	12.8
	$3 \leq I < 4$			346	10.4	13.0
	$4 \leq I < 5$			408	12.2	11.1
	$5 \leq I < 6$			357	10.7	9.6
	$6 \leq I < 7$			293	8.8	7.7
	$7 \leq I < 8$			271	8.1	6.3
	$8 \leq I < 9$			244	7.3	5.2
	$9 \leq I < 10$			216	6.5	4.0
	$10 \leq I < 11$			136	4.1	2.8
	$11 \leq I < 12$			75	2.2	2.1
	$12 \leq I < 15$			139	4.2	3.8
	$15 \leq I < 20$			70	2.1	2.0
	$20 \leq I$			25	0.7	1.3
	N. A.			338	10.1	-
Education (Highest completed)	High school or less			785	23.5	63.6 [e]
	Vocational & junior college			668	20.0	32.8
	Bachelor's degree			1,627	48.7	
	Graduate degree			207	6.2	
	Other			52	1.6	3.6

Source: *Survey on Electric Consumption in Japan.* The sources for national data are as follows.

a. Calculated by the authors for ages 20–69 from "Population by Age (Single Years) and Sex, and Sex Ratio (Table 16)" in Ministry of Internal Affairs and Communications (2010), *Final Report of the 2010 Population Census.*

b. Calculated by the authors for ages 20–69 from "Population 15 years of age and over by marital status (Table 21)" *ibid.*

c. "Population, Percent of Population, and Index of Population–Japan and Prefectures (Table 5)" *ibid*.

d. "Relative frequency distribution of households by household income (Table 9)" in Ministry of Health, Labour, and Welfare (2010) *Comprehensive Survey of Living Conditions*.

e. "Population 15 Years of Age and Over, by School Attendance and Type of Last School Completed (6 Groups) (Table 10-1)" Ministry of Internal Affairs and Communications (2010), *ibid*.

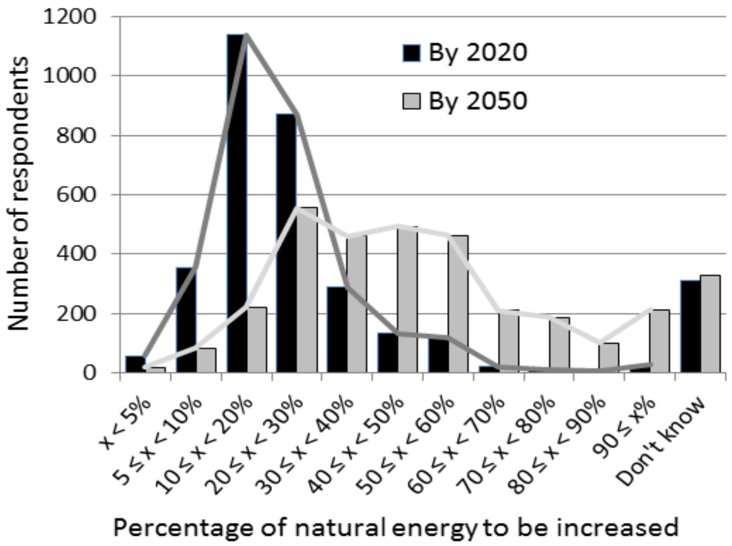

Figure 2.3 Respondents' preferences for natural energy by 2020 and by 2050

Note: The median for "By 2020" is in "10 ≤ x < 20%" and that for "By 2050" is in "40 ≤ x < 50%."
Source: *Survey on Electric Consumption in Japan*

lessen dependence on fossil fuels and nuclear power by setting a new goal to generate 20% of Japan's electricity from renewable resources in the 2020s. The median respondent wants renewable energy to be from 10% to less than 20% by 2020 and from 40% to less than 50% by 2050, with a more substantial variance for the 2050 expectations. People seem to welcome the former Prime Minister's goal and are willing to increase the ratio further.

2.3.2 Effects of Information

Each respondent was randomly assigned to read one of three kinds of information after answering the conjoint questions in the first survey. They were also asked to record their impression of each statement based on a four-point scale that rated the statement in terms of its familiarity, credibility, usefulness, and interestingness, from most to least. To ensure that the information did not affect respondents' conjoint answers, the respondents were told (before reading the information) that they would not be able to go back to the questions already seen. On the second survey, the respondents reread the same information to remind them about the information and answered the second set of conjoint questions.

Table 2.3 shows the information presented to respondents and the corresponding impression scores. We chose positive and negative information on nuclear power electricity in Japan. After the 3.11, nuclear energy's reputation generally decreased, as stated in Section 1, and we expected negative evaluations of nuclear power electricity in Japan to continue. Under this circumstance, we intentionally chose information on nuclear energy because we wanted to reveal how “positive” information can affect respondents.

The first set of information (*Positive*) is the base information with additional positive information on nuclear energy. The second set of information (*Negative*) is the base information with additional negative information on nuclear energy. The third set of information (*Base*) consists only of the base information. Respondents' impressions of each statement in the second survey are scored based on a four-point scale: “very familiar” = 10; “somewhat familiar” = 5; “somewhat unfamiliar” = −5; and “very unfamiliar” = −10. We used the impression from the second survey because when asked twice, respondents clearly recognize what the information implies. The results indicate that the information in *Negative* is judged to be more credible, useful, and interesting than the information in *Positive*, which may be why the proportion of *Negative* respondents who remained in the second survey was higher than the proportion of other respondents.

Table 2.3 Information and the readers' impressions

Information Sample: Number of respondents (Percentage to total) First Survey → Second Survey		
Positive Sample: 1,767 (33.2%) → 1,105 (33.0%)		
In recent times, the future of nuclear power generation concerns the Japanese people. Government officials, scientists, and engineers are discussing the safety issues and the economic impacts of such power generation. **Those who promote nuclear power generation have made the following notes.**		
1. The Fukushima Daiichi Plants' accident occurred because of its aging system, incomplete projection on tsunamis, and repeated human error. New plants that comply with higher safety standards will be safe.	Familiar(+)/Unfamiliar(−)	1.5
	Credible(+)/Noncredible(−)	−3.0
	Useful(+)/Useless(−)	−0.4
	Interesting(+)/Dull(−)	0.9
2. Nuclear power generation discharges less carbon dioxide. If we do not operate nuclear plants, then Japan's discharge levels will increase.	Familiar(+)/Unfamiliar(−)	2.3
	Credible(+)/Noncredible(−)	0.3
	Useful(+)/Useless(−)	0.7
	Interesting(+)/Dull(−)	1.8
3. The cost of plant construction is exorbitant. Using the existing plants will help utilize resources more efficiently.	Familiar(+)/Unfamiliar(−)	−0.2
	Credible(+)/Noncredible(−)	−2.3
	Useful(+)/Useless(−)	−1.6
	Interesting(+)/Dull(−)	−0.9
4. Operating nuclear power plants will help improve Japanese nuclear technology.	Familiar(+)/Unfamiliar(−)	−0.9
	Credible(+)/Noncredible(−)	−1.6
	Useful(+)/Useless(−)	−1.0
	Interesting(+)/Dull(−)	−0.4
5. If the nuclear fuel cycle continues, then it will reduce the used fuel inventory and Japan will not have to import uranium.	Familiar(+)/Unfamiliar(−)	−0.8
	Credible(+)/Noncredible(−)	−2.5
	Useful(+)/Useless(−)	−0.9
	Interesting(+)/Dull(−)	0.0
Negative Sample: 1,759 (33.1%) → 1,125 (33.6%)		
In recent times, the future of nuclear power generation concerns the Japanese people. Government officials, scientists, and engineers are discussing the safety issues and economic impacts of such power generation. **Those who disapprove of nuclear power generation have made the following notes.**		
1. Japan is a land with frequent earthquakes. Whatever the safety standards are, it is highly possible that nuclear power plants can cause severe accidents.	Familiar(+)/Unfamiliar(−)	4.6
	Credible(+)/Noncredible(−)	5.6
	Useful(+)/Useless(−)	5.3
	Interesting(+)/Dull(−)	6.1
2. To make nuclear fuels from uranium, carbon dioxide is discharged.	Familiar(+)/Unfamiliar(−)	−0.9
	Credible(+)/Noncredible(−)	4.4
	Useful(+)/Useless(−)	4.2
	Interesting(+)/Dull(−)	4.7
3. Nuclear plants generate surplus electricity at night, and the power is used for pumped-storage hydroelectricity. If we consider the costs, then nuclear power will be more expensive.	Familiar(+)/Unfamiliar(−)	−1.5
	Credible(+)/Noncredible(−)	4.0
	Useful(+)/Useless(−)	4.4
	Interesting(+)/Dull(−)	5.1
4. Present nuclear technology is never able to detoxify the radiation when it leaves the plants.	Familiar(+)/Unfamiliar(−)	2.9
	Credible(+)/Noncredible(−)	6.1
	Useful(+)/Useless(−)	6.1
	Interesting(+)/Dull(−)	6.4
5. Nuclear waste is a heavy burden to place on our descendants.	Familiar(+)/Unfamiliar(−)	4.7
	Credible(+)/Noncredible(−)	6.1
	Useful(+)/Useless(−)	6.1
	Interesting(+)/Dull(−)	6.7
Base Sample: 1,792 (33.7%) → 1,109 (33.1%)		
In recent times, the future of nuclear power generation concerns the Japanese people. Government officials, scientists, and engineers are discussing the safety issues and economic impacts of such power generation.	Familiar(+)/Unfamiliar(−)	3.2
	Credible(+)/Noncredible(−)	−0.3
	Useful (+)/Useless(−)	1.7
	Interesting(+)/Dull(−)	4.2

Source: *Survey on Electric Consumption in Japan*

Apart from the conjoint questions, we asked the respondents in both Surveys 1 and 2 whether they thought various sources of energy should be increased. The choices for each source and the corresponding points are as follows: “Should be increased” = 10; “May be increased” = 5; “No need to change” = 0; “May be decreased” = −5; “Should be decreased” = −10. Figure 2.4 shows the results. To make their decision making simple, we told respondents to ignore the cost differences between energies. Cost is an important aspect, but publicly estimated costs of energy thus far vary too widely depending on the assumptions used.

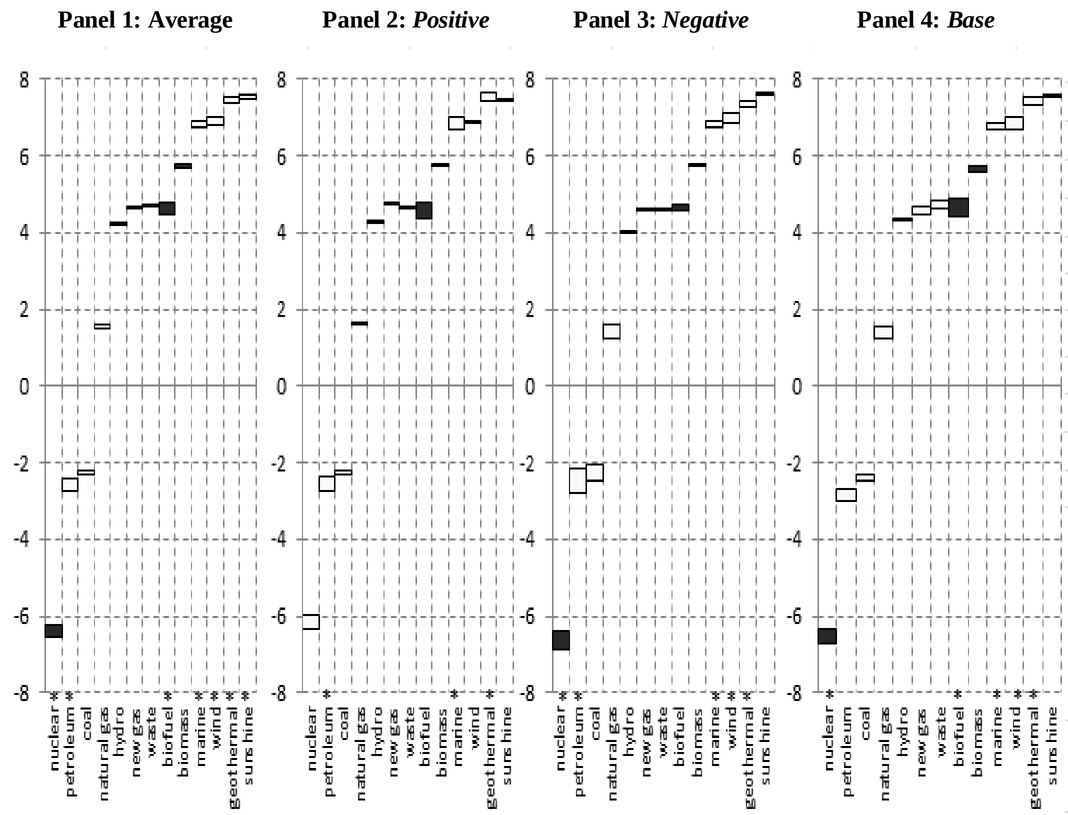

Figure 2.4 Respondents’ preferred sources of energy in the future change after reading the information

Note 1: White boxes indicate the energy sources that gained more points from the first survey to the second; black boxes indicate the energy sources that lost points.

Note 2: Sources of energy that showed statistically significant changes (at the 5% significance level) are denoted with an asterisk.

Source: *Survey on Electric Consumption in Japan*

The source most affected by the information, naturally, is nuclear power. Those who read the *Negative* and *Base* information believed more strongly that nuclear power should be decreased than did those who read the *Positive* information. The *Positive* information, to some extent, eased the belief that nuclear power should be decreased, but the variance is so large that this upward shift is not statistically significant. Petroleum and coal are not viewed so negatively, and after reading the *Negative* or *Positive* information, respondents softened their views on the importance of decreasing the use of petroleum. After reading any information, the respondents showed statistically significant improvement in their preference for marine and geothermal power.

Figure 2.5 shows the changes in the points caused by reading information on nuclear, natural gas, wind, and solar energy, with 95% confidence intervals (CI). The darkness of the diamonds indicates the significance level of the values. Black diamonds show that the change is significant at 5%, gray ones show 10% significance, and white ones show insignificance.

Readers of the *Negative* and *Base* information definitely lowered their evaluation of nuclear power electricity. Concerning natural gas, the changes were not significant in any group. For solar and wind power, those who read both *Positive* and *Negative* information widened the variance. The information solely affects respondents' evaluation of nuclear energy, and substitute or complementary effects on the other three energy choices were not apparent.

Four sources of energy in Figure 2.5 are baseloads in the conjoint questions. When we placed the four energies in sequence, we chose the scores in the first survey to

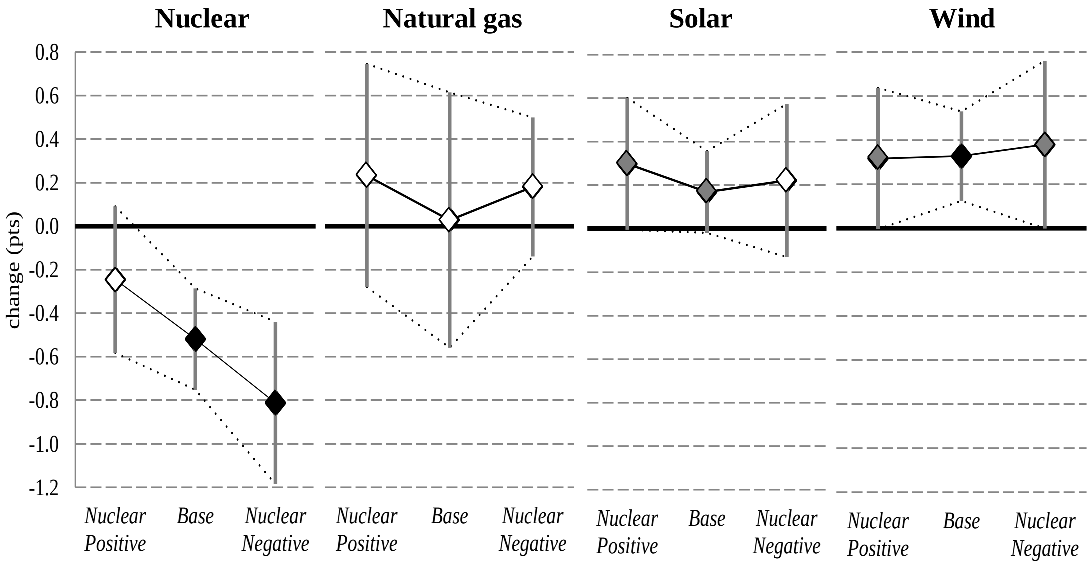

Figure 2.5 Respondents' preferred sources of energy in the future – CI of change for selected energy sources

Note 1: Bars represent 95% confidence intervals for changes.
Note 2: Black diamonds show that the change is significant at 5%, gray diamonds show 10% significance, and white diamonds show insignificance.
Source: *Survey on Electric Consumption in Japan*

quantify their attributes. We used the average scores here as proxies to set up the scale: nuclear = −6.2; natural gas = 1.5; wind = 6.8; and solar = 7.5.

2.3.3 Results of the Conjoint Analysis

2.3.3.1 *Choice Probability and Dichotomous Choice*

Blass et al. (2010) insist that eliciting choice probabilities overcomes the inadequacy of stated-choice analysis by permitting respondents to express uncertainty about their behavior in incomplete scenarios. In this research, we apply choice probability in Models B1, B2, and C1. Models B1 and C1 use the basic MNL model, and Model B2 uses Blass et al.'s approach, median regression. In the rest of the models, assuming that respondents always choose the alternative with higher choice probabilities, when they have to choose one (such as when they face general choice questions), we transformed choice probabilities to dichotomous choices to deal with the data as with general types of stated-choice analysis. Thus far, we have not found papers applying choice probability for estimating WTP other than by Blass et al. (2010). Our effort contributes to the literature.

2.3.3.2 *Estimated WTP*

Since our primary purpose is to derive WTP for electricity, we have shown the estimation results for marginal utility in Appendix 2.B. Here, WTP indicates marginal WTP, i.e., a change of payments that keeps an individual's utility constant when the attribute of one unit of consumption changes. This change is computed as the marginal rate of substitution between the cost and the consumption of attribute *x*. By setting $V_n = \boldsymbol{\beta}'\mathbf{x}_{nj}$, where V_n is the observed utility from our experiments, $\boldsymbol{\beta}$ is the $K \times 1$ vector of parameters for individual *n*, and $\mathbf{x}_{nj}$ is a $K \times 1$ vector of observed variables relating to alternative j[7] and assuming cost attribute *c* is a component of $\mathbf{x}_{nj}$, WTP for an attribute x_i for an individual *n* can be shown as a change in cost that is indifferent to the change in the consumption of attribute *i*.

$$WTP_{x_i n} = \frac{dc_n}{dx_{in}} = -\frac{\partial V_n / \partial x_{in}}{\partial V_n / \partial c_n} = -\frac{\beta_{x_{in}}}{\beta_{c_n}} \tag{2.1}$$

We show only the estimated WTP for the models in Table 2.4 (models that give quantitative levels to qualitative attributes) and Table 2.5 (models that measure each level of qualitative attribute). For each attribute, the first row presents the averages of all respondents, and the second to fourth rows represent the results for groups that read either *Negative, Base,* or *Positive* information. WTPs that are significant at the 5% level are depicted with an asterisk (*). The fifth and sixth rows show the difference compared with the base. The first groups of columns indicate the result of the first survey, the second group presents results from the second survey, and the third group shows the change from the first to the second survey.

Model A in Table 2.4 shows the results of using the maximum score method; just as shown in Blass et al. (2010), the results of the maximum score method were not too far from those scores of median regressions (Model B2), but there were

Table 2.4 Estimated WTP for Models A1, A2, B1, and B2

<table>
<tr><th></th><th></th><th colspan="4">First Survey
(Before reading the information)</th><th colspan="4">Second Survey
(After reading the information)</th><th colspan="4">Change</th></tr>
<tr><th></th><th></th><th>A1</th><th>A2</th><th>B1</th><th>B2</th><th>A1</th><th>A2</th><th>B1</th><th>B2</th><th>A1</th><th>A2</th><th>B1</th><th>B2</th></tr>
<tr><td rowspan="6">Energy</td><td>All</td><td>146.0|166.7</td><td>229.5 *</td><td>214 *</td><td>218 *</td><td>146.0|166.7</td><td>201.6 *</td><td>197.7 *</td><td>195.4 *</td><td>-</td><td>-27.8 #</td><td>-16.4 #</td><td>-22.8 #</td></tr>
<tr><td>Negative</td><td>〃</td><td>207.0 *</td><td>194 *</td><td>196 *</td><td>〃</td><td>193.1 *</td><td>169.8 *</td><td>161.6 *</td><td>-</td><td>-13.9 #</td><td>-24.0 #</td><td>-34.7 #</td></tr>
<tr><td>Base</td><td>〃</td><td>216.8 *</td><td>206 *</td><td>213 *</td><td>〃</td><td>185.1 *</td><td>185.5 *</td><td>182.3 *</td><td>-</td><td>-31.7 #</td><td>-20.1 #</td><td>-30.4 #</td></tr>
<tr><td>Positive</td><td>〃</td><td>258.7 *</td><td>243 *</td><td>231 *</td><td>〃</td><td>242.7 *</td><td>230.9 *</td><td>236.7 *</td><td>-</td><td>-16.0 #</td><td>-11.9 #</td><td>5.7 #</td></tr>
<tr><td>Negative-Base</td><td>-</td><td>-9.8 #</td><td>-12 #</td><td>-16 #</td><td>-</td><td>8.0 #</td><td>-15.7 #</td><td>-20.7 #</td><td>-</td><td>17.8 #</td><td>-3.8 #</td><td>-4.4 #</td></tr>
<tr><td>Positive-Base</td><td>-</td><td>41.9 #</td><td>37.1 #</td><td>18.3 #</td><td>-</td><td>57.6 #</td><td>45.4 #</td><td>54.4 #</td><td>-</td><td>15.7 #</td><td>8.3 #</td><td>36.1 #</td></tr>
<tr><td rowspan="6">Stability</td><td>All</td><td>-1500|-1000</td><td>-733.1 *</td><td>-950 *</td><td>-1008 *</td><td>-1500|-1000</td><td>-677.9 *</td><td>-918.4 *</td><td>-957.1 *</td><td>-</td><td>55.2 #</td><td>31.7 #</td><td>50.7 #</td></tr>
<tr><td>Negative</td><td>〃</td><td>-770.7 *</td><td>-991 *</td><td>-998 *</td><td>〃</td><td>-857.9 *</td><td>-952.5 *</td><td>-938.2 *</td><td>-</td><td>-87.2 #</td><td>38.7 #</td><td>59.5 #</td></tr>
<tr><td>Base</td><td>〃</td><td>-711.3 *</td><td>-937 *</td><td>-985 *</td><td>〃</td><td>-692.2 *</td><td>-909.3 *</td><td>-963.3 *</td><td>-</td><td>19.1 #</td><td>27.2 #</td><td>21.3 #</td></tr>
<tr><td>Positive</td><td>〃</td><td>-835.4 *</td><td>-1005 *</td><td>-1003 *</td><td>〃</td><td>-634.2 *</td><td>-918.8 *</td><td>-949.7 *</td><td>-</td><td>201.2 #</td><td>86.2 #</td><td>53.2 #</td></tr>
<tr><td>Negative-Base</td><td>-</td><td>-59.4 #</td><td>-55 #</td><td>-13 #</td><td>-</td><td>-165.7 #</td><td>-43.2 #</td><td>25.1 #</td><td>-</td><td>-106.2 #</td><td>11.5 #</td><td>38.2 #</td></tr>
<tr><td>Positive-Base</td><td>-</td><td>-124.1 #</td><td>-68 #</td><td>-18 #</td><td>-</td><td>58.0 #</td><td>-9.4 #</td><td>13.6 #</td><td>-</td><td>182.1 #</td><td>59.0 #</td><td>31.9 #</td></tr>
<tr><td rowspan="6">CO_2</td><td>All</td><td>16.6|25.0</td><td>-2.7</td><td>-2.3</td><td>-0.4</td><td>16.6|25.0</td><td>-1.2</td><td>-0.2</td><td>2.1 *</td><td>-</td><td>1.5</td><td>2.1</td><td>2.5</td></tr>
<tr><td>Negative</td><td>〃</td><td>-10.0 *</td><td>-10.7 *</td><td>-9.9 *</td><td>〃</td><td>-14.2 *</td><td>-8.6 *</td><td>-9.2 *</td><td>-</td><td>-4.3 #</td><td>2.1 #</td><td>0.7 #</td></tr>
<tr><td>Base</td><td>〃</td><td>-0.5</td><td>-1.3</td><td>0.8</td><td>〃</td><td>2.3</td><td>2.6</td><td>3.9 *</td><td>-</td><td>2.8</td><td>4.0</td><td>3.1</td></tr>
<tr><td>Positive</td><td>〃</td><td>0.9</td><td>2.3</td><td>9.5 *</td><td>〃</td><td>4.7</td><td>3.5</td><td>8.6 *</td><td>-</td><td>3.8</td><td>1.1</td><td>-0.9 #</td></tr>
<tr><td>Negative-Base</td><td>-</td><td>-9.5</td><td>-9.4</td><td>-11</td><td>-</td><td>-16.6</td><td>-11.2</td><td>-13.1 #</td><td>-</td><td>-7.1</td><td>-1.8</td><td>-2.4</td></tr>
<tr><td>Positive-Base</td><td>-</td><td>1.4</td><td>3.6</td><td>8.7</td><td>-</td><td>2.4</td><td>0.8</td><td>4.7 #</td><td>-</td><td>1.0</td><td>-2.8</td><td>-4.1</td></tr>
</table>

* 5% significance level.
# Changes or differences with significant minuend and subtrahend
Note 1: The resulting WTPs for Model A1 are shown as ranges. See Appendix 2.B for details.
Note 2: Energy: WTP for a point increase in energy score
Stability: WTP for “a short blackout could happen” compared with “stable”
CO_2: WTP for a percentage increase in CO_2 emission
Source: *Survey on Electric Consumption in Japan*

[7] See Appendix 2.A.

