Essays on Market-Based Climate Policy Evaluation

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Chapter 1

Introduction

Climate change is one of the most urgent issues faced by countries all over the world. Measures for combating climate change issues are divided broadly into three types: economic instruments, regulatory instruments, and voluntary instruments. Especially since the Paris Agreement, a growing number of countries have adopted economic instruments as an environmental policy. Economic instruments provide economic incentives for individuals and firms to mitigate climate change through price signals, with carbon pricing included as its primary methodology. Carbon pricing, including carbon taxes and emissions trading schemes (ETSs), allows for reducing environmental externalities arising from economic activities in an efficient way. Meanwhile, along with carbon pricing, feebate policies are also widely taken as an environmental policy. Feebate policies incentivize the purchase of energy-efficient products by imposing a fee or giving a rebate according to products' energy performance, with the purpose of promoting individual and firm behavioral changes and environmental awareness. Since these market-based environmental policies are closely connected with a nation's industrial and fiscal policies, evaluating their performance from economic and environmental perspectives is an important theme.

Countries around the world are advancing the introduction of carbon taxes, feebates, and ETSs at the national and regional levels. Since the carbon tax was introduced in Scandinavian countries in the early 1990s, the introduction of such a tax has spread globally. In Japan, a carbon tax has been phased in since 2012; currently, a tax of 289 JPY per ton of CO_2 is imposed on top of the existing fuel taxes.

Feebate policies are widely seen in various markets in many countries. Feebates for automobiles were first adopted in several states in the United States in the early 1990s; circa 2007, they were introduced in European countries such as Denmark, France, and the Netherlands at the national level (Bunch et al., 2011). Especially after the financial crisis in 2008, feebates were given attention as an attractive policy instrument for combating economic recession as well as climate change issues. In Japan, the feebate for automobiles has been in place since the beginning of the 2000s and was largely expanded as part of the Green New Deal in 2009. The Japanese feebate consisting of tax incentive measures and subsidy programs for eco-friendly cars has contributed substantially to the spread of hybrid vehicles. Given the duration and financial scale of the program, the feebate policy plays a pivotal role in automobile greening policy in Japan.

The introduction of ETSs has become the mainstream for climate change policy worldwide since the establishment of the world's largest emissions trading market in the EU in 2005. This movement is also spreading in Asia. For example, Korea and China launched nationwide ETSs in 2015 and 2017, respectively. While Japan has not yet reached the introduction of a national ETS, Tokyo and Saitama began their regional ETSs in 2010 and 2011, respectively. The ETS implemented in Tokyo is the first scheme in the world to regulate CO_2 emissions from the industrial and commercial sectors. To date, the Tokyo ETS has already completed its first and second phases and has been running in its third phase.

This thesis examines the effects of a carbon tax, a feebate policy, and an ETS implemented in Japan. The issues to be considered and contributions to literature are as follows. First, I examine the impacts of a tax on fuels on market outcomes and social welfare in the automobile market. The current carbon tax rate in Japan is extremely low compared with the social cost of carbon, whereas taking gasoline as an example, the existing gasoline tax is already set at a high tax rate and is comparable with the carbon tax rates in European countries. Understanding the welfare consequence of fuel tax plays an important role in a debate for revising the rate of taxes on fuel in the future. I evaluate the welfare effect by employing a structural model in the automobile market, following Bento et al. (2009). To the best of my knowledge, my empirical work is the first to study the welfare effect of the fuel tax in Japan while taking into account the influence of the fuel tax on household decisions regarding car ownership and utilization.

Second, I analyze the impacts of a fuel tax and a feebate policy on households in different income classes. The difference in the distributional impacts of the two policies remains to be defined. On the one hand, several studies have investigated the efficiency and distributional impacts of feebate policies in different countries (e.g., D'Haultfœuille et al. (2014) and Durrmeyer (2022) for the French feebate, Adamou et al. (2014) for the German feebate, Huse and Lucinda (2014) for the Swedish feebate, and Konishi and Zhao (2017) and Kitano (2016, 2022) for the Japanese feebate). On the other hand, there is no study that has compared the distributional impacts of the two policies. Grigolon et al. (2018) document the efficiency of a fuel tax over a product tax using data for automobile markets in several EU countries. The Japanese feebate for automobiles is essentially a tax break for product taxes, which are levied at the time of purchase and during ownership, such as the weight tax and the automobile tax. I contribute to the literature by comparing the distributional effects of a fuel tax and a product tax on households with different incomes. Understanding the impacts of the two taxes in terms of distributional equity, as well as efficiency, is helpful in guiding the design of a fair automobile taxation system in the future.

Third, I identify the source of environmental externalities that arise from a feebate policy. Prior studies that measure the impact of energy efficiency programs share the same finding that the realized energy savings are significantly lower than those projected by ex-ante engineering analyses before the programs were enacted (e.g., Davis et al., 2014; Fowlie et al., 2018; Levinson, 2016). A crucial factor that explains the gap between the realized and predicted energy savings is a rebound effect. A rebound effect refers to an unintended increase in energy use caused by individuals' behavioral change after a program introduction. I quantify the contribution of the rebound effect to a change in energy use due to a feebate, an energy efficiency program, by correcting a method of D'Haultfœuille et al. (2014), who analyzed the impact of the French feebate policy.

Fourth, I examine the influences of the Tokyo ETS introduction on energy use and the economic activities of regulated business establishments. Before the introduction of the ETS, there were strong concerns from the industry about potential negative damage to economic activity by the regulation. Many empirical studies have measured the causal effects of the antecedent EU ETS using multiple outcome variables (e.g., Colmer et al., 2022; Marin et al., 2018; Petrick and Wagner, 2014). I study whether the Tokyo ETS contributed to a decrease in the energy consumption of regulated establishments and whether the region-specific regulation forces economically disadvantaged competition on regulated establishments relative to unregulated establishments located in other regions. To the best of my knowledge, my work is the first to evaluate the impacts of the Tokyo ETS during its first and second phases from two different perspectives.

The abstracts of the remaining chapters are as follows. Chapter 2 examines an interregional difference in the rebound effect of automobiles in Japan using a household survey. The Japanese government has promoted eco-friendly vehicles such as hybrid vehicles with subsidies and tax reductions, particularly since 2009. The eco-car promotion policy selects target vehicles for promotion according to their fuel economy performance. Previous studies in Japan have observed a rebound effect when improved fuel economy increases vehicle miles traveled; however, these studies do not address the differences in this rebound effect across regions. The existence of a gap in rebound effects across regions would render the uniform nationwide policy cost-inefficient. The empirical results show that while there is no rebound effect in urban regions, the rebound effect reaches approximately 38% in rural regions. These results suggest that the eco-car promotion policy is less cost-effective in rural regions than in urban regions. Thus, the government needs to set different eco-car promotion policies for rural and urban regions and promote the use of public transport systems in rural regions.

Chapter 3 examines the efficiency and distributional effects of fuel tax and feebate policies in the automobile market. I employ a model in which households make two-stage decisions on car ownership and utilization. I estimate model parameters by combining micro-level data from a household survey and macro-level aggregate data on the Japanese new car market from 2006 through 2013. Interestingly, several system changes in the Japanese feebate created rich variations in vehicle prices across vehicles and over time during the sample period. I use such exogenous variation to overcome the vehicle price endogeneity associated with demand estimation. Counterfactual analyses show that the Japanese feebate results in a significant increase in social welfare while augmenting environmental externalities. In particular, the rebound effect induced by the feebate cancels out approximately 7% of the reduction in CO_2 emissions that would originally have been attained by the improvement in fuel economy. In addition, I find that the fuel tax at the current tax rate in Japan is 1.7 times less costly than the product tax, an alternative feebate scheme considered in the counterfactuals, in reducing negative environmental externalities by the same amount. I also find that the fuel tax is less regressive than the externality-equivalent product tax.

In Chapter 4, I estimate the policy impacts of the Tokyo ETS on energy usage and economic activities during the scheme's first phase (2010–2014) and the first four years of its second phase (2015–2018) using business establishment-level panel data from 2007 to 2018. From the matching-based difference-in-differences (DID) estimation results, I find that while regulated business establishments reduced their energy usage beyond their reduction targets set by ETS regulation, the unregulated business establishments chosen by the matching strategy as a comparison group also decreased their energy usage to the same extent. Additionally, the Tokyo ETS did not have a negative impact on the economic activities of regulated business establishments during phases I and II. These results suggest that the emissions cap levels in each phase may not have been sufficiently demanding to induce regulated business establishments to implement additional energy-saving practices.

In the last chapter, I discuss the policy implications obtained from my empirical studies and conclude this thesis.

Chapter 2

Rebound Effects for Passenger Vehicles in Urban and Rural Regions: An Analysis of Household Survey Data[*]

2.1 Introduction

In recent years, increasing attention has been paid to eco-cars due to subsidy programs that provide preferential treatment for eco-cars and the soaring price of gasoline. In particular, hybrid vehicles have experienced a dramatic increase from 74,000 units registered in 2002 to 4.68 million units registered in 2015, accounting for 35.2% of total passenger car sales in Japan in 2013.[1,2] In addition, the Top Runner emissions regulation introduced in 1998 tightens automobile fuel economy standards each year. Partially due to the proliferation of hybrid vehicles and fuel efficiency regulations, the average fuel economy of automobiles has improved over time from 12.3 km/ℓ in 1993 to 21.1 km/ℓ in 2012.[3]

While eco-cars are becoming increasingly popular, the number of miles driven per vehicle has increased continuously since 2008.[4] One of the causes of this trend is an economic phenomenon called a rebound effect. For example, suppose that an individual who switches from a less fuel-efficient car to a more fuel-efficient eco-car can reduce the operating cost per unit mile traveled.

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[*]This chapter is based on "Rebound effects for passenger vehicles in urban and rural regions: an analysis of household survey data," *Environmental Science*, 2017, Volume 30, Issue 3, pp.203–214 (in Japanese), which is a joint work with Shigeru Matsumoto and Kazuyuki Iwata.

[1] See https://airia.or.jp/publish/statistics/ao1lkc00000000z4-att/03_7.pdf (accessed March 15, 2016) on the website of the Automobile Inspection & Registration Information Association.

[2] See the website of the Japan Automobile Dealers Association and the Next Generation Vehicle Promotion Center.

[3] These values are the average fuel economy of all gasoline-powered passenger vehicles, measured in 10.15 mode. See http://www.mlit.go.jp/common/001031306.pdf (accessed June 8, 2016) on the website of the Ministry of Land, Infrastructure, Transport, and Tourism.

[4] See http://www.env.go.jp/earth/ondanka/ghg/2014yoin2_5.pdf (accessed November 7, 2016) on the website of the Ministry of the Environment.

The decrease in the unit cost of driving may then increase the frequency of car use and the distance driven. Through these behavioral changes, some of the improvement in fuel economy gained by switching vehicles is offset. This offset portion of the technical fuel economy improvement is called the rebound effect. Therefore, if the rebound effect is substantial, little energy savings would be expected from switching to eco-cars because a large portion of the improved fuel economy is offset by the increase in miles traveled.

The effectiveness of greenhouse gas (GHG) reduction measures such as eco-car subsidies crucially depend on the magnitude of the rebound effect. For example, if the rebound effect is large, policies that encourage the substitution of public transportation for private car use will be effective, and if the rebound effect is small, policies that promote the replacement of fuel-inefficient cars with eco-cars will be effective. Therefore, understanding the rebound effect is crucial in planning policies to reduce GHG emissions from automobiles. For these reasons, many researchers have investigated the magnitude of the rebound effect.

However, few studies examine the rebound effect of automobiles in Japan. For example, Mizobuchi (2011) and Iwata and Matsumoto (2016) confirm the existence of a rebound effect in Japan, with a short-term effect of approximately 18% and a long-term effect of approximately 23%, respectively. However, these studies do not account for regional differences in the rebound effect. Since public transportation is extensive in urban areas, switching to an eco-car may not increase the demand for driving the eco-car in those areas, but it may increase the demand for other modes of transportation such as buses and trains due to the income effect caused by being able to travel the same distance at a lower cost than before.[5] Furthermore, prior studies have demonstrated that the rebound effect is smaller in urban areas because congestion is generally higher in urban than in rural areas. Wang et al. (2012a) and Gillingham (2014) show that the rebound effect varies across regions within China and California, respectively. Therefore, the aim of this study is to examine whether the rebound effect of automobiles in the household sector differs between metropolitan and other areas in Japan.

Estimating the rebound effect by region also has important implications for future environmental policy planning. The requirements for the application of eco-car policies, such as subsidies and tax exemptions for eco-cars, are based on the fuel efficiency of the vehicles and are uniform throughout the country.[6] However, if the rebound effect differs across regions, the policy effect on GHG reduction will also differ across regions. Therefore, to maximize the cost-effectiveness of eco-car policies, it is necessary to understand the differences in rebound effects across regions and to reflect these differences in the policies.

The structure of this chapter is as follows. Section 2.2 describes the rebound effect and reviews the literature, and Section 2.3 describes the model for estimating the rebound effect by region.

[5] Therefore, energy consumption will increase when individuals increase the use of buses and trains. This is called the "indirect rebound effect," which will be discussed below.

[6] Some municipalities in Japan have their eco-car subsidy programs.

Section 2.4 introduces the questionnaire survey and descriptive statistics for data used in the analysis, and Section 2.5 presents the empirical results. Finally, Section 2.6 concludes this chapter.

2.2 Rebound Effects and Existing Literature

2.2.1 Rebound Effects

The rebound effect refers to the phenomenon whereby an improvement in the energy efficiency of a good causes a decrease in the operating cost of the good, which in turn increases the energy consumption of the good. The debate on the rebound effect began with Khazzoom (1980), and many studies have confirmed the existence of the rebound effect and estimated its magnitude. However, estimates found in prior studies cannot simply be compared because of various issues related to rebound effects. In what follows, I briefly describe the four issues related to the rebound effect and clarify the treatment of the rebound effect in this study.

First, existing studies examine the different scopes of the rebound effect. The rebound effect concerns not only automobile use but also all goods that consume energy and electricity, such as home appliances. For example, Hass and Biermayr (2000), Caird et al. (2008), and Mills and Schleich (2014) analyze the rebound effects of heating systems, solar panel systems, and LEDs, respectively.

The extent to which the rebound effect is measured also differs across studies. Taking automobiles as an example, the increased consumption of automobile services resulting from fuel efficiency improvements is called the "direct rebound effect," while the increase in the consumption of other goods, such as public transportation, resulting from the income effect associated with the fuel efficiency improvement is called the "indirect rebound effect." Since this study uses a questionnaire survey on automobile use for analysis, the indirect rebound effect cannot be estimated. This study therefore focuses only on the direct rebound effect of automobiles, and hereafter, the direct rebound effect is simply called the rebound effect unless otherwise specified.