Table 2.5 Estimated WTP for Models C1, C2, and D

			First Survey			Second Survey			Change		
			C1	C2	D	C1	C2	D	C1	C2	D
Energy (Compared to Natural gas)	Nuclear	All	-2626.6 *	-2577.8 *	-2379.7 *	-2318.6 *	-2036.3 *	-1961.3 *	308.0 #	541.5 #	418.3 #
		Negative	-2620.1 *	-2859.4 *	-2514.0 *	-2126.0 *	-2007.1 *	-1877.3 *	494.1 #	852.3 #	636.7 #
		Base	-2573.1 *	-2470.7 *	-2245.5 *	-2117.6 *	-1876.6 *	-1756.9 *	455.5 #	594.1 #	488.6 #
		Positive	-2871.9 *	-2576.1 *	-2502.2 *	-2738.7 *	-2436.8 *	-2373.6 *	133.2 #	139.3 #	128.6 #
		Negative-Base	-47.0 #	-388.7 #	-268.5 #	-8.4 #	-130.5 #	-120.4 #	38.6 #	258.2 #	148.1 #
		Positive-Base	-298.9 #	-105.4 #	-256.8 #	-621.1 #	-560.2 #	-616.7 #	-322.2 #	-454.8 #	-360.0 #
	Solar	All	485.4 *	389.2 *	725.6 *	535.1 *	623.4 *	863.9 *	49.7 #	234.2 #	138.3 #
		Negative	304.6	-89.6	396.6 *	336.5	511.9 *	787.7 *	31.9	601.6	391.0 #
		Base	482.7 *	438.4 *	705.9 *	530.3 *	575.5 *	799.1 *	47.6 #	137.1 #	93.3 #
		Positive	561.7 *	733.3 *	974.7 *	565.8 *	673.8 *	1023.2 *	4.1 #	-59.5 #	48.4 #
		Negative-Base	-178.1	-528.0	-309.2 #	-193.9	-63.5 #	-11.4 #	-15.7	464.5	297.8 #
		Positive-Base	78.9 #	294.9 #	268.9 #	35.5 #	98.3 #	224.1 #	-43.5 #	-196.6 #	-44.8 #
	Wind	All	112.5	-9.8	251.8 *	189.9	244.1 *	389.6 *	77.4	253.8	137.8 #
		Negative	-157.7	-508.8 *	-78.4	-11.6	192.1	321.3	146.2	700.9	399.7
		Base	127.2	44.6	251.2	250.8	249.7 *	423.3 *	123.6	205.1	172.0
		Positive	279.3	279.4	525.1 *	191.6	235.6	512.5 *	-87.7	-43.8	-12.6 #
		Negative-Base	-284.9	-553.4	-329.6	-262.4	-57.6	-101.9	22.6	495.8	227.7
		Positive-Base	152.1	234.8	273.8	-59.2	-14.1	89.2 #	-211.3	-248.9	-184.6
Stability		All	-910.1 *	-878.2 *	-913.0 *	-877.3 *	-808.1 *	-885.2 *	32.8 #	70.1 #	27.9 #
		Negative	-935.0 *	-882.2 *	-944.6 *	-923.0 *	-969.9 *	-989.3 *	11.9 #	-87.7 #	-44.6 #
		Base	-889.1 *	-813.4 *	-896.3 *	-877.8 *	-806.5 *	-852.1 *	11.3 #	7.0 #	44.2 #
		Positive	-952.6 *	-994.2 *	-966.3 *	-862.2 *	-806.3 *	-882.6 *	90.4 #	187.9 #	83.7 #
		Negative-Base	-45.9 #	-68.8 #	-48.3 #	-45.3 #	-163.5 #	-137.2 #	0.6 #	-94.6 #	-88.8 #
		Positive-Base	-63.5 #	-180.8 #	-70.0 #	15.6 #	0.1 #	-30.5 #	79.1 #	180.9 #	39.5 #
CO_2 (Compared to no change)	CO_2 -20	All	290.2 *	304.2 *	354.0 *	240.5 *	226.5 *	251.2 *	-49.6 #	-77.7 #	-102.8 #
		Negative	287.6 *	264.7 *	334.7 *	325.0 *	367.8 *	333.3 *	37.4 #	103.0 #	-1.5 #
		Base	258.5 *	290.8 *	297.7 *	131.8	135.1 *	155.7 *	-126.7	-155.7 #	-142.0 #
		Positive	247.1	284.1 *	367.2 *	172.9	122.5	225.6	-74.3	-161.6	-141.7
		Negative-Base	29.2 #	-26.1 #	37.0 #	193.2	232.7 #	177.6 #	164.0	258.7 #	140.6 #
		Positive-Base	-11.3	-6.7 #	69.5 #	41.0	-12.6	69.9	52.4	-5.9 #	0.4 #
	CO_2 -10	All	420.3 *	451.1 *	314.4 *	270.3 *	244.6 *	118.9 *	-150.0 #	-206.5 #	-195.5 #
		Negative	549.6 *	631.4 *	466.5 *	422.4 *	423.7 *	245.5 *	-127.3 #	-207.8 #	-220.9 #
		Base	353.3 *	384.6 *	307.6 *	251.5 *	233.4 *	110.6	-101.7 #	-151.3 #	-197.0
		Positive	319.0 *	272.0	116.3	276.2	201.1	62.2	-42.8	-70.9	-54.1
		Negative-Base	196.4 #	246.8 #	158.9 #	170.8 #	190.3 #	134.9	-25.5 #	-56.5 #	-24.0
		Positive-Base	-34.3 #	-112.6	-191.3	24.6	-32.3	-48.5	58.9 #	80.3	142.9
	CO_2 +10	All	-642.6 *	-704.7 *	-232.5 *	-494.7 *	-409.7	-30.8	148.0 #	295.0	201.7
		Negative	-1081.5 *	-1376.0 *	-841.0 *	-731.0 *	-714.8 *	-255.7	350.4 #	661.2 #	585.4
		Base	-624.3 *	-559.9 *	-166.1	-437.8 *	-354.4 *	32.0	186.5 #	205.5 #	198.1
		Positive	-672.2 *	-566.4 *	-78.3	-613.1 *	-502.3 *	76.0	59.1 #	64.1 #	154.3
		Negative-Base	-457.2 #	-816.1 #	-674.9 #	-293.2 #	-360.5 #	-287.6	164.0 #	455.7 #	387.3
		Positive-Base	-47.9 #	-6.5 #	87.8	-175.3 #	-147.9 #	44.1	-127.4 #	-141.4 #	-43.8
	CO_2 +20	All	-625.0 *	-775.8 *	-531.8 *	-474.2 *	-387.1	-217.7 *	150.8 #	388.7	314.1 #
		Negative	-1034.0 *	-1420.0 *	-1121.4 *	-656.0 *	-681.6 *	-572.7 *	378.0 #	738.4 #	548.7 #
		Base	-641.9 *	-732.8 *	-427.7 *	-315.2	-250.5	-86.0	326.7	482.3	341.7
		Positive	-439.4	-390.3	-194.8	-567.5	-474.5	-243.9	-128.2	-84.2	-49.1
		Negative-Base	-392.1 #	-687.2 #	-693.8 #	-340.8	-431.1	-486.7	51.2	256.1	207.0
		Positive-Base	202.6	342.5	232.8	-252.3	-223.9	-157.9	-454.9	-566.5	-390.7
Constant		All	-86.4 *	542.9 *	3187.9 *	-75.9 *	429.8 *	3085.6 *	10.5	-113.0 #	-102.3 #
		Negative	-145.7	467.6 *	3438.2 *	-54.1	436.1 *	3019.5 *	91.6	-31.5 #	-418.8 #
		Base	-166.4 *	401.2 *	3104.7 *	-49.0	384.2 *	2878.5 *	117.4	-17.0 #	-226.2 #
		Positive	-73.3	615.7 *	3056.6 *	-111.1	510.0 *	3234.4 *	-37.8	-105.7 #	177.8 #
		Negative-Base	20.8	66.4 #	333.5 #	-5.1	51.9 #	141.0 #	-25.8	-14.5 #	-192.5 #
		Positive-Base	93.2	214.5 #	-48.1 #	-62.0	125.8 #	356.0 #	-155.2	-88.8 #	404.1 #

* 5% significance level
# Changes or differences with significant minuend and subtrahend
Source: *Survey on Electric Consumption in Japan*

differences to be noted. Above all, the effect of the information was not apparent. All ranges are identical regardless of which information the respondents saw, which implies that the difference of the information effect is not large enough to change the minimum of the objective score function (see Appendix 2.A.1). In the maximum score method, the value of the score of the source of electricity is less than that derived by median regression. Stability is more important in the maximum score method, and the value of the outage was the least (¥−1,500) compared with the results of the median regression. The values of CO_2 emission are positive, which was unexpected, and absolute values are more abundant.

The characteristics by attributes are as follows. As Table 2.4 shows, values for the energy score decreased after respondents read the information. This decrease implies that the distance between the most preferred energy source (solar) and the least preferred source (nuclear) decreased. For those who read the Positive information, reading the information did not make much difference. Table 2.5 shows that the WTP for nuclear energy varies from ¥−2,626.6 per month (C1) to ¥−2,379.7 (D) in the first survey, and from ¥−2,318.6 to ¥−1,961.3 in the second. The evaluations were negative but improved after information, no matter which information the respondents read. Contrary to our anticipation, readers of the Negative information improved their evaluation more than did those who read Base, while those who read the Positive information worsened their evaluation. Negative readers also valued wind power better, while Positive readers devalued it. Some WTP figures for solar and wind power are not significant.

Concerning the stability of the electricity supply, both Tables 2.4 and 2.5 show that the disutility of blackouts varies from ¥634.2 per month to ¥1,007.8, except with the maximum score method (A1), which revealed a band from ¥1,000 to ¥1,500. Readers of the Positive information clearly became less sensitive to stability after reading the information.

On evaluations of CO_2, most of the average WTPs for 1% increases are positive, contrary to our anticipation in Table 2.4. It is clear from Table 2.5 that the evaluation is not linear; the order is CO_2 +10% < CO_2 +20% < CO_2 −20% < CO_2 −10%. This order did not change after information, except with Model D.

Overall, the impact of the 3.11 was strong enough to make the effect of Positive information not clear enough. One of the reasons for this result may be the credibility of Positive information (as depicted in Table 2.3). The impact made respondents doubt the positive aspects of nuclear power electricity.

2.3.3.3 *Latent Class Analysis*

Here, we consider the heterogeneity in consumer preferences regarding the source of energy. Using the results of a survey of Queensland households regarding their WTP for renewable energy, Ivanova (2012) demonstrated that there is significant heterogeneity in WTP. Ivanova used Tobit regression models to estimate the bid functions for each group and found that age, gender, and education could be significant predictors of respondents' WTP for renewable energy. Among the studies that applied the latent class model to WTP, Zito and Salvo (2012) showed how unreliable information (defined there as inaccurate information) influenced user behavior and how much it discouraged public transport use. Besides, they found that consumer heterogeneity was caused by several factors: information inaccuracy, waiting time cutoff, household income, and an alternative specific constant.

To find the latent class clearly, we made the 50%–50% choice an outside option. The results are shown in column D in Table 2.5 and in Table 2.6. While the data in Table 2.5 show the results of the averages, Table 2.6 shows the results of each latent class. Respondents' attributes considered are in Table A2.8 in Appendix 2.B.

There are considerable differences among latent class groups. Class 1 is notable because its members would give approximately ¥800 per month for nuclear energy electricity, although the possibility for a respondent to be included in this group is only 5.6%. In contrast, respondents in Class 2, which could include approximately one-half of the respondents, value nuclear energy the least (they would like to

Table 2.6 Estimated WTP for each latent class (Model E)

		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Class probabilities		5.6%	48.6%	17.6%	14.8%	13.5%	0.0%
WTP derived from utility parameters (yen/month)							
Constants (base case):							
Natural gas, stable, constant CO_2		2941.8 ***	4209.8 ***	1433.2 ***	−762.6	5452.2 ***	−1741.0
Source of power	Nuclear	799.0 *	−5704.8 ***	−80.8	−4456.8 ***	274.8	1856.1
	Wind	844.2 *	676.6 ***	277.6 ***	2486.8 ***	−2440.8 ***	−18362.0
	Solar	576.7	1260.3 ***	295.7 ***	3616.0 ***	−1028.0 **	17495.4
Stability		−2589.4 ***	−1044.2 ***	−315.7 ***	−939.0 ***	−1277.1 ***	−3752.8
CO_2 emission changes by 2020	−20%	516.1 ***	398.9 ***	107.8 **	−1184.9 ***	750.3 **	6816.6
	−10%	545.6 ***	252.7 **	33.9	−2080.0 ***	698.3 **	−6830.8
	+10%	477.9	−239.1 *	−135.4 *	1755.7 ***	−205.1	−16917.7
	+20%	301.7	−372.5 **	−248.1 ***	1294.0 **	−209.5	−17973.7
Respondents' attributes							
Constant		<base>	0.53	1.76 ***	−0.44	0.18	3.85
Age			0.04 ***	−0.01	0.04 ***	0.01 *	−0.31
High income			−0.29	−0.50 *	−0.85 ***	−0.18	−1.20
Male			−0.94 ***	−0.52 **	−0.46 *	−0.28	−1.55
Fee conscious			0.44 **	0.44 *	0.07	0.00	−7.83
Read *Positive*			0.01	−0.05	0.06	0.56 **	−0.86
Read *Negative*			0.26	0.05	0.34	0.37	0.60
Number of observations		26712		Number of groups			3339
Log-likelihood function		−19889		Restricted log-likelihood			−29346
McFadden Pseudo R-squared		0.322					

*** 1%, ** 5%, and *10% significance levels
Source: *Survey on Electric Consumption in Japan*

subtract ¥5,704.8 per month if they change their source from thermal to nuclear). Compared with Class 1 respondents, Class 2 respondents are older, more likely to be female, and more cost-conscious.

2.4 Discussion—Policy Analysis

In this section, we evaluate the three government scenarios for the Japanese energy mix in 2030, as illustrated in Figure 2.6. Following Nomura and Akai (2004), we have calculated WTP for renewable energy,[8] and now we use WTP to appraise the actual scenarios for the future.

Taking the simple average of WTPs for wind and solar power as the WTP for renewable energy, we calculated the marginal change in total WTP for each scenario. These sums are considered the monthly payment changes that keep respondents' utility constant when the energy composition changes, assuming that other attributes remain unchanged.[9] Although greenhouse gas is in the scenarios, we assumed CO_2 to be constant because most of the estimated WTPs for CO_2 are not statistically significant. The results are shown in Table 2.7.

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[8] At the time of Nomura and Akai's (2004) research, the WTP for wind power was ¥2,000 per month, which is higher than our estimation. Nomura and Akai explain that the estimation in their survey is higher than that in other research due to factors such as the design of the questionnaire and the date of the survey.

[9] WTPs are derived from partial derivatives, and we cannot add up the WTPs of different attributes. However, if we assume a respondent n's total utility as a function of attributes, $U_n = U_n(x_1, x_2, c)$, where x_i (i = 1,2,c) represents the attribute and c is the cost for electricity, then by setting $dU_n = 0$,

$$dU_n = \frac{\partial U_n}{\partial x_{n1}} dx_{n1} + \frac{\partial U_n}{\partial x_{n2}} dx_{n2} + \frac{\partial U_n}{\partial c_n} dc_n = 0 \text{ and } dc_n = -\left(\frac{\partial U_n}{\partial x_{n1}} \Big/ \frac{\partial U_n}{\partial c_n}\right) - \left(\frac{\partial U_n}{\partial x_{n2}} \Big/ \frac{\partial U_n}{\partial c_n}\right).$$

By assuming $\left(\frac{\partial U_n}{\partial x_{n1}} \Big/ \frac{\partial U_n}{\partial c_n}\right) \simeq \left(\frac{\partial V_n}{\partial x_{n1}} \Big/ \frac{\partial V_n}{\partial c_n}\right) = WTP_{n1}$, the right-hand equality from equation (2.1), $WTP_{n1} + WTP_{n2}$, can be approximately dc_i, which keeps total utility constant.

Panel A: Nuclear zero scenario

	2010		2030
Nuclear	26%	⇨	0% (−25%)
Renewable	10%	⇨	35% (+25%)
Thermal	63%	⇨	65% (const.)
Greenhouse gas emission	-0.3%	⇨	-23%
Fossil fuel imports	17 T yen	⇨	16 T yen

Panel B: Nuclear 15% scenario

	2010		2030
Nuclear	26%	⇨	15% (−10%)
Renewable	10%	⇨	30% (+20%)
Thermal	63%	⇨	55% (−10%)
Greenhouse gas emission	-0.30%	⇨	-23%
Fossil fuel imports	17 T yen	⇨	16 T yen

Panel C: Nuclear 25～30% scenario

	2010		2030
Nuclear	26%	⇨	20% (−5%) ~ 25% (−1%)
Renewable	10%	⇨	30% (+20%) ~ 25% (+15%)
Thermal	63%	⇨	50% (−15%)
Greenhouse gas emission	-0.30%	⇨	-25%
Fossil fuel imports	17 T yen	⇨	15 T yen

Figure 2.6 Japanese energy mix scenarios for 2030

Source: National Policy Unit (2011b), modified by authors

Table 2.7 Marginal WTP change for the government's scenarios

	Nuclear Power Zero Scenario	Nuclear Power 15% Scenario	Nuclear Power 20−25% Scenario	
Amount to be changed (percentage points) in each scenario				
Nuclear power	*−25%*	*−10%*	*−5%*	*−1%*
Renewable energy power	*25%*	*20%*	*20%*	*15%*
Thermal power	*0%*	*−10%*	*−15%*	
Model A1: Choice probability—Maximum Score Method (1pt. = ¥156.3: mean of ¥146.0 and ¥166.7) (Nuclear = ¥−969, Renewable = ¥1118, Thermal = ¥234)				
Nuclear power	242.3	96.9	48.5	9.7
Renewable energy power	279.4	223.6	223.6	167.7
Thermal power	0.0	−23.4	−35.2	
Total	**521.8**	**297.0**	**236.8**	**177.4**
Model A2: Dichotomous choice—Binomial logit (1pt. = ¥201.6) (Nuclear = ¥−1250, Renewable = ¥1441, Thermal = ¥302)				
Nuclear power	312.5	125.0	62.5	12.5
Renewable energy power	360.4	288.3	288.3	216.2
Thermal power	0.0	−30.2	−45.4	
Total	**672.8**	**413.3**	**350.8**	**183.4**
Model B1, B2: Choice probability—Binomial logit and Median Regression (1pt. = ¥196.6) (Nuclear = ¥−1219, Renewable = ¥1406, Thermal = ¥295.0)				
Nuclear power	304.7	121.9	60.9	12.2
Renewable energy power	351.4	281.1	281.1	210.9
Thermal power	0.0	−29.5	−44.2	
Total	**656.2**	**373.5**	**297.8**	**178.8**
Model C1, C2, D: Multinomial logit (nuclear = ¥−2105, renewable = ¥474)				
Nuclear	526.3	210.5	105.3	21.1
Renewable	118.5	94.8	94.8	71.1
Total*	**644.8**	**305.3**	**200.1**	**92.2**
Model E: Latent class 1 (nuclear = ¥799, renewable = ¥710)				
Nuclear	−199.8	−79.9	−40.0	−8.0
Renewable	177.5	142.0	142.0	106.5
Total*	**−22.3**	**62.1**	**102.1**	**98.5**
Model E: Latent class 2 (nuclear =¥ −5705, renewable = ¥968)				
Nuclear	1,426.3	570.5	285.3	57.1
Renewable	242.0	193.6	193.6	145.2
Total*	**1,668.3**	**764.1**	**478.9**	**202.3**

Note: For Models C1, C2, D, and E, WTPs are relative to thermal energy electricity.

Source: *Survey on Electric Consumption in Japan*

The results of the median regression and the MNL model present the average WTP. Respondents that potentially belong to Latent Class 2 showed the highest WTP for the scenario with zero nuclear power. Considering that the respondents' average electricity fee per month is approximately ten thousand yen, the change in fee they can accept amounts to approximately 16.5% of the current fee (¥1,650 per month). In the public comment mentioned in Section 1, more than 80% of the Japanese citizens who posted public comments supported this scenario (Nuclear Power Zero), and more than half of the respondents from our survey are willing to accept that electricity prices will rise. This acceptance indicates that the respondents evaluate the risk of nuclear accidents as high, with the exception of the Latent Class 1 respondents (the population has a 5% probability to be in this group). These respondents accept the Nuclear Power Zero scenario only if they obtain ¥37.5 per month. Since they show a positive WTP for renewable energy, they can pay a positive amount for scenarios with 15% or more nuclear power.

After our survey, the Liberal Democratic Party-New Komeito ruling coalition overtook the government in December 2012. Subsequently, they changed the outlook of the long-term energy supply and demand and established nuclear power electricity as "an important baseload power source" with the expectation of covering 20%–22% of the total electricity by the fiscal year 2030. This outlook is closest to the "Nuclear Power 20%−25% Scenario" in Table 2.7. The respondents expressed the lowest WTPs for this scenario in all cases except for the Latent Class 1 respondents. Assuming no significant changes in consumer preferences over the next several years, if the expected deregulation in Japanese household electricity allows each household to choose the source of electricity (similar to Germany and other EU countries), then a majority of Japanese consumers will most likely choose renewable energy electricity (even if the price is higher than nuclear electricity). In other words, ironically, the latest energy mix outlook may not be realized if the household electricity market becomes completely deregulated and more competitive.

2.5 Conclusion

Recognition of the risk and uncertainty of the electrical power supply after the 3.11 earthquake and following nuclear power accidents changed consumer electricity demand both quantitatively and qualitatively. Consumers became more conscious of saving energy while they recognized the uncontrollability of nuclear power plants in the event of accidents. We conducted surveys to understand their WTP for various kinds of electricity.

We challenge the existing literature in two ways:

1) We measured the impacts of the information by letting respondents answer two conjoint questions: one before reading the information, and the other after reading it, with an interval between the two. Information that was positive to nuclear power electricity affected a small group of consumers, and negative information seemed to strengthen the preference for renewable energy.
2) We adopted choice probability analysis and the usual choice analysis. The results of the choice probability analysis are not very different from the choice analysis and can be a useful tool where consumers are conscious of their probability to choose one alternative among others.

Additionally, we calculated a monetary evaluation based on the governments' scenarios for the future Japanese energy mix. On average, Japanese consumers are willing to pay approximately 6% or more of the electricity fee for a scenario with an increased ratio of renewable energy. The results of our research indicate consumers' WTP for a shift to renewable energy, but the WTPs, on average, are not enough for an actual transition. There may be an economic cognitive dissonance, as indicated in Akerlof and Dickens (1982). Recent energy-mix prospects for 2030 are closest with Panel C of Figure 2.6, with nuclear 20-22%, renewable 22-24%, and thermal 56%[10]. The target can be accomplished without much additional payment from consumers. However, if consumers would like a drastic shift to renewable energy, as they indicated through their WTPs, they will have to pay more than they are ready to pay.

Our research reveals several problems that still need to be solved. Technically, we need to investigate better ways to translate qualitative data into quantitative data. As the situation concerning energy is continuously and rigorously changing, we need to conduct these kinds of surveys frequently. We propose that liberalization of the electricity industry will reflect the various tastes of Japanese consumers efficiently.

[10] Agency for Natural Resources and Energy (2018)

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Appendix 2.A: Theory

A2.A.1 Multinomial Logit (MNL) Model

The MNL theory is explained in Train (2003) as follows. The indirect utility function of individual n choosing alternative *j* among *J* alternatives at a choice occasion *t* is written as

$$U_{nj} = V_{nj} + \varepsilon_{nj}, \qquad i = 1, ..., J \tag{A2.1}$$

where $V_{nj} = V(x_{nj}, s_n)\ \forall j$ is the representative utility, representing attributes of the alternatives as faced by the decision maker, and s_n represents attributes of the individual. Factors affecting utility but not included in V_{nj} are represented by ε_{nj}. The logit model is obtained by assuming ε_{nj} to have an *iid* extreme value distribution.

The density of each unobserved component of utility is

$$f(\varepsilon_{nj}) = \exp(-\varepsilon_{nj}) \cdot \left\{\exp\left(-\exp(-\varepsilon_{nj})\right)\right\} \tag{A2.2}$$

and the cumulative distribution function is as follows:

$$F(\varepsilon_{nj}) = \exp\left(-\exp(-\varepsilon_{nj})\right).$$

Since the difference between two extreme value variables is distributed logistically, $\varepsilon^*_{nji} = \varepsilon_{nj} - \varepsilon_{ni}$ follows.

$$F(\varepsilon^*_{nji}) = \frac{\exp(\varepsilon^*_{nji})}{1 + \exp(\varepsilon^*_{nji})}. \tag{A2.3}$$

The probability that decision maker n chooses alternative i is

$$\begin{aligned} P_{ni} &= \text{Prob}\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \quad \forall j \neq i\right) \\ &= \text{Prob}\left(\varepsilon_{nj} < \varepsilon_{ni} + V_{ni} - V_{nj} \quad \forall j \neq i\right) \end{aligned}$$

It is the cumulative distribution for each ε_{nj} evaluated at $\varepsilon_{ni}+V_{ni}-V_{nj}$ and is equal to $\exp\left(-\exp\left(-(-\varepsilon_{ni}+V_{ni}-V_{nj})\right)\right)$ if ε_{ni} is considered given. This cumulative distribution over all $j \neq i$ is $P_{ni}\left|\varepsilon_{ni}=\prod_{j\neq i}\exp\left(-\exp\left(-(\varepsilon_{ni}+V_{ni}-V_{nj})\right)\right)\right.$. A value for ε_{ni} is not actually given, so the choice probability is the integral of $P_{ni}|\varepsilon_{ni}$ over all values of ε_{ni} weighted by its density (2A.2),

$$\begin{aligned}P_{ni} &= \int \left(P_{ni}|\varepsilon_{ni}\right) f(\varepsilon_{ni}) d\varepsilon_{ni} \\ &= \int \left(\prod_{j\neq i}\exp\left\{-\exp\left(-(\varepsilon_{ni}+V_{ni}-V_{nj})\right)\right\}\right)\exp(-\varepsilon_{ni})\cdot\left\{\exp\left(-\exp(-\varepsilon_{ni})\right)\right\} d\varepsilon_{ni}\end{aligned}$$

and the result is

$$P_{ni}=\frac{\exp(V_{ni})}{\sum_j \exp(V_{nj})},$$

which is the logit choice probability.

If we assume the utility function to take a linear-in-parameter functional form, $V_{nj}=\boldsymbol{\beta}'\mathbf{x}_{nj}$, then the logit probability becomes

$$P_{ni}=\frac{\exp(\boldsymbol{\beta}'\mathbf{x}_{ni})}{\sum_j \exp(\boldsymbol{\beta}'\mathbf{x}_{nj})}. \tag{A2.4}$$

Let K denote the number of covariates; then $\boldsymbol{\beta}$ is the $K\times 1$ vector of parameters for individual *n*, and $\mathbf{x}_{nj}$ is a $K\times 1$ vector of observed variables relating to alternative *j*.

In the empirical model, accounting for correlations between choices made by an individual, maximum-likelihood procedure can be applied. The probability of person *n* choosing the alternative that he or she was actually observed to choose can be expressed as

$$\prod_i (P_{ni})^{y_{ni}} ,$$

where y_{ni} = 1 if person n chose I, and y_{ni} = zero otherwise. Assuming that each decision maker's choice is independent of that of other decisionmakers, the likelihood function is

$$L(\boldsymbol{\beta}) = \prod_{n=1}^{N} \prod_i (P_{ni})^{y_{ni}} .$$

The log-likelihood function is then

$$LL(\boldsymbol{\beta}) = \sum_{n=1}^{N} \sum_i y_{ni} \ln P_{ni} , \qquad \text{(A2.5)}$$

and the estimator is the value of $\boldsymbol{\beta}$ that maximizes this function. MNL is called binomial logit when J = 2. This method is applied in Models A2, C2, and D, in Figure 2.2.

A2.A.2 Latent Class Model

We can cover consumer heterogeneity using the latent class model, where we assume that $\boldsymbol{\beta}$ takes a finite set of distinct values.[11] This application is one of the MNL models.[12] Supposing $\boldsymbol{\beta}$ takes R possible values, the probability of an individual who belongs to class r to choose is

$$P_{ni|r} = \frac{\exp(\boldsymbol{\beta}_r' \mathbf{x}_{ni})}{\sum_j \exp(\boldsymbol{\beta}_r' \mathbf{x}_{ni})} \qquad r = 1 \ldots R. \qquad \text{(A2.6)}$$

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[11] This explanation of the latent class model is derived from Greene and Hensher (2003).

[12] The MNL model is commonly extended to the mixed logit model. Although the authors do not deal with it here, we applied the panel mixed-logit model used in Uchida et al. (2014) to understand consumer heterogeneity.

Considering that an individual with a set of observable characteristics **z** who enters the model for class membership has a probability H_{nr} = $\exp(\theta_r'\mathbf{z}_n)\Big/\sum_{r=1}^{R}\exp(\theta_r'\mathbf{z}_n)$ ($\boldsymbol{\theta}_R$ = $\mathbf{0}$, r = 1, …, R) for class r, the probability for an individual n to choose profile i is (A2.7).

$$P_{ni} = \frac{\exp(\boldsymbol{\theta}_r'\mathbf{z}_n)}{\sum_r \exp(\boldsymbol{\theta}_r'\mathbf{z}_n)} \frac{\exp(\boldsymbol{\beta}_r'\mathbf{x}_{ni})}{\sum_j \exp(\boldsymbol{\beta}_r'\mathbf{x}_{ni})} \quad r = 1 \dots R. \tag{A2.7}$$

The log-likelihood function is

$$LL = \sum_n y_{ni} \ln P_n = \sum_n y_{ni} \ln\left[\sum_r H_{nr} P_{ni|r}\right].$$

Model E in Figure 2.2 applies this method.

A2.A.3 Choice Probability Model

When we use the choice probability model, we can define y_{ni} in equation (A2.5) as the proportion such that for each choice, $\sum_{i=1}^{J} y_{ni} = 1$ [13] (Models B1 and C1). We can also apply the choice probability method used by Blass et al. (2010). They developed the approach of Manski (1999), who described how elicited choice probabilities might be used to estimate random utility models with random coefficients.

The explanation below is summarized from Blass et al. (2010). An individual n's utility function (A2.1) can be rewritten as

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \mathbf{x}_{nj}\boldsymbol{\beta}_n + \varepsilon_{nj}. \qquad i = 1, ..., J\ . \tag{A2.8}$$

Suppose person n forms a subjective distribution for ε_n, derives the subjective probability that he or she would choose each alternative in an actual choice setting, and reports his or her subjective probabilities to the researcher. Let q_{nj} be the person's choice probability for alternative j. Then, q_{nj} is the subjective probability that person n places on the event that the realizations of ε_n will make option j optimal. Suppose that person n has a utility function (A2.8) and places a continuous subjective distribution Q_n on ε_n. Then, this person's subjective choice probability for alternative j is

$$q_{nj} = Q\left[\mathbf{x}_{nj}\boldsymbol{\beta}_n + \varepsilon_{nj} > \mathbf{x}_{nk}\boldsymbol{\beta}_n + \varepsilon_{nk}, \quad all\ k \neq j\right], \tag{A2.9}$$

of which the right-hand side yields a subjective random utility interpretation of elicited choice probabilities.[14] Applying the log-odds transformation to the result yields the linear mixed logit model,

$$\ln\left(\frac{q_{nj}}{q_{n1}}\right) = (\mathbf{x}_{nj} - \mathbf{x}_{n1})\boldsymbol{\beta}_n = (\mathbf{x}_{nj} - \mathbf{x}_{n1})\mathbf{b} + u_{nj} \qquad j = 2,\dots,J\ , \tag{A2.10}$$

where $\boldsymbol{\beta}_n = \mathbf{b} + \eta_n$, $u_{nj} = (\mathbf{x}_{nj} - \mathbf{x}_{n1})\eta_n$, and the alternative designated j = 1 is arbitrarily chosen.

We assume that the cross-sectional distribution of $\boldsymbol{\beta}$, hence $\boldsymbol{\eta}$, is statistically independent of $\mathbf{x}$. Set $E(\boldsymbol{\eta}) = 0$ as a normalization; it follows that $\mathbf{b} = E(\boldsymbol{\beta})$, $E(\boldsymbol{\mu}|\mathbf{x}) = 0$, and equation (2A.10) is the linear mean regression model.

$$E\left[\ln\left(\frac{q_{nj}}{q_{n1}}\right)\middle|\mathbf{x}\right] = (\mathbf{x}_{nj} - \mathbf{x}_{n1})\mathbf{b}\ . \tag{A2.11}$$

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[13] See Greene (2008) n. 55, p. 844 for details.
[14] The close relationship between elicited choice probabilities and stated choices is described in Blass et al. (2010, p. 423).

In equation (A2.11), the mean-preference parameters **b** can be consistently estimated using least squares, without the need to assume anything about the shape of the distribution of $\boldsymbol{\beta}$. One problem is the rounding of subjective probabilities. This problem can be resolved if preferences are symmetrically distributed with the center at **b**. This symmetry implies that the unobserved $\mathbf{u}_{nj}$ is symmetrically distributed around zero conditional on $\mathbf{x}_n$ and has a median zero conditional on $\mathbf{x}_n$. Then, we have the linear median regression model in equation (2A.9), the parameters of which may be estimated using least absolute deviations (LAD) in the absence of rounding:

$$M\left[\ln\left(\frac{q_{nj}}{q_{n1}}\right)\middle|\mathbf{x}\right] = (\mathbf{x}_{nj} - \mathbf{x}_{n1})\mathbf{b}\ . \qquad \text{(A2.12)}$$

The median of a random variable is known to have an invariance property to transformations that do not alter the ordering of values relative to the median. Thus, if y is a random variable with median M, then M is also the median of any function $f(y)$ such that $y < M \Rightarrow f(y) < M$ and $y > M \Rightarrow f(y) > M$. Equation (A2.12) continues to be the same linear median regression if small values of q are replaced by zero and large values by one. The coefficient **b** is the center of symmetry of the preference distribution, but it can also be referred to as the mean preference. Model B2 in Figure 2.2 applies this model.

A2.A.4 Maximum Score Estimation

All models described above need to assume that each respondent n believes (ε_{nj}, $j = 1, \ldots, J$) to be *iid* with an extreme value distribution. Manski (1999) presented a method that does not set this assumption. He suggested assuming only that each person n places subjective median zero on $\varepsilon_{nj} - \varepsilon_{ni}$ and that the cross-sectional distribution of $\boldsymbol{\beta}$ is symmetric. By this first assumption,

$$q_{nj} \geq 0.5 \Leftrightarrow (\mathbf{x}_{nj} - \mathbf{x}_{nk})\boldsymbol{\beta}_i \geq 0$$

holds, and by the second assumption,

$$P\left(q_{nj} \geq 0.5 \middle| \mathbf{x}\right) \geq 0.5 \Leftrightarrow (\mathbf{x}_{nj} - \mathbf{x}_{nk})\mathbf{b} \geq 0 \tag{A2.13}$$

holds. Inequality (A2.13) can be exploited to estimate b using the maximum score method (Manski, 1975, 1985).[15]

Assuming that each person n places subjective median zero on $\varepsilon_{nj} - \varepsilon_{ni}$, we can apply the maximum score method.

Defining y_{ng} for each game g = 1, …, G_n played by individual n to be

$$y_{ng} = \begin{cases} 1 & \text{if } q_{n2}^{g} \geq 0.5 \\ 0 & \text{otherwise} \end{cases}$$

where q_{n2}^{g} is the elicited probability of choosing alternative 2 in game g, the score function can be written

$$S(b) = \sum\nolimits_n G_i - \sum\nolimits_n \sum\nolimits_g \left| y_{ng} - I\left\{ \left(x_{n2g} - x_{n1g} \right) b \geq 0 \right\} \right|, \tag{A2.14}$$

where $I\{\bullet\}$ is the indicator function taking the value one when the expression within the brackets is true, and zero otherwise. The maximum score estimate is the set of values of b that minimizes the number of wrong predictions:

$$S^{*}(b) = \sum\nolimits_n \sum\nolimits_g \left| y_{ng} - I\left\{ \left(x_{n2g} - x_{n1g} \right) b \geq 0 \right\} \right|. \tag{A2.15}$$

This method is the one used in Model A1.

[15] Sherman (2012) concisely explains the developments of the maximum score method.

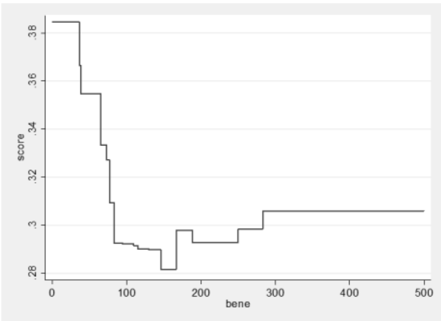
Appendix 2.B: Descriptive Statistics and Estimation Results for Each Model

A2.B.1 Model A1 (Maximum Score Method)

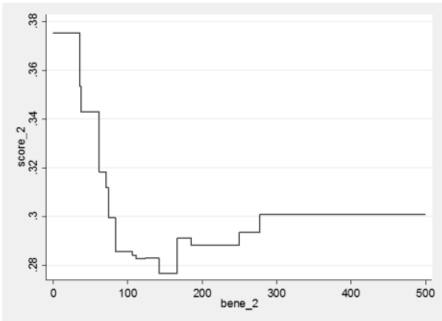
When we solve the objective function (A2.14), because the function is a step function and neither continuous nor smooth, the solution could take a range. In our case, all the solutions were derived as ranges, and there were no apparent differences among the respondents reading different information. As shown in Figure A2, the shape of the objective function changes before and after the information, but the ranges of the global minimum were the same except regarding the source of energy. In energy, the range expanded in the second survey. Among each kind of information, there was no difference in the range before and after respondents read the information.

Panel 1. Source of electricity (horizontal axis: yen per point)

a. Before reading information

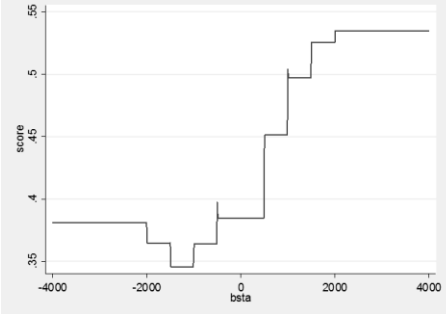


b. After reading information

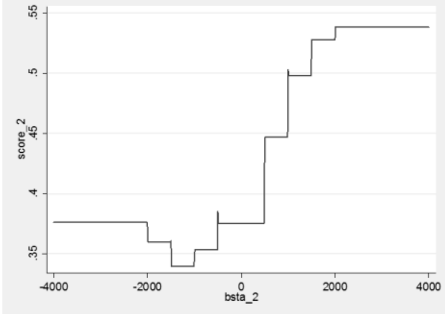


Panel 2. Stability (horizontal axis: yen for outage)

a. Before reading information



b. After reading information



Panel 3. CO_2 emissions (horizontal axis: yen per 1% increase)

a. Before reading information b. After reading information

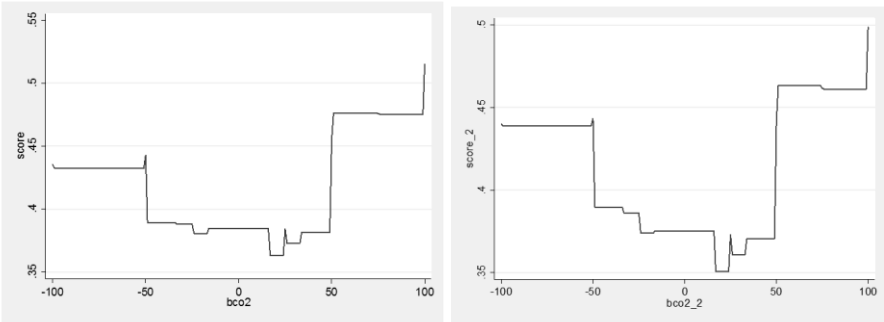


Figure A2 The objective function of choice probability, before and after information

Note: Functions before information are on the left; functions after information are on the right.
Source: *Survey on Electric Consumption in Japan*

A2.B.2 Model A2 (Dichotomous Choice–Binomial Logit)

When we investigated the effects of WTP among those who read *Positive* and *Negative* information, we chose those whose answers were inconsistent with the information. Therefore, the number of respondents we included for the information effect analysis was 490 of 1,105 for *Positive* and 509 of 1,125 for *Negative*; the total number of respondents (respondents multiplied by eight) was 3,920 and 4,072, respectively. In Table A2.1, we scaled the probability into dichotomous choice.

A2.B.3 Model B1 (Choice Probability–Binomial Logit)

We used choice probability in Model B1 and the results are in Table A2.2. Model B1 is comparable to Model A2.

Table A2.1 Estimation results of Model A2

		First Survey (Before reading the information)					Second Survey (After reading the information)				
		Coefficient	Standard Error	z-value	p-value		Coefficient	Standard Error	z-value	p-value	
All	Energy	0.1096 ***	0.0017	63.48	0.0000	N = 26712	0.1150 ***	0.0018	64.68	0.0000	N = 26712
	Stability	−0.3502 ***	0.0170	−20.63	0.0000	log L = −15422.6	−0.3866 ***	0.0173	−22.4	0.0000	log L = −15027.9
	CO_2	−0.0013 *	0.0007	−1.82	0.0694	AIC/N = 1.155	−0.0007	0.0007	−0.96	0.3361	AIC/N = 1.125
	Price	−0.0478 ***	0.0014	−35.17	0.0000		−0.0570 ***	0.0014	−40.88	0.0000	
Negative	Energy	0.1001 ***	0.0043	23.47	0.0000	N = 4072	0.1102 ***	0.0045	24.33	0.0000	N = 4072
	Stability	−0.3728 ***	0.0432	−8.63	0.0000	log L = −2377.7	−0.4893 ***	0.0447	−10.95	0.0000	log L = −2297.4
	CO_2	−0.0048 ***	0.0018	−2.65	0.0081	AIC/N = 1.17	−0.0081 ***	0.0019	−4.4	0.0000	AIC = 1.13
	Price	−0.0484 ***	0.0035	−14.01	0.0000		−0.0570 ***	0.0036	−16.07	0.0000	
Base	Energy	0.1145 ***	0.0031	37.42	0.0000	N = 8872	0.1200 ***	0.0032	37.76	0.0000	N = 8872
	Stability	−0.3756 ***	0.0298	−12.61	0.0000	log L = −5042.6	−0.4488 ***	0.0305	−14.69	0.0000	log L = −5042.6
	CO_2	−0.0003	0.0013	−0.22	0.8258	AIC/N = 1.138	0.0015	0.0013	1.17	0.2428	AIC/N = 1.099
	Price	−0.0528 ***	0.0024	−21.84	0.0000		−0.0648 ***	0.0025	−26.07	0.0000	
Positive	Energy	0.1209 ***	0.0047	25.86	0.0000	N = 3920	0.1228 ***	0.0047	25.9	0.0000	N = 3920
	Stability	−0.3905 ***	0.0454	−8.61	0.0000	log L = −2207.7	−0.3208 ***	0.0450	−7.13	0.0000	log L = −2191.7
	CO_2	0.0004	0.0019	0.21	0.8355	AIC/N = 1.128	0.0024	0.0019	1.23	0.2194	AIC/N = 1.12
	Price	−0.0467 ***	0.0036	−13.03	0.0000		−0.0506 ***	0.0036	−14.03	0.0000	

Note: 1%, 5%, and 10% significance levels are indicated by ***, **, and *.
Source: *Survey on Electric Consumption in Japan*

Table A2.2 Estimation results of Model B1

		First Survey (Before reading the information)					Second Survey (After reading the information)				
		Coefficient	Standard Error	z-value	p-value		Coefficient	Standard Error	z-value	p-value	
All	Energy	0.0874 ***	0.0016	54.25	0.0000	N = 26712	0.0907 ***	0.0016	55.37	0.0000	N = 26712
	Stability	−0.3878 ***	0.0164	−23.58	0.0000	log L = −16206.5	−0.4212 ***	0.0166	−25.36	0.0000	log L = −15955
	CO_2	−0.0009	0.0007	−1.34	0.1810	AIC/N = 1.214	−0.0001	0.0007	−0.11	0.9158	AIC/N = 1.195
	Price	−0.0408 ***	0.0013	−31.56	0.0000		−0.0459 ***	0.0013	−35.03	0.0000	
Negative	Energy	0.0806 ***	0.0040	20.04	0.0000	N = 4072	0.0833 ***	0.0042	20.02	0.0000	N = 4072
	Stability	−0.4123 ***	0.0421	−9.80	0.0000	log L = −2481.7	−0.4669 ***	0.0428	−10.92	0.0000	log L = −2448.2
	CO_2	−0.0045 **	0.0018	−2.51	0.0119	AIC/N = 1.221	−0.0042 **	0.0018	−2.38	0.0173	AIC/N = 1.204
	Price	−0.0416 ***	0.0033	−12.58	0.0000		−0.0490 ***	0.0033	−14.69	0.0000	
Base	Energy	0.0883 ***	0.0028	31.47	0.0000	N = 8872	0.0942 ***	0.0029	32.54	0.0000	N = 8872
	Stability	−0.4021 ***	0.0286	−14.05	0.0000	log L = −5358.9	−0.4617 ***	0.0292	−15.81	0.0000	log L = −5216.2
	CO_2	−0.0006	0.0012	−0.47	0.6390	AIC/N = 1.209	0.0013	0.0012	1.08	0.2779	AIC/N = 1.177
	Price	−0.0429 ***	0.0023	−18.91	0.0000		−0.0508 ***	0.0023	−21.99	0.0000	
Positive	Energy	0.0974 ***	0.0043	22.53	0.0000	N = 3920	0.1001 ***	0.0044	22.76	0.0000	N = 3920
	Stability	−0.4032 ***	0.0437	−9.23	0.0000	log L = −2334.8	−0.3984 ***	0.0436	−9.14	0.0000	log L = −2311.9
	CO_2	0.0009	0.0019	0.50	0.6156	AIC/N = 1.193	0.0015	0.0019	0.80	0.4213	AIC/N = 1.182
	Price	−0.0401 ***	0.0034	−11.78	0.0000		−0.0434 ***	0.0034	−12.67	0.0000	

Note: 1%, 5%, and 10% significance levels are indicated by ***, **, and *.
Source: *Survey on Electric Consumption in Japan*

A2.B.4 Model B2 (Median Regression)

Differences between the variables on Cards A and B are the explanatory variables. To measure the difference, we assigned values for the sources of electricity according to the score as measured in Figure 2.4 in Subsection 2.3.2. Table A2.3 demonstrates descriptive statistics, and Table A2.4 indicates the estimation results.

Table A2.3 Descriptive statistics for the median regression

		First Survey (Before reading the information)						Second Survey (After reading the information)					
		Mean	S.D.	Min	Max	Med	N	Mean	S.D.	Min	Max	Med	N
All	Choice probability (log)	−0.70	6.76	−11.513	11.513	0	26712	−0.74	6.84	−11.513	11.513	0	26712
	Energy (points)	0.20	9.00	−13.7	13.7	0.7	26712	0.24	8.98	−13.7	13.7	0.7	26712
	Stability	0.28	0.78	−1	1	0	26712	0.29	0.78	−1	1	0	26712
	CO_2	0.39	19.17	−40	30	10	26712	−0.20	19.18	−40	30	0	26712
	Price	204.1	1048.2	−2000	2000	500	26712	198.0	1050.8	−2000	2000	500	26712
Negative	Choice probability (log)	−0.82	6.71	−11.513	11.513	0	4072	−0.79	6.69	−11.513	11.513	0	4072
	Energy (points)	0.14	9.07	−13.7	13.7	0.7	4072	0.22	8.94	−13.7	13.7	0.7	4072
	Stability	0.27	0.78	−1	1	0	4072	0.27	0.78	−1	1	0	4072
	CO_2	−0.01	19.21	−40	30	0	4072	0.32	19.49	−40	30	10	4072
	Price	202.2	1045.4	−2000	2000	500	4072	192.7	1057.8	−2000	2000	500	4072
Base	Choice probability (log)	−0.87	6.75	−11.513	11.513	0	8872	−0.79	6.92	−11.513	11.513	0	8872
	Energy (points)	0.15	9.03	−13.7	13.7	0.7	8872	0.24	8.99	−13.7	13.7	0.7	8872
	Stability	0.27	0.78	−1	1	0	8872	0.29	0.78	−1	1	0	8872
	CO_2	0.66	19.06	−40	30	10	8872	−0.20	19.23	−40	30	0	8872
	Price	213.4	1042.2	−2000	2000	500	8872	197.0	1051.4	−2000	2000	500	8872
Positive	Choice probability (log)	−0.50	6.73	−11.513	11.513	0	9848	−0.69	6.80	−11.513	11.513	0	9848
	Energy (points)	0.28	8.92	−13.7	13.7	0.7	9848	0.18	9.02	−13.7	13.7	0.7	9848
	Stability	0.28	0.78	−1	1	0	9848	0.29	0.78	−1	1	0	9848
	CO_2	0.34	19.30	−40	30	10	9848	−0.48	19.03	−40	30	0	9848
	Price	200.1	1052.8	−2000	2000	500	9848	200.4	1046.4	−2000	2000	500	9848

Note: 1%, 5%, and 10% significance levels are indicated by ***, **, and *.
Source: *Survey on Electric Consumption in Japan*

Table A2.4 Estimation results of Model B2

		First Survey (Before reading the information)						Second Survey (After reading the information)				
		Coefficient	Standard Error	z-value	p-value			Coefficient	Standard Error	z-value	p-value	
All	Energy	0.1427 ***	0.0018	79.87	0.0000	N = 26712		0.6931 ***	0.0013	538.22	0.0000	N = 26712
	Stability	−0.6590 ***	0.0206	−32.06	0.0000			−0.7922 ***	0.0031	−259.68	0.0000	
	CO_2	−0.0003	0.0008	−0.31	0.7590	Pseudo R^2		0.0099 ***	0.0001	79.47	0.0000	Pseudo R^2
	Price	−0.0007 ***	0.0000	−42.61	0.0000	= 0.068		−0.0008 ***	0.0000	−349.92	0.0000	= 0.073
	Constant	−0.0365 **	0.0173	−2.11	0.0350			0.0000	0.0026	0.00	1.0000	
Negative	Energy	0.1302 ***	0.0046	28.35	0.0000	N = 4072		0.6202 ***	0.0215	28.91	0.0000	N = 4072
	Stability	−0.6615 ***	0.0535	−12.35	0.0000			−0.7661 ***	0.0508	−15.07	0.0000	
	CO_2	−0.0066 **	0.0022	−3.03	0.0020	Pseudo R^2		−0.0005	0.0020	−0.24	0.8080	Pseudo R^2
	Price	−0.0007 ***	0.0000	−16.63	0.0000	= 0.064		−0.0008 ***	0.0000	−22.30	0.0000	= 0.074
	Constant	−0.1022 **	0.0450	−2.27	0.0230			0.0033	0.0425	0.08	0.9380	
Base	Energy	0.1483 ***	0.0031	47.81	0.0000	N = 8872		0.7361 ***	0.0180	40.85	0.0000	N = 8872
	Stability	−0.6864 ***	0.0358	−19.19	0.0000			−0.8604 ***	0.0429	−20.07	0.0000	
	CO_2	0.0005	0.0015	0.36	0.7160	Pseudo R^2		0.0105 ***	0.0017	6.02	0.0000	Pseudo R^2
	Price	−0.0007 ***	0.0000	−25.91	0.0000	= 0.072		−0.0009 ***	0.0000	−27.69	0.0000	= 0.068
	Constant	−0.1091 ***	0.0302	−3.61	0.0000			0.0382	0.0361	1.06	0.2900	
Positive	Energy	0.1685 ***	0.0047	35.97	0.0000	N = 3920		0.7972 ***	0.0245	32.59	0.0000	N = 3920
	Stability	−0.7317 ***	0.0543	−13.48	0.0000			−0.7182 ***	0.0578	−12.44	0.0000	
	CO_2	0.0069 **	0.0022	3.14	0.0020	Pseudo R^2		0.0136 ***	0.0024	5.76	0.0000	Pseudo R^2
	Price	−0.0007 ***	0.0000	−18.14	0.0000	= 0.077		−0.0007 ***	0.0000	−17.15	0.0000	= 0.083
	Constant	−0.0442	0.0456	−0.97	0.3320			−0.0073	0.0489	−0.15	0.8820	

Note: 1%, 5%, and 10% significance levels are indicated by ***, **, and *.
Source: *Survey on Electric Consumption in Japan*

A2.B.5 Model C1 (Choice Probability–Binomial Logit)

To measure each energy attribute independently, we used choice probability in Model C1. The result of the binomial logit is presented in Table A2.5.

Table A2.5 Estimation results of Model C1

		First Survey (Before reading the information)					Second Survey (After reading the information)				
		Coefficient	Standard Error	z-value	p-value		Coefficient	Standard Error	z-value	p-value	
All	Constant	−0.0350 **	0.0154	−2.28	0.0227	N = 26712	−0.0347 **	0.0155	−2.23	0.0257	N = 26712
	Nuclear	−1.0630 ***	0.0468	−22.73	0.0000	log L = −16154	−1.0582 ***	0.0478	−22.16	0.0000	log L = −15907.4
	Solar	0.1964 ***	0.0425	4.62	0.0000	AIC/N = 1.21	0.2442 ***	0.0432	5.66	0.0000	AIC/N = 1.192
	Wind	0.0455	0.0447	1.02	0.3086		0.0867 *	0.0453	1.91	0.0557	
	Stability	−0.3683 ***	0.0178	−20.71	0.0000		−0.4004 ***	0.0180	−22.23	0.0000	
	CO_2 +20%	−0.2529 ***	0.0540	−4.69	0.0000		−0.2164 ***	0.0544	−3.98	0.0001	
	CO_2 +10%	−0.2601 ***	0.0482	−5.40	0.0000		−0.2258 ***	0.0490	−4.60	0.0000	
	CO_2 −10%	0.1701 ***	0.0288	5.91	0.0000		0.1234 ***	0.0289	4.27	0.0000	
	CO_2 −20%	0.1174 ***	0.0233	5.03	0.0000		0.1098 ***	0.0236	4.66	0.0000	
	Price	−0.0405 ***	0.0013	−30.21	0.0000		−0.0456 ***	0.0014	−33.60	0.0000	
Negative	Constant	−0.0596	0.0391	−1.52	0.1274	N = 4072	−0.0267	0.0394	−0.68	0.4972	N = 4072
	Nuclear	−1.0714 ***	0.1169	−9.17	0.0000	log L = −2469.9	−1.0507 ***	0.1231	−8.53	0.0000	log L = −2440.1
	Solar	0.1246	0.1072	1.16	0.2454	AIC/N = 1.218	0.1663	0.1120	1.48	0.1376	AIC/N = 1.203
	Wind	−0.0645	0.1133	−0.57	0.5693		−0.0057	0.1181	−0.05	0.9614	
	Stability	−0.3823 ***	0.0455	−8.41	0.0000		−0.4562 ***	0.0462	−9.87	0.0000	
	CO_2 +20%	−0.4228 ***	0.1390	−3.04	0.0023		−0.3242 **	0.1367	−2.37	0.0177	
	CO_2 +10%	−0.4422 ***	0.1213	−3.65	0.0003		−0.3613 ***	0.1266	−2.85	0.0043	
	CO_2 −10%	0.2248 ***	0.0723	3.11	0.0019		0.2087 ***	0.0757	2.76	0.0058	
	CO_2 −20%	0.1176 **	0.0598	1.97	0.0493		0.1606 ***	0.0603	2.66	0.0077	
	Price	−0.0409 ***	0.0034	−11.94	0.0000		−0.0494 ***	0.0035	−14.25	0.0000	
Base	Constant	−0.0691 ***	0.0266	−2.60	0.0094	N = 8872	−0.0249	0.0272	−0.92	0.3589	N = 8872
	Nuclear	−1.0676 ***	0.0799	−13.36	0.0000	log L = −5339.3	−1.0764 ***	0.0836	−12.88	0.0000	log L = −5203.4
	Solar	0.2003 ***	0.0729	2.75	0.0060	AIC/N = 1.206	0.2696 ***	0.0754	3.58	0.0003	AIC/N = 1.175
	Wind	0.0528	0.0770	0.69	0.4932		0.1275	0.0795	1.60	0.1086	
	Stability	−0.3689 ***	0.0309	−11.96	0.0000		−0.4462 ***	0.0316	−14.10	0.0000	
	CO_2 +20%	−0.2663 ***	0.0940	−2.83	0.0046		−0.1602 *	0.0951	−1.68	0.0921	
	CO_2 +10%	−0.2590 ***	0.0825	−3.14	0.0017		−0.2225 ***	0.0856	−2.60	0.0093	
	CO_2 −10%	0.1466 ***	0.0501	2.93	0.0034		0.1279 **	0.0508	2.52	0.0118	
	CO_2 −20%	0.1072 ***	0.0408	2.63	0.0086		0.0670	0.0415	1.62	0.1061	
	Price	−0.0415 ***	0.0023	−17.71	0.0000		−0.0508 ***	0.0024	−21.25	0.0000	
Positive	Constant	−0.0294	0.0406	−0.72	0.4698	N = 3920	−0.0484	0.0415	−1.17	0.2439	N = 3920
	Nuclear	−1.1517 ***	0.1250	−9.21	0.0000	log L = −2327.4	−1.1927 ***	0.1307	−9.13	0.0000	log L = −2303.5
	Solar	0.2252 **	0.1133	1.99	0.0468	AIC/N = 1.193	0.2464 **	0.1168	2.11	0.0349	AIC/N = 1.18
	Wind	0.1120	0.1189	0.94	0.3463		0.0834	0.1218	0.69	0.4932	
	Stability	−0.3820 ***	0.0473	−8.08	0.0000		−0.3755 ***	0.0476	−7.88	0.0000	
	CO_2 +20%	−0.1762	0.1440	−1.22	0.2210		−0.2472 *	0.1450	−1.70	0.0883	
	CO_2 +10%	−0.2696 **	0.1286	−2.10	0.0360		−0.2670 **	0.1330	−2.01	0.0447	
	CO_2 −10%	0.1279 *	0.0763	1.68	0.0938		0.1203	0.0781	1.54	0.1235	
	CO_2 −20%	0.0991	0.0612	1.62	0.1053		0.0753	0.0620	1.21	0.2245	
	Price	−0.0401 ***	0.0035	−11.33	0.0000		−0.0436 ***	0.0036	−12.08	0.0000	

Note: 1%, 5%, 10% significance levels are indicated by ***, **, and *.
Source: *Survey on Electric Consumption in Japan*

A2.B.6 Model C2 (Dichotomous Choice–Binomial Logit)

Model C2 also measures each level of attributes, as in Model C1, but here, we arranged the probability into dichotomous choice. The results are presented in Table A2.6.

Table A2.6 Estimation results of Model C2

		First Survey (Before reading the information)					Second Survey (After reading the information)				
		Coefficient	Standard Error	z-value	p-value		Coefficient	Standard Error	z-value	p-value	
All	Constant	0.2950 ***	0.0163	18.06	0.0000	N = 26712	0.2697 ***	0.0166	16.29	0.0000	N = 26712
	Nuclear	−1.4010 ***	0.0497	−28.21	0.0000	log L = −15141.4	−1.2776 ***	0.0506	−25.23	0.0000	log L = −14815.5
	Solar	0.2116 ***	0.0449	4.71	0.0000	AIC/N = 1.134	0.3912 ***	0.0456	8.57	0.0000	AIC/N = 1.11
	Wind	−0.0053	0.0474	−0.11	0.9109		0.1531 ***	0.0481	3.18	0.0015	
	Stability	−0.4773 ***	0.0188	−25.35	0.0000		−0.5070 ***	0.0192	−26.47	0.0000	
	CO_2 +20%	−0.4216 ***	0.0568	−7.43	0.0000		−0.2429 ***	0.0574	−4.23	0.0000	
	CO_2 +10%	−0.3830 ***	0.0503	−7.62	0.0000		−0.2570 ***	0.0511	−5.03	0.0000	
	CO_2 −10%	0.2452 ***	0.0307	8.00	0.0000		0.1535 ***	0.0309	4.97	0.0000	
	CO_2 −20%	0.1653 ***	0.0242	6.82	0.0000		0.1421 ***	0.0246	5.77	0.0000	
	Price	−0.0544 ***	0.0014	−37.69	0.0000		−0.0627 ***	0.0015	−42.59	0.0000	
Negative	Constant	0.2554 ***	0.0414	6.17	0.0000	N = 4072	0.2790 ***	0.0423	6.60	0.0000	N = 4072
	Nuclear	−1.5618 ***	0.1256	−12.44	0.0000	log L = −2328	−1.2841 ***	0.1308	−9.82	0.0000	log L = −2266
	Solar	−0.0490	0.1139	−0.43	0.6673	AIC/N = 1.148	0.3275 ***	0.1186	2.76	0.0058	AIC/N = 1.118
	Wind	−0.2779 **	0.1214	−2.29	0.0221		0.1229	0.1254	0.98	0.3270	
	Stability	−0.4819 ***	0.0480	−10.04	0.0000		−0.6206 ***	0.0496	−12.52	0.0000	
	CO_2 +20%	−0.7756 ***	0.1458	−5.32	0.0000		−0.4361 ***	0.1446	−3.02	0.0026	
	CO_2 +10%	−0.7516 ***	0.1275	−5.89	0.0000		−0.4574 ***	0.1326	−3.45	0.0006	
	CO_2 −10%	0.3449 ***	0.0773	4.46	0.0000		0.2711 ***	0.0810	3.35	0.0008	
	CO_2 −20%	0.1446 **	0.0619	2.33	0.0196		0.2353 ***	0.0632	3.73	0.0002	
	Price	−0.0546 ***	0.0037	−14.86	0.0000		−0.0640 ***	0.0038	−16.97	0.0000	
Base	Constant	0.2302 ***	0.0283	8.13	0.0000	N = 8872	0.2718 ***	0.0291	9.33	0.0000	N = 8872
	Nuclear	−1.4174 ***	0.0852	−16.65	0.0000	log L = −4970.4	−1.3275 ***	0.0894	−14.84	0.0000	log L = −4806.6
	Solar	0.2515 ***	0.0772	3.26	0.0011	AIC/N = 1.123	0.4071 ***	0.0802	5.08	0.0000	AIC/N = 1.086
	Wind	0.0256	0.0818	0.31	0.7545		0.1767 **	0.0852	2.07	0.0382	
	Stability	−0.4667 ***	0.0328	−14.24	0.0000		−0.5705 ***	0.0339	−16.85	0.0000	
	CO_2 +20%	−0.4204 ***	0.0989	−4.25	0.0000		−0.1772 *	0.1009	−1.76	0.0789	
	CO_2 +10%	−0.3212 ***	0.0860	−3.73	0.0002		−0.2507 ***	0.0897	−2.79	0.0052	
	CO_2 −10%	0.2207 ***	0.0537	4.11	0.0000		0.1651 ***	0.0547	3.02	0.0025	
	CO_2 −20%	0.1668 ***	0.0427	3.90	0.0001		0.0956 **	0.0436	2.19	0.0284	
	Price	−0.0574 ***	0.0025	−22.57	0.0000		−0.0707 ***	0.0026	−26.95	0.0000	
Positive	Constant	0.3299 ***	0.0436	7.57	0.0000	N = 3920	0.2924 ***	0.0441	6.64	0.0000	N = 3920
	Nuclear	−1.3800 ***	0.1323	−10.43	0.0000	log L = −2163.6	−1.3972 ***	0.1374	−10.17	0.0000	log L = −2155.3
	Solar	0.3928 ***	0.1203	3.26	0.0011	AIC/N = 1.109	0.3863 ***	0.1227	3.15	0.0016	AIC/N = 1.105
	Wind	0.1497	0.1262	1.19	0.2354		0.1351	0.1280	1.06	0.2912	
	Stability	−0.5326 ***	0.0507	−10.51	0.0000		−0.4624 ***	0.0504	−9.17	0.0000	
	CO_2 +20%	−0.2091	0.1526	−1.37	0.1707		−0.2721 *	0.1529	−1.78	0.0751	
	CO_2 +10%	−0.3034 **	0.1343	−2.26	0.0238		−0.2880 **	0.1380	−2.09	0.0369	
	CO_2 −10%	0.1457 *	0.0813	1.79	0.0732		0.1153	0.0824	1.40	0.1618	
	CO_2 −20%	0.1522 **	0.0638	2.39	0.0171		0.0703	0.0643	1.09	0.2747	
	Price	−0.0536 ***	0.0038	−14.04	0.0000		−0.0573 ***	0.0039	−14.82	0.0000	

Note: 1%, 5%, 10% significance levels are indicated by ***, **, and *.
Source: *Survey on Electric Consumption in Japan*

A2.B.7 Model D (Dichotomous Choice–Multinomial Logit)

Model D arranges the 50:50 choices as an outside option; i.e., we assume that the respondents did not choose either of the two cards if they give a 50:50 response.