Second, there are multiple measures of the rebound effect used in previous studies. Since the rebound effect indicates the extent to which the expected energy savings are offset by changes in usage patterns, the rebound effect is expressed as

$$\text{(expected energy saving} - \text{actual energy saving)}\big/\text{(expected energy saving)}. \tag{2.1}$$

Panelized individual data are required to calculate the rebound effect based on (2.1), and it is difficult to obtain such detailed data. Therefore, Sorrell et al. (2009) introduce the following five indicators of rebound effects for various data structures, such as individual, aggregate, panel, time series, and cross-sectional:

$$\text{Energy efficiency } (\varepsilon) \text{ elasticity of energy demand } (E)\text{: } \eta_\varepsilon(E), \tag{2.2}$$

$$\text{Energy efficiency } (\varepsilon) \text{ elasticity of energy service demand } (S)\text{: } \eta_\varepsilon(S), \tag{2.3}$$

$$\text{Energy service price } (P_S) \text{ elasticity of energy service demand } (S)\text{: } -\eta_{P_S}(S), \tag{2.4}$$

$$\text{Energy price } (P_E) \text{ elasticity of energy service demand } (S)\text{: } -\eta_{P_E}(S), \tag{2.5}$$

$$\text{Energy price } (P_E) \text{ elasticity of energy demand } (E)\text{: } -\eta_{P_E}(E), \tag{2.6}$$

where $S = \varepsilon E$. Additionally, the price of energy services is expressed as $P_S = P_E/\varepsilon$. In the case of automobiles, energy demand (E) corresponds to gasoline consumption, energy service demand (S) corresponds to the distance traveled, energy efficiency (ε) corresponds to vehicle fuel economy, energy price (P_E) corresponds to the price of gasoline, and energy service price (P_S) corresponds to the cost of gasoline per mile traveled. In this study, due to data availability, I use indicators (2.3) and (2.4) to estimate the rebound effect.

Third, the duration for which the rebound effect is measured differs across studies. In general, the rebound effect in the long run is expected to be larger than that in the short run. This is because, in the short run, the response to changes in operating costs is limited to changes in the frequency of automobile use, whereas in the long run, the response to changes in operating costs includes changes in automobiles and housing. The rebound effect estimated in this study should be interpreted as the long-run rebound effect because I exploit the difference in household status such as car ownership and usage in the cross-sectional survey in the estimation.[7]

Fourth, the rebound effect is also affected by non-price factors such as the knowledge, perceptions, and social norms of the entities consuming the service. For example, if there are regions where many people can appropriately perceive the cost per mile traveled and regions where few people can, the rebound effect may be larger in the latter region. This is because the cost per mile traveled must be calculated by dividing the gasoline price by vehicles' fuel economy, so the percentage improvement in fuel economy when replacing an existing vehicle with an eco-car is not the same as the percentage decrease in the cost per mile traveled. This is known as the miles per gallon illusion, and Allcott (2011) shows that many people fail to properly perceive the cost per mile driven. It is expected that these non-price factors vary across countries and regions; Gillingham et al. (2015) state that estimates of the rebound effect for one country or region should not be applied to other countries or regions.

2.2.2 Existing Studies on the Rebound Effect of Automobiles

Since the 1990s, numerous empirical studies have estimated the rebound effect of automobiles, particularly in Europe and the U.S. Greening et al. (2000) and Sorrell et al. (2009) summarize studies

[7] It is necessary to exploit time series data to measure the short-term rebound effect. Since this study uses a household questionnaire survey for analysis, short-term rebound effects cannot be estimated.

Table 2.1: Literature on the Rebound Effect of Automobiles since 2009

Existing studies	Country: region	Period	Data	Indicator	Estimate	
					Short-run	Long-run
Mizobuchi （2011）	Japan	2006-2008	(b)	4	18%	
Iwata and Matsumoto (2016)	Japan	2008-2013	(c)	1		23%
Hymel et al. (2010)	U.S.	1966-2004	(e)	4	5%	24%
Su (2011)	U.S.	2001-2008	(e)	4	3%	11%
Greene (2012)	U.S.	1966-2007	(d)	4	4%	16%
Su (2012)	U.S.	2009	(a)	4		15%
Linn (2016)	U.S.	2009	(a)	3		30%
Ficano and Thompson (2014)	U.S.	2009	(a)	5		67%
Li et al. (2014)	U.S.	1995, 2001	(c)	5	39%	
Gillingham (2014)	U.S.: California	2006-2009	(c)	5	23%	
Barla et al. (2009)	Canada	1990-2004	(e)	4	8%	20%
Frondel and Vance (2009)	Germany	1997-2006	(b)	3	52%	
				4	51%	
				6	41%	
Frondel et al. (2012)	Germany	1997-2009	(b)	3	42%	
				4	46%	
				5	57%	
				6	90%	
Matiaske et al. (2012)	Germany	1998-2003	(b)	3		
Frondel and Vance (2013)	Germany	1997-2009	(b)	5	68%	
Frondel et al. (2016)	Germany	2000-2014	(b)	5	48%	
Weber and Farsi (2014)	Switzerland	2010	(a)	3		78%
De Borger et al. (2015)	Denmark	2001-2011	(b)	3	9%	
Ajanovic and Haas (2012)	6 countries in EU	1970-2007	(e)	4	22%	44%
Wang et al. (2012a)	China	1994-2009	(d)	1		96%
Wang et al. (2012b)	China: Hongkong	2002-2009	(d)	6	35%	84%
Yu et al. (2013)	China: Beijing	2010	(a)	1	34%	

Note: In the “Data” column, the letters denote the following: (a): individual cross-section, (b): individual panel, (c): individual pooled, (d): aggregate time-series, and (e): aggregate panel data. I report the average value for those estimates that are presented as a range.

up to the 1990s and 2008, presenting results from 22 and 16 studies, respectively. These studies show short-term rebound effects of 5–30% and long-term rebound effects of 20–40%. Gillingham et al. (2016) also state that short-term rebound effects in developed countries range from 5% to 25%.

Since this study uses a survey conducted in 2013 for the analysis, it is advisable to compare the results with those of existing studies in recent years. This is because the situation considered in these studies may differ from the current situation. For example, in 1997, Toyota launched the Prius, a breakthrough hybrid vehicle, whereas the number of registered hybrid vehicles in Japan shows no significant growth until the start of the tax incentive measures for eco-cars and the spike in gasoline prices in 2009, and it is only in recent years that hybrid vehicles have been widely used by households.[8] Furthermore, Small and Van Dender (2007) and Wang et al. (2012a) use long-term aggregate data and find a negative correlation between income level and the rebound effect, and Greene (2012) shows that the rebound effect declines over time. Therefore, I focus only on recent studies after 2009 below.

Table 2.1 summarizes 22 recent studies on the rebound effect of automobiles. The average rebound effects for the studies in Table 2.1 are 35% in the short run and 41% in the long run. Considering North America only, I find that the average rebound effects are 14% in the short run and 26% in the long run. Furthermore, I also find that rebound effect estimates obtained using measures (2.5) and (2.6) are larger than those obtained using measures (2.1) through (2.4).

On the other hand, few studies have estimated the rebound effect of automobiles in Japan. For example, Mizobuchi (2011) uses individual-level panel data with 6,358 observations from 2006 to 2008 and finds a short-term rebound effect of 18% using indicator (2.4). Iwata and Matsumoto (2016) use data on approximately 3.7 million used cars published in used car information magazines between 2008 and 2013 to estimate the long-term rebound effect resulting from the replacement of gasoline cars with hybrid cars using indicator (2.1). However, both studies consider the nationwide rebound effect in Japan. This study is thus unique in that it attempts to estimate the rebound effects by region, using a household questionnaire and examining the effects of detailed individual attributes on the distance traveled.

2.3 Model

In this study, I estimate the rebound effects using indicator (2.3), the fuel economy elasticity of driving distance $\eta_\varepsilon(S)$, and indicator (2.4), the per-kilometer driving cost elasticity of driving distance $-\eta_{P_S}(S)$. The individual's decision on how much to use a car is likely to be affected by factors other than vehicles' fuel efficiency or the per-kilometer cost of driving. For example, those who have easy access to public transportation are expected to use cars less frequently than those who do not. Therefore, it is necessary to account for such factors in estimating the rebound effect.

Let S_i, ε_i, and P_{Ei} denote the average annual mileage of the car owned by household i, the fuel economy of that car, and the average price of gasoline over the ownership period in the area of residence, respectively. In addition, let a vector X_i be other variables that affect the average annual mileage. Assuming that the average annual mileage S_i is explained by a log-linear relationship among ε_i, P_{Ei}, and X_i, the estimation equation for capturing the rebound effect with indicator (2.3) is expressed as

$$\log(S_i) = \delta_0 + \theta_1 \log(\varepsilon_i) + \alpha \log(P_{Ei}) + \log(X_i)'\beta + u_i. \tag{3.1}$$

[8] See https://airia.or.jp/publish/statistics/ao1lkc00000000z4-att/03_7.pdf (accessed March 15, 2016) on the website of the Automobile Inspection & Registration Information Association.

Here, δ_0, θ_1, α, and β are parameters to be estimated, and u_i is an error term with $E(u_i|\varepsilon_i, P_{Ei}, X_i) = 0$. In equation (3.1), the parameter θ_1 represents $\eta_\varepsilon(S)$. Therefore, I estimate (3.1) by ordinary least squares to capture the magnitude of θ_1.

I estimate the following equation to capture the rebound effect with indicator (2.4):

$$\log(S_i) = \delta_2 + \theta_2 \log(P_{Ei}/\varepsilon_i) + \log(X_i)'\gamma + v_i, \tag{3.2}$$

where δ_2, θ_2, and γ are parameters to be estimated and v_i is an error term which is assumed to satisfy $E(v_i|\varepsilon_i, P_{Ei}, X_i) = 0$. In this expression, the negative sign of the estimated θ_2 corresponds to the rebound effect $-\eta_{P_S}(S)$.

Following previous studies, I include variables related to the attributes of the car and household and the area in which the households reside into a vector X_i. For the automobile attributes, I use variables representing vehicle age, engine displacement, and whether the vehicle was purchased new. For the household attributes, I use variables such as the age and sex of the main driver of the vehicle, household income, family size, and the number of vehicles owned. Additionally, for the residential area attribute, I use the population density of the residential area, time from home to the nearest bus or train public transportation station, and the frequency of that public transportation service.

To estimate the rebound effects by region, I divide the sample into metropolitan areas and other regions according to the definition of the Ministry of Internal Affairs and Communications.[9] Specifically, I define as metropolitan areas those municipalities in the Tokyo, Nagoya, and Kansai metropolitan areas with particularly high population concentrations.

2.4 Data

The main data set used for the analysis comes from a household survey. I conducted a household survey in November 2013, targeting households in Japan that purchased a passenger car or a mini-vehicle for private use within the past five years. The survey was commissioned by the Nippon Research Center, and I obtained responses from 1,163 households via the Internet.[10]

The survey consists mainly of questions about car ownership and usage as well as household attributes. Because respondents did not always have an accurate understanding of the status of their car ownership, I asked respondents to prepare the automobile inspection certificate of the car they own and to fill in the automobile information on the automobile inspection certificate, such as the year and month of registration, model name, grade, and displacement, to ensure accurate

[9] See http://www.soumu.go.jp/main_content/000354244.pdf (accessed November 2, 2016) on the website of the Ministry of Internal Affairs and Communications.

[10] To ensure a sufficient sample size in metropolitan areas and other regions, I surveyed an equal number of households living in the 23 wards of Tokyo and government ordinance-designated cities and households living in other regions.

Table 2.2: Summary Statistics in the Three Metropolitan Areas

	Mean	St. dev.	Min	Max
average annual mileage (km)	6007.01	9654.07	100.00	180280.00
fuel economy (km/ℓ; 10.15 mode)	22.07	9.19	6.50	40.00
gasoline price (JPY/ℓ)	145.51	5.43	120.32	159.00
displacement (cc)	1649.85	628.48	598.00	4965.00
new car dummy (1 when purchased in new)	0.77	0.42	0.00	1.00
vehicle age	3.76	2.04	1.00	16.00
main driver's gender dummy (male=1)	0.80	0.40	0.00	1.00
main driver's age	52.47	11.79	20.00	79.00
household income (10,000 JPY per year)	780.30	465.23	90.00	3300.00
household size	2.86	1.12	1.00	6.00
number of owned vehicles	1.19	0.45	1.00	4.00
population density (person/km^2)	7597.96	4250.11	795.69	20189.22
dummy for time to nearest public transportation (1 when less than 15minutes)	0.89	0.32	0.00	1.00
dummy for number of services at the nearest public transportation (1 when greater than 6 per hour)	0.47	0.50	0.00	1.00

Note: The table reports summary statistics in the three metropolitan areas. The sample size is 428.

information. If respondents owned multiple cars, I asked them to provide information on the car they use most frequently.

For the accumulated mileage, I asked respondents to check the mileage meter of their car and fill in the date on which the meter was checked and the accumulated mileage. Using this accumulated mileage and the registration date on the vehicle inspection certificate, I calculated the average annual mileage during the period of ownership. Households whose main vehicle was purchased used were asked to provide additional information on the cumulative mileage of the used vehicle at the time of purchase, and the average annual mileage was calculated from this information.

In addition, I complement the household survey with other publicly open data sources. I matched the vehicle names and models with the list of automobile fuel efficiency measured in the 10.15 mode published by the Ministry of Land, Infrastructure, Transport, and Tourism. Although fuel efficiency is currently measured in the JC08 mode, I use the 10.15 mode fuel efficiency values because JC08 mode fuel efficiency values are not publicly available for older model vehicles.[11]

[11] The 10.15 mode that was the official fuel efficiency measurement method used until March 2011 was replaced with the JC08 mode, a new measurement method. Fuel efficiency values in both modes are listed together in the catalog until March 2013, and only the JC08 mode has been used since April 2013.

Table 2.3: Summary Statistics in Other Regions

	Mean	St. dev.	Min	Max
average annual mileage (km)	7644.04	5507.43	100.00	45931.67
fuel economy (km/ℓ; 10.15 mode)	19.86	7.64	7.80	40.00
gasoline price (JPY/ℓ)	146.14	6.81	123.23	162.50
displacement (cc)	1546.26	688.44	598.00	4608.00
new car dummy (1 when purchased in new)	0.66	0.48	0.00	1.00
vehicle age	4.30	2.90	1.00	16.00
main driver's gender dummy (male=1)	0.74	0.44	0.00	1.00
main driver's age	48.83	11.87	22.00	79.00
household income (10,000 JPY per year)	646.67	412.65	60.00	3790.00
household size	3.07	1.33	1.00	8.00
number of owned vehicles	1.55	0.71	1.00	4.00
population density (person/km^2)	2428.84	2284.57	20.16	11785.27
dummy for time to nearest public transportation (1 when less than 15minutes)	0.83	0.37	0.00	1.00
dummy for number of services at the nearest public transportation (1 when greater than 6 per hour)	0.12	0.33	0.00	1.00

Note: The table reports summary statistics in other regions. The sample size is 362.

Moreover, data on gasoline prices are collected from the Oil Information Center, Japan. To obtain data on the gasoline prices that each household faces, average gasoline prices during the period of car ownership are compiled by prefecture based on information on the place of residence of each household.

I also use population density, which is defined as population per inhabitable land area, by municipality to characterize the area where each household resides. Moreover, in the household survey, I asked about the time to the nearest public transportation stop (bus stop or train station) and the number of service times per hour of that public transportation service to capture the accessibility of public transportation by location of residence. These are dummy variables; the first takes value one if the time to the stop is 15 minutes or less and zero otherwise, and the second takes value one if the public transportation system offers service six or more times per hour.

Tables 2.2 and 2.3 report descriptive statistics for each variable for the three metropolitan areas and other regions, respectively. I use 790 of the 1,163 households in the sample for analysis for the following reasons. First, I remove from the sample households with extremely large annual mileage and household income. Specifically, I treat households with an average annual mileage and household income that deviate from the means by more than four standard deviations as outliers.