Table A2.7 Estimation results of Model D

		First Survey (Before reading the information)					Second Survey (After reading the information)				
		Coefficient	Standard Error	z-value	p-value		Coefficient	Standard Error	z-value	p-value	
All	Constant	1.7243 ***	0.0402	42.94	0.0000	N = 26712	1.8554 ***	0.0414	44.87	0.0000	N = 26712
	Nuclear	−1.2872 ***	0.0467	−27.57	0.0000	log L = −23089.7	−1.1794 ***	0.0476	−24.80	0.0000	log L = −22259.4
	Solar	0.3925 ***	0.0423	9.28	0.0000	AIC/N = 1.72953	0.5195 ***	0.0431	12.05	0.0000	AIC/N = 1.66744
	Wind	0.1362 ***	0.0441	3.09	0.0020		0.2343 ***	0.0448	5.23	0.0000	
	Stability	−0.4939 ***	0.0178	−27.78	0.0000		−0.5323 ***	0.0179	−29.74	0.0000	
	CO_2 +20%	−0.2876 ***	0.0537	−5.36	0.0000		−0.1309 **	0.0539	−2.43	0.0151	
	CO_2 +10%	−0.1258 ***	0.0453	−2.77	0.0055		−0.0185	0.0464	−0.40	0.6895	
	CO_2 −10%	0.1701 ***	0.0280	6.06	0.0000		0.0715 **	0.0283	2.53	0.0114	
	CO_2 −20%	0.1915 ***	0.0252	7.61	0.0000		0.1511 ***	0.0253	5.98	0.0000	
	Price	−0.0541 ***	0.0014	−39.62	0.0000		−0.0601 ***	0.0014	−43.52	0.0000	
Negative	Constant	1.9178 ***	0.1014	18.92	0.0000	N = 4072	1.9162 ***	0.1075	17.83	0.0000	N = 4072
	Nuclear	−1.4023 ***	0.1168	−12.00	0.0000	log L = −3510.2	−1.1913 ***	0.1225	−9.73	0.0000	log L = −3386.8
	Solar	0.2213 **	0.1071	2.07	0.0388	AIC/N = 1.729	0.4999 ***	0.1120	4.46	0.0000	AIC/N = 1.668
	Wind	−0.0437	0.1122	−0.39	0.6968		0.2039 *	0.1168	1.75	0.0809	
	Stability	−0.5269 ***	0.0455	−11.57	0.0000		−0.6278 ***	0.0467	−13.45	0.0000	
	CO_2 +20%	−0.6255 ***	0.1396	−4.48	0.0000		−0.3635 ***	0.1375	−2.64	0.0082	
	CO_2 +10%	−0.4691 ***	0.1148	−4.09	0.0000		−0.1623	0.1198	−1.35	0.1755	
	CO_2 −10%	0.2602 ***	0.0713	3.65	0.0003		0.1558 **	0.0734	2.12	0.0337	
	CO_2 −20%	0.1867 ***	0.0648	2.88	0.0039		0.2115 ***	0.0652	3.25	0.0012	
	Price	−0.0558 ***	0.0035	−15.89	0.0000		−0.0635 ***	0.0036	−17.82	0.0000	
Base	Constant	1.8060 ***	0.0692	26.10	0.0000	N = 8872	1.9628 ***	0.0727	27.00	0.0000	N = 8872
	Nuclear	−1.3062 ***	0.0804	−16.24	0.0000	log L = −7537.1	−1.1980 ***	0.0834	−14.36	0.0000	log L = −7204
	Solar	0.4106 ***	0.0729	5.63	0.0000	AIC/N = 1.701	0.5449 ***	0.0756	7.21	0.0000	AIC/N = 1.626
	Wind	0.1461 *	0.0765	1.91	0.0561		0.2886 ***	0.0789	3.66	0.0003	
	Stability	−0.5214 ***	0.0311	−16.75	0.0000		−0.5811 ***	0.0316	−18.40	0.0000	
	CO_2 +20%	−0.2488 ***	0.0939	−2.65	0.0081		−0.0586	0.0942	−0.62	0.5336	
	CO_2 +10%	−0.0966	0.0780	−1.24	0.2154		0.0218	0.0810	0.27	0.7880	
	CO_2 −10%	0.1789 ***	0.0491	3.65	0.0003		0.0754	0.0498	1.52	0.1294	
	CO_2 −20%	0.1732 ***	0.0442	3.92	0.0001		0.1062 **	0.0446	2.38	0.0172	
	Price	−0.0582 ***	0.0024	−24.23	0.0000		−0.0682 ***	0.0025	−27.86	0.0000	
Positive	Constant	1.6212 ***	0.1062	15.26	0.0000	N = 3920	1.7175 ***	0.1108	15.50	0.0000	N = 3920
	Nuclear	−1.3272 ***	0.1245	−10.66	0.0000	log L = −3350.6	−1.2604 ***	0.1282	−9.83	0.0000	log L = −3304.3
	Solar	0.5170 ***	0.1125	4.60	0.0000	AIC/N = 1.715	0.5433 ***	0.1151	4.72	0.0000	AIC/N = 1.691
	Wind	0.2785 **	0.1165	2.39	0.0169		0.2721 **	0.1184	2.30	0.0215	
	Stability	−0.5125 ***	0.0474	−10.82	0.0000		−0.4687 ***	0.0465	−10.07	0.0000	
	CO_2 +20%	−0.1033	0.1418	−0.73	0.4660		−0.1295	0.1424	−0.91	0.3632	
	CO_2 +10%	−0.0415	0.1200	−0.35	0.7292		0.0404	0.1234	0.33	0.7435	
	CO_2 −10%	0.0617	0.0740	0.83	0.4049		0.0330	0.0747	0.44	0.6584	
	CO_2 −20%	0.1948 ***	0.0660	2.95	0.0032		0.1198 *	0.0657	1.82	0.0681	
	Price	−0.0530 ***	0.0036	−14.74	0.0000		−0.0531 ***	0.0036	−14.76	0.0000	

Note: 1%, 5%, and 10% significance levels are indicated by ***, **, and *.
Source: *Survey on Electric Consumption in Japan*

A2.B.8 Model E (Latent Class Model)

We used only the results of Survey 2 (after reading information) to explore the latent class. When we did not consider any individual attributes, we found the number of classes to be six. Then, we included some of the attributes given by the other questions on the survey and identified those attributes in Table A2.8 to form six latent classes. The information criteria for these classes are presented in Table A2.9, and the results are indicated in Table A2.10.

Table A2.8 Attributes considered in the latent class model

Variables		Mean	Standard Deviation	Min	Max
Age	Age of each respondent	47.353	13.458	20	69
High income	Annual income ¥9 million or more = –1, 0 otherwise.	0.198	0.399	0	1
Male	Male = 1, 0 otherwise.	0.559	0.497	0	1
Fee conscious	"Mind monthly electricity fee" = 1, 0 otherwise.	0.786	0.410	0	1
Read *Positive*	Read nuclear electricity positive information = 1, 0 otherwise.	0.331	0.471	0	1
Read *Negative*	Read nuclear electricity negative information = 1, 0 otherwise.	0.337	0.473	0	1

Note: The number of samples is 80,136.
Source: *Survey on Electric Consumption in Japan*

Table A2.9. Information criteria by the number of classes

	Multinomial logit	Number of latent classes			
		5	6	7	8
AIC	1.66737	1.52306	**1.49663**	1.49714	1.51463
Finite sample AIC	1.66737	1.52308	**1.49666**	1.49718	1.51469
Bayes IC	1.67043	1.54821	**1.52730**	1.53334	1.55635
Hannan Quinn IC	1.66836	1.53118	**1.50652**	1.50882	1.52809

Source: *Survey on Electric Consumption in Japan*

Table A2.10 Estimation results of Model E (after information)

		Coefficient		Standard Error	z-value	p-value
Class 1	Constant	5.8543	***	0.8830	6.63	0.0000
	Price	−0.0020	***	0.0002	−8.94	0.0000
	Nuclear	1.5900	*	0.8817	1.80	0.0713
	Solar	1.1475		0.8298	1.38	0.1667
	Wind	1.6800	*	0.9216	1.82	0.0683
	Stability	−5.1530	***	0.5254	−9.81	0.0000
	CO_2 +20%	0.6005		0.8649	0.69	0.4875
	CO_2 +10%	0.9511		0.8503	1.12	0.2633
	CO_2 −10%	1.0858	***	0.2814	3.86	0.0001
	CO_2 −20%	1.0270	***	0.3653	2.81	0.0049
Class 2	Constant	2.8626	***	0.0788	36.34	0.0000
	Price	−0.0007	***	0.0000	−22.49	0.0000
	Nuclear	−3.8793	***	0.1464	−26.49	0.0000
	Solar	0.8570	***	0.0820	10.45	0.0000
	Wind	0.4601	***	0.0815	5.65	0.0000
	Stability	−0.7100	***	0.0347	−20.48	0.0000
	CO_2 +20%	−0.2533	**	0.1068	−2.37	0.0177
	CO_2 +10%	−0.1626	*	0.0891	−1.82	0.0681
	CO_2 −10%	0.1718	**	0.0707	2.43	0.0151
	CO_2 −20%	0.2713	***	0.0651	4.17	0.0000
Class 3	Constant	−0.1983		0.1356	−1.46	0.1438
	Price	−0.0003	***	0.0001	−5.02	0.0000
	Nuclear	−1.1588	***	0.1994	−5.81	0.0000
	Solar	0.9402	***	0.1462	6.43	0.0000
	Wind	0.6466	***	0.1543	4.19	0.0000
	Stability	−0.2441	***	0.0661	−3.69	0.0002
	CO_2 +20%	0.3364	**	0.1653	2.04	0.0418
	CO_2 +10%	0.4565	***	0.1653	2.76	0.0057
	CO_2 −10%	−0.5408	***	0.1080	−5.01	0.0000
	CO_2 −20%	−0.3081	***	0.1016	−3.03	0.0024
Class 4	Constant	3.2965	***	0.1895	17.40	0.0000
	Price	−0.0023	***	0.0001	−21.25	0.0000
	Nuclear	−0.1859		0.2039	−0.91	0.3619
	Solar	0.6802	***	0.1849	3.68	0.0002
	Wind	0.6385	***	0.2236	2.86	0.0043
	Stability	−0.7262	***	0.0787	−9.23	0.0000
	CO_2 +20%	−0.5706	***	0.2165	−2.64	0.0084
	CO_2 +10%	−0.3113	*	0.1823	−1.71	0.0877
	CO_2 −10%	0.0780		0.1330	0.59	0.5573
	CO_2 −20%	0.2480	**	0.1173	2.11	0.0345
Class 5	Constant	1.4176	***	0.1401	10.12	0.0000
	Price	−0.0003	***	0.0000	−5.15	0.0000
	Nuclear	0.0715		0.1482	0.48	0.6298
	Solar	−0.2673	**	0.1356	−1.97	0.0486
	Wind	−0.6346	***	0.1454	−4.37	0.0000
	Stability	−0.3321	***	0.0547	−6.07	0.0000
	CO_2 +20%	−0.0545		0.1838	−0.30	0.7669
	CO_2 +10%	−0.0533		0.1611	−0.33	0.7406
	CO_2 −10%	0.1816	**	0.0917	1.98	0.0477
	CO_2 −20%	0.1951	**	0.0769	2.54	0.0112
Class 6	Constant	−2.2284		0.7823e+10	0.00	1.0000
	Price	−0.0013		0.1549e+08	0.00	1.0000
	Nuclear	2.3758		0.1552e+11	0.00	1.0000
	Solar	22.3941		0.2059e+11	0.00	1.0000
	Wind	−23.5033		0.1850e+15	0.00	1.0000
	Stability	−4.8035		0.7823e+10	0.00	1.0000
	CO_2 +20%	−23.0063		0.1804e+19	0.00	1.0000
	CO_2 +10%	−21.6546		0.5085e+11	0.00	1.0000
	CO_2 −10%	−8.7435		0.7777e+10	0.00	1.0000
	CO_2 −20%	8.7253		0.7789e+10	0.00	1.0000

Note: 1%, 5%, and 10% significance levels are indicated by ***, **, and *.
Source: *Survey on Electric Consumption in Japan*

Chapter 3 Evaluations of New Technology Policy

— Two Types of Dilemmas for Autonomous Vehicles —

3.1 Introduction

Autonomous driving technologies are advancing rapidly, and the time when consumers will ride on a daily base in driverless vehicles is coming closer. Since the start of Google's (now parent company Alphabet's) Self-Driving Car Project in 2009, various companies, including Uber, Apple, Tesla Motors, Alibaba, and Softbank, to name a few, have been working to develop driverless vehicles. WAYMO, which succeeded the Google project in 2016, introduced a self-driving taxi service to limited customers in Phoenix, Arizona, in December 2018. A newcomer, Pony.ai, founded in November 2016, released a market-ready, fully autonomous vehicle in September 2018. The Japanese government supports the technical development of autonomous driving technology, and driverless taxis were officially tested in Tokyo during the period August 27, 2018, to September 8, 2018.[16] Since the Japanese government expects our future to involve autonomous driving technologies, creating blueprints for the future is essential.

In this study, using an online survey that produced approximately 10,000 effective responses from all over Japan, we elicited consumer preferences for options to use conditionally or fully automated driving systems, together with their relative preferences for hybrid or electric engines compared to the traditional gasoline engine. To clarify the degrees of automation, we used SAE's standard J3016 (Table 3.1) and

[16] See, for example, Leon (2018) or Nikkei Asian Review (2018).

Table 3.1 SAE levels

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
Human driver monitors the driving environment						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	System	Human driver	Human driver	Some driving modes
Automated driving system ("system") monitors the driving environment						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	System	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving *system* of all aspects of the dynamic driving *task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	System	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	All driving Modes

Source: SAE International (2014)

defined SAE level 3 as Conditional Automation and SAE level 5 as Full Automation. We omitted SAE level 4, High Automation, to make it easier for respondents to distinguish between the attribute levels. Second, using the estimated individual WTP as the base WTP that was not affected by moral considerations, we study people's attitudes toward the morality of the algorithms that should be installed in autonomous vehicles (AVs) and toward their purchase intention, and we discuss the possibility of social dilemmas regarding these algorithms. The remainder of this paper is organized as follows: Section 2 introduces previous research on this topic; Sections 3 and 4 provide an overview of our survey and its respondents' attributes; Section 5 estimates the WTP for autonomous functions at Levels 3 and 5 to compare them with the WTP for different fuel types (hybrid and electricity) using conjoint analysis; Section 6 examines psychological attitudes toward AI programs for AVs and attitudes about purchase intention and regulation; Section 7 discusses the results; and Section 8 concludes.

3.2 Literature Review

Survey questionnaires designed for choice experiments are commonly used to gather information about opinions regarding the future of transportation (e.g., Ito et al., 2013; Zhang et al., 2014: Tamaki et al., 2019). Following the development of automated driving technologies, numerous studies on AVs have been published. Drivers' acceptance of autonomous driving was analyzed in the 1990s, as in Bekiaris et al. (1997), a pan-European study that evaluated users' needs regarding driving aids. In the 2010s, when Google's project made self-driving cars realistic, the number of studies analyzing the potential demand for full automation increased substantially.

In one of the earlier studies, a consulting company, J.D. Power and Associates (2012, 2013), released the results of their survey of vehicle owners in the U.S., showing the level of interest in fully automated AVs. Payre et al. (2014) focused on the acceptance of fully automated driving, showing that 68.1% of participants in France in an online survey (n = 421 drivers) *a priori* accepted fully automated driving. The respondents showed interest in autonomous vehicles for use for when they were impaired (by alcohol, drug use, medication that could affect driving abilities, and fatigue). Bansal et al. (2016) explicitly estimated the average willingness to pay (WTP) for adding full automation ($7253) for drivers in the state of Texas as being much higher than the WTP for adding partial automation ($3300). Daziano et al. (2017) also estimated WTP nationwide in the US as $3500 for partial automation and $4900 for full automation on average. Schoettle and Sivak (2015b) examined motorists' preferences across varying levels of vehicle automation and found that the largest percentage of motorists preferred no self-driving (43.8%), followed by partially self-driving (40.6%), with complete self-driving being the least preferred (15.6%). König and Neumayr (2017) focused on potential psychological barriers of drivers toward self-driving cars and found that such barriers do exist.

Some researchers performed international comparisons. Schoettle and Sivak (2015a) compared attitudes among the driving public in the US, the UK, and Australia and found the willingness to pay for connected-vehicle technology was very similar across the three countries. Kyriakidis et al. (2015) collected 5,000 responses from 109 countries (40 countries had at least 25 respondents) and showed that 69% of respondents believe that fully automated driving will reach a 50% market share by 2050. Concerns were also revealed; these were mainly regarding software hacking/misuse, safety, legal issues, and the transmission of data concerning automated driving. Uniquely, Bazilinski et al. (2015) investigated anonymous textual comments regarding fully automated driving, based on data extracted from three online surveys, with 8,862 respondents from 112 countries. They found that public opinion regarding fully automated driving was split, but there were 1.7 times more positive comments than negative ones. Focusing on gender, Hohenberger et al. (2016) reported that gender differences in the willingness to use automated cars arise because women feel less pleasure toward automated cars and have more anxiety about them.

Because AVs may be used as shared cars, several studies have analyzed the demand for shared AVs[17]. However, we will use respondents' perceptions of shared cars without autonomous driving systems as an explanatory variable in Section 5.

Along with the increase in the number of studies, literature surveys concerning AVs have also been conducted. Johnsen et al. (2017) provided a massive survey covering diversified aspects of vehicle automation, and Gkartzonikasa and Gkritza (2019) offered a literature survey focusing on stated preference and choice studies. Review studies of Adnan et al. (2018) focused on the ethics of and trust in AVs. They insisted that one of the most significant challenges to user acceptance of AVs was to build trust toward the technology. They emphasized the need for future studies on user acceptance that incorporate the ethical implications of the use of AVs. Our study aims to be one such study.

[17] Schoettle and Sivak (2014) hinted that a general lack of trip overlap between drivers within a majority of households opens up the possibility for a significant reduction in average vehicle ownership per household based on car sharing. Krueger et al. (2016) propose that while multimodal travelers may adopt SAVs to facilitate their multimodality, individuals whose modality is centered around the use of the private car may be reluctant to use SAVs. Hohenburger et al. (2017) found high overall hesitation towards autonomous vehicle adoption, with 44% of choice decisions remaining with regular vehicles. Early AV adopters will likely be relatively young and well-educated adults who spend a greater than average amount of time in vehicles. They also found that even if an SAV was completely free, only 75% of individuals would be willing to use it. Using rank-ordered probit modeling, Nair et al. (2018) revealed four alternative uses of AVs: as a taxi with a backup driver, as a taxi without a backup driver, individual ownership, and use in car-share mode, by socio-demographic attributes of the respondents. Nazari et al. (2018) jointly modeled public interest in private AVs and multiple SAV configurations (car sharing, ride sourcing, ridesharing, and access/egress mode) in daily use by commuters with explicit treatment of the correlations across (S)AV types. Safety concerns hinder public acceptance of (S)AVs, whereas green travel patterns and mobility-on-demand savviness promote interest in (S)AVs. Masoud and Jayakrishnan (2017) introduce a shared vehicle ownership and ridership (SVOR) program in which a group of households jointly own and use a set of autonomous vehicles. Households can share rides if the spatial-temporal distributions of their trips allow for it. They propose analytical optimization schemes to study the impact of SVOR.

3.3 Research Overview

Our research, covering a representative panel of households in Japan, was administered in 2016 by Nikkei Research, Inc., funded by the Research Institute of Economy, Trade and Industry, IAA (RIETI). We conducted two pilot studies to select the appropriate method of estimating respondents' revealed preferences (Table 3.2). In the first pilot study, we tried both the contingent valuation method (CVM) and conjoint analysis to test whether WTP could be estimated in association with other attributes using conjoint analysis or CVM should directly estimate WTP. Dividing respondents into two groups, we compared the results of the two estimating methods. We found we could obtain satisfactory results from conjoint analysis[18], so we concentrated on that approach in the second pilot study, adjusting the attributes and levels of the choice profiles and adopting conjoint analysis in the main study.

Table 3.3 shows the attributes and levels for the choice settings in the main study. The base case is a gasoline-powered car without autonomous driving. (It is excluded from the combinations because we measure the WTP only with respect to the price of the options, regardless of the price of the base-case car.) After the pretest, we selected additional charges: 100 thousand yen, 200 thousand yen, 400 thousand yen, and 600 thousand yen. The price is modest for new technologies since this kind of option is not yet accessible. We judged that respondents can hardly select options if the listed price is too high.

[18] We compared the estimates of conjoint analysis with that of CVM, focusing on the role of respondents' attributes to determine the WTP. We found that the effects of each attribute are common in the two methods and judged that the CA will endure our further analysis.

All possible combinations for each card are 3*3*4 = 36 patterns, and because we show two cards at a time, theoretically, the number of *r*-combinations from a given set of *n* elements is ${}_nC_r = {}_{36}C_2 = 36 * 35 / 2 = 22,680$ combinations. Since one respondent cannot answer every pattern, we constructed a *D*-efficient design[19] with 48 patterns using Ngene 1.1.2. To minimize the burden of having to make many repeat choices, we blocked the design into six sets, each consisting of eight choice occasions. We randomly assigned one of the six blocks and presented one choice set at a time to each respondent, in random order, to minimize any effects of respondents' learning or fatigue.

Table 3.2 Summary of the research schedule

	Method	**Periods**	**Number of Samples (Response Rate)**
Pilot Study 1	CVM and Conjoint	January 13 - 16, 2017	1,483 (9.6%)
Pilot Study 2	Conjoint	February 23 - 27, 2017	815 (11.3%)
Main Study	Conjoint	March 16 - 21, 2017	18,526 (12.6%)

Source: *Surveys on Auto Driving*

Table 3.3 Attributes and levels for the combination

Attributes	**Levels**
Levels of Autonomous Driving	No Autonomous Driving (base), Level 3: Conditional Automation, Level 5: Full Automation
Fuel	Gasoline (base), Change to Hybrid, Change to Electric
Additional Charge	100 thousand yen, 200 thousand yen, 400 thousand yen, 600 thousand yen

Note: US$1 = 113.2 yen, as of March 2017
Source: *Surveys on Auto Driving*

[19] D-efficient design minimizes the correlation in the data for estimation purposes and aims to result in data that generate parameter estimates with as small as possible standard errors, utilizing the results of pilot studies or similar prior literature. See ChoiceMetrics (2014) for details.

Respondents read the following vignette immediately before the choice sequence. The operational costs may vary among fuels and autonomous levels, but this time, we did not state them because the expected operational costs are hard to forecast correctly. To avoid misleads by imprecise information, we asked respondents to assume fuel consumption equal across fuels so that the reason they choose a fuel would be any factor other than fuel consumption, e.g., CO_2 emission or engine sound. The last sentence is the customary "cheap talk" for the choice settings, intended to prevent upper bias on estimated WTP by making respondents select the option realistically.

> "Imagine you are to purchase a car. You are at a car dealer and find an ideal style and color of a gasoline-powered car, with no autonomous driving functions. The dealer offers you two kinds of options: one is adding an autonomous driving system, the other is changing the fuel type, with specific additional charges.
>
> Now you will see the two combinations of options (A and B). Compare the two combinations – which would you like to buy? The price is the additional price for the options; it does not include the price of the car. Please assume fuel consumption is the same among three kinds of engine fuels. If you would like to buy the car as is (no autonomous driving, with a gasoline engine), choose "neither." You will make choices for eight combinations of options.
>
> Please note that if you pay for the options, you will not be able to buy any other goods and/or services for that price."

Eight profiles shown to each respondent had text that defined the levels of autonomous driving. Figure 3.1 is a sample profile. The text explaining Level 5 says, "No driver's license required," which is not defined by the Society of Automobile Engineers (SAE) (Table 3.1). No such deregulation has been planned from the time of the study research onward, but we added this statement to allow respondents to distinguish between the two levels easily.

For the autonomous driving options, you can choose one from two types of autonomous driving systems.

【Level 3】Driving is mostly autonomous, but a human driver must respond as needed. (Conditional Automation)

【Level 5】Driving is completely autonomous, and the human driver will not have to drive. (Full Automation). No driver's license is required.

	Option A	Option B	
Level of Autonomous Driving	Level 3: Conditional Automation	Level 5: Full Automation	**Neither**
Fuel	Hybrid	Gasoline	
Additional Charge	400 thousand yen	600 thousand yen	

Figure 3.1 Sample profiles for the online survey

Note: 1. Every profile is accompanied by the text above so that respondents can be certain of what each level means.
2. Original text and profiles are given in Japanese.

Source: *Surveys on Auto Driving*

3.4 Sample Characteristics

Among the 18,526 valid responses obtained in the main study, 16,327 disclosed family income. Using that subset, we excluded those who did not have any intention of buying an AV[20] (n = 6,876 respondents) and estimated the WTP for the remaining 9,451 respondents. Sample characteristics (variables) of the respondents are described in Table 3.4.

Interest in gadgets, shown as the variable *LikeGadget* in Table 3.4, is a composite variable (simple average omitting "never used one") of respondents' interest in the five items smartphone, tablet, personal computer, digital TV controller, and remote

[20] We excluded those who answered "(I) Do not want to purchase autonomous driving options even if the price of the car becomes lower" to a question that follows the choice sequences, and those who answered another question as "I have no intention of buying an autonomous driving vehicle."

Table 3.4 Attribute variables and descriptive statistics

Variable	Description	Mean	Standard Deviation	Max	Min
Male	Male = 1, Female = 0.	0.625	0.484	0	1
Age	Age (scaled by one)	47.598	12.572	18	69
Age60	Age group of 60s (60-69) = 1; 0 otherwise.	0.206	0.404	0	1
HighEducation	Respondents who graduated from a university, graduate school, or equivalent (Years of Education ≥ 16) = 1; 0, otherwise.	0.599	0.490	0	1
Income (log)	Log value of the respondent's annual household income.	6.420	0.665	3.912	8.161
DislikeShareCars	Choices range from "Shared cars are totally acceptable" (1) to "Shared cars are totally unacceptable" (10). Those who chose a score of 6 or higher = 1; 0, otherwise.	0.306	0.461	0	1
LikeGadget	A simple average of respondents' choices ranging from "Dislike very much" (1) to "Like very much" (5) regarding six kinds of gadgets: smartphones, PCs, tablets, robots, TV controllers, remote controls for home electronics.	3.512	0.564	1	5
Pride	Choices range from "Do not take pride in owning cars at all" (0) to "Take substantial pride in owning cars" (10). Those who chose a score of 6 or higher = 1; 0, otherwise.	0.314	0.464	0	1
FavDrive	Among respondents with a driver's license, those who chose a score of 8 or higher from the choice "Dislike driving very much" (1) to "Like driving very much" (10) = 1; 0, otherwise.	0.337	0.473	0	1
CausedAccidents	Respondents who have caused a car accident = 1; 0, otherwise.	0.362	0.481	0	1
Credibility	A number selected from the slider, which ranged from "If all cars in the county become fully autonomous, I think car accidents will increase significantly (0)" to "..., I think car accidents will decrease significantly (100)."	69.636	19.885	0	100
Altruism	Composed of two responses: (A) opinion of the statement "No matter what circumstances we are in, we should help those in need," ranging from "Strongly Disagree" (1) to "Strongly Agree" (5); and (B) frequency of charitable donations.	3.547	0.881	0.772	6.402

Source: *Surveys on Auto Driving*

controller for home electronics. We created this indicator to see whether those who like gadgets had a greater willingness to buy AVs and whether they had different ethical attitudes toward AV behavior than did those who did not like gadgets. Male respondents (62.5%) outnumber females, and age distribution is concentrated in the range of 40 to 59 years. They represent the population of potential buyers of autonomous vehicles in Japan.

3.5 Willingness to Pay for Autonomous Driving Options

3.5.1 Theory

We used the random utility model for our choice experiment. The indirect utility function of individual i choosing alternative j among J alternatives at a choice occasion t is as follows:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}\text{, where } i = 1,\ldots,I;\ j = 1,\ldots,J;\ t = 1,\ldots,T \qquad (3.1)$$

The first term V_{ijt} is the deterministic component of the utility function and is assumed to take a linear-in-parameter functional form:

$$V_{ijt} = \boldsymbol{\beta}_i{}'\mathbf{x}_{ijt}\text{, where } i = 1,\ldots,I;\ j = 1,\ldots,J;\ t = 1,\ldots,T \qquad (3.2)$$

Denoting the number of covariates as K, $\boldsymbol{\beta}_i$ is the $K \times 1$ vector of parameters for individual i, and $\mathbf{x}_{ijt}$ is the $K \times 1$ vector of the characteristics of alternative j at choice occasion t for individual i. The individual parameters $\boldsymbol{\beta}_i$ are assumed to be drawn from a population distribution, $g(\boldsymbol{\beta}|\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is the population parameter for the distribution. The second term in (3.1), ε_{ijt}, is the random component, and it is assumed to have an *iid* extreme value distribution.

The conditional mean for parameters $\bar{\boldsymbol{\beta}}_i$ can be simulated based on individual i's sequence of choices, s_i, given the choice profile, x_i, as the following:

$$\bar{\boldsymbol{\beta}}_i = \sum_{r=1}^{R}\left(\frac{\Pr\left(s_i \middle| x_i, \boldsymbol{\beta}_{ir}\right)}{\sum_{r=1}^{R}\Pr\left(s_i \middle| x_i, \boldsymbol{\beta}_{ir}\right)}\boldsymbol{\beta}_{ir}\right). \qquad (3.3)$$

3.5.2 Estimated Parameters and Individual-Specific WTP

We set parameters of autonomous driving level and fuel type and their cross effects as normally distributed.[21] Price parameters and constants are set as nonrandom variables. The estimations were made using NLOGIT Ver.5 software with 500 Halton draws[22] for random parameter simulations, allowing correlation among the parameters.[23] As shown in Table 3.4, all of the standard deviations (SDs) for the random parameters are significant at the 1% level, and respondents have heterogeneous preferences. Among the attributes that may determine the heterogeneity, we selected four attributes: sex (*Male*), age in 60s (*Age60*), log of income (*Income*), and favor driving very much (*FavDrive*).

We further include the individual specific parameter for *Male*, *Age60*, *Income*, and *FavDrive*. Then, equation (3.2), omitting subscripts *j* and *t*, the deterministic component in utility function for an *i*-th individual can be written,

$$\begin{aligned} V^i &= \alpha + \beta_{Price} \times Price + \beta^i_{Level} \times Level + \beta^i_{Fuel} \times Fuel + \beta^i_{Level\_Fuel} \times Level \times Fuel \\ &= \alpha + \beta_{Price} \times Price + (\beta_{Level} + \delta_{1L} Male^i + \delta_{2L} Age60^i + \delta_{3L} Income^i + \delta_{4L} FavDrive^i) \times Level \\ &\quad + (\beta_{Fuel} + \delta_{1F} Male^i + \delta_{2F} Age60^i + \delta_{3F} Income^i + \delta_{4F} FavDrive^i) \times Fuel \\ &\quad + (\beta_{Level\_Fuel} + \delta_{1LF} Male^i + \delta_{2LF} Age60^i + \delta_{3LF} Income^i + \delta_{4LF} FavDrive^i) \times Level \times Fuel \end{aligned} \tag{3.4}$$

---

[21] Since we have no way of knowing the distributions *a priori*, assuming a normal distribution is natural given our large samples.

[22] The Halton draw is an intelligent draw that lowers simulation errors compared to random draws. The Halton draw draws from the standard continuous uniform distribution, *U*[0,1]. See Greene (2012).

[23] The results were stable with different numbers of draws and starting points. The panel mixed-logit specification (AIC =120384.5) was favored over the conditional logit (AIC = 14488.4.)

where we set $\beta^i = \beta + \delta z^i + \sigma v^i, \quad v^i \sim N[0,1]$. β is the conditional mean and σ is the standard deviation. Marginal utility for the Level 3 plus hybrid option, for example, is calculated from observed coefficients:

$$\begin{aligned} MU^i_{Level3+Hybrid} &= \hat{\beta}_{Level3} + \hat{\beta}_{Hybrid} + \hat{\beta}_{Level3\times Hybrid} \\ &+ \left(\hat{\delta}^i_{1Level3} + \hat{\delta}^i_{1Hybrid} + \hat{\delta}^i_{1Level3\times Hybrid}\right) \times Male^i \\ &+ \left(\hat{\delta}^i_{2Level3} + \hat{\delta}^i_{2Hybrid} + \hat{\delta}^i_{2Level3\times Hybrid}\right) \times Age60^i \\ &+ \left(\hat{\delta}^i_{3Level3} + \hat{\delta}^i_{3Hybrid} + \hat{\delta}^i_{3Level3\times Hybrid}\right) \times Income^i \\ &+ \left(\hat{\delta}^i_{4Level3} + \hat{\delta}^i_{4Hybrid} + \hat{\delta}^i_{4Level3\times Hybrid}\right) \times FavDrive^i \end{aligned} \quad . \tag{3.5}$$

WTP is estimated dividing marginal utilities by price coefficient, which we assumed as nonrandom. In Table 3.5, the coefficients of main effects are for the person for who all the attribute variables = 0, so we first focus on the effect of each attribute.

Male (*Male* = 1) shows higher marginal utility for both autonomous driving options and fuel options than does female (*Male* = 0). Marginal utility for the Level 5 option for the gasoline car is the highest, 1.063. Male shows marginal utility of 1.063 + 0.297 − 0.659 = 0.701 for Level 5_Hybrid, and 1.063 + 0.482 − 0.651 = 0.894 for Level 5_Electric.

For the elder people (Age60 = 1), every option yields higher marginal utility than for younger people, and the combination yields much higher marginal utility. Income also raises the marginal utility when combined, where Level 3_Gasoline can be regarded to add nothing (insignificant).

Those who like driving much (*FavDrive* = 1) have negative marginal utilities to autonomous driving compared to others (*FavDrive* = 0). They have positive marginal utility to Hybrid without auto-driving (0.254), but once combined with Level 3, that

Table 3.5 Estimation results of mixed logit model

	Coefficient		Standard Error
Main Effects			
ASC (Add Options)	-0.235	***	0.012
Price	-0.070	***	0.001
Level 3	1.827	***	0.265
Level 5	1.244	***	0.380
Hybrid	1.261	***	0.380
Electric	0.753	*	0.452
Interaction Terms			
Level 3 × Hybrid	0.476	***	0.105
Level 3 × Electric	-0.484	***	0.120
Level 5 × Hybrid	-0.964	***	0.077
Level 5 × Electric	-1.213	***	0.086
Standard Deviations of Parameter Distribution			
Level 3	2.065	***	0.039
Level 5	3.281	***	0.049
Hybrid	2.796	***	0.065
Electric	3.411	***	0.075
Level 3 × Hybrid	2.386	***	0.071
Level 3 × Electric	3.089	***	0.088
Level 5 × Hybrid	2.669	***	0.086
Level 5 × Electric	3.015	***	0.100
Interaction Terms with Attributes			
Male			
Level 3	0.311	***	0.058
Level 5	1.063	***	0.084
Hybrid	0.297	***	0.081
Electric	0.482	***	0.095
Level 3 × Hybrid	-0.138		0.102
Level 3 × Electric	-0.142		0.122
Level 5 × Hybrid	-0.659	***	0.109
Level 5 × Electric	-0.651	***	0.122
Age60s			
Level 3	0.425	***	0.069
Level 5	0.368	***	0.098
Hybrid	0.212	**	0.096
Electric	0.457	***	0.116
Level 3 × Hybrid	0.385	***	0.120
Level 3 × Electric	0.225		0.143
Level 5 × Hybrid	0.309	**	0.133
Level 5 × Electric	0.240	*	0.146
Income			
Level 3	0.141	***	0.041
Level 5	0.232	***	0.058
Hybrid	0.154	***	0.059
Electric	0.001		0.070
Level 3 × Hybrid	0.061		0.074
Level 3 × Electric	0.194	**	0.085
Level 5 × Hybrid	0.122		0.078
Level 5 × Electric	0.182	**	0.087
FavDrive			
Level 3	-0.261	***	0.059
Level 5	-0.779	***	0.085
Hybrid	0.254	***	0.082
Electric	-0.039		0.097
Level 3 × Hybrid	-0.256	**	0.105
Level 3 × Electric	-0.385	***	0.125
Level 5 × Hybrid	-0.211	*	0.112
Level 5 × Electric	-0.206		0.126
Log likelihood	-83064		
McFadden Pseudo R-square	0.2763		

Notes: Estimations based on 300 draws.
*** Significance levels are indicated by 1%
** Significance levels are indicated by 5%
* Significance levels are indicated by 10%
Source: *Survey on Auto Driving*

Table 3.6 Estimated WTP (Thousand Yen)

	Mean WTP	95% Confidence Interval		Rank
		Low	High	
No Auto Driving				
Gasoline (Base)	0	0	0	9
Hybrid	350	243	456	7
Electricity	147	21	274	8
Level 3				
Gasoline	402	328	476	5
Hybrid	467	340	593	2
Electricity	360	205	515	6
Level 5				
Gasoline	442	336	548	4
Hybrid	490	356	624	1
Electricity	446	296	596	3

Note: 1. Individual attributes are all assumed average.
2. Rank shows the order of the mean WTP.
Source: *Survey on Auto Driving*

utility declines to -0.263, and with Level 5 to -1.033 (regarding the insignificant cross-term Level5 × Electric zero).

Using the data of Table 3.5, constrained mean WTP is calculated for the individual with average attributes (*Male* = 0.625, *Age60* = 0.206, *Income* = 6.420, and *FavDrive* = 0.337 are applied) in Table 3.6. The WTP here is the value of adding any options listed. The left column shows the rank of mean WTP. Among autonomous driving options, the most preferred type is the Level 5_Hybrid option, with 490 thousand yen, approximately $4331 ($1 = 113.15 yen as of February 2017, around when the Survey was taken.) The least preferred type is Level3_Electric and only 360 thousand yen, approximately $3182, could be paid. From these results, we can see that in Japan, WTP is lower than that for people in the studies by Bansal et al. (2016) and Daziano (2017).

In the next section, we use the individual WTP for Level 5 as a control variable to estimate people's ethical perceptions regarding AVs. To obtain the individual's specific WTP for the Level 5 autonomous driving options, we simplified the estimation to avoid the aggregation errors of the marginal utilities when we estimate considering individual attributes (equation 3.4). The result is shown in Appendix 3.C.

3.6 Ethical Considerations

An artificial intelligence (AI)-equipped AV that drives fully autonomously may have to "choose between two evils such as running over a pedestrian or sacrificing its passengers."[24] This dilemma is in the category of the widely known "Trolley Problem," to which Foot (1967) initially drew attention and which was discussed by Thomson (1985).

To allow the AVs to choose from the two alternatives under the "Trolley Problem," carmakers should program actions of AVs or provide some guidelines for the vehicles' AI. Each AV should be designed with either a preference for saving pedestrians or a preference for saving passengers. In several consecutive surveys conducted in the United States, Bonnefon et al. (2016) revealed that "people would like AVs to be utilitarian, i.e., to behave as a moral actor to save as many lives as possible even though that means the AVs will occasionally sacrifice passengers, whereas people will prefer to purchase AVs that are programmed to save its passengers (themselves)." This result is one of the "social dilemmas." A social dilemma is defined as a situation where "private interests are at odds with collective interests" (Van Lange, 1989).[25] We now test the existence of two social problems in

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[24]Bonnefon et al. (2016, p. 1573).
[25]Van Lange et al. (2013) review the literature of social dilemmas.

Japan, compare them with US studies, and study the factors that may affect the dilemmas.

3.7 Comparisons of Social Dilemmas: the US vs. Japan

In this section, we compare our results to those of previous research in the study by Bonnefon et al. (2016) in the US. Our research selected two experiments from Bonnefon et al.'s six consecutive studies. They are the following:

Study I: The social dilemma of morality and purchasing behavior; and

Study II: The social dilemma of morality and regulation.

Our study differs from that by Bonnefon et al. because we carried out both studies I and II in a single survey of the 9500 respondents that answered the WTP questions, while Bonnefon et al. conducted six online surveys completed by different respondents. Our study A is taken from Bonnefon et al.'s Study 3 (n = 259 respondents), and our Study B is modified from their Study 6 (n = 393 respondents).

As a background that applies generically to both studies, we explained the situation using the scenario below (translated from Japanese) and in Figure 3.2:

> "You [and a coworker or an acquaintance/a family member] are in the car traveling down a main road on a bridge. Suddenly, 10 pedestrians appear ahead, in the direct path of the car. If the car swerves to the side of the road, it will plunge into the river, killing you [and your coworker or acquaintance/family member] but leaving the pedestrians unharmed. If the car stays on your current path, it will kill the 10 pedestrians, but you and your [coworker or acquaintance/family member] will be unharmed."[26]

[26] This scenario originated in Bonnefon et al.'s (2016) Study 3. Their supplementary material provides the prototype.

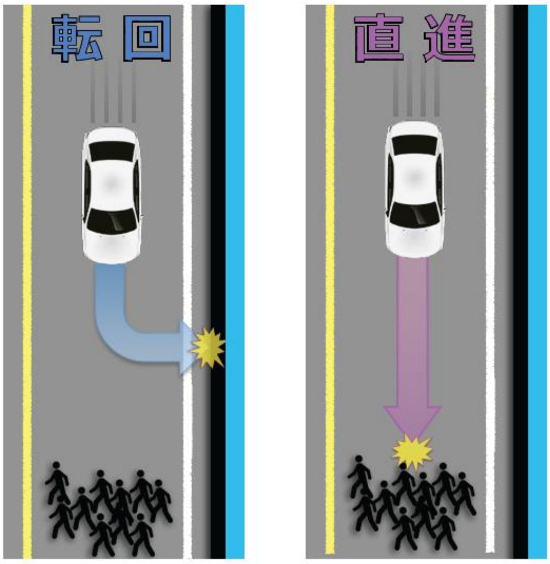

Figure 3.2 The two alternatives for AVs to choose

Note: The figure on the left means “swerve,” while the one on the right means “stay.”
Source: *Survey on Auto Driving*, modified from Bonnefon et al. (2016), Figure 1, p. 1574.

One-third of the respondents are set to imagine riding alone and read the text beginning with, “You are in the car traveling down a main road...,” while another one-third imagine riding with a coworker or an acquaintance and reading, “You and a coworker or an acquaintance are in the car traveling down a main road...” The last one-third of the respondents read, “You and a family member are in the car traveling down a main road...”

3.7.1 Study I: Morality and Purchasing Behavior

In the first setting, a social dilemma occurs if people do not buy the AVs that they think are moral. Morality in the first setting (we call it *Morality_I*) concerns moral actions in general, defined by the response to the following question: Rate what action you think is the most moral, on a 0–100 sliding scale anchored at “stay, saving you [and your coworker or your acquaintance/and your family member] but killing the 10 pedestrians" and "swerve, sparing the 10 pedestrians but killing you [and your coworker or your acquaintance/and your family member]." The following questions address how inclined respondents would be to buy an AV that was programmed to swerve (minimize the number of deaths, i.e., sacrifice the passengers), and how inclined they would be to buy an AV that was programmed to stay the course (i.e., be "self-protective"). Respondents select the answer on a 0–100 sliding scale anchored by "not at all likely (0)" and "extremely likely (100)" for each question. This 101-point scale is superior to 5- or 7-point Likert scales because, as explained in Section 2.2, respondents can express their uncertainty with their own choice. Respondents can also use more response options with more points[27]. They do not have to write down the numbers, and they can choose the number using a slide-bar on the screen (the number is automatically displayed along with the movement of the slide-bar).

In Figure 3.3, we contrast our results with those in the study by Bonnefon et al., although the research setting is different, and the results are not entirely comparable. Boxes in Figure 3.3 show the 95% CIs from the mean (the horizontal line in the center of each box). We see that respondents' tendencies are similar in both countries, except that the intention to purchase a protective AV when riding with families is lower in Japan.

[27] Comparing the result of 5-point, 7-point and 10-point scale experiments, Dawes (2008) exhibits that they can simply be converted to each other. Dawes suggests 10 and more points can give respondents more options for their choices.

Panel A: The United States **Panel B: Japan**

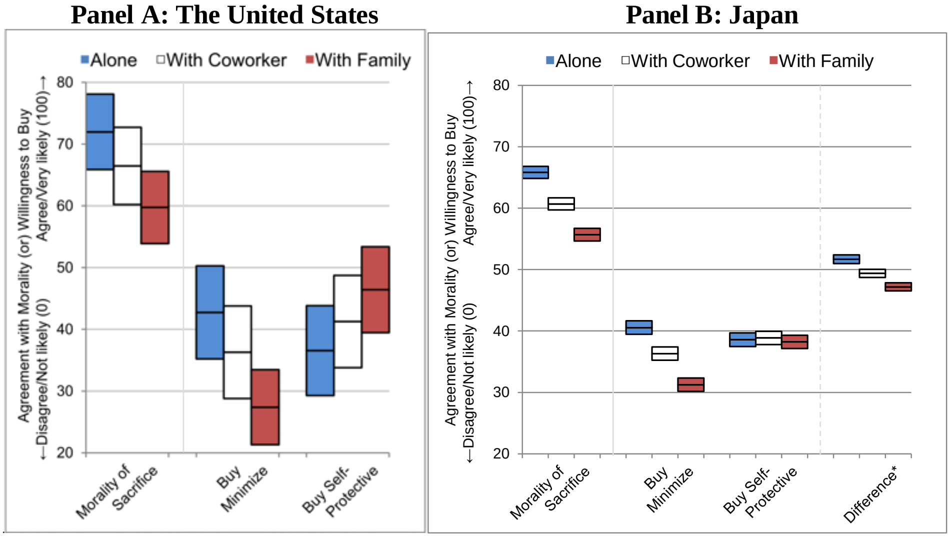

Figure 3.3 Morality_I and purchase intentions (United States and Japan)

Note 1. *Difference* in Panel B is calculated as follows: *Buy Minimize* minus *Buy Self-Protective*, linearly transformed to use values from 0 to 100. If *Difference* >50, *Buy_Minimize* is preferred.

2. Each box depicts a 95% CI from the mean (the horizontal center line in each box)

Source: Bonnefon et al., Figure 3.A, p. 1575, (A); *Surveys on Auto Driving* (B)

In both countries, participants expressed moral preferences (difference > 50) for AVs sacrificing their passengers to save a greater number of pedestrians. However, in both countries, participants did not express a comparable intention to buy utilitarian AVs that minimize the number of sacrifices, especially when asked to imagine their family member riding in the car. The finding that "even though participants still agreed that utilitarian AVs were the most moral, they preferred the self-protective model for themselves" (Bonnefon et al., 2016, p. 1574) is common, but citizens in Japan are less protective of their family members.

We note a difference between the countries here. Respondents in the US had a higher intention of buying self-protective AVs when riding with their family members than when riding alone, while the Japanese respondents did not show any significant distinctions between riding with family members and riding alone.

To make discussions of Study I more explicit, we created a new variable called *Difference*, i.e., each respondent's "relative intention to buy a 'minimize' (utilitarian) AV" was calculated as the "subtracting intention to buy a 'protective' AV from intention to buy a 'minimize' AV."

In our case, *Morality_I* is highest when riding alone, and the relative intention to buy a "minimize" AV is also highest. Having fellow passengers does not change the relationship between *Morality_I* and purchase intentions.

3.7.2 Study II: Morality and Regulations

In the second setting, a social dilemma is created if a regulation to force AVs to minimize sacrifice is counterproductive. If people believe AVs can be regulated to minimize sacrifice, but they do not agree to impose such regulations, moral AVs may not prevail in the market. Morality in this setting (we call it *Morality_II*) refers to the actions of AVs defined by the response to the question, "Which do you think is the morally appropriate action for an AV to take? (using a sliding scale anchored at "stay, saving you [and your child/family member] but killing the 10 pedestrians (0)" or "swerve, sparing the 10 pedestrians but killing you [and your child/family member]. (100).")

Following this question, respondents answered another question, "Do you think the government should require all AVs be programmed to minimize the number of casualties in accidents, even if it means killing the passenger(s)? (using a sliding scale anchored at "No, not at all (0)" and "Yes, definitely (100).")

After answering this question, participants indicated how likely they were to buy an AV under each of two situations (using a sliding scale anchored at "not at all likely" to "extremely likely.") We divided the respondents in half. One-half of the respondents (n = 4771) were informed that all AVs were regulated by the government to minimize the number of casualties in accidents, even if those regulations meant killing the passenger(s). The other half (n = 4680) were informed that the government did not regulate AVs and allowed the private sector (car manufacturers and consumers) to choose whether their AVs would seek at all costs to minimize the total number of casualties or to minimize the harm to the passenger(s).

Figure 3.4 again compares the US and Japan. In the US, the respondent's child is assumed to be the passenger instead of a coworker or acquaintance. Despite this difference, the respondent's desire to regulate AVs to be moral is lower than their *Morality_II*, and the intention to purchase a regulated AV is even lower.

Conversely, the difference between the two countries is noticeable in three aspects: (1) On average, Japanese respondents do not agree with the idea of

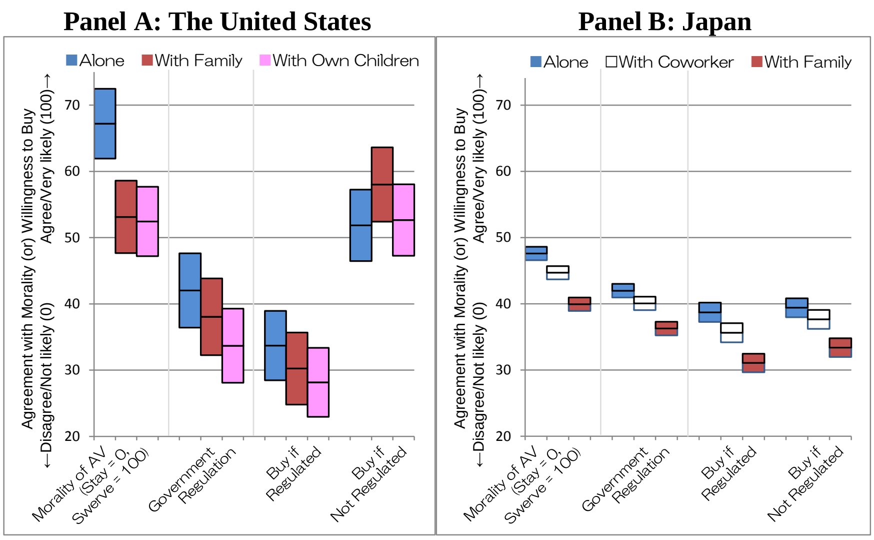

Figure 3.4 Morality_II, need for regulation, and purchase intentions (United States and Japan)

Note: 1. Each box depicts a 95% confidence interval from the mean (the horizontal center line in each box).
2. In Panel B, the respondents are divided into "Buy if regulated" and "Buy if not regulated."

Source: Bonnefon et al., Figure 3.D, p. 1575, (A) (X-axis titles are modified by authors); *Surveys on Auto Driving* (B) programming AVs to swerve to spare the pedestrians if the AV kills the passenger, even if there are no additional passengers. (2) The disparity between the morality score and the desire for regulation is more substantial in the US. (3) When the car companies and consumers both choose to have their AVs minimize the total number of casualties, the US respondents' purchasing intention conspicuously rises, while that of the Japanese respondents does not show a significant increase.

The second dilemma may be stronger in the US than in Japan, and Japanese respondents did not wish to choose how the AV would be programmed. They seemed to be less independent and less willing to make this decision themselves than were respondents in the US.

3.8 Factors Affecting the Moralities and Purchase Intentions

Using simple ordinary least squares (OLS) estimation, we explore the determinants of perceptions of morality and need for regulation (*Morality_I*, *Morality_II*, and *NeedRegulation*) and the relative intention to purchase moral AVs (*Difference*). In equations (3.6) and (3.7), $\mathbf{X}_p^*$ is an $n \times 3$ matrix whose columns indicate randomly assigned passenger type as $[Alone \quad WithCoworker \quad WithFamily]$ = $[0 \quad 1 \quad 1]$, where n is the number of respondents, $\boldsymbol{\beta}_p^*$ is a 3×1 vector, $\mathbf{X}_j^*$ is an $n \times k$ matrix, and $\boldsymbol{\beta}_j^*$ ($j = 1, \dots k$ where k is the number of respondent attributes) is a $k \times 1$ vector. $\mathbf{Y}^*$ is the $n \times 1$ vector of an independent variable.

$$\underline{Perceptions} = \mathbf{Y}^P = \mathbf{X}_p^P \left(\boldsymbol{\beta}_p^P \right) + \mathbf{X}_j^P \left(\boldsymbol{\beta}_j^P \right) + \boldsymbol{\varepsilon}^P \tag{3.6}$$

$$\underline{Difference} = \underline{BuyMoral} - \underline{BuyProtective} = \mathbf{Y}^D = \mathbf{X}_p^D \left(\boldsymbol{\beta}_p^D \right) + \mathbf{X}_j^D \left(\boldsymbol{\beta}_j^D \right) + \boldsymbol{\varepsilon}^D \tag{3.7}$$

The definitions of the independent variables are shown in Table 3.7. We used Zellner's seemingly unrelated regression (SUR)[28], assuming that the error terms are correlated, which, in fact, they are, as shown in the notes of Table 3.8, which provides the result of the estimations.

Table 3.7 List of the variables

Variable	Description	Mean	Standard Deviation	Max	Min
Morality_I	An action that respondents think is the most moral, selected from the slider ranging from "stay (0)" and "swerve (100)"	59.749	28.688	0	100
Difference	Each respondent's reply to *BuyMinimize* minus *BuySelfProtective* (Linearly transformed to 0-100 scale)	48.747	19.402	0	100
Morality_II	An action that respondents think is morally appropriate for the AV to take, selected from the slider ranging from "stay (0)" and "swerve (100)"	43.068	28.984	0	100
NeedRegulation	The answer to the question "do you think the government should require that all AVs be programmed to minimize the number of casualties in accidents, even if it means killing the passenger(s)?", selected from the slider ranging from "No, not at all (0)" to "Yes, definitely (100)"	38.404	29.587	0	100
WithCoworker	Respondents who were asked to imagine themselves in the car together with a coworker or acquaintance = 1; 0, otherwise	0.336	0.472	0	1
WithFamily	Respondents who were asked to imagine themselves in the car together with a family member = 1; 0, otherwise	0.332	0.471	0	1
WTP_Level5	Willingness to pay for adding Level 5 technology to the respondents' desired car; derived from the conjoint analysis in Section 3	35.746	36.714	-66.170	130.656

Note: $N = 9449$.
Source: *Survey on Auto Driving*

[28] See Zellner (1962), Zellner and Huang (1962), and Zellner (1963).

Table 3.8 Effects of the respondents' attributes

	OLS				Seemingly Unrelated Regression			
	Social Dilemma I		Social Dilemma II		Social Dilemma I		Social Dilemma II	
	Morality_I	*Difference*	*Morality_II*	*NeedRegulation*	*Morality_I*	*Difference*	*Morality_II*	*NeedRegulation*
WithCoworker	-5.098 ***	-2.224 ***	-2.714 ***	-1.669 *	-5.085 ***	-2.226 ***	-2.714 ***	-1.669 *
	(0.699)	(0.475)	(0.711)	(0.726)	(0.699)	(0.475)	(0.710)	(0.726)
WithFamily	-10.160 ***	-4.489 ***	-7.371 ***	-5.413 ***	-10.160 ***	-4.489 ***	-7.371 ***	-5.413 **
	(0.702)	(0.477)	(0.713)	(0.729)	(0.701)	(0.476)	(0.712)	(0.728)
Male	-5.381 ***	-1.216 **	4.054 ***	5.158 ***	-5.338 ***	-1.265 **	4.054 ***	5.158 **
	(0.639)	(0.434)	(0.650)	(0.664)	(0.622)	(0.423)	(0.649)	(0.663)
Age	0.206 ***	0.152 ***	0.156 ***	0.142 ***	0.214 ***	0.156 ***	0.156 ***	0.142 **
	(0.024)	(0.016)	(0.024)	(0.025)	(0.023)	(0.016)	(0.024)	(0.025)
HighEducation	-1.838 **	-2.302 ***	-0.982	-1.980 **	-1.946 **	-2.305 ***	-0.982	-1.980 **
	(0.621)	(0.422)	(0.631)	(0.645)	(0.618)	(0.420)	(0.630)	(0.644)
Income (log)	-1.471 ***	-1.322 ***	-1.839 ***	-1.368 **	-1.548 ***	-1.301 ***	-1.839 ***	-1.368 **
	(0.445)	(0.302)	(0.452)	(0.462)	(0.441)	(0.300)	(0.451)	(0.461)
DislikeShareCars	0.658	0.279	-2.168 ***	-2.965 ***			-2.168 ***	-2.965 **
	(0.637)	(0.433)	(0.647)	(0.661)			(0.646)	(0.661)
LikeGadget	0.520	-0.233	2.275 ***	2.274 ***			2.275 ***	2.274 **
	(0.523)	(0.356)	(0.532)	(0.543)			(0.531)	(0.543)
Pride	-0.998	0.428	3.639 ***	4.644 ***			3.639 ***	4.644 **
	(0.640)	(0.435)	(0.650)	(0.664)			(0.649)	(0.664)
FavDrive	-0.308	-0.530	-4.361 ***	-5.140 ***			-4.361 ***	-5.140 **
	(0.650)	(0.442)	(0.661)	(0.675)			(0.660)	(0.675)
CausedAccidents	0.730	0.351	-2.490 ***	-3.924 ***			-2.490 ***	-3.924 **
	(0.618)	(0.420)	(0.628)	(0.641)			(0.627)	(0.641)
Credibility	0.049 **	-0.046 ***	0.029 +	-0.026 +	0.050 ***	-0.047 ***	0.029 +	-0.026 +
	(0.015)	(0.010)	(0.015)	(0.015)	(0.015)	(0.010)	(0.015)	(0.015)
Altruism	4.674 ***	3.312 ***	3.950 ***	3.512 ***	4.656 ***	3.263 ***	3.950 ***	3.512 **
	(0.332)	(0.226)	(0.338)	(0.345)	(0.327)	(0.222)	(0.337)	(0.345)
WTP_Level5	-0.004	-0.019 ***	0.047 ***	0.057 ***	-0.004	-0.018 ***	0.047 ***	0.057 **
	(0.008)	(0.005)	(0.008)	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)
Constants	47.210 ***	47.130 ***	25.060 ***	22.660 ***	49.260 ***	46.400 ***	25.060 ***	22.660 **
	(3.628)	(2.466)	(3.687)	(3.768)	(3.172)	(2.156)	(3.684)	(3.765)
R-square	0.065	0.055	0.054	0.051	0.064	0.055	0.054	0.051
Log Likelihood	-44807.3	-41158.8	-44959.0	-45165.7	-84990.5		-87688.4	
BIC	89752.0	82454.9	90055.4	90468.8	170164.1		175651.5	
AIC	89644.7	82347.6	89948.1	90361.5	170021.1		175436.8	
N	9,449	9,449	9,449	9,449	9,449		9,449	

Note 1. The correlation of residuals for *Morality_I* and *Difference* is 0.4328, and the Breusch-Pagan test of independence ensured the correlation among the residuals with χ^2 (1) = 1770.200, P = 0.0000.