Second, I also exclude obvious response errors and blank responses for some variables from the sample. Third, since I use only vehicles with published 10.15 mode fuel efficiency values to ensure the sample size, the latest vehicles whose fuel efficiency is available in only the JC08 mode are missing.

2.5 Empirical Results

Columns 1 to 3 of Table 2.4 show the estimation results of expression (3.1) by OLS.[12] Columns 1 and 2 present the estimation results when the sample is divided into metropolitan areas and other regions, respectively, while Column 3 shows the estimation results for the full sample. In the metropolitan areas, the estimated coefficient of fuel economy is not statistically significant, indicating that there is no rebound effect in these areas. On the other hand, in the other regions, the estimated fuel economy coefficient is 0.34 and is statistically significant. This means that the rebound effect is approximately 34.0% in the non-metropolitan areas. Therefore, my estimation results suggest that there is no rebound effect associated with improved fuel efficiency in metropolitan areas, whereas a rebound effect exists in rural areas. This difference in the rebound effect across regions is likely attributable to the difference in traffic congestion. Alternatively, since more fuel-efficient vehicles are driven in urban areas than in other areas, the effect of an additional 1% improvement in fuel economy on the increase in distance traveled may be smaller, and as a result, the rebound effect in urban areas could not be confirmed in the estimation. In fact, Tables 2.2 and 2.3 show that the average fuel economy in urban and other areas is 22.07 km/ℓ and 19.86 km/ℓ, respectively, confirming a statistically significant difference between the two values.

Furthermore, I find that the rebound effect for the full sample is approximately 19.1%. This value is comparable to the estimates of Mizobuchi (2011) and Iwata and Matsumoto (2016). Therefore, the rebound effect in Japan is considered to be approximately 20%; however, the reality is that there is little rebound effect in metropolitan areas and a large rebound effect of nearly 40% in rural areas, indicating the heterogeneity of the rebound effect. This result is consistent with those obtained by Wang et al. (2012a) and Gillingham (2014).

Columns 4 to 6 of Table 2.4 show the estimation results of expression (3.2). The results present the same trend as the estimation results in Columns 1 to 3. While the rebound effect in all areas together is approximately 19.5%, the rebound effect is zero in metropolitan areas and 34.3% in other areas. Similarly, I observe a similar trend for the coefficients of the other variables across both specifications. Table 2.4 shows that the larger the displacement of the vehicle is, the longer the distance traveled, reflecting the fact that cars with larger displacement or size are more user-friendly

[12] To test whether fuel efficiency is an endogenous variable, I conducted the Hausman test by using as an instrument a dummy variable that takes value 1 if one replaces a vehicle because tax reduction measures targeting eco-cars were applied and 0 otherwise. As a result, the null hypothesis that fuel efficiency is an exogenous variable was not rejected at the 1% level, and henceforth this study assumes fuel efficiency to be exogenous.

Table 2.4: Estimation Results

	Dependent variable: log(average annual mileage)					
	Specification (3.1)			Specification (3.2)		
	urban	others	all	urban	others	all
	(1)	(2)	(3)	(4)	(5)	(6)
intercept	8.987	19.155	12.064	6.074***	6.932***	6.913***
	(12.737)	(11.946)	(8.712)	(1.361)	(1.041)	(0.813)
log(fuel economy)	0.114	0.340**	0.191*			
	(0.135)	(0.135)	(0.100)			
log(gasoline price)	-0.689	-2.757	-1.206			
	(2.460)	(2.327)	(1.690)			
log(gasoline price/fuel economy)				-0.116	-0.343**	-0.195**
				(0.134)	(0.134)	(0.099)
log(displacement)	0.217*	0.336***	0.267***	0.219*	0.336***	0.268***
	(0.118)	(0.119)	(0.085)	(0.117)	(0.119)	(0.085)
new car dummy	0.022	0.066	0.050	0.020	0.066	0.048
	(0.121)	(0.118)	(0.084)	(0.120)	(0.118)	(0.084)
log(vehicle age)	0.838**	0.354	0.543***	0.853**	0.392*	0.564***
	(0.333)	(0.235)	(0.194)	(0.331)	(0.233)	(0.193)
$(\log(\text{vehicle age}))^2$	-0.339**	-0.155	-0.205**	-0.328**	-0.104	-0.185**
	(0.141)	(0.100)	(0.083)	(0.131)	(0.087)	(0.075)
main driver's gender dummy	0.088	0.068	0.056	0.088	0.075	0.058
(male=1)	(0.100)	(0.104)	(0.072)	(0.100)	(0.105)	(0.072)
log(main driver's age)	0.327	0.152	0.213	0.325	0.159	0.214
	(0.227)	(0.204)	(0.150)	(0.227)	(0.201)	(0.150)
log(household income)	0.050	-0.067	-0.019	0.051	-0.068	-0.017
	(0.086)	(0.094)	(0.064)	(0.086)	(0.094)	(0.064)
log(household size)	0.040	0.113	0.074	0.040	0.102	0.072
	(0.126)	(0.120)	(0.088)	(0.125)	(0.120)	(0.087)
log(number of owned vehicles)	0.447**	0.254**	0.351***	0.443**	0.237*	0.342***
	(0.178)	(0.127)	(0.103)	(0.176)	(0.129)	(0.104)
log(population density)	-0.147*	-0.073	-0.142***	-0.146*	-0.071	-0.139***
	(0.078)	(0.045)	(0.033)	(0.078)	(0.046)	(0.033)
dummy for time to nearest	-0.057	-0.254**	-0.152*	-0.057	-0.252**	-0.152*
public transportation	(0.123)	(0.123)	(0.089)	(0.123)	(0.124)	(0.089)
dummy for number of services at	-0.143	-0.121	-0.171**	-0.140	-0.116	-0.167**
the nearest public transportation	(0.094)	(0.118)	(0.076)	(0.092)	(0.118)	(0.075)
Sample size	428	362	790	428	362	790
Adjusted R^2	0.069	0.080	0.109	0.071	0.080	0.110

Note: Heteroskedasticity-robust standard errors are reported in parentheses. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

for driving a long distance. De Borger et al. (2015), who analyze Danish data, similarly show that the greater the vehicle weight is, the longer the driving distance, and Iwata and Matsumoto (2016), who target used cars in Japan, also show that the driving distance of regular passenger vehicles is greater than that of mini passenger vehicles.

In the estimation, I include a squared term of vehicle age as an explanatory variable. The sign of the squared term is negative, so the relationship between vehicle age and average annual mileage takes an inverted U-shape, except for the estimation result in other regions using specification (3.2). The estimation results in Table 2.4 suggest that annual mileage will decrease over approximately 3.4 years in metropolitan areas and 3.8 years in Japan as a whole. This implies that mileage tends to increase every year from the time of purchase of a new car until approximately the time of the first vehicle inspection, which is three years later, and to decrease thereafter. Although Su (2012) and Ficano and Thompron (2014) find that the newer the vehicle is, the longer the miles traveled, my estimation result suggests that the relationship between the two variables is not a simple linear relationship but has an inverse U-shape.

In metropolitan areas, the signs of the estimated coefficients on the number of cars owned and population density are positive and negative, respectively, and are both statistically significant. However, in rural areas, only the number of cars owned is positive with statistical significance. Thus, in metropolitan areas, households that own multiple cars and live in areas relatively far from the center of the city tend to have higher average annual vehicle miles traveled. Weber and Farsi (2014) and Ficano and Thompron (2014) find a negative correlation between population density and vehicle mileage. However, this study finds no negative correlation between population density and distance traveled in rural areas in Japan.

Since, in metropolitan areas, there are no significant regional differences in the degree of development of public transportation systems, the two dummy variables indicating the accessibility of public transportation are not estimated with statistical significance. On the other hand, in rural areas, the time to the nearest public transportation system decreases the annual average distance traveled. This means that the shorter the time to the nearest public transportation from home is, the lower the frequency of car use. Regarding this point, Su (2012) and Frondel et al. (2016) show that households with access to railroads drive fewer miles, which is consistent with my results.

2.6 Discussion and Conclusions

The Plan for Global Warming Countermeasures formulated in May 2016 by the Japanese government cited the spread of eco-cars as a means of reducing GHG emissions from automobiles.[13] However, if there is a rebound effect, i.e., an increase in miles traveled due to fuel efficiency improvement, the intended GHG reduction will not be realized even though the use of eco-cars becomes

[13] Regarding the Plan for Global Warming Countermeasures by the Global Warming Prevention Headquarters, see http://www.kantei.go.jp/jp/singi/ondanka/kaisai/dai35/pdf/honbun.pdf (accessed June 8, 2016).

widespread. Therefore, it is crucial to understand the magnitude of the rebound effect to plan future GHG reduction measures.

This study attempts to quantitatively evaluate the magnitude of the rebound effect of automobiles in Japan using a household survey. In particular, different from existing studies, I focus on the difference in the rebound effects between metropolitan and other areas. As a result of the analysis, no rebound effect was found in metropolitan areas, while the rebound effect in rural areas was found to be slightly less than 40%. This result suggests that the eco-car promotion policy in rural areas yields a fuel efficiency improvement of less than 40% due to the increase in the frequency of car use.

The findings from my study have policy implications for future eco-car promotion policies. If the rebound effect is large, it is desirable to introduce policies that encourage the substitution of private car use for public transportation use. By contrast, if the rebound effect is small, it is desirable to introduce eco-car subsidies and other eco-car promotion policies. This is because subsidy policies are not cost-effective when the rebound effect is large. In addition, other external costs such as traffic congestion and traffic accidents are also expected to increase in places where the rebound effect is large when the frequency of car use increases significantly. The eco-car subsidy and tax reduction programs that have been introduced in Japan include eligibility requirements based on vehicle attributes. In other words, the amount of subsidy or tax reduction applied by these policies is independent of where in Japan a particular eco-car was purchased or registered. The results of this study indicate that the eco-car subsidy and tax-reduction programs in Japan are cost-inefficient. To efficiently reduce GHG emissions from automobiles, it is necessary to develop region-specific GHG reduction strategies, such as setting lower subsidy rates in rural areas than in metropolitan areas and instead providing more alternatives that promote substitution to public transportation in rural areas.

I acknowledge some limitations of my study. First, I do not analyze automobile purchasing behavior and the substitution relationship between automobile use and public transportation. I thus do not discuss changes in social welfare associated with the introduction of policies that encourage substitution to public transportation. Second, due to data limitations, I do not consider the differences in knowledge levels and social norms among households that use automobiles. This may be attributable to the fact that my estimation results have small values of the adjusted coefficient of determination. Third, this study does not use actual fuel efficiency that reflects the actual use by individuals but instead fuel efficiency values reported in the catalog. Some note actual fuel efficiency is less than the catalog values, and if this point is correct, this study underestimates the rebound effect.[14] I would like to make these points the subject of future research.

[14] See http://www.jama.or.jp/user/pdf/jitsunenpi.pdf (accessed November 2, 2016) on the website of the Japan Automobile Manufacturers Association.

Chapter 3

Welfare Effects of Fuel Tax and Feebate Policies in the Japanese New Car Market*

3.1 Introduction

Reducing fuel consumption from car driving is an urgent challenge common to most countries. Among the policy instruments for resolving this challenge, feebate policies have gained popularity. Feebate policies provide price incentives for automobiles depending on fuel efficiency to encourage households to replace old fuel-inefficient vehicles with new fuel-efficient vehicles. When facing the financial crisis in 2008, a growing number of countries adopted green economic stimulus programs such as feebates with the aim of combatting the economic recession and climate change. On the other hand, while policymakers would agree that a carbon tax is an effective policy instrument for reducing environmental externalities from car driving, they tend to avoid raising a fuel tax or introducing a carbon tax for several reasons. The foremost reason is that policymakers have concerns about the distributional impacts of taxes on fuel. Hence, this study attempts to empirically answer the following questions: Can we simultaneously achieve these economic and environmental goals with feebate policies? Is a fuel tax more regressive than a comparable feebate?

In this chapter, I evaluate the welfare effects of a fuel tax and a feebate policy, focusing on efficiency and distributional equity. In particular, the interest of this study is in examining the impacts of the two policies on multiple stages of households' decisions. This has important implications for assessing the welfare effects of policies, including their environmental impacts. For example, a fuel tax is expected to affect not only driving distances but also car choices by changing expected future fuel costs. Similarly, a feebate policy directly affects car choices by incentivizing individuals to purchase fuel-efficient vehicles, while it should presumably affect mileage choices by altering the attributes of cars purchased. Therefore, I resort to a structural model that incorporates decisions on the purchase and use of cars into its demand model for policy evaluation.

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Moreover, the social outcomes of the two policies largely depend on a rebound effect. The rebound effect here refers to the upward pressure on driving demand that results from the improvement of fuel economy followed by a downward shift in the per-kilometer marginal cost of driving. Because of the rebound effect, policies that encourage improvements in fuel economy do not always result in the intended reduction of fuel consumption. Many researchers have empirically identified the existence of the rebound effect (e.g., Gillingham et al., 2016). Since a fuel tax directly suppresses driving demand by imposing a tax on marginal environmental externalities from car use, it can control upward pressure on driving demand spurred by the rebound effect. In addition, a fuel tax can be an efficient policy instrument because it equates marginal abatement costs incurred by individuals even when actual individual car usage varies. However, a feebate promotes the dissemination of fuel-efficient cars by providing tax incentives for their purchase; however, it fails to control driving demand after purchase. Thus, the feebate is expected to encourage households to drive more through the rebound effect (Anderson and Sallee, 2016).

To account for the rebound effect in evaluating policy impacts, I model two household decisions, one concerning which car to purchase and, thereafter, another regarding how far a household drives the car. Several studies have focused on two-stage decision-making; however, the number of studies has been limited due to issues of data availability. For instance, Goldberg (1998), West (2004), and Bento et al. (2009) model the two decisions to analyze the effects of fuel economy standards and a fuel tax using data from a large sample of households in the United States. Such analyses requires large-scale household-level data, including detailed information on the choice and usage of cars. However, in many cases, such micro-level data are not available, and this data limitation has hindered the analysis.

In this study, I attempt to overcome this problem by combining two data sets. The first data set comes from a household survey administered in 2013 to households in Japan who had purchased a passenger vehicle within the past five years. This survey provides detailed information on car ownership and utilization for each household, such as the car model, the year purchased, and the distance traveled. The survey also reports household demographics, such as household income, family size, and residential address. On the other hand, the second set of data comes from an aggregate data set on the Japanese new car market between 2006 and 2013. This aggregate market data set contains information on sales volume, price, and other car attributes for each base model and covers nearly all models in the Japanese new car market. Importantly, the combination of the data sets at the different levels helps construct choice sets faced by surveyed households in each market. I match the micro-level information from the household survey and the macro-level information from the aggregate data set by using a model name common across the two data sets.

The Japanese automobile market provides an interesting situation for this study for several reasons. First, during the 2006–2013 sample period, the Japanese feebate policy experienced multiple system changes. Importantly, the system changes expanded the monetary amounts and coverage of the feebate, leading to variations in vehicle prices across vehicles and over time. These exogenous variations are crucial to identifying model parameters. The second is attributed that the Japanese feebate policy being an attribute-based regulation (Ito and Sallee, 2018). Under the scheme, the amounts of the rebate are determined according to vehicle weight and displacement as well as vehicle fuel economy. Regarding this point, some offer the critique that the Japanese feebate provides more subsidies to heavy, fuel-inefficient vehicles rather than light, fuel-efficient vehicles. Hence, I conduct a counterfactual analysis to examine whether a change in the design of the scheme to address such criticisms improves social welfare. The third is related to the fact that a carbon tax was newly introduced during the sample period. In Japan, gasoline and diesel have long been subject to fuel taxes with high rates, with the gasoline tax representing approximately one-third of the gasoline price. In addition to the existing fuel taxes, a carbon tax was phased in 2012, the introduction of which led to exogenous variation in fuel prices. I use such variation to identify the responses of consumers and producers to fuel price changes.

I begin by constructing a model that describes the behaviors of households and firms in the automobile market. On the demand side, I model the household's behavior as a two-stage problem. Specifically, I describe the joint demand for vehicle and use with the discrete-continuous choice (DCC) model following Bento et al. (2009). On the supply side, I model the pricing strategies of car manufacturers in an oligopolistic market, and following Berry et al. (1995, henceforth BLP) and subsequent studies, I assume that differentiated, multiproduct firms determine their prices based on those of rival firms. The model in this study has two advantages. First, it allows me to drop the restrictive assumption made in most previous studies that driving demand is completely inelastic with respect to operating costs; I thus evaluate the policy effects without making any assumptions concerning the elasticity of driving demand. Second, by following the estimation strategy proposed by BLP (1995), I address the car price endogeneity associated with demand estimation based on aggregate market data. In particular, I identify parameters of the DCC model using micro-level and macro-level moment conditions and estimate the parameters with the maximum likelihood estimation (MLE), following Goolsbee and Petrin (2004) and Train and Winston (2007).

Moreover, I account for the heterogeneity of the rebound effect across individuals in the model. Existing empirical studies find that since actual car usage patterns differ considerably between urban and rural areas, the magnitude of the rebound effect varies across regions even within the same country (e.g., Gillingham, 2014). I then attempt to capture the heterogeneity by introducing a random coefficient into the structural model. The micro-level data used in this study help to identify the heterogeneity.

I perform several counterfactuals and quantify welfare effects of policies with four different measures of surplus: consumer surplus, producer surplus, tax revenues, and environmental externalities. There are two primary findings from the simulation. First, I find that the Japanese feebate policies significantly stimulate demand for automobiles and result in an increase in social welfare while exacerbating environmental externalities. This increase in the negative externality is due to not only the increase in the number of cars purchased by households but also the rebound effect. In fact, a decomposition analysis reveals that the rebound effect induced by the feebate cancels out approximately 7% of the reduction in CO_2 emissions that would originally have been attained by the improvement in fuel economy. The results demonstrate that green economic stimulus policies such as the feebate fail to achieve both their economic and environmental goals.

In addition, the simulation results suggest that altering the feebate scheme design can improve consumer welfare, with the environmental externality being held unchanged. I find that, compared with the actual, attribute-based feebate scheme, an alternative feebate scheme that determines subsidy amounts based solely on vehicle fuel economy increases the consumer surplus of low-income households by subsidizing light, fuel-efficient vehicles. However, this change in scheme design reduces producer surplus and tax revenues because it decreases the sales of heavy, large-sized vehicles relative to the actual feebate.

Second, the simulation presents the cost-effectiveness of a fuel tax over a product tax, which is an alternative feebate scheme considered in the counterfactual analysis. Specifically, the fuel tax at the current tax rate in Japan is 1.7 times less costly than a product tax for reducing environmental externalities by the same amount. Furthermore, I find that the fuel tax is slightly less regressive than the product tax. The simulation analysis confirms that both policies are regressive until the fourth quintile income group and become progressive in the fifth quintile income group. Finally, my simulation analysis also provides some findings on elasticities associated with the carbon tax rate. In particular, I find that a 1% increase in the carbon tax in the future leads to a 0.22% decrease in Japanese CO_2 emissions.

This study contributes to two strands of the literature. First, this study relates to the literature that evaluates feebate policies in car markets. Several papers have studied the welfare impacts of feebate policies in car markets (see, e.g., Konishi and Zhao (2017) and Kitano (2016, 2022) for a study on the Japanese feebate and D'Haultfœuille et al. (2014) and Durrmeyer (2022) for a study on the French feebate). I contribute to the literature by examining the economic and environmental consequences of the Japanese feebate policy, while accounting for rebound effects and the equilibrium in the car market. Importantly, Tinbergen (1952) notes that achieving multiple policy targets requires more policies than the number of policy targets. In this study, I demonstrate Tinbergen's rule by indicating that the feebate stimulates demand while augmenting environmental damage.[1]

Second, this study also contributes to the argument about the distributional effects of a fuel tax and a feebate policy. Seminal papers that analyze the distributional impacts of car market

[1] Li et al. (2021) analyze the impacts of the cash-for-clunkers program in the United States and find that the program failed to achieve its economic stimulus and environmental objectives, indicating that Tinbergen's (1952) rule does not hold. My work complements the results of Li et al. (2021) by evaluating the impacts of a feebate policy on households' choices of vehicle and miles traveled.

regulations are Bento et al. (2009) and Jacobsen (2013), who study the impacts of the fuel tax and the corporate average fuel economy standards in the United States. Recently, Davis and Knittel (2019) and Levinson (2019) also argue about the regressivity of these regulations. Regarding the feebate policy, Durrmeyer (2022) examines the distributional impacts of the French feebate. I compare the distributional impacts of the fuel tax and feebate policy on households with different incomes by employing a structural model. My contribution is to argue for the regressivity of the two policies in terms of consumer welfare while accounting for households' decisions on car choice and use.

The remainder of this chapter is organized as follows. Section 3.2 describes the data sets and institutional background of the Japanese feebate policy. Sections 3.3 and 3.4 outline the model and the estimation strategy, and Section 3.5 discusses the estimation results. Section 3.6 presents the results of counterfactual analysis, and Section 3.7 concludes this chapter.

3.2 Data and Institutional Background

In this section, I first explain the data sets used in the analysis. I then outline the institutional background of the feebate scheme in Japan. In particular, I highlight exogenous variation in vehicle prices generated by several system changes of the Japanese feebate that is helpful for the identification of model parameters.

3.2.1 Data

The data used for the analysis stem mainly from two data sets. The first data set is a household survey commissioned by the Nippon Research Center (NRC). This survey was conducted online in November 2013 and targeted households nationwide who had purchased passenger cars in the past five years. The survey provides 548 observations for this study. The household survey contains information on the model purchased, purchase year, total travel distance for each vehicle, and household demographics such as income, the age of the household head, and the residential area address.

The second data set is a market-level aggregate data set for the period from 2006 to 2013. Using these market-level data enables me to construct the choice set faced by households in selecting a car. I obtain information on sales volumes of automobiles made by Japanese manufacturers from the Annual Report on New Motor Vehicle Registrations (*shinsha-touroku-daisuu-nennpou* in Japanese) published by the Japan Automobile Dealers Association and from statistics on mini-vehicles released by the Japan Mini Vehicles Association. On the other hand, the information on the sales volumes of imported vehicles comes from statistics released by the Japan Automobile Importers Association (JAIA). The statistics include sales data on the top-20 best-selling imported vehicles sold in Japan for each year.[2] In addition to the sales data, I obtain information on the car attributes, including price, curb weight, size, and fuel economy, on the Carview! website. Consequently, the market aggregate data set has 1,302 observations over eight years for each base model, with nine Japanese and seven overseas car manufacturers. I combine the household survey and aggregate data based on the model name common to both data sets.

In addition, I supplement the main data sets with the following data sources. First, to construct the population density for household demographics, I make use of the Comprehensive Survey of Living Conditions (CSLC) in 2013 administrated by the Ministry of Health, Labor and Welfare. Second, to calculate the annual averages of gasoline and diesel prices nationwide, I collect statistics on retail fuel prices released by the Oil Information Center of the Institute of Energy Economics, Japan. Finally, I exploit the 2015-base consumer price index released by the Statistics Bureau of Japan to deflate the household income, car prices, and fuel prices.

Table 3.1 presents the summary statistics for variables used in the analysis. The first row in Panel A reports the annual vehicle kilometers traveled (VKT) for each vehicle owned by households.[3] The annual VKT is approximately 5,480km on average. This value is close to the average travel distance obtained from the nationwide survey of the Japan Automobile Manufacturers Association (JAMA).[4] In addition, I find that the household incomes are slightly higher than the national average because the NRC's survey only targets households who have purchased cars. Indeed, the household income in my sample is 7.56 million JPY on average, while the population average reported in the CSLC for 2013 is 5.28 million JPY. On the other hand, other demographics such as family size, the age of the household head, and the urban dummy take values close to the population averages, where the urban dummy indicates whether a household resides in ordinance-designated cities.

The variables in Panel B are defined as follows. The rental price represents the annual cost of vehicle ownership and is calculated based on the purchase price. Specifically, I construct the rental price as the sum of depreciation, repayment amount of car loan interest, and annualized automobile taxes in each year.[5] The automobile-related taxes shown in Panel B indicate the total tax amount

[2] In Japan, imported vehicles sales constitute a small portion of total new vehicle sales. Indeed, JAIA (2016) reports that the share of imported vehicles in total new vehicle sales in 2013 was approximately 6.5%.

[3] I define the annual VKT as the total travel distance divided by years of use.

[4] The JAMA conducts a market-trend survey of passenger vehicles of households nationwide every two years and reports an average monthly VKT of 380km for 2013 (JAMA, 2013). Therefore, a rough estimate of the annual VKT comes to 4,560km.

[5] The depreciation is calculated based on the legal durable years by vehicle types. The National Tax Agency of Japan stipulates that the legal durable years are six years for ordinary passenger vehicles and four years for mini-vehicles (Kei-cars). Repayment amounts of car loan interest are calculated by the purchase price times the annual interest rate of 3%, which is roughly the average interest rate of car loans in Japan. Note that the purchase price here includes the excise tax-inclusive price, an acquisition tax, and a subsidy amount in the presence of the feebate policy. Finally, annualized automobile taxes consist of the total amounts of a motor vehicle tonnage tax and an automobile tax that car owners are obligated to pay every year.

Table 3.1: Summary Statistics

	Unit	Mean	St. Dev.	1st Q.	3rd Q.
Panel A. Household survey ($N = 548$)					
Annual vehicle kilometers traveled (VKT)	10,000km	0.55	0.33	0.30	0.75
Household income	million JPY	7.56	4.23	4.35	9.64
Family size	person	2.92	1.13	2.00	4.00
Age of household head	age	54.62	12.59	45.00	64.00
Urban dummy	binary	0.47	0.50	0.00	1.00
Panel B. Aggregate data, 2006-2013 ($N = 1,302$)					
Sales	1,000	24.70	40.05	3.11	28.31
Price	million JPY	2.68	1.90	1.50	3.08
Rental price	million JPY	0.58	0.37	0.36	0.65
Automobile-related taxes	million JPY	0.19	0.11	0.13	0.23
Cost of driving per kilometer	100 JPY/km	0.11	0.04	0.08	0.13
Horsepower per weight	ps/kg	0.10	0.03	0.08	0.11
Size	10 meters	0.75	0.07	0.69	0.81
Kei-car dummy	binary	0.20	0.40	0.00	0.00
Transmission dummy (AT/CVT)	binary	0.98	0.13	1.00	1.00

Note: This table summarizes descriptive statistics for the household survey and aggregate data. The 1st Q. and 3rd Q. in the table stand for the first and third quantiles. The automobile-related taxes in Panel B indicate the lump-sum tax amount at the time of purchase before applying the tax cut under the feebate.

before applying the tax cut under the feebate.[6] Table 3.1 shows that the automobile-related taxes amount to approximately 8% of the purchase price on average in the absence of the feebate policy. In addition, the cost of driving per kilometer is defined as the fuel price (JPY/ℓ) divided by the fuel economy (km/ℓ), and the vehicle size is measured as the sum of the length, width, and height of the vehicle. Finally, the transmission dummy (AT/CVT) is a dummy variable indicating vehicles with an automatic transmission (AT) or a continuously variable transmission (CVT).

3.2.2 Japanese Feebate Scheme

Here, I briefly describe the Japanese feebate scheme and show how several system changes produced variations in the vehicle prices consumers faced. The details of the scheme are provided in Appendix 3.A.1.

[6] During the sample period, the automobile-related taxes are composed of the acquisition tax, the motor vehicle tonnage tax, and the automobile tax. See Appendix 3.A.1.1 for details on the automobile-related taxes.

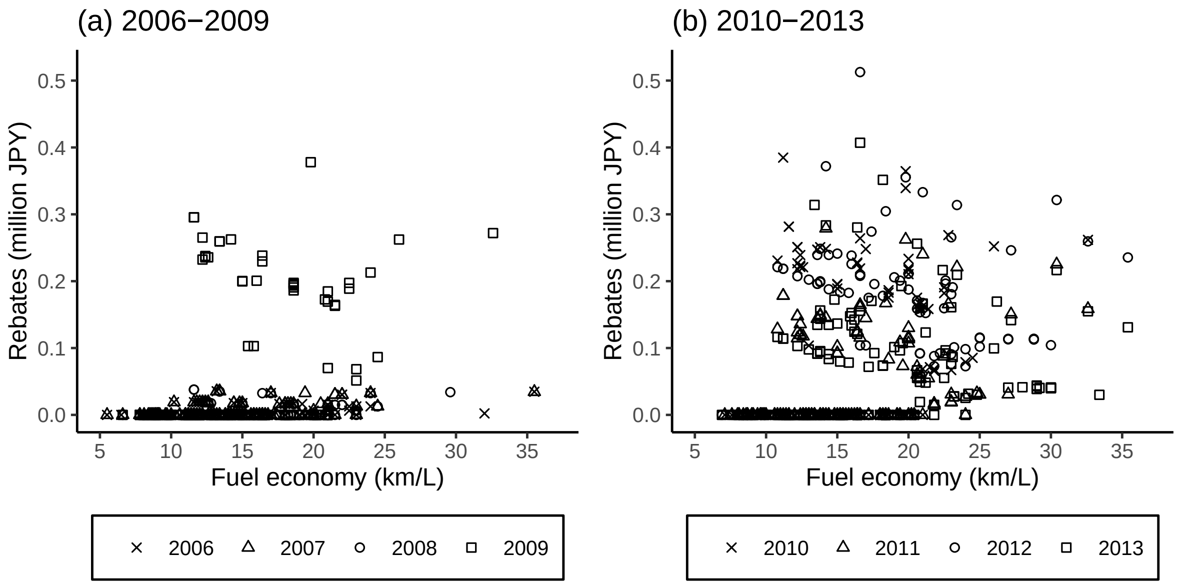

Figure 3.1: Variation in Rebates between 2006 and 2013

Note: The figure plots the amounts of rebates applied for each vehicle under the feebate policy during 2006–2009 (left figure) and 2010–2013 (right figure). The rebates here are defined as the sum of the tax cut and subsidy amounts.

The Japanese feebate scheme is essentially a rebate program, consisting of (i) the tax incentive measures for automobile-related taxes and (ii) the subsidy program for fuel-efficient vehicles.[7] During the sample period from 2006 to 2013, each of the tax incentive measures and the subsidy program experienced three and one system changes, respectively. The implementation periods of the tax incentive measures are divided into 2006, 2007–2008, April 2009–April 2012, and May 2012–2013.[8] Similarly, the subsidy program introduced in 2009 has two implementation periods of April 2009–September 2010 and January 2012–September 2012.[9]

In particular, the feebate scheme was substantially expanded as one of the Green New Deal programs in 2009. Figure 3.1 displays rebates, the sum of the tax cut and subsidy amounts, applied for each vehicle under the feebate by year. I first find that the system reform in 2009 substantially expanded both the amounts and coverage of the tax cut and subsidy. Importantly, several system reforms during the sample period generated cross-vehicle price variations and time-series price

[7] In addition to these programs, there was a cash-for-clunkers program for replacing gasoline vehicles registered for more than 13 years with fuel-efficient vehicles between 2009 and 2010. For details of the cash-for-clunkers program, see Kitano (2022).