2. The correlation of residuals for *Morality_II* and *NeedRegulation* is 0.6348, and the Breusch-Pagan test of independence ensured the correlation among the residuals with χ^2 (1) = 3807.087, P = 0.0000.

3. The correlation matrix of the variables is in the Appendix, Table A1.

Source: *Survey on Auto Driving*

The results of the SUR show that even after controlling for several factors, *Morality_I* in Study I is highest when people assume they are riding in AVs alone (base case and not shown in Table 3.8), next highest when people assume they are riding with coworkers, and lowest when they assume they are riding with families.

This result is consistent with what is described in Figure 3.3, Panel B. *Morality_I* is higher for respondents who are female, older, less educated, with lower incomes, who believe in AVs, or are altruistic. An individual's WTP for Level 5 function is irrelevant to *Morality_I*. For *Difference*, the relative tendency to buy moral cars is higher for respondents with the same attributes except for Belief in AVs (*Credibility:* who believe car accidents will decrease if all the cars become fully autonomous). The coefficient of the *Credibility* variable is negative, so the more respondents believe in AVs, the less likely they are to buy moral cars. The first dilemma, wherein people do not buy what they think is moral, could be accelerated by the factors whose coefficients in *Morality_I* and *Difference* have opposite signs, and the critical factor here is *Credibility*. In other words, this factor led people to feel more moral while allowing them to be less likely to buy moral AVs relative to self-protective AVs.

The passenger factors determining *Morality_II* in Study II work the same as *Morality_I*. Other factors are generally analogous to *Morality_I* except that gender has the opposite effect. Males tend to think that choosing to make AVs swerve is more moral. Those factors that apply only for *Morality_II* are the following: reluctance to share cars (−); like gadgets (+); have pride in owning cars (+); like driving (−); and have caused car accidents (−). The second dilemma with respect to morality and regulation could also be accelerated by the factor whose coefficients in *Morality_II* and *NeedRegulation* have opposite directions. *Credibility* may again work against morality, as those who have more faith in AVs feel less need for regulation, although the significance levels are 5.7% for *Morality_II* and 9.7% for *NeedRegulation*.

3.9 Discussions

3.9.1 WTP for AVs

Japanese citizens' WTP for Level 3 and Level 5 AV options average only US$2687 and US$3164, respectively, and may not be high enough for autonomous vehicles to enter existing car markets. Bansal and Kockelman (2017) insist that there is a need for both a higher WTP and drastic reduction of production costs of (connected) AVs, even though they obtained a much higher WTP for AVs in Texas compared to our respondents' WTP. We need much more significant cost reductions to make AVs succeed with consumers in Japan.

Our analysis of Table 3.5 and Table 3.6 indicates that consumer heterogeneity could influence the spread of AVs. The gender difference is clear, as indicated by Hohenberger et al. (2016). Male respondents give higher marginal utility than female respondents for AVs with any fuel types. Age is not a simple factor because, as Owens et al. (2015) indicate, there is a complicated relationship between generational membership and driver attitude toward advanced in-vehicle technology. Nielsen et al. (2018) discuss the heterogeneity by dividing their respondents into three groups: skeptics, indifferents, and enthusiasts. Respondents in their 60s have a higher ratio of skeptics compared to those aged 18−29 and have a lower ratio of enthusiasts. However, in our survey, those in their 60s have higher WTP than others, even after controlling for their income. Gish et al. (2017) found that older people consider advanced vehicle technologies useful, due to health-related and functional changes occurring within the aging body, which may be one reason for their having higher WTP.

The Japanese government's primary purpose in supporting AV technologies is to reduce the number of traffic accidents, but those who have caused a car accident are *more* reluctant to buy AVs. Those who enjoy driving have a lower WTP, most likely because AVs will deprive them of the joy of driving. Schoettle and Sivak (2015b) find that motorists least prefer completely self-driving cars to partially self-driving and traditional cars. AVs are more likely to be bought by new customers who do not enjoy driving themselves and are less likely to be bought by driving enthusiasts. This factor may change the automobile market drastically; Rödel et al. (2014, p.8) suggest that the automotive industry develop highly autonomous cars adapted to drivers' preferences in terms of "a pleasurable and authentic driving experience."

3.9.2 Morality and the Social Dilemma

3.9.2.1 *Study I: Morality and Purchase Intentions*

Our study revealed a similarity between the US and Japan because there is a possibility that people may not buy what they think is moral. Dissimilarities were also found. Consumers in Japan will not buy moral cars if they expect to ride with family members, but whether they buy self-protective cars does not depend on the existence of fellow passengers (Figure 3.3, Panel B,). In the US, people may select protective cars when they are with a coworker or with a family member. This difference may be understood in terms of a stronger sense of family belonging.

Shariff et al. (2017) offer two suggestions to overcome the dilemma: one is to shift the discussion from a relative risk of injury to passengers to an absolute reduction of risk due to overall accident reduction, and the other is to appeal to consumers' desire to signal virtue. Our results contradict that of Sharif et al.'s (2017) first idea that overall accident reduction by AVs may help to overcome the social dilemma. As AVs become more credible, more people will start to make judgments that it is more moral to swerve (sparing the 10 pedestrians but killing passengers, including themselves), but they would not become more willing to buy AVs that are programmed to swerve. Interpretation of the behavioral discrepancies between morality and difference could be twofold. One is that, as credibility rises, people (perhaps unintentionally) assume the AVs' programming will become more accurate and believe that the "minimize" program will be better at saving pedestrians, which will result in more cases where passengers (including themselves) are sacrificed. The other interpretation may be that as credibility rises, it will become acceptable to purchase self-protecting cars because they can assume the number of such incidents they will face will decrease thanks to what they expect will be "foolproof" AVs. If this interpretation is correct, reducing overall accidents, ceteris paribus, may make the social dilemma more serious. The social dilemma will not be solved until both types of AVs (moral and self-protecting) can save both pedestrians and passengers.

Heterogeneous consumers may determine the "should be" behaviors of AVs in various ways. Making collective decisions in each country is easy. One means of reaching decisions is shown in the study by Awad et al. (2018), which extended Bonnefon et al. (2016), through the result of a worldwide online survey project named "The Moral Machine." People who visited the online interface made moral decisions to vote for behaviors that AVs should take. Noothigattu et al. (2017) use swap-dominance efficient voting rules for the 1,303,778 voters surveyed by the Moral Machine to efficiently aggregate those preferences to identify a desirable choice. This approach is a leading effort, but we believe their settings are too simple, as our two studies and the reliability of the decisions of each respondent are questionable in terms of making realistic rules.

3.9.2.2 *Study II: Morality and Regulations*

In Study II, we find that attitudes toward the regulation of AVs differ between the two countries, and the contrast is more evident than in Study I. Not only do Japanese respondents think AVs should be programmed to be less moral and US respondents see less need for regulations that mandate the desired behavior for AVs but also, as Bonnefon (2016, p. 1575) denotes, “regulation for AVs may be necessary but also counterproductive” in the US. Peoples’ purchase intention is higher if the AVs are not regulated (Figure 3.4, Panel A). In Japan, the existence of regulation makes a minor difference in purchasing intention (Figure 3.4, Panel B).

To deal with an unwillingness to regulate the morality of AVs, Contissa et al. (2017) propose to install an “Ethical Knob” that gives basic moral choices to the AV’s passenger, rather than preprogramming him or her. The Knob starts from an altruistic mode, giving preference to third parties, then moves to an impartial mode giving equal importance to passenger(s) and third parties, and reaches egoistic mode, giving preference to the passenger(s). The results of Study II suggest that this freedom for passengers to choose may be useful in the US, but not in Japan.

3.10 Conclusion

We found the WTP for autonomous driving in Japan is, on average, higher than the WTP for hybrid or electric engines, but not as high as the WTP in the US, even before we propose the existence of the moral dilemmas. The burden of the dilemmas may limit the WTP further, and we need to find ways to solve these ethical problems. Our text-mining analysis on the free answer at the end of the survey showed the "first impression" of consumers regarding the fact that AVs may have to face Trolley Problems. Among 9,451 respondents, 1,991 expressed negative feelings about this result, compared to 1,406 respondents who reported, "Good to know about the problem" feelings (422 respondents had both positive and negative feelings at the same time).

In the study of morality and purchasing behavior (Study I), we found the existence of the social dilemma; i.e., in Japan, people may not buy what they think is moral, just as in the US. Here, the role of credibility of AVs was found to be relevant. The credibility reported by consumers should be backed by a real decrease in the number of accidents. On the road to technological advancement, it is possible that consumers will tend to buy the self-protective, nonutilitarian AVs "because people believe that accidents will decrease thanks to the AVs."

We have yet to reach a solution to the first dilemma. Nevertheless, in the case of Japan, government regulation will not be averted, as shown in Study II, and once we find the solution, it will be easier for citizens than in the US to implement the solution. If we can construct ideal behavior conceptually, it can be applied to the AV's programming as done by Thornton et al. (2017)—create models with the best combination of ethical considerations. For that, as Bringsjord (2016) indicates, computational logicians that deal with various kinds of dilemmas that AVs may face are strongly needed. If the moral solution and technology are both supplied, the government can regulate AVs to behave as they should. Japanese respondents are more agreeable to such regulations than are people in the US (Study II). Credibility regarding AVs again works in a weakly adverse way; as credibility rises, people think AVs should act more morally, but they feel less need to regulate AVs to behave morally.

We analyzed only two scenarios among many because we needed to start from straightforward concepts, but we know there is a need for further investigation. As Nyholm and Smids (2016) indicate, the literature of the “Trolley Problem” should include important topics such as moral and legal responsibilities and decision-making uncertainty. We agree with their suggestion, and we will continue to work on the ethical problems of artificial intelligence.

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Appendix 3.A: Correlation Matrix

Table A3.1 Correlation matrix of variables for SUR

	Morality_I	*Difference*	*Morality_II*	*Need Regulation*	*With Coworker*	*With Family*	*Male*
Morality_I	1.000						
Difference	0.460 *	1.000					
Morality_II	0.326 *	0.286 *	1.000				
NeedRegulation	0.250 *	0.252 *	0.652 *	1.000			
WithCoworker	-0.001	-0.001	0.015	0.015	1.000		
WithFamily	-0.125 *	-0.081 *	-0.101 *	-0.075 *	-0.501 *	1.000	
Male	-0.086 *	-0.046 *	0.060 *	0.064 *	0.007	-0.007	1.000
Age	0.100 *	0.105 *	0.075 *	0.060 *	-0.008	0.005	0.135 *
HighEducation	-0.062 *	-0.080 *	-0.001	-0.011	-0.007	-0.005	0.265 *
Income (log)	-0.027	-0.043 *	-0.024	-0.017	-0.014	0.013	0.036
DislikeShareCars	0.014	0.013	-0.042 *	-0.055 *	-0.002	0.018	-0.026
LikeGadget	0.021	0.003	0.057 *	0.054 *	0.008	-0.006	0.017
Pride	-0.019	0.000	0.045 *	0.056 *	-0.002	0.010	0.022
FavDrive	-0.006	-0.003	-0.046 *	-0.061 *	0.013	0.014	0.172 *
CausedAccidents	0.016	0.020	-0.030	-0.055 *	0.018	-0.001	0.165 *
Credibility	0.030	-0.053 *	0.040 *	0.004	0.016	-0.016	0.111 *
Altruism	0.153 *	0.157 *	0.126 *	0.110 *	-0.003	-0.002	-0.020
WTP_Level5	-0.001	-0.045 *	0.084 *	0.090 *	0.002	-0.008	0.090 *

	Age	*High Education*	*Income (log)*	*Dislike ShareCars*	*LikeGadget*	*Pride*
Age	1.000					
HighEducation	-0.024	1.000				
Income (log)	0.075 *	0.196 *	1.000			
DislikeShareCars	0.127 *	-0.059 *	0.016	1.000		
LikeGadget	-0.041 *	-0.025	0.005	-0.003	1.000	
Pride	-0.020	0.049 *	0.123 *	0.102 *	0.146 *	1.000
FavDrive	0.041 *	0.037	0.060 *	0.121 *	0.175 *	0.199 *
CausedAccidents	0.183 *	-0.014	0.015	0.055 *	-0.005	0.010
Credibility	0.109 *	0.057 *	0.045 *	0.020	0.052 *	0.019
Altruism	0.117 *	0.007	0.077 *	-0.055 *	0.115 *	0.040 *
WTP_Level5	0.055 *	0.045 *	0.050 *	-0.027	0.043 *	0.001

	Favor Driving	*Caused Accidents*	*Credibility*	*Altruism*	*WTP_Level5*
FavDrive	1.000				
CausedAccidents	0.146 *	1.000			
Credibility	0.058 *	0.058 *	1.000		
Altruism	0.096 *	0.015	-0.009	1.000	
WTP_Level5	-0.099 *	-0.031	0.209 *	0.009	1.000

Source: *Surveys on Auto Driving*

Appendix 3.B: Theory of Random Parameters Logit Model

We account for the correlation between choices made by an individual following the discussion of panel mixed models in Train (2009). The probability that individual i will choose a choice sequence $s_i = \{s_{i1}, s_{i2}, \ldots, s_T\}$ given the choice profiles $x_i = \{x_{i1}, x_{i2}, \ldots, x_T\}$ is then written as follows:

$$\Pr\left(s_i \middle| x_i, \boldsymbol{\beta}_i\right) = \prod_{t=1}^{T} \left[\frac{\exp\left(\boldsymbol{\beta}_i' \mathbf{x}_{iS_{it},t}\right)}{\sum_{j=1}^{J} \exp\left(\boldsymbol{\beta}_i' \mathbf{x}_{ijt}\right)} \right]. \qquad \text{(A3.1)}$$

Integrating the right side of equation (A3.1) over the distribution of $\boldsymbol{\beta}$ yields the following:

$$\Pr\left(s_i \middle| x_i, \boldsymbol{\theta}\right) = \int \Pr\left(s_i \middle| x_i, \boldsymbol{\beta}_i\right) g\left(\boldsymbol{\beta} \middle| \boldsymbol{\theta}\right) d\boldsymbol{\beta}\,. \qquad \text{(A3.2)}$$

This mixed-logit probability can be evaluated numerically with the simulation method. The value of the integral is approximated by drawing $\boldsymbol{\beta}_{ir}$ from the distribution for $r = 1, \ldots, R$ (R is the number of draws). The parameter estimates are obtained by maximizing the following simulated log-likelihood:

$$SLL = \sum_{i=1}^{I} \sum_{t=1}^{T} d_{ij} \ln\left(\frac{1}{R} \sum_{r=1}^{R} \frac{\exp\left(\boldsymbol{\beta}_i' \mathbf{x}_{iS_{it},t}\right)}{\sum_{j=1}^{J} \exp\left(\boldsymbol{\beta}_i' \mathbf{x}_{ijt}\right)} \right), \qquad \text{(A3.3)}$$

where d_{ij} is a dichotomous variable, i.e., d_{ij} = 1 if individual i chose j and zero otherwise.

The population distribution, $g\left(\boldsymbol{\beta} \middle| \boldsymbol{\theta}\right)$, reflects the degree of heterogeneity in preferences. The distribution, which is conditional on a sequence of choices, s_i, characterized by choice profiles, x_i, is obtained using Bayes' rule:

$$h\left(\boldsymbol{\beta}_i \middle| s_i, x_i, \boldsymbol{\theta}\right) = \frac{\Pr\left(s_i \middle| x_i, \boldsymbol{\beta}_i\right) g\left(\boldsymbol{\beta} \middle| \boldsymbol{\theta}\right)}{\Pr\left(s_i \middle| x_i, \boldsymbol{\theta}\right)}. \tag{A3.4}$$

h is the density of $\boldsymbol{\beta}_i$ in the subpopulation of those who would choose sequence s_i when facing x_i. h is proportional to the density of $\boldsymbol{\beta}$ in the entire population multiplied by the probability that s_i would be chosen if the respondent's coefficients were $\boldsymbol{\beta}_i$ because $\Pr\left(s_i \middle| x_i, \boldsymbol{\theta}\right)$ is the integral of the numerator and a constant.

Appendix 3.C: Personal WTP

Calculating personal WTP becomes more complicated when we consider cross effects, and the calculation includes attributes variables, as we have done in Subsection 3.5.2. Thus, we estimated a straightforward utility function that includes $V^i = \beta^i_{Level} \times Level + \beta^i_{Fuel} \times Fuel + \beta_{Price} \times Price$ where price coefficient is nonrandom, to make use of individual WTP for Level 5. Estimated parameter and standard deviations of random parameters are in Table A3.2.

Table A3.2 Parameter Estimates

		Parameter Estimates	Standard Deviations of Parameter Distributions
Autonomous Driving	Level 3	2.234 ***	2.210 ***
		(0.037)	(0.033)
	Level 5	2.625 ***	3.075 ***
		(0.044)	(0.041)
Fuel	Hybrid	1.691 ***	2.259 ***
		(0.035)	(0.035)
	Electricity	0.795 ***	2.723 ***
		(0.038)	(0.041)
Price		-0.073 ***	-
		(0.001)	
Log Likelihood			-83063.9
McFadden Pseudo R-squared			0.255

Note: 1. Standard errors in parenthesis
2. Estimations based on 500 Halton draws
*** Significance levels are indicated by 1%
Source: *Survey on Auto Driving*

The simulated distributions are shown in Figure A3. The distributions of the coefficients of autonomous driving (thicker lines) and fuel types (thinner lines) are independent and not directly comparable, but we include them in Figure A3 for reference. On average, the parameters indicate that people may prefer autonomous driving systems to hybrid or electric motors, and the heterogeneity in the coefficient for Level 5 is extensive.

Focusing on the preference for autonomous driving, we estimated the individual WTP of the respondents. Calculated from the specific choice conditional WTP, the average for Level 3 is 304 thousand yen, with a SD of 166 thousand yen. The average for Level 5 is 358 thousand yen with a SD of 198 thousand yen, slightly lower than the estimation performed in Chapter 5 considering cross effect. The WTP values in US dollars are $2,687 and $3,164, respectively[29]. When used in the estimation in Chapter 6, the distribution rather than the level of the WTP is important, so we adopted the individual Level 5 WTP here.

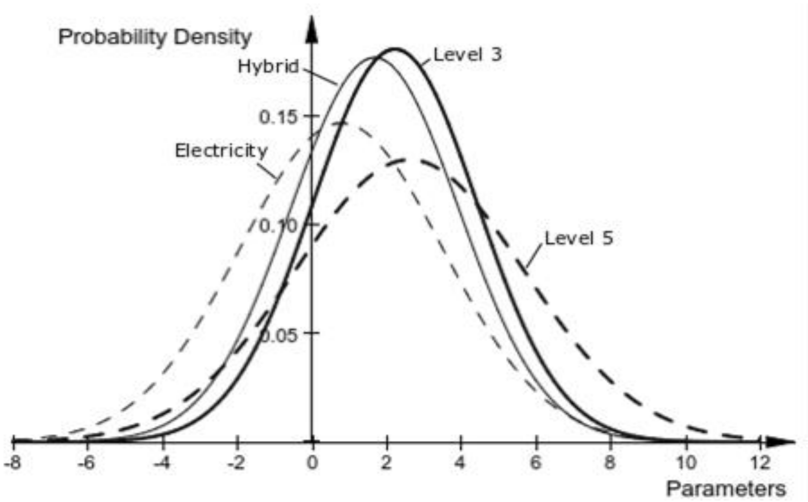

Figure A3 Probability density functions of estimated random parameters

Source: Table A3.2

[29] $1 = 113.15 yen as of February 2017.

Chapter 4 Evaluations of Human Resource Policy

― The relationship between school-based career education and subsequent incomes: empirical evidence from Japan ―

4.1 Introduction

With recent changes in Japan's economic structure and employment environment, students' career paths have changed significantly. In the 1990s, Japanese-style employment practices, based on lifetime employment and seniority-based wages, began to deviate from their historical norms in response to an economic downturn. Companies began to suppress the hiring of new, fulltime graduates to control the number of fulltime employees. Since young people were not able to find the job they desired, their incentives to work decreased, and an increasing proportion of this younger generation remained unemployed, compared to pre-1990 levels. Figure 4.1.1 shows the midterm trend in the percentage of people not in the labor force. This rate has gradually increased due to a significant increase in the ratio of people categorized as "other," which denotes people who are not in the labor force except that of home keepers and students. The proportion of people in these last two categories (home keepers and students) has decreased over time; hence, the reason behind the net increase in people not in the labor force is smaller than the increase observed in the "other" category. Figure 4.1.2 shows a shorter-term trend of those not in the labor force, this time focusing just on young people (aged 15 to 34). Decreasing numbers of young people are receiving the chance to determine their pathways in society.

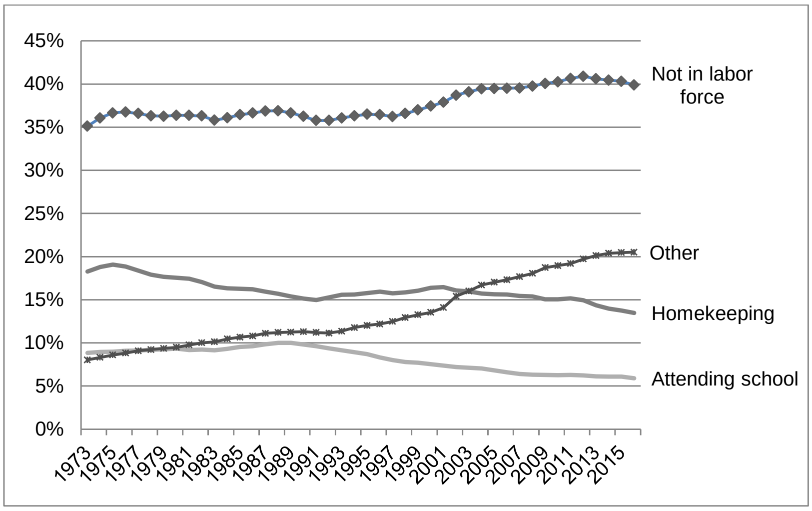

Figure 4.1.1 Ratio of people who are not in labor force

Note: 1. The ratio of the population aged 15 years and older.
2. "Not in labor force" = "Attending school" + "Homekeeping" + "Other"
Source: Statistics Bureau, Ministry of Internal Affairs and Communications (2017)

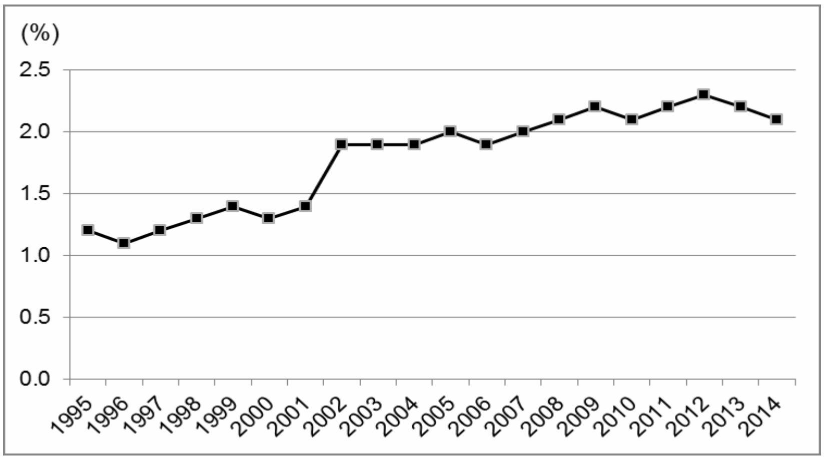

Figure 4.1.2 Non-employed people of the population aged between 15 and 34 years from 1995 to 2014

Source: Modified from Figure 34 (2), "Percentage of non-employed of the population of people aged 15 to 34," Cabinet Office (2016, p.16)

Note 1: Non-employed young people means people who are (i) aged from 15 to 34 years, (ii) not in the labor force, and (iii) are neither homemakers nor school attendees.

2: The figures for 2011 exclude those for Iwate, Miyagi, and Fukushima.

The increase witnessed regarding the young non-employed may reflect changes in their decisions and preferences versus whether to participate in the labor force and the sluggishness of the economy. In 2012, 20 percent of students graduating from college and 10 percent of students graduating from high school were neither employed nor continuing to further or higher education. Students who terminated education at junior high school (middle school) represent only 8 percent of all young people, but they make up 20 percent of the not in education, employment or training (NEET) population, according to a Cabinet Office survey.

With the background described above, the need to incorporate education fostering the motivation and qualities required for students' future social and vocational independence (career-oriented and vocational education, hereafter referred to as career education) in the school curriculum has emerged. The Ministry of Education, Culture, Sports, Science and Technology (MEXT) advocated the promotion of career education in the 1999 Central Council for Education report, "On Improving the Connection between Elementary and Secondary Education and Higher Education." Later, the Ministry introduced various measures to expand career education actively (discussed in Section 2). After several policies were implemented, as of 2012, people responsible for career education were deployed in approximately 80 percent of elementary schools and in nearly all middle and high schools; further, 50 percent of elementary schools and 80 percent of middle and high schools instituted annual guidance plans for career education. Additionally, in 2012, 98.0 percent of students in public middle schools had undertaken work experience placements, while the completion rate of internships in high schools was 79.8 percent. Opportunities to cultivate reason and motivation aimed at students' future vocational independence are increasing.

Whether career education in the school curriculum has achieved its goal has not been established in Japan thus far. There is an insufficiency of research that documents how helpful (or unhelpful) career education is to graduates. Although

Recruit (2009, 2011, 2013, 2015, 2017) consecutively surveys teachers concerning whether they feel career education is helpful for students, Recruit did not ask students directly how valuable it was for them. Yamaoka (2009) suggested positive outcomes of career education from labor and vocational perspectives; however, whether it is effective has yet to be determined.

Based on a postal survey targeting young people nationwide aged between 23 and 27, the Japan Institute for Labor Policy and Training (2010) suggests it is possible that respondents' evaluations of career education influence their employment status and income. This study, however, does not perform quantitative analysis of the data obtained. From a quantitative analysis of an online survey targeting high school and vocational school graduates nationwide and aged 17 and 27, Ariga (2012) revealed that school characteristics and job placement services in high schools, along with students' academic performance and social skills, influence job market outcomes immediately after school. This study differs from the work we present here because it does not focus specifically on the analysis of career policies.

Using a quantitative analysis of the survey data, this study aims to clarify the effects of career education issued in 2004 as the "Youth Independence Challenge Plan" (see Section 2). We used respondents' recognition of the career policy as a proxy for the "input of career education"; we aim to determine whether this input affects respondents' annual incomes.

Next, in Section 4.2, we provide a brief history of Japan's education policies; Section 4.3 reviews relevant existing literature in this domain; Section 4.4 presents methodological details and results; and, finally, Section 4.5 ends the paper with discussion and conclusions.

4.2 Japanese Career Education Policies

Japanese career education in schools has its roots in vocational guidance provided during the 1920s with a social policy orientation (Ishioka, 2007). In the wake of a 1925 notification from the Japanese central government, local governments acted in concert with school officials to develop and secure employment placements for the young people of the country to meet the demands of the laborers (Yamooka, 1998). The background was far different from today, and the number of young laborers that left their villages looking for jobs in large cities steadily increased during the interwar era (Takase, 1998).

Schools have been providing contemporary career guidance regarding students' advancement to continuing education and employment. However, until the end of the 20th century, such guidance only covered students in middle and high schools, and most career guidance was called exit guidance—in other words, support and guidance for passing entrance and employment exams. When lifetime employment and employing new graduates were the norm, students attained vocational independence within the company that hired them; simultaneously, the familial and communal organizational culture of Japanese enterprises encouraged social self-reliance, and the students grew into "adults" (Komikawa, 2007). Thus, although career guidance in schools was "education for a predetermined destination" (Mochikawa, 2013) to transition from school to society, there were no major issues. However, along with the changes in social conditions, this "predetermined destination" gradually vanished.