[8] The amounts of the tax cut and the eligibility requirements for the tax incentive measures differ by the implementation period. See Appendix Table 3.A.2 for details. In addition, the fuel economy standards that are the basis for determining the tax cut and subsidy amounts also changed with the scheme changes.

[9] The second period of the subsidy program was initially scheduled to last until December 2012; however, due to budget constraints, it was completed by September 2012.

variations within a given vehicle. Figure 3.1 demonstrates that the rebates vary substantially across years even within a given vehicle, ranging from 0 JPY to 0.5 million JPY. These multidimensional fluctuations in vehicle price that are exogenous to consumers are crucial for the identification of model parameters. I use the variations to construct instrumental variables, as explained in a later section.

In addition, Figure 3.1 shows that the amount of the rebate is determined not only by the fuel economy but also the vehicle weight. This is attributable to the fact that the Japanese feebate policy is an attribute-based regulation, as studied by Ito and Sallee (2018). Figure 3.1 shows that fuel-efficient vehicles do not necessarily enjoy a relatively higher rebate than less fuel-efficient vehicles. In fact, many vehicles receive more rebates than hybrid vehicles with a fuel economy of over 35 km/ℓ.

Since the data available in this study are annual, I divide the implementation periods of the tax incentives and subsidy programs after 2009 into the following two periods: the first period from 2009 to 2011 and the second period from 2012 to 2013. As discussed in later sections, even with such definitions, the results obtained in this study are consistent with external data. This indicates that summarizing the monthly regulatory effects into annual effects does not have a significant impact on the analysis.

3.3 Model

In this section, I construct a structural model of the new car market. I assume for the demand model that each household makes two decisions about car purchase and use. For the supply model, I assume differentiated, multiproduct firms that compete in an oligopolistic market in a Bertrand-Nash manner.

3.3.1 Demand

I first present the demand model and describe its specification. Following Goldberg (1998) and Bento et al. (2009), I construct a model with two household decisions—car choice and car usage—by using the DCC model developed by Hanemann (1984) and Dubin and McFadden (1984). Specifically, each household makes a car choice decision based on its indirect utility and then decides how far to drive the purchased car; the latter decision is described by a demand function for driving derived from Roy's identity.

Suppose that there exist N_t potential households in the automobile market, which is divided by year t $(= 1, \ldots, T)$. I assume that household i $(= 1, \ldots, N_t)$ buys at most one car j $(= 1, \ldots, J_t)$ or an outside option $(j = 0)$ each year. I define the indirect utility U_{ijt} of household i conditional on purchasing car j or the outside option in year t as

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \tag{3.1}$$

where V_{ijt} is part of the indirect utility that depends on both observed and unobserved car attributes and observed household attributes. The indirect utility U_{ijt} includes an idiosyncratic shock ε_{ijt} in the last term. In the real world, even though all households with the same characteristics face the same product-choice set, they do not necessarily all make the same choice. The inclusion of the idiosyncratic shock ε_{ijt} allows me to explain this choice variation across households. I assume ε_{ijt} to be an independently and identically distributed stochastic variable that follows the type I extreme value distribution.

Each household decides which car to buy based on (3.1). Specifically, I assume that a household chooses the car with the highest conditional indirect utility. Given the model parameters, the conditional probability of household i in year t choosing car j or the outside option is written as

$$\frac{\exp\left(V_{ijt}\right)}{\sum_{k=0}^{J_t}\exp\left(V_{ikt}\right)}.$$

Given purchasing car j in year t, household i determines VKT M_{ijt} subject to the budget constraint,

$$p_{jt}^{M}M_{ijt}+X_{it}=y_i-r_{jt}.$$

In the budget constraint, p_{jt}^{M} denotes the per-kilometer cost of driving, which is defined as the gasoline price p_t^{gas} at the time of purchase divided by car j's fuel economy. The second term X_{it} expresses the Hicksian composite good consumption for household i, where the price of the composite good is normalized to one.[10] On the right-hand side, y_i denotes household i's income, and r_{jt} represents the rental price that is calculated based on the purchase price p_{jt}, so that $y_i - r_{jt}$ expresses the residual income after purchasing car j.

Here, I specify V_{ijt} in the indirect utility (3.1) as follows:[11]

$$V_{ijt}=\alpha_i\left(y_i-r_{jt}\right)+\lambda\exp\left(x_{jt}'\beta+h_i'\gamma-\rho_i p_{jt}^{M}\right)+w_{jt}'\psi+\xi_{jt} \tag{3.2}$$

In this specification, x_{jt} and w_{jt} each represent vectors of observed car attributes, and h_i represents a vector of household characteristics. As shown below, x_{jt} appears in both the car choice and usage equations, whereas w_{jt} appears only in the car choice equation. Note that the second term of (3.2) expresses the interaction term between the car and household attributes. Additionally, ξ_{jt} captures car attributes observed by households and firms but unobserved by researchers. As in BLP (1995), I assume the rental price r_{jt} to be endogenous because r_{jt} may correlate with unobserved car attributes ξ_{jt}. Indeed, several factors in ξ_{jt}, such as advertisements and the brand image of automobile firms, are expected to affect the rental price. Finally, I normalize the indirect utility

[10] To make the normalization, I divide both sides of the budget constraint by the composite good price.

[11] I do not consider the situation where households misperceive fuel costs when making vehicle choices. Several studies that have analyzed the degree of undervaluation of future fuel cost savings obtained by purchasing fuel-efficient cars find that there is little such undervaluation by households (see, e.g., Busse et al., 2013, Sallee et al., 2016, and Grigolon et al., 2018).

from the outside option ($j = 0$) to $V_{i0t} = \alpha_i y_i$. Regarding a direct utility function assumed under the indirect utility specification above, see Appendix 3.A.2.

The specification of V_{ijt} involves random coefficients. I specify coefficients α_i and ρ_i as

$$\alpha_i = \alpha_0 + \alpha_1 y_i + \sigma_\alpha v_{i\alpha}, \quad \rho_i = \exp\left(\rho + \sigma_\rho v_{i\rho}\right), \tag{3.3}$$

where $v_{i\alpha}$ and $v_{i\rho}$ are independently distributed standard normal. In the specification of α_i, α_0 represents a mean parameter when household income is zero, and σ_α represents a standard deviation parameter. As assumed in BLP (2004), I include household income y_i as a preference shifter in α_i to capture the heterogeneity of price elasticities of demand across households with different incomes. I expect that households with higher incomes are unlikely to respond to the vehicle price change so that the coefficient α_1 becomes negative. On the other hand, the coefficient ρ_i captures the heterogeneous impacts of the driving cost on households' preferences. Specifically, ρ and σ_ρ correspond to the mean and standard deviation parameters for the distribution of ρ_i, respectively. In specification (3.2), the remaining parameters λ, β, γ, and ψ are assumed to be constant.

Under specification (3.2), I derive the demand for distance traveled M_{ijt}. When household i purchases car j in year t, applying Roy's identity to the indirect utility yields the driving demand M_{ijt} as follows:[12]

$$\begin{aligned}\log(M_{ijt}) &= \log\left(-\frac{\partial V_{ijt}/\partial p^M_{jt}}{\partial V_{ijt}/\partial y_i}\right) \\ &= \log\left(\frac{\lambda \rho_i}{\alpha_i}\right) + x'_{jt}\beta + h'_i\gamma - \rho_i p^M_{jt}.\end{aligned} \tag{3.4}$$

3.3.2 Supply

Next, I consider the pricing strategies of car manufacturers. I assume that differentiated, multiproduct firms strategically determine the prices of their products in an oligopolistic market to maximize their profits, given the prices of rival firms' products. From the conditions for profit maximization, I derive pricing equations for each firm that arrive at a Bertrand-Nash equilibrium.

I denote a set of cars that firm f produces in year t as $\mathcal{J}_{ft}$. Firm f determines its prices to maximize variable profit defined as follows:

$$\sum_{j \in \mathcal{J}_{ft}} \left(p^e_{jt} - mc_{jt}\right) N_t s_{jt}(r_t),$$

where p^e_{jt} is the tax-exclusive price of car j in year t and $s_{jt}(r_t)$ is the market share obtained under a $J_t \times 1$ vector of tax-inclusive rental prices r_t. Additionally, mc_{jt} denotes the marginal cost, which is assumed to be constant in quantity.

[12] Note that the income y_i that appears in (3.3) is not structurally embedded in the indirect utility but in a reduced form way.

For the profit maximization, the first-order condition to be satisfied by p^e_{jt} is written as

$$s_{jt}(r_t) + \left(1 + \tau^{ad}_{jt}\right) \frac{dr_{jt}}{dp_{jt}} \sum_{k \in \mathcal{J}_{ft}} \left(p^e_{kt} - mc_{kt}\right) \frac{\partial s_{kt}(r_t)}{\partial r_{jt}} = 0,$$

where τ^{ad}_{jt} represents an ad valorem tax. Note that in the derivation of the first-order conditions, the rental price r_{jt} is a function of the purchase price p_{jt}. I can rewrite these J_t first-order conditions for profit maximization in matrix form and obtain pricing equations for each firm. I define a $J_t \times J_t$ matrix S_t, comprising partial derivatives of market share $s_{jt}(r_t)$ with respect to r_{jt} times (-1), and denote the (j,k) element as $S_{jk,t} = -\partial s_{kt} / \partial r_{jt}$. I also define the ownership matrix Ω^*_t with (j,k) element $\Omega^*_{jk,t}$,

$$\Omega^*_{jk,t} = \begin{cases} 1 & \text{if } \exists f \text{ s.t. } \{j,k\} \subset \mathcal{J}_{ft} \\ 0 & \text{otherwise.} \end{cases}$$

With these matrices, defining $J_t \times J_t$ matrix $\Omega_t = \Omega^*_t \odot S_t$, where operator $\odot$ denotes the element-wise Hadamard product, I obtain the $J_t \times 1$ vector of tax-exclusive prices p^e_t from the following expression:

$$p^e_t = mc_t + \Omega_t^{-1} s^e_t(r_t) \tag{3.5}$$

In the expression, mc_t is a column vector of marginal costs, and $s^e_t(r_t)$ is a column vector with $s_{jt}(r_t)/\{(1 + \tau^{ad}_{jt}) dr_{jt}/dp_{jt}\}$ as its jth element.

3.4 Estimation and Identification

I explain the estimation and identification strategies for the model parameters. The basic idea for the estimation is that I embed the estimation procedure of the DCC model in the framework of BLP (1995), following Goolsbee and Petrin (2004) and Train and Winston (2007). I attempt to identify the parameters with micro-level and macro-level moments and address price endogeneity when estimating the demand function. Based on the demand parameters and conditions for profit maximization, I recover the marginal costs faced by each firm in the production process.

3.4.1 Estimation Strategy

I first present the overview of the estimation strategy before describing the details. First, I divide the parameters in V_{ijt} into two parts and denote them by vectors θ_1 and θ_2:

$$V_{ijt} = \delta_{jt}(\theta_1) + \mu_{ijt}(\theta_2), \tag{4.1}$$

where $\delta_{jt}(\theta_1)$ and $\mu_{ijt}(\theta_2)$ represent a mean utility that is common to all households and the part of utility depending on household characteristics, respectively. Specifically, for $j = 1, \ldots, J_t$, vectors

θ_1 and θ_2 are composed of

$$\theta_1 = (\alpha_0, \psi), \quad \theta_2 = (\alpha_1, \lambda, \beta, \gamma, \rho, \sigma_\alpha, \sigma_\rho),$$

and for the outside option ($j = 0$), both $\delta_{0t}(\theta_1)$ and $\mu_{i0t}(\theta_2)$ are zero by definition. Both of the parameter vectors are supposed to be estimated via MLE when household-level data are available. However, a likelihood function defined under this specification includes over 1,300 fixed effects $\{\delta_{jt}\}_{j,t}$, and it is unrealistic to conduct a nonlinear search over all these parameters using MLE. Then, the market aggregate data help reduce the number of parameters to be estimated in a nonlinear search. Specifically, Berry's inversion (Berry, 1994; BLP, 1995) based on market shares in the aggregate data set enables me to express the fixed effects $\{\delta_{jt}\}_{j,t}$ as a function of the θ_2 parameter only. Finally, using estimated θ_1 and θ_2 parameters, I recover the marginal costs in the supply model.

As the first step, I express fixed effects $\{\delta_{jt}\}_{j,t}$ as a function of parameter vector θ_2. Under the assumption that ε_{ijt} in (3.1) follows the type I extreme value distribution, I calculate the predicted market share s_{jt} of car j in year t as follows:

$$s_{jt}(\{\delta_{jt}\}_j, \theta_2) = \int\int \frac{\exp\{\delta_{jt} + \mu_{ijt}(\theta_2)\}}{\sum_{k=0}^{J_t} \exp\{\delta_{kt} + \mu_{ikt}(\theta_2)\}}\, dF(D_i)\, dG(v_i),$$

where $D_i = (y_i, h_i')'$ and $v_i = (v_{i\alpha}, v_{i\rho})'$ and $F(\cdot)$ and $G(\cdot)$ are cumulative distributions of D_i and v_i, respectively. I compute the multiple integrals in the market share s_{jt} by simulation.[13] Using the predicted market share s_{jt} and observed market share S_{jt}, I define a contraction mapping $T(\delta)$ as proposed by Berry (1994) and BLP (1995):

$$T(\delta) = \delta + \log(S_{jt}) - \log(s_{jt}(\{\delta_{jt}\}_j, \theta_2))$$

I find that the predicted market share s_{jt} matches the observed market share S_{jt} at a fixed point of the mapping $T(\delta)$. Given the parameter θ_2, I solve for the fixed point for mapping $T(\delta)$ by iterating the following calculation:

$$\delta_{jt}^{h+1} = \delta_{jt}^{h} + \log(S_{jt}) - \log(s_{jt}(\{\delta_{jt}^{h}\}_j, \theta_2))$$

I obtain the fixed point for $T(\delta)$ as the convergent point when iterating the calculation until $\|\delta_{jt}^{h+1} - \delta_{jt}^{h}\|_\infty < \epsilon^{tol}$ is satisfied and back out the fixed point $\delta_{jt} = s_{jt}^{-1}(S_{jt}, \theta_2)$.[14] The crucial point

[13] I generate R times random numbers from demographic and stochastic variable distributions and denote them as v_{iD}^r and v_i^r ($r = 1, \ldots, R$). In this study, I construct the distribution $F(\cdot)$ using the CSLC data. With these random draws, I approximate market share s_{jt} as follows:

$$s_{jt}(\{\delta_{jt}\}_j, \theta_2) \approx \frac{1}{R}\sum_{r=1}^{R} \frac{\exp\{\delta_{jt} + \mu_{ijt}(v_{iD}^r, v_i^r, \theta_2)\}}{\sum_{k=0}^{J_t} \exp\{\delta_{kt} + \mu_{ikt}(v_{iD}^r, v_i^r, \theta_2)\}}.$$

[14] I set the tolerance criterion ϵ^{tol} at 10^{-12}.

here is that all the fixed effects $\{\delta_{jt}\}_{j,t}$ are expressed in the function of parameter θ_2. This implies that the number of parameters to be estimated by nonlinear search in MLE decreases dramatically.

As the second step, I estimate θ_1 using the fixed point δ_{jt} obtained in the previous step. Recall that δ_{jt} in (4.1) can be written as

$$\delta_{jt} = -\alpha_0 r_{jt} + w'_{jt}\psi + \xi_{jt}. \tag{4.2}$$

Since assuming that rental price r_{jt} correlates with unobservable attribute ξ_{jt}, I estimate parameters α_0 and ψ by the generalized method of moments (GMM). For the GMM estimation, I prepare a $L \times 1$ vector z_{jt} as an instrument for r_{jt} that satisfies moment conditions $E[z_{jt}\xi_{jt}] = 0$. Given parameter θ_2, the GMM estimates $\hat{\theta}_1$ are defined as

$$\hat{\theta}_1 = \underset{\theta_1}{\operatorname{argmin}}\, \xi' Z W Z' \xi,$$

where Z is a $JT \times L$ ($J = \sum_{t=1}^{T} J_t$) matrix for instruments z_{jt} and ξ is a $JT \times 1$ vector for ξ_{jt}. Additionally, W is an efficient weight matrix and a consistent estimate of $E[\xi_{jt}^2 z_{jt} z'_{jt}]^{-1}$. In the estimation, I implement the two-step GMM by setting $W = (Z'Z)^{-1}$ in the first-stage estimation.

Finally, for the estimation of θ_2, I define a likelihood function based on individual car choice and mileage choice. When household i purchases car j in year t, let $\tilde{M}_{ijt}$ denote the observed annual mileage and η_{ijt} be the error between the log of observed mileage $\tilde{M}_{ijt}$ and the log of mileage predicted by the model M_{ijt},[15]

$$\eta_{ijt} \equiv \log \tilde{M}_{ijt} - \log M_{ijt}.$$

Moreover, assuming that η_{ijt} follows a normal distribution with mean zero and variance σ_η^2, it follows that the conditional density of observing $\tilde{M}_{ijt}$ takes the form

$$\ell\left(\tilde{M}_{ijt} \middle| i \text{ chooses } j \text{ at } t,\ X_{ijt}\right) = \frac{1}{\sqrt{2\pi\sigma_\eta^2}} \exp\left\{-\frac{1}{2}\left(\frac{\log \tilde{M}_{ijt} - \log M_{ijt}}{\sigma_\eta}\right)^2\right\},$$

where $X_{ijt} = (x'_{jt}, p^M_{jt}, w'_{jt}, D'_i, v'_i)'$. In the expression, $\log(M_{ijt})$ is the log of the driving demand obtained in (3.4). Denoting $\tilde{\theta}_2 = (\theta_2, \sigma_\eta)$, I define the likelihood function for each household $L_{ijt}(\tilde{\theta}_2)$

[15] Following Bento et al. (2009) and D'Haultfœuille et al. (2014), I assume that error η_{ijt} is independent of the car choice decision of households. Under this assumption, although I construct joint demand for cars and use, accounting for unobservables that enter both demands through random coefficients, the possibility of overestimating the rebound effect remains (Dubin and McFadden, 1984; Newey, 2007). However, because the model in this study allows for estimating parameters in the driving demand equation controlling for fixed effects δ_{jt}, car attributes x_{jt}, and demographics h_i, I expect that the biases of the estimates to be small compared with the results of Bento et al. (2009) and D'Haultfœuille et al. (2014).

as[16]

$$L_{ijt}(\tilde{\theta}_2) = \int \left[\frac{1}{\sqrt{2\pi\sigma_\eta^2}} \exp\left\{ -\frac{1}{2} \left(\frac{\log \tilde{M}_{ijt} - \log M_{ijt}}{\sigma_\eta} \right)^2 \right\} \cdot \frac{\exp\left(V_{ijt}\right)}{\sum_{k=0}^{J_t} \exp\left(V_{ikt}\right)} \right] dG(v_i).$$

In the integral of this function, the first term of the multiplication expresses the density of mileage conditional on purchasing car j, and the second term expresses the choice probability of the car. Therefore, this likelihood function forms the joint probability of car choice and use, allowing for joint estimation of parameters in the two demand equations. I approximate the likelihood function L_{ijt} by simulation and use $\check{L}_{ijt}$ to denote the simulated likelihood function. Consequently, the simulated log-likelihood function to be maximized is written as

$$\sum_{t=1}^{T} \sum_{i=1}^{N_t} \sum_{j=1}^{J_t} d_{ijt} \cdot \log \check{L}_{ijt}(\tilde{\theta}_2),$$

where $d_{ijt} = 1[i \text{ chooses } j \text{ at } t]$. I maximize the above objective function, with the parameters θ_1 being replaced with the estimates $\hat{\theta}_1$.[17]

In the supply model, marginal cost mc_{jt} is a parameter to be estimated. Based on the estimates of the demand parameters, I obtain the following expression for marginal costs by rearranging the pricing equation (3.5):

$$\widehat{mc}_t = p_t^e - \Omega_t^{-1} s_t^e(r_t).$$

On the left-hand side of the expression, $\widehat{mc}_t$ is a $J_t \times 1$ vector of estimated marginal costs in year t.

3.4.2 Identification

I face a price endogeneity issue in estimating the demand parameters. In the automobile market, there are many cases where vehicle models with a high market share are sold at higher prices. I can interpret this phenomenon as automobile manufacturers assigning high prices to high-quality vehicles. This fact produces the correlation between car prices and unobserved attributes such as product quality and brand image. Following BLP (1995), I then assume a possibility that rental price r_{jt} is correlated with unobserved attribute ξ_{jt}. Since I expect a positive correlation between them, the coefficient of the rental price will be overestimated in a positive direction if the endogeneity issue is ignored.

[16] Note that the likelihood function does not include the probability of choosing the outside option because the household survey used in this study is targeted at households who purchased cars in the preceding years and does not include any information about households who have not purchased cars.

[17] Note that although α_i appears in the constant term of the driving demand expression defined in (3.4), it primitively captures the relationship between the quantity demanded for vehicles and the prices and thus should not be estimated from the driving demand expression but from the expression for δ_{jt} in (4.2). Therefore, I first retrieve α_0 by running the regression in (4.2) with the parameter θ_2 holding fixed and, thereafter, maximize the simulated log-likelihood function with the estimate $\hat{\alpha}_0$ being embedded in the constant term for driving demand M_{ijt}.

I address this endogeneity problem using an instrumental variable approach. I construct a vector of instrument variables z_{jt} that satisfies the following condition:

$$E[\xi_{jt}|z_{jt}] = 0$$

For the instruments, I consider tax-location instruments following Konishi and Zhao (2017) and Kitano (2022). The tax-location instruments are constructed based on tax reduction amounts applied under the feebate scheme, which I will explain in Appendix Section 3.A.1. There are two advantages to using the tax reduction amounts as instruments. First, under the feebate scheme in Japan, tax reduction amounts are determined by observed vehicle attributes, such as fuel economy, weight, and engine displacement. Thus, I expect the tax reduction amounts to be uncorrelated with the unobserved attribute ξ_{jt} after controlling for the vehicle attributes in the demand estimation and to satisfy the exclusion restriction. Second, the Japanese feebate underwent several scheme changes during the study period, so the tax reduction amounts applied for each vehicle model change over time. As a consequence, the tax reduction amounts have two-dimensional variation across vehicles and over time. I construct tax-location instruments based on the tax reduction and subsidy amounts. Specifically, I use as the instruments the sum of the tax reduction and subsidy amounts applied to vehicles produced by the same producer and the sum of those applied to vehicles produced by the other producers.[18] Moreover, I also use the per-kilometer operating cost p^M_{jt} and car attribute w_{jt} as instruments since they are assumed to be uncorrelated with ξ_{jt}. In addition to the tax-location instruments, I also use BLP instruments in the estimation. As mentioned in the next section, I find that the tax-location instruments perform well in the first-stage estimation relative to the BLP instruments.

Other parameters in the demand model are identified by exploiting several variations in the sample. Since parameters β, γ, and ρ are coefficients of interaction terms between car and household attributes in the indirect utility function, I expect that they are identified from the joint distribution of car ownership and household demographics. For the identification of the heterogeneity of households' preferences, I need a micro-level variation other than the car choice variation across households. Parameters in the random coefficients are thus identified from the variation in travel distances and in car choices across households. In addition, parameter λ appears in the second term of the indirect utility function and captures the degree to which factors determining driving demand affect car choice. Therefore, λ is also identified by the variations in car choice and travel distance across households. Finally, since parameter vector ψ appears only in the car

[18] I exclude the tax reduction and subsidy amounts themselves from the instruments because of their performance in the first-stage estimation. In addition, as I explain in Section 3.A.1, three taxes are applicable for the tax break under the feebate scheme during the study period: the acquisition tax, the tonnage tax, and the automobile tax. As Kitano (2022) notes, because the acquisition tax is an ad valorem tax, it is correlated with the unobservable ξ_{jt} and fails to satisfy the exclusion restriction. As such, I construct the tax-location instruments based on the tax reduction amounts of the tonnage tax and automobile tax, in addition to the amount of subsidy provided under the feebate policy.

choice expression, I expect ψ to be estimated from the variation in car purchase decisions across households.

On the supply side, the parameter to be estimated is the marginal cost mc_{jt}. The identification of this parameter relies on the demand parameters. In particular, the variation in car prices and market share across models and years allow me to identify the marginal cost mc_{jt}.

3.5 Empirical Results

In this section, I present the estimation results for the demand and supply models. Table 3.2 displays the results of the demand estimation. In the estimation, I use horsepower per weight, vehicle size, the Kei-car dummy, and other dummies as car attributes and family size, age of household head, and the urban dummy as household demographics.

Panel A in Table 3.2 reports the GMM regression results obtained by using the BLP instruments and the tax-location instruments. I find that the tax-location instruments provide a sufficiently large F statistic in the first-stage estimation, and the estimates of the rental price coefficient α_0 obtained using each instrument are similar and statistically significant. In addition, the results indicates that the demand for mini-vehicles (Kei-cars) is high relative to regular vehicles, while the demand for regular vehicles tends to be higher for vehicles with greater size.

Panel B reports the results of estimating the DCC by MLE. The results show that all the estimates of coefficients have the expected signs. Since the coefficients of horsepower per weight and vehicle size have positive signs, this suggests that as engine power and vehicle size increase, the demand for driving increases. By contrast, the estimate of the coefficient of the Kei-car dummy has a negative sign, which reflects the fact that households tend not to drive long distances in mini-vehicles.

The estimate of the rebound effect is calculated based on the results in Table 3.2. Panel B in the table shows that both the estimates of the mean parameter ρ and variance parameter σ_ρ of the random coefficient ρ_i are statistically significant. With these estimates, I obtain the estimate of the rebound effect by calculating the elasticity of driving demand M_{ijt} with respect to the driving cost p^M_{jt} as follows:

$$\frac{\partial M_{ijt}}{\partial p^M_{jt}} \frac{p^M_{jt}}{M_{ijt}} = -\rho_i p^M_{jt}$$

Figure 3.2 displays the histogram of the rebound effect calculated using the estimates of model 2 in Table 3.2. The figure shows that the mean value of the estimated rebound effect is 0.09, meaning that a 1% decrease in the per-kilometer cost of driving will increase driving demand by 0.09%. Figure 3.2 also confirms that the rebound effect is unevenly distributed across households, with an interquartile rage of 0.07–0.11%. Existing studies show that estimates of the rebound effect differ substantially with the type of data set and estimation model (e.g., Graham and Glaister, 2002;

Table 3.2: Estimation Results

		(1)		(2)	
	Coefficients	Est.	S.E.	Est.	S.E.
Panel A. Results of regression of δ_{jt} by GMM					
Rental price	α_0	11.799	0.754	11.208	0.759
Horsepower/Weight	ψ_1	31.651	5.037	30.123	5.067
Size	ψ_2	12.352	1.934	10.857	1.969
Kei-car dummy	ψ_3	36.091	3.139	34.794	3.166
AT/CVT	ψ_4	1.154	0.420	1.050	0.423
Hybrid dummy	ψ_5	1.419	0.294	1.389	0.295
Maker dummies		Yes		Yes	
Year dummies		Yes		Yes	
Instrumental variables		BLP IV		Tax-location IV	
First-stage F statistic		28.6		79.9	
Hansen J statistic (d.f.)		16.4 (8)		1.7 (2)	
Panel B. Result of the DCC model by MLE					
Mean parameters:					
Rental price × income	α_1	-0.232	0.025	-0.222	0.012
Constant	λ	1.932	0.311	1.991	0.333
Horsepower/Weight	β_1	0.670	0.412	0.577	0.388
Size	β_2	1.705	0.172	1.716	0.164
Kei-car dummy	β_3	-0.140	0.250	-0.148	0.232
Family size	γ_1	1.882	0.427	1.770	0.435
Age of household head	γ_2	-1.716	0.264	-1.643	0.364
Urban dummy	γ_3	0.946	0.106	0.910	0.103
Cost of driving per kilometer	ρ	-0.357	0.155	-0.447	0.138
Standard deviation parameters:					
Rental price	σ_α	1.202	0.136	1.138	0.057
Cost of driving per kilometer	σ_ρ	0.793	0.006	0.789	0.006
Error term in the driving demand eq.	σ_η	0.020	0.004	0.019	0.004
Log-likelihood		-7.560		-7.561	
Observations in the aggregate data set		1,302		1,302	
Observations in the household survey		548		548	

Note: This table reports estimation results with 2,000 random draws. The estimations are run with the family size measured per 100 persons, the age of household head measured by age times 0.001, and the Kei-car dummy and urban dummy multiplied by 0.1. For the other variables, I follow the units listed in Table 3.1.

Gillingham et al., 2016). However, the estimate of the rebound effect in this study falls in the range

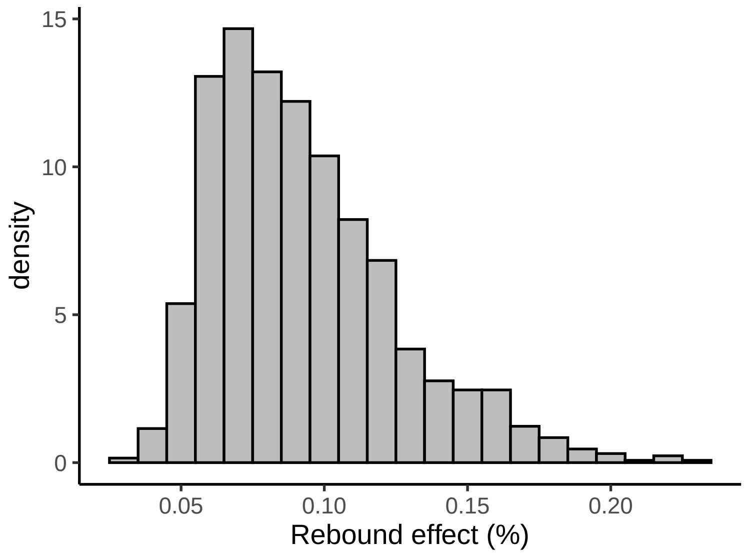

Figure 3.2: Heterogeneity of the Rebound Effect

of estimates obtained in the most recent studies.[19] Indeed, my estimate, obtained by combining the household-level cross-sectional data and the market-level panel data, is comparable to the estimate of Gillingham et al. (2015), who estimate a short-run rebound effect of 0.10 using a very large individual-level panel data set in a US state.[20]

Table 3.3 presents the summary statistics of estimated own-rental price elasticities, marginal costs, and markups. Here, I calculate the own- and cross-rental price elasticities of market share as follows:

$$\frac{\partial s_{jt}}{\partial r_{kt}} \frac{r_{kt}}{s_{jt}} = \begin{cases} -\frac{r_{jt}}{s_{jt}} \int \int \alpha_i s_{ijt}(1 - s_{ijt}) \, dF(D_i) \, dG(v_i) & \text{if } j = k, \\ \frac{r_{kt}}{s_{jt}} \int \int \alpha_i s_{ijt} s_{ikt} \, dF(D_i) \, dG(v_i) & \text{otherwise,} \end{cases}$$

where $s_{ijt} = \exp(V_{ijt}) \big/ \sum_{k=0}^{J_t} \exp(V_{ikt})$. Table 3.3 reports that the estimated own-rental price elasticity is -4.68 on average.[21] In addition, the estimated markups are, on average, approximately 27%. These estimates are comparable to those found in BLP (1995) and Grigolon et al. (2018) using data from the United States and European countries, respectively.