In contrast to career guidance, career education refers to activities that support the transition from school to society. These activities are incorporated in all educational levels, from preschool to elementary, all through middle school, and then high school education. Career education, as it stands today, has its roots in the 1999 Central Council report entitled, "Improvements in Articulation between Elementary and Secondary Schools, and Higher Education Institutions." The report suggests that delivering career education in a planned manner is crucial while emphasizing experiential classes, from the elementary to higher education. This finding placed the spotlight on career education as one of the pillars of youth employment policy. Moving forward, in 2003, the "Youth Independence and Challenge Strategy Council," composed by four relevant ministries, established the "Youth Independence and Challenge Plan." The Plan cited career education as one of the central elements of the policy. The four politicians involved were the Ministers of MEXT, Health, Labor and Welfare, Economy, Trade and Industry (METI), and, finally, the Minister of State for Economic and Fiscal Policy of the Cabinet Office. Later, the Council established the "Youth Independence and Challenge Action Plan," and in 2006, the "Youth Independence and Challenge Plan" (revised edition). Additionally, the "Basic Plan for Education Promotion" in 2008 prioritized career education as an "education policy that should be addressed in the next five years."

"Promotion of Education that Cultivates Young Students' Vocation and Labor Perspectives (Research Report)," published by the National Institute for Educational Policy Research Student Guidance Research Center in 2002, explained the basis of career education by referencing the 1999 Central Council report. The Research Report classifies four various abilities related to vocational development: ability to (1) form human relationships, (2) use information, (3) plan, and (4) make decisions. The report recommends nurturing these four abilities, for example, through experiences such as responsible activities in elementary school and work experience and internships in middle and high school. Based on the above, specific career education material was formed, with different objectives: exploring the region, investigating jobs of people close to the students, interviewing professionals, and experiential classes in advanced schools.

In January 2011, the Central Council for Education changed the definition of Career Education to “education that encourages career development by cultivating the competencies and attitudes needed to raise the social and vocational independence of individuals” (Fujita, 2016). Then, the Council reconfirmed that career education programs should be implemented at all levels of education and that each school's overall educational processes and activities were significant for developing career-relevant skills.

4.3 Previous Studies

Effects of career education policies are hard to measure quantitatively, and researchers have hitherto set various factors as outputs in attempting to do so. We set people’s annual income as an output because it not only represents people’s lives (their options, opportunities, and their wellbeing to the extent that it is a function of income) but also serves the welfare of the nation through contributing to national income.

4.3.1 Income as an Output of Education

We selected earning capacity, specifically current annual income (log-transformed), as an indicator to measure career education achievements. We posit the hypothesis that career education helps people earn more.

Griliches (1977) discusses the widely used education function:

$$y_i = \ln Y_i = \alpha + \beta S_i + X_i \delta + u_i \tag{4.1}$$

where y is a measure of income, earnings, or wage rates, and S is a measure of schooling, usually in units of years or grades completed. X is a set of other variables assumed to affect earnings; u is an error term, representing other factors that affect earnings but are not explicitly measured, and it is assumed to be distributed independently of the Xs and possibly of S; and i is an index identifying a particular individual in the sample. His assertion is that equation (4.1) suffers from estimation bias, and we should instead adopt a simultaneous equations approach, for instance:

$$Y = p_h H e^u \tag{4.2}$$

$$H = e^{\beta S} \cdot e^v \tag{4.3}$$

$$y = \ln Y = \ln p_h + \beta S + u + v \tag{4.4}$$

where p_h is the market rental price, which may vary over time and space, H is the implied unobserved quantity of human capital, while u denotes other random influences on wages. Equation (4.3) is an implicit production function for human capital with time spent in school (S) as the primary input and other human capital-augmenting influences such as differences in the quality of schooling, or differences in the efficiency (ability) with which the time in school was spent by different individuals, represented by the v variable. Griliches (1977) states, "Most of the issues of 'ability bias' and simultaneity can be discussed regarding the content of the u and v variables and the relationship of S to them," and he used a two-stage least squares approach.

Many studies have estimated the effect of education on earnings or income, dealing with these biases. Gaston and Sturm (1991) treat schooling as a continuous variable and estimate selection bias-corrected earnings equations for young Australians. They found the biased estimates give from 3.0 to 3.6 percent higher returns of education (earnings.) Using sample data based on twins to eliminate endogeneity bias, Ashenfelter and Krueger (1994) show that an additional year of schooling increases wages by 12–16 percent. Angrist and Krueger (1991), taking each student's birth quarter as the instrumental variable, estimated the effect of attendance mandated by a compulsory schooling law on their subsequent earnings and found that an additional year of obligatory schooling increases earnings by approximately 7.5 percent. Harmon and Walker (1995) also used the instrumental variable method (IV), complemented by a selectivity model approach; they measured the rate of return to schooling at approximately 16 percent. Kane and Rouse (1995) estimated returns to postsecondary education and found that forgone earnings are approximately equal between two- and four-year college graduates when they control the ability and background of the students. Card (2001) provides informative reviews of the studies that have attempted to measure the causal effect of education on labor market earnings using institutional features on the supply side of the education system as exogenous determinants of schooling outcomes. His review includes, in addition to Angrist and Kruger (1991), Harmon and Walker (1995), and Kane and Rouse (1995), early versions of Staiger and Stock (1997), Card (1995), Conneely and Uusitalo (1998), Ichino and Winter-Ebmer (1998), Lemieux and Card (2001), Meghir and Palme (1999), Malucchio (1998), and Duflo (2001).

Other studies contribute to the literature on the relationship between education and labor, or earnings, from other respects. Alam and Mamun (2016) indicated a feedback effect between educational attainment and labor market status. They applied a simultaneous system of two-equation models and found the effects of achieving higher educational attainment on the probability of being employed have been statistically significant, and the effect is negative in the labor market equation. Focusing on a university in Australia, Koshy et al. (2016) examine the impact of various factors on university graduate earnings, including institutional factors. They found limited evidence for an earnings premium associated with the university attended.

4.3.2 Difference-in-Differences Approach to Measure Policy Effects

Strictly speaking, to isolate policy effects, the same people should be tested at the same time comparing "with" and "without" policy alternatives. Since we are never able to implement the test in the real world, we instead adopt a second-best and quasi-experimental method, i.e., a difference-in-differences (DID) estimation. We compare trends in income among those who graduated from strategically targeted schools to trends in income among a comparison group who graduated from other schools.

DID has been applied to a broad range of economic issues. To name a few in education, Hampf and Woessmann (2016), followed by Hanushek et al. (2017), compared the effect of vocational and general education on employment over the life cycle. The results are impressive because an initial employment advantage of individuals with vocational compared to general education turns into a disadvantage later in life, especially in apprenticeship-oriented countries that provide the highest intensity of industry-based vocational education. Oosterbeek et al. (2010) analyze the impact of a leading entrepreneurship education program on college students' entrepreneurship skills and motivation. Their results show that the program does not have the intended effects; the effect on students' self-assessed entrepreneurial skills is insignificant, and the effect on the intention to become an entrepreneur is even adverse.

Beyond career education, many studies use DID in the field of education. Leer (2016) estimates the effects of decentralization on educational outcomes in Indonesia; there was no overall effect on achievement, but there was a negative effect on teacher effort, particularly on that in rural areas and among schools with inactive school committees. Walker and Zhu (2008) estimated the college wage premium using DID with quantile regression. While labor supply exceeded demand in the UK, they found no significant fall in the premium for men and even a sizable, but insignificant, increase for women. Their quantile regression results reveal a fall in the premium only for men in the bottom quartile of the distribution of unobserved skills. Jakubowski (2010) tested the robustness of the findings presented in the seminal work by Hanushek and Woessmann (2006), who claimed, through an international DID analysis, that tracking or ability grouping of students has a negative impact on educational inequality and no positive effect on their average performance. Jakubowski demonstrated the robustness checks of Hanushek and Woessmann method and found that there are crucial differences between the data of PIRLS, TIMSS, and PISA that could bias the results obtained from the DID, difference-in-differences method (country-level DID); he then conducted micro (student)-level DID. With data limited to native students, who were in modal grades and of the same age, the results changed markedly. He found no evidence of a negative impact of tracking on either mean performance or educational inequality.

4.4 Survey and Results

From March 30 to April 01, 2013, with the help of Nikkei Research, Inc., we conducted an online Survey on Vocation-related Education in School,[30] targeting 16- to 31-year-olds living in Japan and no longer in school. We limited the upper age to 31 to compare the generation before and after receiving career education policies. The response rate was 23%; 3,068 valid responses were captured. We inquired about whether career education obtained in elementary, middle, or high school helped respondents form their current careers; respondents' current incomes and sociodemographic characteristics were also elicited. Before distributing the online survey, we convened two focus group sessions (*n* = 6 in each session). We then piloted the survey (*n* = 235; response rate = 28%) to identify ambiguities and missing information.

Our analysis is twofold. First, we quantified the differences between people exposed to school-based career education programs designed by the government and those who were not. This quantification is a policy effect analysis based on the DID method. We clarify the policy effects of the government's "Career Education Promotion Region-Designated Project (FY2004–2006)" and career education policies in general from the perspective of whether they influenced graduates'

[30] The survey is funded by the National Graduate Institute for Policy Studies, Japan.

earning capacity. Second, we considered that those who remember taking career programs had experienced career education policies. We also included qualified daily activities as explanatory variables.

4.4.1 Respondents' Attributes

This section introduces respondents' attributes and attitudes toward career education. We start from sociodemographic characteristics, then consider how useful career activities have been for respondents and their expectations of career policies.

4.4.1.1 *Sociodemographic characteristics*

Among the 3,067 respondents, 45% are male, and 55% are female. Females thus had a higher propensity to complete the survey, given that 51% (49%) of the national population is male (female) as of March 2013. Our respondents' age distribution is somewhat concentrated in the 25–29 range, as in Table 4.1.

Table 4.1 Nonstudent population by age group

		Ages 16-19	20-24	25-29	30-31	All (16-31)
Authors' Survey		11	668	1,816	572	3,067
	(ratio)	0.4%	21.8%	59.2%	18.7%	100.0%
National	(thousands)	937 *	4,640	6,780	2,987 *	15,345
	(ratio)	6.1%	30.2%	44.2%	19.5%	100.0%

Source: *Survey on Vocation-related Education in School*; Ministry of Health, Labour and Welfare (2013a, 2013c); Statistics Bureau, Ministry of Internal Affairs and Communications (2013).

Notes: Because the Labour Force Survey publishes population only by age group and not by each age, we estimated the population of the 16–19 and 30–31 age groups using the ratio from the population census.

Table 4.2 Labor force status

	Age Group	Nonstudents	Employed	Unemployed	Not in the labor force	House-keeping	Other
Authors' Survey	16-31						
		3,067	2,336	111	620	329	291
(ratio)		100.0%	76.2%	3.6%	20.2%	10.7%	9.5%
Labor Force Survey	15-34						
(thousands)		20,300	16,220	1,140	2,940	2,010	930
(ratio)		100.0%	79.9%	5.6%	14.5%	9.9%	4.6%

Source: *Survey on Vocation-related Education in School*, Ministry of Health, Labour and Welfare (2013a, 2013c)
Note: Because of the data constraint, we cannot present the results of the 16–31 age group in the Labour Force Survey.

Our targeted respondents are those who are not attending school, and their jobs are shown in Table 4.2. Nine and one-half percent of respondents were not in the labor force or classed as homemakers ("Other" in Table 4.2); this result is higher than the national equivalent.

Parents' education affects children's education. Table 4.3 displays respondents' education with their fathers' and mothers' education. We also categorized respondents by their labor participation status. Note that education here is represented by the "standard" school leaving age. We grouped respondents who left education after high school, a specialized training college equivalent, or less, into "18" regardless of their actual age of leaving. When the highest education level is junior college, upper secondary specialized training school or equivalent, then "20"; university equivalent is "22"; and graduate school is "24," however long the respondents stayed in graduate school.

The dependent variable, respondents' own income, is a function of education and gender (Figure 4.2). Education is represented by respondents' standard school leaving age, just as in Table 4.2. The higher the education, the more they earn. In

Table 4.3 Respondents' and parents' education

Respondents' Education	Fathers' Education					Mother's Education				
	N = 2,715					*N* = 2,766				
All respondents	18	20	22	24	Total	18	20	22	24	Total
18 (High Schools Equivalent or Less)	65.7%	4.7%	28.4%	1.2%	100%	72.3%	19.0%	8.4%	0.2%	100%
20 (Junior Colleges Equivalent)	51.6%	2.8%	41.9%	3.7%	100%	60.0%	25.5%	13.2%	1.4%	100%
22 (Universities Equivalent)	40.0%	4.7%	50.7%	4.5%	100%	47.2%	26.6%	25.0%	1.2%	100%
24 (Graduate Schools Equivalent)	33.3%	5.1%	52.8%	8.7%	100%	38.6%	29.4%	29.9%	2.0%	100%
Total	49.5%	4.6%	42.3%	3.6%	100%	56.6%	24.0%	18.5%	0.9%	100%
Respondents in the labor force	*N* = 2,191					*N* = 2,233				
(Including unemployed)	18	20	22	24	Total	18	20	22	24	Total
18	65.8%	5.1%	28.0%	1.2%	100%	72.3%	19.4%	8.1%	0.3%	100%
20	53.8%	2.5%	40.6%	3.1%	100%	60.4%	23.2%	14.6%	1.8%	100%
22	40.5%	4.4%	50.4%	4.6%	100%	46.4%	27.2%	25.3%	1.2%	100%
24	32.3%	5.3%	54.0%	8.5%	100%	37.7%	29.8%	30.4%	2.1%	100%
Total	48.7%	4.6%	42.9%	3.7%	100%	55.0%	24.6%	19.4%	1.0%	100%
Respondents not in the labor force	*N* = 524					*N* = 533				
(Excluding homemakers)	18	20	22	24	Total	18	20	22	24	Total
18	65.6%	3.8%	29.4%	1.1%	100%	72.5%	18.2%	9.3%	0.0%	100%
20	45.5%	3.6%	45.5%	5.5%	100%	58.9%	32.1%	8.9%	0.0%	100%
22	37.3%	6.5%	52.2%	4.0%	100%	52.0%	23.3%	23.8%	1.0%	100%
24	66.7%	0.0%	16.7%	16.7%	100%	66.7%	16.7%	16.7%	0.0%	100%
Total	52.7%	4.8%	39.7%	2.9%	100%	63.2%	21.6%	14.8%	0.4%	100%

Source: Survey on Vocation-related Education in School

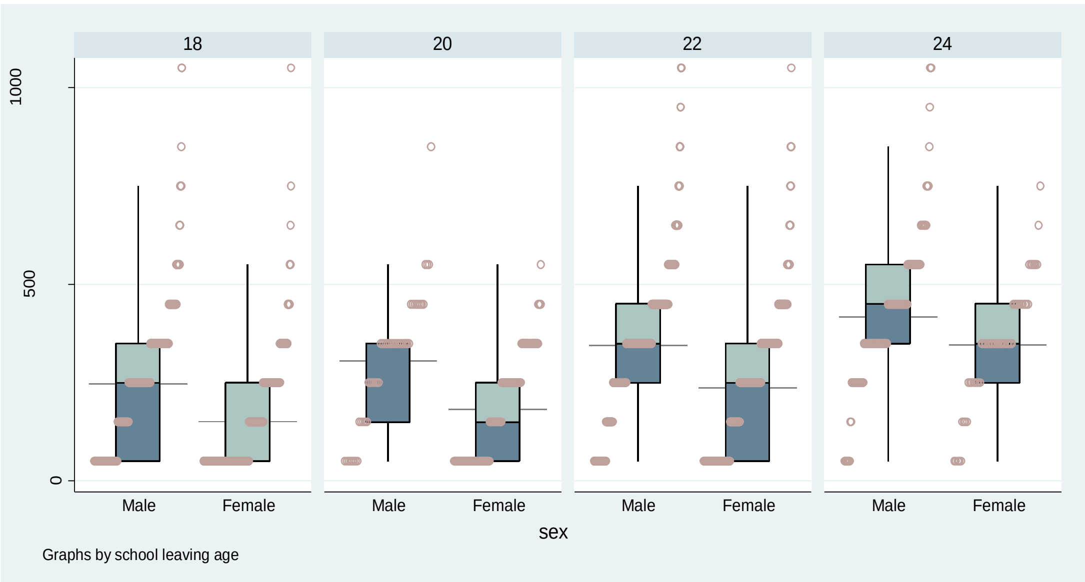

Figure 4.2 Respondents' income by education and sex

Source: Survey on Vocation-related Education in School

Note: The box shows the interquartile range; the top of the upper box is the 75th percentile, the bottom of the lower box is the 25th percentile, the vertical line shows the 1.5 quantile range, the thin horizontal line is the average, and the superimposed dots are the quantile plot.

every educational category, females make less than males on average. We will control for these factors (education and sex) later in the subsequent analysis.

4.4.1.2 *Usefulness*

We measured how respondents evaluate career education activities provided in elementary school, junior high school, and high school. The activities include job shadowing or interviews with workers and more regular, daily activities, such as being a leader or coordinator of school-based events.

Respondents who experienced these activities expressed how beneficial they were to themselves in aggregated options 1 and 2 as “Useful” and choices 4 and 5 as “Useless” (Figures 4.3.1–4.3.3; diffusion indices, calculated as the average percentage of “Useful” minus “Useless,” are in parentheses).

According to Figure 4.3.1, respondents do not seem to value specialized career education activities in elementary school. Instead, they feel that daily classroom activities and experiences are valuable, such as harmonious interactions and helping others.

In middle school (Figure 4.3.2), seven of nine career activities, including “Field trip” and “Job shadowing”, are considered useful.

All the career education activities directly connected to the workplace are popular (DI > 0) in high school (Figure 4.3.3), with “Internship” being considered most useful.

From these descriptive statistics, we observe that coordinating, between being a good team player and being a leader, is useful for respondents. Helping others is

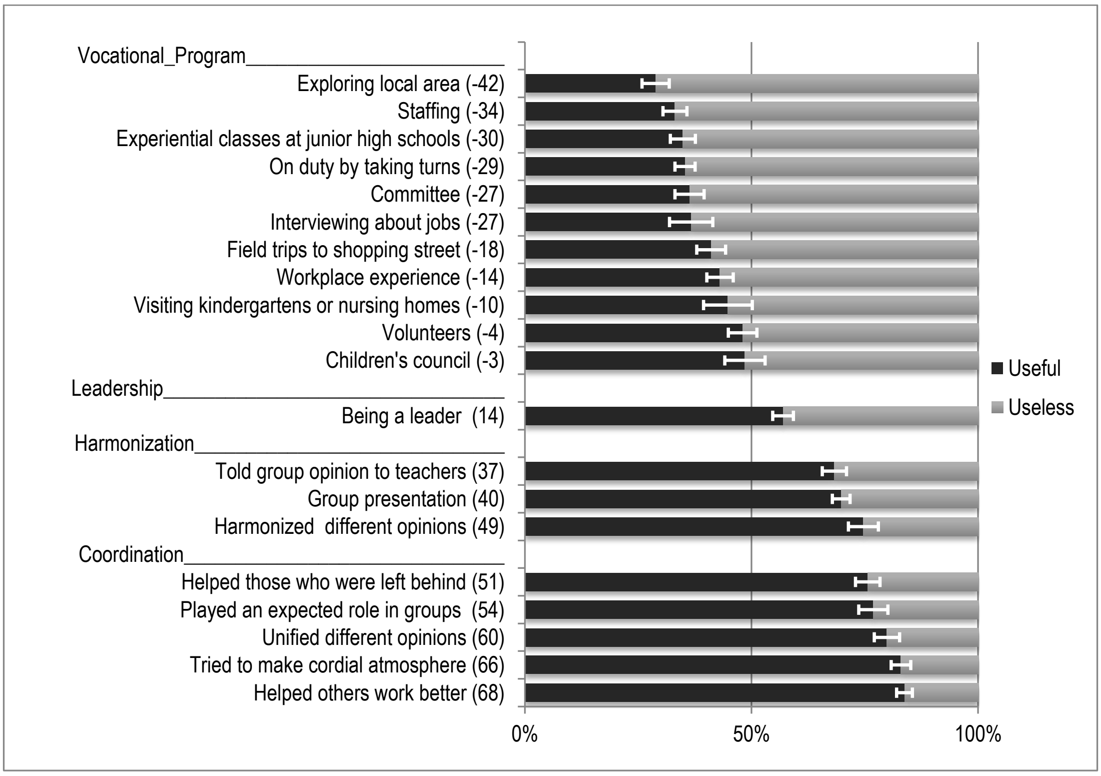

Figure 4.3.1 Usefulness of career education activities (Elementary school)

Note: Diffusion index of average (Useful–Useless) in parenthesis; 95% confidence interval is depicted in each bar.

Source: *Survey on Vocation-related Education in School*

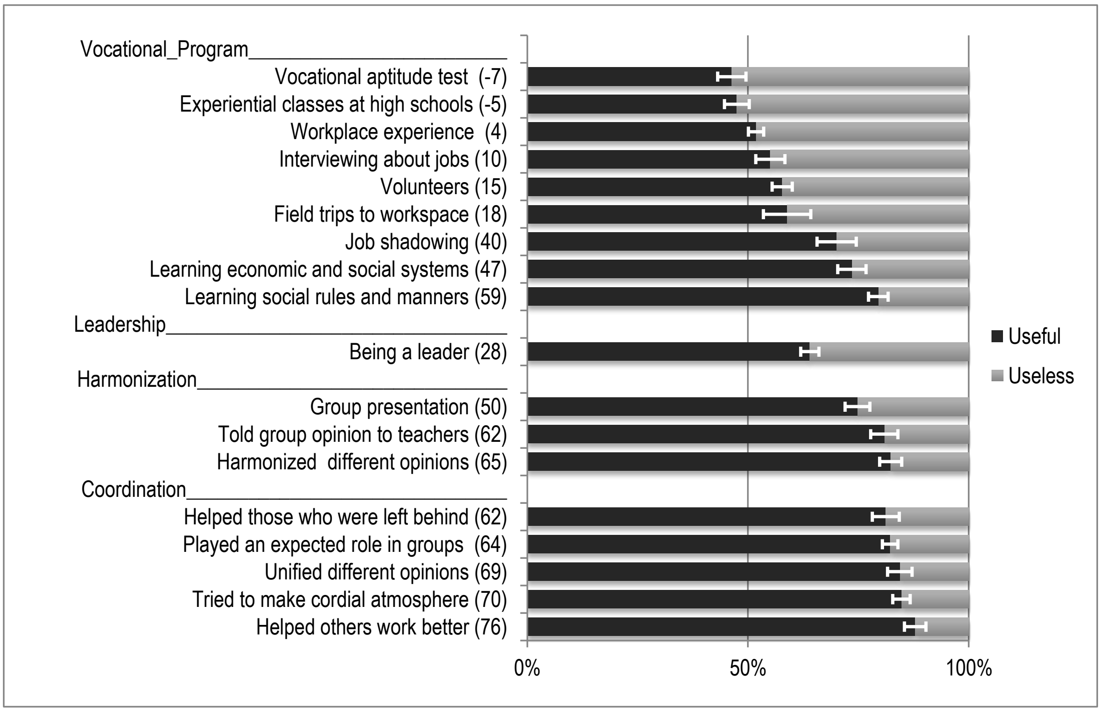

Figure 4.3.2 Usefulness of career education activities (Junior high school)

Source and Notes: See Figure 4.3.1.

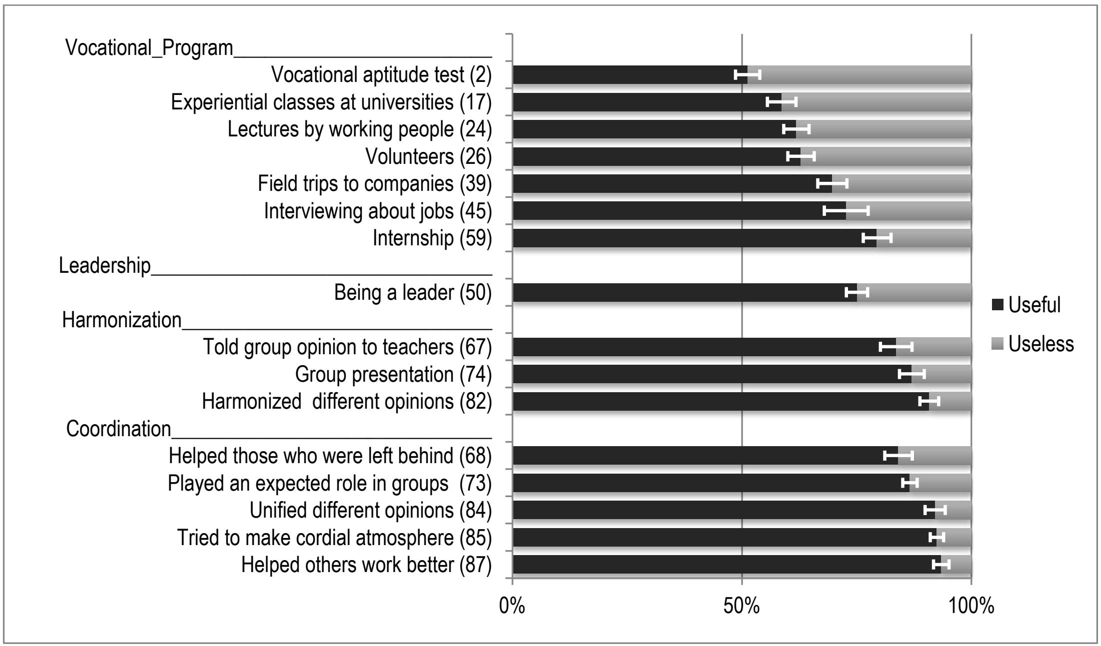

Figure 4.3.3 Usefulness of career education activities (High school)

Source and Notes: See Figure 4.3.1.

evaluated as being more useful than being a leader. The importance of everyday activities that nourish general social skills should be emphasized. Simultaneously, programs of career education activities connecting to the workplace in elementary and middle schools exhibit much room for improvement.

4.4.1.3 *Expectations*

In the question asking when respondents should have started thinking about jobs, approximately 15 percent answered that this point in time occurred when they had been in "elementary school (Age 6–12)" (Figure 4.4). Middle school (Age 12–15) is the most common time that respondents think schools should let students think about jobs, except for those with a graduate school education, who tended to prefer university (Age 18–22) in this respect.

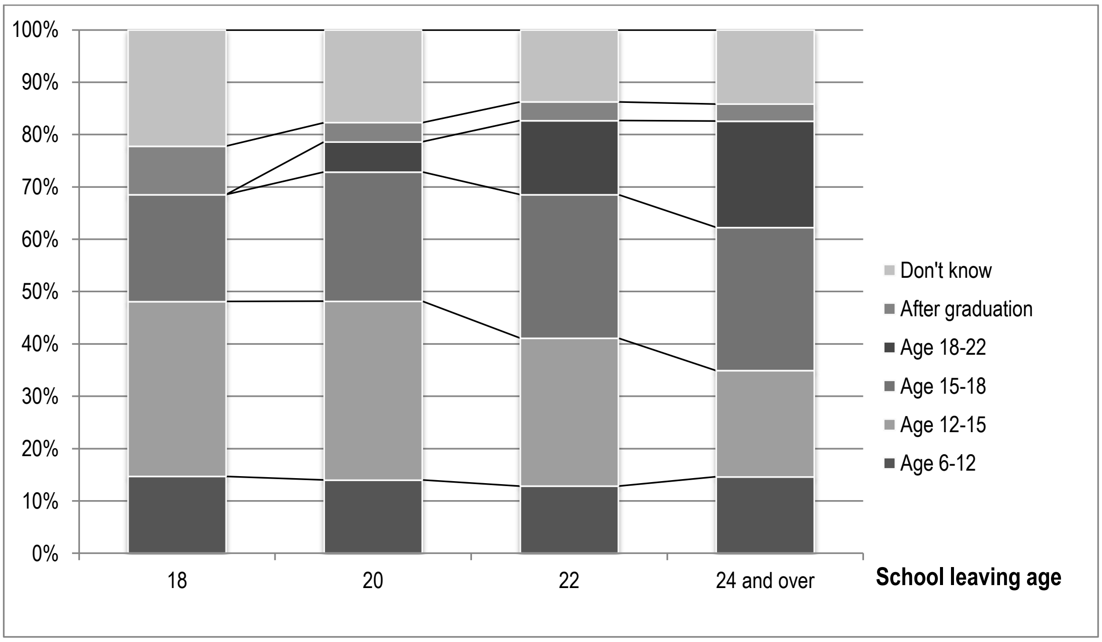

Figure 4.4 When the respondents think they should have started thinking about their jobs, by school leaving age

Source: *Survey on Vocation-related Education in School*

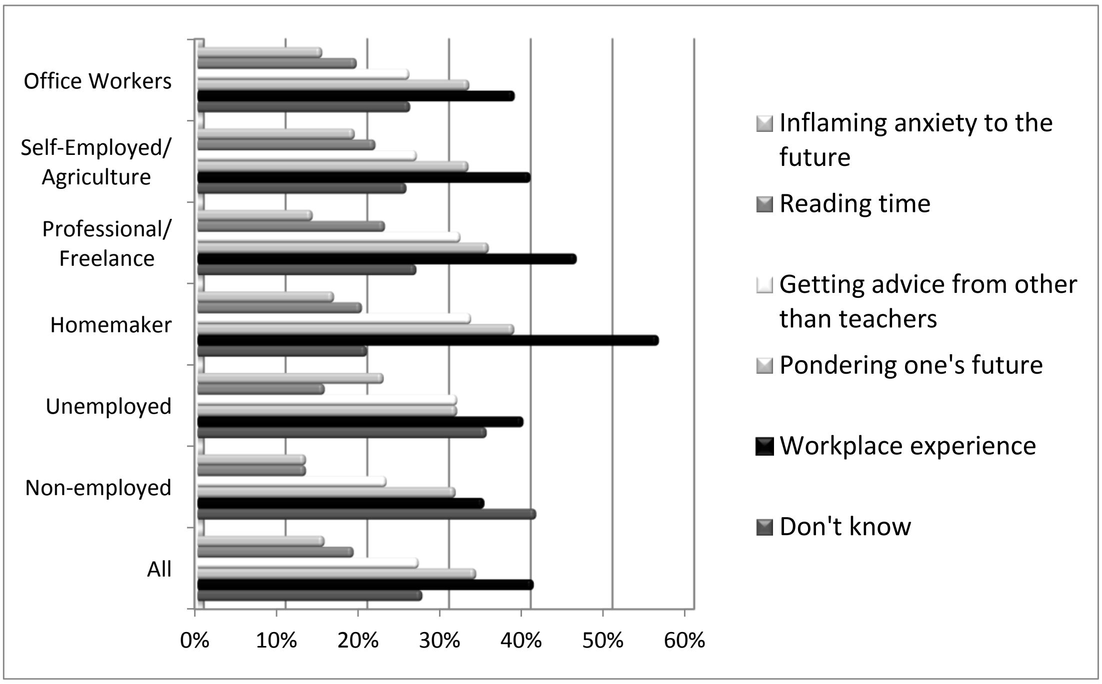

Figure 4.5 What respondents think they should have been taught during compulsory education, by profession (Multiple choices)

Note: Non-employed represents those who are not in the labor force and are not homemakers.
Source: *Survey on Vocation-related Education in School*

Respondents do not think middle school career education activities have been useful for them, but they wish they could have started thinking about jobs during middle school. Their impressions suggest the potential for government intervention and direction to improve the program at the middle school level.