[19] Gillingham et al. (2016) review recent empirical studies on the rebound effect and conclude that the short- and medium-run elasticities of gasoline/driving demand with respect to gasoline price in developed countries fall in the range from 0.05 to 0.25.

[20] Gillingham et al. (2015) estimate the gasoline price elasticity of driving demand.

[21] For comparison, I report that the sales-weighted average of the own-rental price elasticities in 2012 is -3.55. Konishi and Zhao (2017), who use quarterly data from Japan for almost the same period as this study, report a sales-weighted average of elasticities in 2012 of -2.66. Although my estimate indicates a larger value in absolute magnitude than that of Konishi and Zhao (2017), note here that the estimate of Konishi and Zhao (2017) is not for the rental price elasticity but for the price elasticity.

Table 3.3: Elasticities, Marginal Costs, and Markups

	Mean	St. Dev.	1st Q.	3rd Q.
Own-rental price elasticities of demand	-4.68	2.01	-5.48	-3.30
Marginal costs (in millions of JPY)	1.85	1.61	0.86	2.16
Markups	0.27	0.10	0.20	0.34

Note: This table shows estimates of marginal costs and markups for all firms during the sample period, 2006-2013. The markups are defined as $(p-mc)/p$. The 1st Q. and 3rd Q. in the table stand for the first and third quantiles.

Table 3.4: List of Counterfactual Scenarios

Scenarios	Fuel tax	Tax measures	Subsidy
[1] Baseline	0	No	No
[2] Pigouvian fuel tax	4,000	No	No
[3] Fuel tax at current tax rate in Japan	21,603	No	No
[4] Actual feebate scheme	0	tax reduction	Yes
[5] Alternative feebate: product subsidy	0	No	Yes
[6] Alternative feebate: product tax	0	tax increase	No

Note: The unit of the fuel tax is JPY per ton of CO_2. The tax measures and the subsidy indicate tax measures for automobile-related taxes and subsidy programs applied at the time of purchase, respectively.

3.6 Counterfactual Analysis

I perform counterfactual analyses based on the estimated parameters to examine the efficiency and distributional effects of the fuel tax and the feebate policy. I also conduct a decomposition analysis of CO_2 emissions to demonstrate the contribution of the rebound effect to environmental externalities in various policy scenarios. I first describe the policy scenarios assumed in the analyses and then assess the policy impacts on various outcome variables and welfare.

3.6.1 Scenarios

The policy scenarios that I consider in the counterfactuals are summarized in Table 3.4. I compare the baseline scenario with two fuel tax scenarios and three feebate policy scenarios. Based on the estimated parameters, I simulate a baseline scenario in which neither fuel tax nor feebate policies are enforced. The remaining scenarios are generated and introduced into the baseline to assume situations in which fuel taxes at different tax rates and feebate policies take effect during the sample period in Japan.

3.6.1.1 Fuel Taxes

In the second and third scenarios, I consider situations in which fuel taxes at the same rate as the social cost of carbon (SCC) and the current tax rate in Japan are added to the pre-tax prices.

I first briefly outline the fuel tax situation in Japan. There has long been a fuel tax of 55.84 JPY/ℓ for gasoline.[22,23] Beginning in October 2012, the Japanese government phased in a carbon tax in addition to the pre-existing fuel tax. The rate of the newly introduced carbon tax has been set at 0.76 JPY/ℓ (289 JPY/ton of CO_2) since 2016.[24] Thus, the price of gasoline p_t^{gas} that households face in year t is written as[25]

$$p_t^{gas} = p_t^{pre\text{-}tax} + \tau^{gas} + \tau^{carbon},$$

where

- $p_t^{pre\text{-}tax}$ is the pre-tax price of gasoline in year t,
- τ^{gas} is the pre-existing gasoline tax rate of 55.84 JPY/ℓ, and
- τ^{carbon} is the carbon tax rate of 0.76 JPY/ℓ.

Since the price of gasoline averages approximately 150 JPY/ℓ during the sample period, the current gasoline tax rate of 56.6 JPY/ℓ accounts for approximately one-third of the gasoline price.

The second scenario in the simulation is for analyzing the welfare impact of the Pigouvian tax for fuels in the automobile market. In the scenario, I impose the SCC of 4,000 JPY/ton of CO_2 (10.48 JPY/ℓ), which is approximately 40 USD/ton of CO_2, on the pre-tax price of fuels $p_t^{pre\text{-}tax}$.[26,27] In

[22] The existing tax on gasoline is divided into a petroleum and coal tax levied upstream and a gasoline tax and a local gasoline tax levied downstream. The rate of the petroleum and coal tax is 779 JPY/ton of CO_2 (2.04 JPY/ℓ), and the sum of the rates of the gasoline tax and the local gasoline tax amounts to 23,173 JPY/ton of CO_2 (53.8 JPY/ℓ).

[23] Diesel fuel is subject to a diesel handling tax of 32.1 JPY/ℓ.

[24] The carbon tax rate has reached the current level in two phases. For example, the carbon tax rate for petroleum was set to 95 JPY/ton of CO_2 (0.25 JPY/ℓ) from October 2012 to March 2014, 190 JPY/ton of CO_2 (0.5 JPY/ℓ) from April 2014 to March 2016, and 289 JPY/ton of CO_2 (0.76 JPY/ℓ) from April 2016.

[25] For expositional simplicity, I omit the excise tax τ^{ex} on fuel prices in the main body of this chapter. In practice, however, the excise tax τ^{ex} is imposed on gasoline and diesel prices, and thus p_t^{gas} and p_t^{diesel} are calculated as follows:

$$p_t^{gas} = \left(p_t^{pre\text{-}tax} + \tau^{gas} + \tau^{carbon}\right) \times (1 + \tau^{ex}),$$

and

$$p_t^{diesel} = \left(p_t^{pre\text{-}tax} + \tau^{petroleum} + \tau^{carbon}\right) \times (1 + \tau^{ex}) + \tau^{diesel},$$

where $\tau^{petroleum}$ represents the petroleum and coal tax of 2.04 JPY/ℓ and τ^{diesel} represents the diesel handling tax rate of 32.1 JPY/ℓ. I use these formulas in the analysis below.

[26] The SCC comes from IWG (2016) and corresponds to the estimate for 2020, which is calculated with a discount rate of 3%.

[27] I set both the pre-existing gasoline tax τ^{gas} and the carbon tax τ^{carbon} to zero in this scenario.

the third scenario, I explore the effect of the fuel tax using the current tax rate in Japan of 21,603 JPY/ton of CO_2 (56.6 JPY/ℓ).[28]

3.6.1.2 Feebate Schemes

In the remaining scenarios, I examine the effects of the feebate policies implemented in Japan and alternative feebate schemes.

Actual Feebate Scheme The fourth scenario assumes a situation where the feebate scheme implemented in Japan during the sample period is introduced into the baseline scenario. As described in Section 3.2.2, the Japanese feebate scheme is essentially a rebate program, consisting of a tax incentive measure for automobile-related taxes and a subsidy program for fuel-efficient vehicles. Here, let T_{jt} denote a vector of automobile-related taxes and $p(p^e_{jt}, T_{jt})$ denote a function of the tax-exclusive vehicle price p^e_{jt} and T_{jt} that represents the total amount of taxes paid by a new car purchaser at the time of purchase. See Appendix 3.A.1.1 for details on the automobile-related taxes during the sample period in Japan. With the function, the tax-inclusive vehicle price p_{jt} under the feebate scheme is written as

$$p_{jt} = p^e_{jt} + p\left(p^e_{jt}, tr_{jt} \cdot T_{jt}\right) - ES_{jt},$$

where tr_{jt} denotes a vector of tax reduction rates and ES_{jt} is the amount of subsidy for fuel-efficient cars. The tax reduction rates and the subsidy amount are determined according to fuel economy standards. See Appendix 3.A.1 for details.

Alternative Feebate Schemes I consider alternative feebate schemes in the fifth and sixth scenarios. Specifically, I design a product subsidy and a product tax, such that each of them determines the subsidy amounts and the tax burden based solely on the vehicle's CO_2 emissions per kilometer. Under the product subsidy and product tax schemes, the tax-inclusive prices p_{jt} are determined as follows:

$$p_{jt} = p^e_{jt} + p\left(p^e_{jt}, T_{jt}\right) - \tau^E \cdot \frac{1}{e_{jt}},$$

and

$$p_{jt} = p^e_{jt} + p\left(p^e_{jt}, T_{jt}\right) + \tau^E e_{jt}.$$

In the expressions, τ^E represents the subsidy/tax rates in each scenario, and e_{jt} denotes CO_2 emissions per kilometer (kg-CO_2/km) from driving car j in year t.[29] For comparison with the

[28] For diesel, I set different tax rates from gasoline and add to the pre-tax price of diesel the tax rate of 34.9 JPY/ℓ, which is the sum of the pre-existing fuel tax rate and the additional carbon tax rate.

[29] Per-kilometer CO_2 emissions e_{jt} are defined as fuel economy divided by the CO_2 emission factor per liter of fuel consumption. The CO_2 emission factor per liter of gasoline (diesel) is 2.322 kg-CO_2/ℓ (2.621 kg-CO_2/ℓ), which is obtained by multiplying the calorific value per liter of gasoline, 34.6 MJ/ℓ (38.2 MJ/ℓ), by CO_2 emission factor per calorific value of gasoline, 0.0671 kg-CO_2/MJ (0.0686 kg-CO_2/MJ).

policy effects of the actual feebate scheme and the fuel tax, I set each τ^E such that the product subsidy and the product tax achieve the same environmental externalities as those caused by the actual feebate and the current fuel tax, respectively.

3.6.2 Measurement of Social Welfare

I evaluate the welfare effects of policies in the equilibrium of the automobile market. To calculate equilibrium prices, I exploit the method proposed by Morrow and Skerlos (2011).[30] See Appendix 3.A.3 for the computation of equilibrium prices. Given estimated equilibrium prices, I evaluate policies using four measures of surplus: consumer surplus (CS), producer surplus (PS), tax revenues (TR), and environmental externalities (EXT). Following Small and Rosen (1981), the change in consumer surplus due to a policy change is calculated as follows:

$$\Delta E(CS) = N_t \int\int \frac{1}{\alpha_i}\left[\log\left\{\sum_{j=0}^{J_t}\exp\left(V^1_{ijt}\right)\right\} - \log\left\{\sum_{j=0}^{J_t}\exp\left(V^0_{ijt}\right)\right\}\right] dF(D_i)\, dG(v_i),$$

where V^0_{ijt} and V^1_{ijt} represent the indirect utility under the baseline scenario and after a policy change, respectively. In addition, the other measures of surplus are calculated as follows:

$$\begin{aligned}
PS &= \sum_{f\in\mathcal{F}}\sum_{j\in\mathcal{J}_{ft}}\left(p^e_{jt} - \widehat{mc}_{jt}\right) N_t s_{jt}(r_t),\\
TR &= \int\int\sum_{f\in\mathcal{F}}\sum_{j\in\mathcal{J}_{ft}}\left(p\left(p^e_{jt}, dr_{jt}\cdot T_{jt}\right) - ES_{jt} + T^{fuel}_{ijt}\right) N_t s_{ijt}(r_t)\, dF(D_i)\, dG(v_i),\\
EXT &= \text{SCC}\times\int\int\sum_{f\in\mathcal{F}}\sum_{j\in\mathcal{J}_{ft}} e_{jt}M_{ijt}N_t s_{ijt}(r_t)\, dF(D_i)\, dG(v_i),
\end{aligned}$$

where T^{fuel}_{ijt} in the second expression represents the fuel tax amount from household i's driving of car j in year t, and SCC in the last expression denotes the value of the SCC.[31] In the second expression, the tax revenues consist of the sum of tax revenues from the automobile-related taxes and fuel taxes minus resources used for the feebate policies. Consequently, I define the sum of the above as the total surplus (TS).

3.6.3 Simulation Results

3.6.3.1 Policy Impacts on Outcome Variables

I first examine the impacts of the policy changes on the outcome variables. Table 3.5 reports the mean values of the outcome variables obtained under each policy scenario using the sample for 2012. The table confirms that fuel taxes are less likely to affect the equilibrium prices of automobiles, which is consistent with the results of Grigolon et al. (2018) and Tan et al. (2019). While the fuel

[30] See Conlon and Gortmaker (2020) for the advantages of this method.

[31] The amount of fuel tax T^{fuel}_{ijt} is calculated by $(M_{ijt}/fe_{jt})(\tau^{gas}+\tau^{carbon})$, where fe_{jt} is the fuel economy (km/ℓ).

Table 3.5: Impacts of Policies on Various Outcomes in 2012

Scenarios	Tax-exclusive price p^e_{jt} (million JPY)	Tax-inclusive price p_{jt} (million JPY)	Sales	VKT (10,000km)	Fuel usage (kℓ)
[1] Baseline	2.378	2.672	23,483	13,664	7,571
[2] Pigouvian fuel tax	2.378	2.672	22,892	13,034	7,179
[3] Current fuel tax in Japan	2.378	2.672	20,465	10,651	5,728
[4] Actual feebate scheme	2.382	2.594	29,930	17,365	9,285
[5] Product subsidy	2.376	2.669	30,542	17,424	9,285
[6] Product tax	2.385	2.679	17,920	10,574	5,728

Note: This table reports the mean values for each outcome variable.

tax at current tax rate moderates total VKT by 22% relative to the baseline scenario, it results in an additional reduction of fuel usage because it improves the average fuel economy of purchased vehicles. Indeed, the sales-weighted average of fuel economy in 2012 in the current fuel tax scenario is 20.83km/ℓ, which is 1.6% higher than that obtained in the baseline scenario.

In contrast, the actual feebate scheme has significant impacts on the outcomes. As expected, the actual feebate scheme boosts the sales of automobiles, particularly the sales of fuel-efficient vehicles, raising the equilibrium tax-exclusive prices relative to the baseline scenario. I find that the feebate increases sales volume by 27% on average and improves the sales-weighted average of fuel economy in 2012 by 3.6% relative to the baseline scenario. Moreover, the feebate also drives up fuel usage. I investigate the channels through which the feebate augments fuel usage by decomposition analysis in Section 3.6.4.

Table 3.5 also presents the impacts of the alternative feebate schemes on outcomes. I perform a grid search to obtain the rate of subsidy/tax τ^E for each alternative scheme.[32] Table 3.5 shows that the product subsidy achieves the same fuel usage as the actual feebate without entailing a reduction in sales volumes. On the other hand, the product tax considerably decreases sales volumes relative to the fuel tax. This is because the product tax must ensure the same fuel usage as the fuel tax by reducing the sales volumes to control total driving demand, while the fuel tax can achieve the same objective by directly suppressing driving demand.