Figure 4.5: "What respondents think they should have been taught during compulsory education" provides useful information. Therein, respondents state that pondering one's future and workplace experience should have been prioritized better, on average. Of note, homemakers are more likely to feel the need for workplace experience compared to other respondents. In Japan, a certain percentage of women believe they should be homemakers before they start thinking about obtaining jobs,and the responses tend to suggest that their decisions may have been different if they had benefited from workplace experience.

We also asked respondents to identify school-level requirements. As Table 4.4 shows, respondents think that elementary school students should learn that there are various kinds of jobs and that they do not have to learn deeply about each job. In

Table 4.4 Ideal workplace experience in each school (Multiple choices)

	Ages 6 to 12 (Elementary School)		Ages 12 to 15 (Junior High School)		Ages 15 to 18 (High School)	
	Yes	% to all	Yes	% to all	Yes	% to all
Learn about many kinds of jobs	2,003	65.3%	1,554	50.7%	1,023	33.4%
Learn about one job precisely	511	16.7%	1,728	56.3%	1,631	53.2%
Visit a workplace	678	22.1%	1,601	52.2%	1,775	57.9%

Source: *Survey on Vocation-related Education in School*

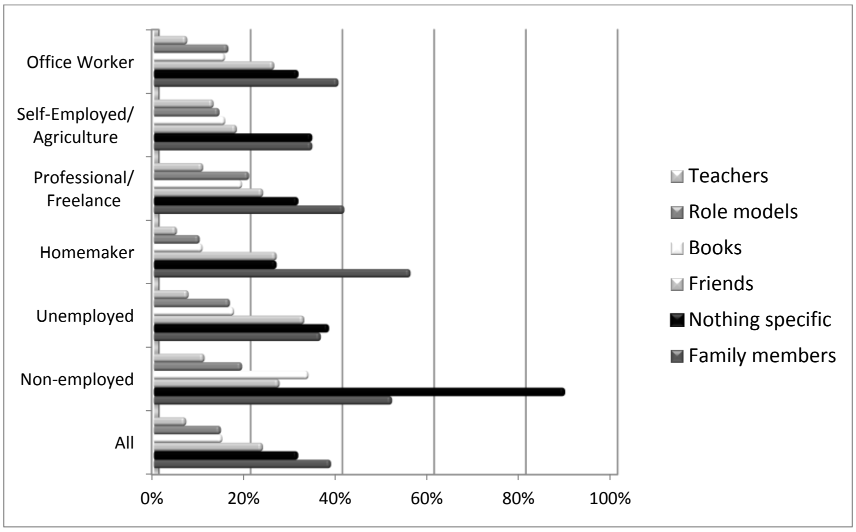

Figure 4.6 Things that affected respondents, by profession (Multiple choices)

Source: *Survey on Vocation-related Education in School*

junior high schools, students should learn about many jobs in general and one job in detail. More than one-half of respondents consider visiting workplaces important. In high schools, respondents think students should learn about a specific job, rather than many kinds.

4.4.1.4 *Influences*

Influences that have helped determine respondents' current life situations are listed in Figure 4.6. Career education, especially specific vocational education, does not seem to play much of a role in explaining and understanding respondents' lives. Interestingly, what affects them most are their families and friends. The existence of role models is relatively vital to professionals and freelancers.

4.4.2 Effect of Career Education Policies

In this section, we analyze the effect of the government's career policies using econometric methods.

4.4.2.1 *Methods*

We use the value of respondents' annual incomes as the dependent variable. Since some of the respondents do not search for jobs (because they either become homemakers, willingly choose not to work, or gave up searching for jobs), we applied Heckman's (1974) method to reveal the effects of career education policy. We assume the policy affects both the decision of respondents to participate in the labor force and their income levels.

We set 10 models. Models 1–6 use a differences-in-differences approach to measure the effect of the career education policies enshrined in the "Career Education Promotion Region-Designated Project" that was initiated in 2004. Since we can identify regions and names of schools that participated in the program from Miyake et al. (2006), we asked respondents whether they graduated from those schools. The estimation is expressed as

$$y_i = \ln Y_i = \alpha + \beta_1 S_{Post,i} + \beta_2 S_{School,i} + \beta_3 (S_{Post,i} \cdot S_{School,i}) + X_i \delta + u_i \,, \qquad (4.5)$$

where S_{Post} = the age group who had been in school in 2004 and after (age under 27) and S_{School} = those who graduated from the school that the policy has provided.

Then, the difference-in-differences estimate is β_3. (Policy School & Post Policy $\alpha + \beta_1 + \beta_2 + \beta_3 + X_i\delta$ − Policy School & Pre Policy $\alpha + \beta_2 + X_i\delta$) − (Other School & Post Policy $\alpha + \beta_1 + X_i\delta$ − Other School & Pre Policy $\alpha + X_i\delta$) = β_3.

For X in equation (4.5), the explanatory variables for *Income*, we chose *Female*, *Married*, *Female*Married*, *Experience*, *Unemployed*, and *Education*. Here, respondents' education (*Education*) is endogenous. Therefore, we chose respondents' parents' education to explain respondents' education because parents' education does not directly affect respondents' incomes, only indirectly through respondents' education. This education variable comprises four groups formed on the standard age of graduation from one's highest educational establishment. The endogenous variable is then explained using an ordered probit model.

Models 3–6 are concerned with respondents' willingness to participate in the labor force. The following simultaneous equations explain the fundamental tenet of our estimation, based on Heckman (1979):

$$Y_i = S_{Yi}^{\beta_Y} \cdot Labor\_participation_i \cdot e^{u_i} \tag{4.6}$$

$$Labor\_Participation_i = e^{\beta_P S_{Pi}} \cdot e^{v_i} \tag{4.7}$$

$$y_i = \ln Y_i = \ln S_{Yi}^{\beta_Y} + \beta_P S_{Pi} + u_i + v_i \tag{4.8}$$

where $S_{Yi}^{\beta_Y}$ is that which may vary over time and space, *Labor_Participation* is a dichotomous variable that equals one when respondents participate in the labor force, and zero otherwise.[31] Here, *u* and *v* denote random influences on income and labor participation, respectively. When we use Heckman's sample selection model, we assume that both error terms are normally distributed with mean zero;

$$(u, v) \sim N(0, 0, \sigma_u^2, \sigma_v^2, \rho_{uv})$$

where ρ_{uv} is the correlation coefficient between *u* and *v*. In addition, we set an assumption that the variance of the error term in the probit regression equals one, i.e.,

$$Var(v) = \sigma_v^2 = 1\,.$$

[31] Based on the International Labour Organization (ILO) international statistical standards, the population of working age (15 and over) in a country is classified into three groups: people in employment, unemployed people, and people outside the labor force for other reasons. Since our respondents exclude school pupils and all kinds of students, the variable

Model 3 treats the labor participation decision as exogenous and independent of any other explanatory variable. Models 4 and 5 represent a two-part model, where Model 4 estimates factors affecting labor force participation, and Model 5 estimates income using only data for those respondents who do participate therein. Model 6 is a Heckman selection model.

Models 7–10 institute changes concerning policy variables in recognition of career education policy in general and the experience of daily activities. Model 7 treats labor participation as exogenous; Models 8 and 9 constitute a two-part model as described above, and Model 10 is the selection model.

In all models that estimate income, because the original data were elicited from respondents using intervals, we applied interval regressions. Interval regression is such that determining income (expressed by $\breve{y}_i$), $\breve{y}_i = \beta_0 + \mathbf{x}_i\boldsymbol{\beta} + e_i.y$ takes the form of estimation, where y^{lb} and y^{ub} specify the lower and upper bound of each interval where each income y lies. In the lowest category, $y_i^{lb} = -\infty$, we only know $\breve{y}_i \le y_i^{ub}$, and the observation is left-censored. Moreover, in the highest category, $y_i^{ub} = +\infty$, we only know $y_i^{lb} \le \breve{y}_i$, and the observation is right-censored. Finally, $e.y$ is assumed to be normally distributed, with mean 0 and variance σ^2.

4.4.2.2 *Results*

Descriptive statistics for our sample (n = 2,389) are provided Table 4.5; a majority of these respondents (n = 1,944) are in the workforce.

Labor force = 1 if respondents have jobs or are unemployed and seeking jobs and 0 if respondents are homemakers or are unemployed but not seeking jobs.

Table 4.5 Descriptive statistics

		Mean	S.D.	Min.	Max.	N. of Obs.
Dependent Variables						
Income (log) (lower bounds)	Respondents' annual income	5.544	0.525	4.605	7.601	1,710
	(log of 10 thousand yen)	5.549	0.520	4.605	7.601	1,686
(higher bounds)		5.525	0.663	4.595	7.600	2,389
		5.726	0.555	4.595	7.600	1,941
Explanatory Variables						
Policy Variables						
After_policy	Age under 27 =1; 0, otherwise.	0.578	0.494	0	1	2,392
		0.602	0.490	0	1	1,944
Policy_school	Respondents who were in the policy	0.032	0.177	0	1	2,392
	provided schools = 1; 0, otherwise.	0.032	0.177	0	1	1,944
After_policy*Policy_school	Cross term	0.020	0.139	0	1	2,392
		0.021	0.144	0	1	1,944
Recognize_Career_Policy	Remember career activities being provided	0.298	0.458	0	1	2,392
	=1, 0 otherwise	0.307	0.461	0	1	1,944
Coordinator_in_Junior_High	Experienced being a coordinator in	0.380	0.485	0	1	2,392
	elementary school = 1; 0, otherwise.	0.384	0.487	0	1	1,944
Leader_in_Elementary	Experienced being a leader in elementary	0.364	0.481	0	1	2,392
	school = 1; 0, otherwise	0.369	0.483	0	1	1,944
Attributes						
Education	Respondents' school leaving age (18, 20, 22,	20.659	2.041	18	24	2,392
	or 24)	20.840	2.025	18	24	1,944
	Respondents' school leaving age = 20	0.074	0.262	0	1	1,944
	Respondents' school leaving age = 22	0.535	0.499	0	1	1,944
	Respondents' school leaving age = 24	0.092	0.288	0	1	1,944
Female	Female = 1; 0, otherwise.	0.570	0.495	0	1	2,392
		0.508	0.500	0	1	1,944
Married	Marrital status: Marriied = 1; 0, otherwise	0.292	0.455	0	1	2,392
		0.208	0.406	0	1	1,944
*Female*Married*	Cross term	0.217	0.412	0	1	2,392
		0.115	0.319	0	1	1,944
Educ_f	Father's school leaving age (18, 20, 22, or	19.995	2.068	18	24	2,392
	24)	20.030	2.075	18	24	1,944
	Father's school leaving age = 20	0.044	0.206	0	1	2,392
		0.043	0.203	0	1	1,944
	Father's school leaving age = 22	0.420	0.494	0	1	2,392
		0.426	0.495	0	1	1,944
	Father's school leaving age = 24	0.038	0.190	0	1	2,392
		0.040	0.195	0	1	1,944
Educ_m	Mother's school leaving age (18, 20, 22, or	19.285	1.623	18	24	2,392
	24)	19.336	1.639	18	24	1,944
	Mother's school leaving age = 20	0.241	0.428	0	1	2,392
		0.249	0.433	0	1	1,944
	Mother's school leaving age = 22	0.187	0.390	0	1	2,392
		0.194	0.395	0	1	1,944
	Mother's school leaving age = 24	0.009	0.095	0	1	2,392
		0.010	0.101	0	1	1,944
Experience	Work experience (age minus school leaving	4.597	3.395	0	13	2,392
	age)	5.656	2.861	0	13	1,944
Unemployed	Unemployed and seeking jobs = 1; 0,	0.032	0.177	0	1	2,392
	otherwise.	0.040	0.195	0	1	1,944
Labor_participation	In the labor force =1, 0 otherwise.	0.813	0.390	0	1	2,392
Family_member_income (log)	Family members' total annual income excluding respondents' own income (log of 10 thousand yen)	3.582	2.991	0	7.601	2,392
Altruism	Answers to "Do you think you should help others whatever happens?": Strongly Agree = 5, Agree= 4, Undecided = 3, Disagree= 2, Strongly Disagree = 1.	3.393	0.743	1	5	2,392
Tokyo	Respondents from schools in Tokyo = 1; 0, otherwise.	0.141	0.348	0	1	2,392

Source: *Survey on Vocation-related Education in School*

Table 4.6 presents our inferential results. Model 1 measures the policy effect by DID without covariates; the policy effect therein is statistically insignificant (the cross term is insignificant). Model 2 includes valid control variables (unmarried female, married male, married female, education, work experience, and unemployment). Assuming some latent factors independent of other explanatory variables make the decision whether to participate in the labor market, we see that the policy has an effect, albeit at the 0.1 level (P = 0.060). Model 3 uses the same explanatory variables as Model 2. Model 3 assumes, though, that respondents' education is endogenous and controls it with their parents' education (education variables here are constructed as index variables of graduation: 18, graduated from high school or lower; 20, two-year college; 22, university; and 24, graduate school). Here, the covariance of errors of income and education is significantly nonzero (−0.492); thus, education is endogenous. In Model 3, the impact of policy becomes slightly more pronounced than in Model 2 but is still somewhat tenuous (P = 0.090).

Models 4 and 5 constitute the simple two-part model that considers the error terms of equation (6) and equation (7) independent. Model 4 is the probit and Model 5 is the regression with endogenous variables, and the regression only incorporates data for those respondents who are participating in the labor force (respondents are neither homemakers nor nonworking respondents who are not searching for jobs.) Therein, the policy effect becomes insignificant. Model 4 reveals that being female (here, marital status and the married female cross term were insignificant) and family members' income both serve to reduce the probability of participating in the labor force. By contrast, altruism and graduating from schools in Tokyo both exert positive effects on this probability. Income is a positive function of married males, work

Table 4.6 Results

	Schools provided the policies							Recognition of career policy and experience of activities				
			Endogenous *Education*	Income estimated from those participating in the labor force				Endogenous *Education*	Income estimated from those participating in the labor force			
				Two parts model		Selection model			Two parts model		Selection model	
	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)	(10)	
	Income	*Income*	*Income*	*LP*	*Income*	*LP*	*Income*	*Income*	*LP*	*Income*	*LP*	*Income*
Policy Variables												
After_policy	-0.077 *	-0.055	-0.056	0.242 ***	-0.049	0.332 ***	-0.097 *					
	(0.037)	(0.045)	(0.044)	(0.065)	(0.048)	(0.062)	(0.048)					
Policy_school	-0.020	-0.012	-0.000	-0.049	0.018	0.134	0.053					
	(0.165)	(0.121)	(0.120)	(0.277)	(0.121)	(0.261)	(0.129)					
*After_policy*Policy_school*	0.309	0.281 +	0.252 +	0.030	0.120	-0.116	0.060					
	(0.210)	(0.150)	(0.149)	(0.375)	(0.150)	(0.350)	(0.162)					
Recognize_Career_Policy								0.061 *	0.155 *	0.067 *	0.137 *	0.028
								(0.028)	(0.071)	(0.028)	(0.067)	(0.031)
Coordinator_in_Middle								0.106 ***		0.114 ***		0.111 ***
								(0.027)		(0.026)		(0.026)
Leader_in_Elementary								0.082 **		0.085 **		0.072 **
								(0.027)		(0.026)		(0.026)
Attributes												
Female				-0.781 ***		-0.603 ***			-0.807 ***		-0.651 ***	
				(0.072)		(0.070)			(0.072)		(0.071)	
Female (not married)		-0.151 ***	-0.161 ***		-0.158 ***		-0.033	-0.181 ***		-0.179 ***		-0.046
		(0.030)	(0.029)		(0.029)		(0.032)	(0.029)		(0.029)		(0.032)
Married (male)		0.367 ***	0.359 ***		0.364 ***		0.340 ***	0.336 ***		0.338 ***		0.328 ***
		(0.048)	(0.048)		(0.046)		(0.048)	(0.047)		(0.046)		(0.048)
Married Female		-0.551 ***	-0.533 ***		-0.500 ***		-0.390 ***	-0.512 ***		-0.477 ***		-0.392 ***
		(0.063)	(0.063)		(0.062)		(0.061)	(0.062)		(0.062)		(0.061)
Experience		0.022 *	0.022 *		0.023 *		0.024 **	0.031 ***		0.032 ***		0.030 ***
		(0.009)	(0.009)		(0.009)		(0.009)	(0.005)		(0.005)		(0.005)
Unemployed		-1.098 ***	-1.091 ***		-1.079 ***		-0.988 ***	-1.079 ***		-1.063 ***		-0.985 ***
		(0.080)	(0.079)		(0.077)		(0.072)	(0.079)		(0.076)		(0.072)
Family_member_income (log)				-0.112 ***		-0.092 ***			-0.113 ***		-0.095 ***	
				(0.012)		(0.010)			(0.012)		(0.011)	
Altruism				0.088 *		0.062 +			0.077 +		0.041	
				(0.044)		(0.036)			(0.044)		(0.037)	
Tokyo				0.303 **		0.339 ***			0.286 **		0.319 ***	
				(0.100)		(0.083)			(0.100)		(0.085)	
Education (20)		0.131 *	0.356 ***		0.342 ***		0.355 ***	0.369 ***		0.346 ***		0.361 ***
		(0.055)	(0.072)		(0.065)		(0.065)	(0.072)		(0.063)		(0.063)
Education (22)		0.346 ***	0.793 ***		0.741 ***		0.789 ***	0.817 ***		0.754 ***		0.792 ***
		(0.042)	(0.104)		(0.088)		(0.090)	(0.102)		(0.083)		(0.086)
Education (24)		0.595 ***	1.460 ***		1.336 ***		1.457 ***	1.496 ***		1.346 ***		1.447 ***
		(0.065)	(0.192)		(0.161)		(0.167)	(0.191)		(0.156)		(0.162)
Constants	5.300 ***	3.864 ***	3.550 ***	1.407 ***	4.995 ***	1.219 ***	5.077 ***	3.451 ***	1.558 ***	4.828 ***	1.488 ***	4.917 ***
	(0.029)	(0.073)	(0.103)	(0.170)	(0.119)	(0.146)	(0.115)	(0.096)	(0.164)	(0.076)	(0.142)	(0.074)

Table 4.6 Results (continued)

	Schools provided the policies							Recognition of career policy and experience of activities				
			Endogenous *Education*	Income estimated from those participating in the labor force				Endogenous *Education*	Income estimated from those participating in the labor force			
				Two parts model		Selection model			Two parts model		Selection model	
	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)	(10)	
	Income	*Income*	*Income*	*LP*	*Income*	*LP*	*Income*	*Income*	*LP*	*Income*	*LP*	*Income*
Labor_participation		1.436 ***	1.442 ***					1.368 ***				
		(0.082)	(0.082)					(0.068)				
Ordered probit explanatory variables												
Father's Education (20)			0.243 *		0.209 +		0.254 *	0.249 *		0.216 +		0.256 *
			(0.108)		(0.123)		(0.107)	(0.107)		(0.123)		(0.108)
Father's Education (22)			0.312 ***		0.317 ***		0.321 ***	0.308 ***		0.316 ***		0.319 ***
			(0.054)		(0.059)		(0.053)	(0.054)		(0.060)		(0.053)
Father's Education (24)			0.639 ***		0.624 ***		0.649 ***	0.637 ***		0.629 ***		0.654 ***
			(0.124)		(0.136)		(0.121)	(0.124)		(0.136)		(0.122)
Mother's Education (20)			0.273 ***		0.291 ***		0.263 ***	0.269 ***		0.289 ***		0.264 ***
			(0.058)		(0.063)		(0.056)	(0.058)		(0.064)		(0.057)
Mother's Education (22)			0.483 ***		0.504 ***		0.471 ***	0.483 ***		0.504 ***		0.473 ***
			(0.069)		(0.075)		(0.067)	(0.068)		(0.075)		(0.068)
Mother's Education (24)			0.515 *		0.453 +		0.470 *	0.531 *		0.459 +		0.491 *
			(0.222)		(0.241)		(0.219)	(0.222)		(0.242)		(0.220)
Ordered probit dependent variable *Education* (18, 20, 22, 24)												
cut points 1			-0.125 ***		-0.212 ***		-0.126 ***	-0.127 ***		-0.213 ***		-0.125 ***
			(0.037)		(0.040)		(0.036)	(0.037)		(0.040)		(0.036)
cut points 2			0.104 **		0.005		0.103 **	0.102 ***		0.005		0.104 **
			(0.037)		(0.040)		(0.036)	(0.037)		(0.040)		(0.036)
cut points 3			1.829 ***		1.748 ***		1.828 ***	1.825 ***		1.747 ***		1.829 ***
			(0.051)		(0.054)		(0.050)	(0.051)		(0.054)		(0.050)
Variance of error term : *Income*	0.722 ***	0.316 ***	0.382 ***		0.341 ***		0.476 ***	0.379 ***		0.332 ***		0.457 ***
	(0.027)	(0.012)	(0.031)		(0.023)		(0.038)	(0.032)		(0.022)		(0.037)
Covariance of error term: *Income*Education*			-0.492 ***		-0.432 ***		-0.505 ***	-0.500 ***		-0.427 ***		-0.494 ***
			(0.082)		(0.076)		(0.062)	(0.083)		(0.076)		(0.064)
Covariance of error term: *Income*Labor Participation*							-0.828 ***					-0.808 ***
							(0.032)					(0.032)
Covariance of error term: *Education*Labor Participation*							0.224 ***					0.194 ***
							(0.039)					(0.038)
Number of observations	2392	2392	2392	2392	1944	2392		2392	2392	1944	2392	
Non-selected / selected						448	1944				448	1944
Log-likelyhood	-4760.1	-3757.1	-6296.1	-999.7	-5639.0	-7071.4		-6282.2	-1004.4	-5619.2	-7066.5	
Bayesian information criteria	9559.2	7623.2	12779.0	2061.5	11452.1	14399.5		12751.0	2055.4	11412.6	14374.2	
Akaike's information criteria	9530.3	7542.2	12640.2	2015.3	11324.0	14208.8		12612.3	2020.8	11284.4	14195.0	
Model degrees of freedom	3	12	12	7	11	11		12	5	11	11	
Chi-square	8.28	1568.66	1382.05	255.94	508.69	429.31		1391.29	246.51	556.37	432.14	
Model significance	0.041	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	

Source: *Survey on Vocation-related Education in School*

Note: 1. Standard errors are in parentheses: 2. +, *, **, and *** denote 10%, 5%, 1%, and 0.1% levels of significance, respectively.

experience, and education and is a negative function of unmarried females, married females, and unemployment.

Model 6 is the Heckman selection model. The policy effect therein is not as apparent as in Models 4 and 5; labor participation decisions are affected by the same variables as in Model 4. Factors affecting income are also similar to what was revealed by Model 5, but the unmarried female coefficient is insignificant here.

Since the sample size of those respondents who attended policy-enacting schools is small, it is harder by definition to identify statistically significant policy effects. Thus, we used respondents' recognition of receiving career education as a proxy for general career policy (the dichotomous variable *Recognize_Career_Policy*); Model 7 treats labor participation decisions as exogenous, per Model 3. Models 8 and 9 constitute a two-part model that assumes the decision to participate in the labor force and income are independent, per Models 4 and 5.

Finally, Model 10, like Model 6, is a Heckman selection model. Recognizing career policy weakly affects income in Models 7–9; in the selection model (Model 10), it weakly affects only the decision of whether to participate in the labor force, with no discernible effect on income. Being a coordinator in middle school and being a leader in elementary school are both associated with higher incomes.

All results suggest that, at least in early adulthood (under 31), a vicious circle of educational disparity is operating in Japan. Parents' (both fathers' and mothers') education matters to respondents' education and to that of respondents' income.

Education does not affect labor participation but concerns income. Higher education does not assure young people staying in the labor force. Once they start working, then higher education tends them give better earnings.

4.5 Summary and Discussion

Since the 1999 Central Council report, career education promoted by the government has become established as one of the pillars of youth employment policy. This study explored the effects of career policies in school settings by examining graduates' earning capacity (annual income) through quantitative analysis based on results from an online survey. As far as the authors know, this attempt is the first to estimate policy effects quantitatively by focusing on career education policy in Japan.

Results showed that the role of specific career education programs is not clear, at least thus far, but that implementing career education policies in schools might increase graduates' annual income, while certain daily activities help students earn more. If students either take coordinating roles in middle school or leadership roles in elementary school, or both, their subsequent incomes may be higher as a result. In other words, the original purpose of career education policies such as cultivating the “ability to build human relationships,” “ability to utilize information,” “ability to plan the future,” and “ability to make decisions” should be emphasized along with the vocational programs. We should note, however, that families (parents’ education or family member’s income) exhibit significant effects on respondents.

In this study, the impact of Japan’s career education on students’ earning capacity was the dependent variable. A fundamental problem in this respect is that no respondents were older than 31; their incomes have plenty of scope for changes in the future as they become older. Indeed, it would be ideal if we could capture and compare data on lifelong incomes. Finally, although earning capacity is an essential incentive for work, it is not the only reason people choose or remain in their jobs. As evidenced by early retirement trends, job satisfaction is also a substantial incentive when working. Thus, future research challenges in this domain include the need to understand holistically the interplay among government incentives (career and other policies), nonmonetary workplace motivations such as job satisfaction and a sense of self-fulfillment, and the more commonly recognized monetary motivation provided through salaries.

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Chapter 5 Conclusion

Japan's slow economic growth suggests a need to improve productivity to increase economic growth and to enrich our inclusive wealth. The author focused on the demand side of the economy to determine how people evaluate policies to improve productivity and to determine whether they can contribute to improving citizens' lives. The author selected consumers' evaluation of three resource policies—energy, technology, and human resources—all of which relate to "inclusive wealth", which consists of the social values of natural capital, produced capital, and human capital.

Chapter 2 focuses on natural capital and energy policy. The study presents the results of both discrete choice experiments and choice probability experiments to determine citizens' willingness to pay (WTP) for residential electricity produced by solar, wind, nuclear power, and natural gas to evaluate the three energy-mix scenarios presented by the government of Japan. In addition, the author measures the effects of positive or negative information about nuclear energy and discovers that the information matters. The results indicate that, on average, consumers in Japan have a negative WTP for electricity produced by nuclear power regardless of the information they read. The results showed the highest WTP for the highest renewable energy scenario of the government, but the level of WTP for such an energy-mix change is far less than the actual cost of the change. The present energy-mix scenario is not close to that desired by the majority of consumers. To help implement a consumer-driven change in Japan's energy mix, liberalization of the electric power market, in which consumers can choose the source of electricity, will work.

Chapter 3 focuses attention on produced capital and policies on new technologies. The study intends to predict a future with driverless vehicles. Using choice experiments, the author first elicits consumers' willingness to pay (WTP) for autonomous driving systems in Japan and determines that their WTP is insufficient for the merchandising of highly autonomous vehicles (AVs). Second, compared with a previous study in the US, we discuss two expected social dilemmas in Japan. Respondents in both countries tend to not purchase items that they think are moral. AVs can be regulated to implement the best social system only in Japan. We then estimated the factors influencing these dilemmas, and the credibility of AVs was found to be a critical factor.

Chapter 4 centers on human capital and human resource policy. The study concerns the fact that due to macroeconomic factors, young people in Japan are increasingly opting to not participate in the labor force. In the coming age of a declining birthrate and an aging population, when a decrease in the size of the labor force is expected, we need to provide policies that help young people stay in the labor force, and the government has tried to implement specific career education programs. The author explored the effects of career policies in school settings by identifying graduates' earning capacity (annual income) through an online survey, followed by a quantitative analysis of the results. The author reports the evaluation of career policies by respondents and then measures the effects of these policies on both labor participation and income. Although the specific program we focused on did not show apparent effects, career education policies, in general, and daily activities in elementary and middle schools, in particular, affect graduates' incomes. We also identify other key attributes that influence income.

From these studies, the author concludes the following. On natural resource policies, the Japanese government's energy-mix scenarios do not reflect consumers' preferences. Consumers prefer a more renewable-energy-oriented energy-mix. On adopting new technologies such as autonomous driving vehicles, besides subsidizing the technology, the government and the makers of the AVs should recognize that consumers' morality alters their purchasing behavior. Government regulations for reflecting the morality of the public may not be affected in Japan; nevertheless, they may not work in the US. On human resource policies, the effects of providing specific career education are not yet apparent. We determined that the government policies that let students enjoy their daily classroom activities in elementary and junior-high education, rather than specific career education, help students appreciate their future jobs.