Apart from the policy scenarios assumed in the simulation, how will a future carbon tax increase

[32] For the product subsidy, τ^E works out to 15,311 JPY per kg-CO_2 per kilometer such that the product subsidy achieves the same externality as the actual feebate, and for the product tax, 1.21 million JPY per kg-CO_2 per kilometer such that the product tax achieves the same externality as the current fuel tax rate. Under these subsidy/tax rates, the product subsidy scheme provides new car purchasers with subsidies of 45,505–233,459 JPY with an average of 107,489 JPY, and the product tax scheme imposes tax burdens of 79,044–405,532 JPY with an average of 190,632 JPY.

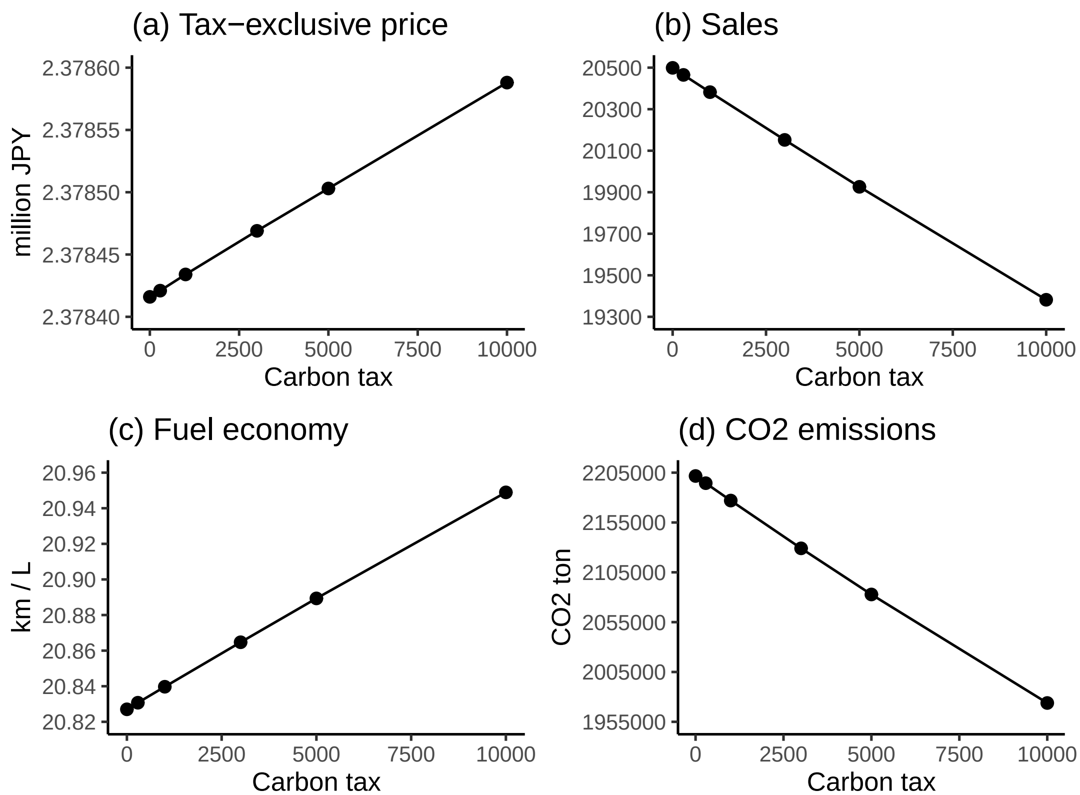

Figure 3.3: Effects of Additional Carbon Taxes

Note: The graphs show the changes in the sales-weighted average of tax-exclusive vehicle prices, sales, the sales-weighted average of fuel economy, and the total CO_2 emissions from driving cars purchased in 2012 when carbon taxes of 289, 1000, 3000, 5000, and 10,000 JPY/ton of CO_2 are added to the pre-existing fuel tax.

in Japan affect outcomes? Figure 3.3 displays the changes in several outcome variables when different carbon tax rates τ^{carbon} of 289, 1000, 3000, 5000, and 10,000 JPY/ton of CO_2 are introduced into the pre-existing fuel tax τ^{gas}. Regarding the graph for CO_2 emissions in the bottom-right figure, I find that the total CO_2 emissions amount to approximately 2.20 million tons of CO_2 when the additional carbon tax is zero.[33] When the carbon tax of 10,000 JPY/ton of CO_2 (26.2 JPY/ℓ) is added, the CO_2 emissions decline by 10.3%, meaning that a 1% increase in the additional carbon tax leads to a 0.22% reduction in CO_2 emissions in Japan. Similarly, I find that the elasticities of the equilibrium price, demand, and fuel economy with respect to the carbon tax are 0.0002%, −0.12%, and 0.01%, respectively.

[33] This situation corresponds to that where the fuel tax rate equates to the pre-existing fuel tax rate of 55.84 JPY/ℓ.

3.6.3.2 Welfare Effects

In this section, I examine the welfare effects of the policies. Table 3.6 shows the results using the sample for 2012. The first row in this table reports the welfare in the baseline scenario, while the remaining rows compare the welfare in each scenario with that obtained in the baseline. Table 3.6 confirms that the fuel taxes reduce environmental externalities with low burdens on consumers and producers. In fact, the fuel tax with the current tax rate reduces the externality by 24% compared to the baseline scenario while it increases the total revenues, or the tax burden, by approximately 5%, suggesting that the fuel tax effectively reduces the environmental externality.

Moreover, Table 3.6 shows that the total surplus declines with the fuel tax rate. The explanation for the decline in total surplus due to the Pigouvian fuel tax requires me to separately consider the changes in welfare in the automobile and fuel markets. As indicated in Table 3.6, the decrease in total surplus due to the fuel tax comes primarily from the decrease in producer surplus. Furthermore, I find that the decrease in the consumer surplus comes primarily from that arising in the fuel market targeted by households' continuous choices, and the remaining decrease in consumer surplus arising in the automobile market targeted by households' discrete choices is relatively small.[34] This finding implies that the welfare loss borne by producers under the fuel tax scenario is the main driver of the decrease in total surplus, and even the Pigouvian tax on fuel does not necessarily improve the overall economic welfare in the two markets.

In contrast to the fuel taxes, the actual feebate augments the environmental externalities, while it raises the total surplus by 591 billion JPY in 2012 relative to the baseline scenario. Table 3.6 confirms that a significant majority of this welfare gain comes through increases in consumer surplus and producer surplus. I believe this is attributable to the fact that the pre-existing automobile-related taxes already result in a deadweight loss in the automobile market, and the feebate plays a role in mitigating the market distortions (Buchanan, 1969; Fowlie et al., 2016).

Here, as shown below, the validity of the predicted result is ensured for the actual feebate scheme. Table 3.6 reports that the annualized feebate expenditures applied to the rental prices paid by car owners in 2012 equal 172 billion JPY, implying that an estimate of the feebate expenditures in 2012 amounts to about 630 billion JPY in total. The actual expenditure for the subsidy program alone, which is a program of the feebate schemes, was 274.7 billion JPY in 2012. Therefore, when the expenditure for the subsidy program is added to the budget for the tax incentives, which is another program composing the feebate scheme, I find that the sum of these expenditures is close

[34] This is due to the following reason. Table 3.6 confirms that fuel tax revenue almost equates to the environmental externality from driving, offsetting this negative externality in the fuel market. In addition, the fuel tax revenue and the decrease in consumer surplus in the fuel market should be of roughly the same magnitude because the estimated rebound effect implies that driving demand is inelastic to the cost of driving per kilometer. Therefore, I find that the remaining decrease in consumer surplus occurs in the automobile market, which accounts for a small portion of the total decrease in consumer surplus.

Table 3.6: Welfare Effects in 2012 (in billions of JPY)

Scenarios	CS	PS	TR: Automobile-related taxes	TR: Fuel tax	TR: Feebate	EXT	TS
[1] Baseline (in levels)	487	1,824	276	0	0	11.6	2,575
[2] Pigouvian fuel tax	-13	-48	-8	+12	±0	-0.6	-57
[3] Current fuel tax in Japan	-67	-246	-40	+53	±0	-2.8	-296
[4] Actual feebate scheme	+134	+552	+79	±0	-172	+2.6	+591
[5] Product subsidy	+145	+492	+66	±0	-165	+2.6	+535
[6] Product tax	-116	-419	-66	±0	+97	-2.8	-501

Note: The first row lists the welfares obtained under the no-policy baseline scenario, and the remaining rows list changes in welfare associated with policy changes from the no-policy baseline. The sum of the tax revenue amounts from the automobile-related taxes and the feebate schemes refer to the annualized amounts paid by car owners over the ownership duration as a part of the rental price, not the lump sum amounts paid at the time of purchase.

to the estimated expenditure above.[35]

Table 3.6 also reveals the welfare effects of alternative feebate schemes. Table 3.6 demonstrates that the externality-equivalent product subsidy is less costly and yields a slightly higher consumer surplus than the actual feebate scheme. The fact that the product subsidy determines the amount of the subsidy depending solely on the CO_2 emissions per kilometer helps the product subsidy to improve the sales-weighted fuel economy relatively easily and achieve the same externality as the actual feebate, with less expenditures for implementation.[36]

On the other hand, compared with the externality-equivalent product tax, I find that the fuel tax at the current tax rate achieves a higher total surplus. In particular, the product tax substantially reduces the consumer surplus and the producer surplus relative to the fuel tax, which is consistent with the result presented in Table 3.5. Moreover, I find that the fuel tax requires fewer resources than the externality-equivalent product tax. Table 3.6 reveals that the product tax is approximately 1.7 times more costly than the fuel tax in reducing environmental externalities by the same amount. The results suggest that the fuel tax is more cost-effective than the product tax.

[35] Note that since the subsidy program in the second period was completed by September 2012 because of budget constraints and this study using yearly data does not control for monthly regulatory effects, my estimate of the resources used for the feebate is likely to overestimate the actual value.

[36] The product subsidy decreases the producer surplus and the tax revenue from the automobile-related taxes relative to the actual feebate scheme because the product subsidy decreases the sales of fuel-inefficient vehicles with relatively large sizes compared with the actual feebate scheme.

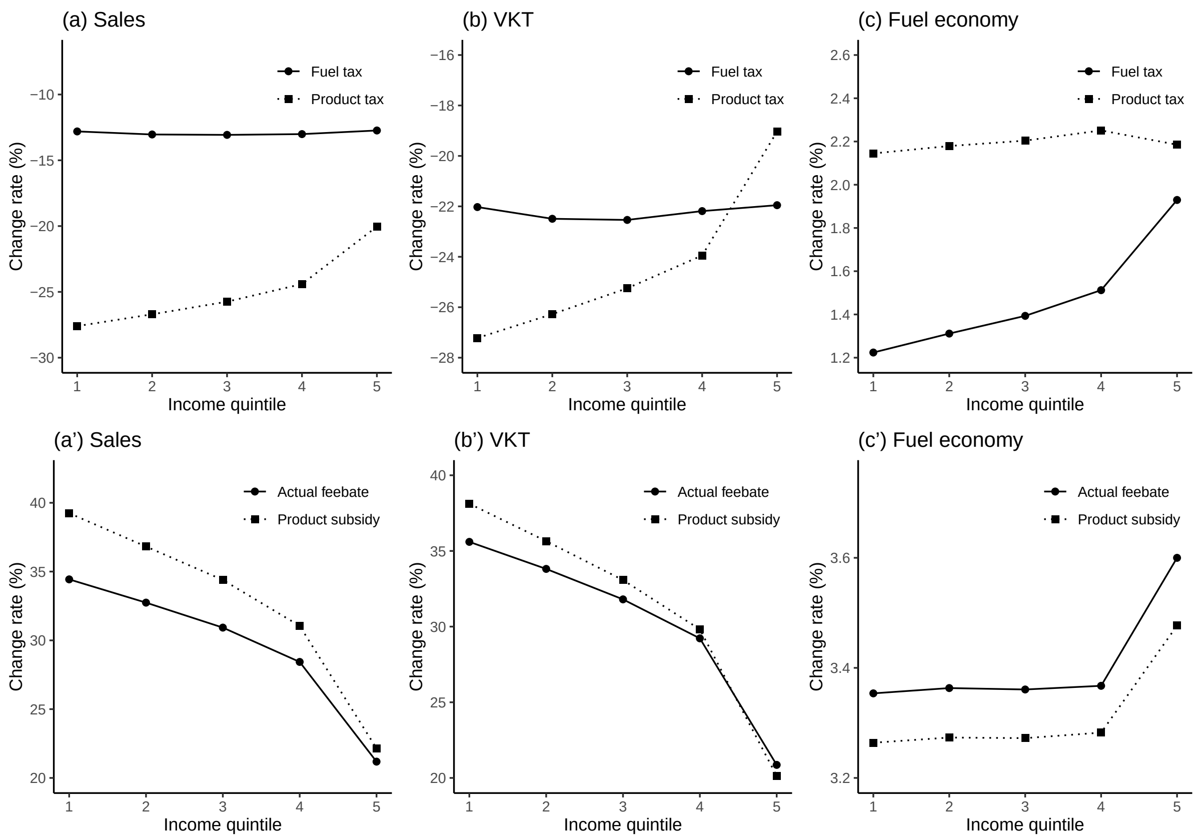

Figure 3.4: Policy Impacts on Various Outcomes by Income Quintile

Note: The graphs display the policy impacts on the sales, VKT, and sales-weighted average of fuel economy of vehicles purchased in 2012 by income quintile from 1 (lowest) to 5 (highest), with the impacts of the fuel tax at the current tax rate and the externality-equivalent product tax on the top and those of the actual feebate and the externality-equivalent product subsidy on the bottom. The vertical axes represent the rates of change in variables when each policy is introduced into the no-policy baseline scenario.

3.6.3.3 Distributional Impacts

In this section, I analyze the distributional impacts of policies. In particular, I investigate how the distributional impacts differ between a fuel tax and a feebate policy and between feebate scheme designs. Through the analyses, I present arguments on the regressivity of the fuel tax and the feebate policy.

Figure 3.4 displays the rates of change of several variables by income quintile when policies are introduced into the baseline scenario. The figures on the top show that the distributional impacts differ considerably between the fuel tax and the externality-equivalent product tax. The fuel tax with the Japanese current tax rate decreases sales volume and suppresses distance traveled evenly in all income groups, while its impact on the average fuel economy of purchased vehicles differs by income quintile. Figure 3.4 suggests that the fuel tax induces high-income households to improve

Table 3.7: Shadow Costs of Policy Implementation

Income quintile	Fuel tax: $\|\Delta CS\|/CO_2$ ton (JPY)	Fuel tax: $\|\Delta CS\|$/income	Externality-equivalent product tax: $\|\Delta CS\|/CO_2$ ton (JPY)	Externality-equivalent product tax: $\|\Delta CS\|$/income
1 (lowest)	97,075	2.47	169,321	5.25
2	94,555	1.43	164,955	2.89
3	93,825	1.09	163,526	2.10
4	94,846	0.96	163,113	1.76
5 (highest)	93,503	1.25	161,685	1.83

Note: The table presents the change in consumer surplus as a percentage of CO_2 reduction and that as a percentage of income due to the implementation of the fuel tax and the product tax in 2012 by income quintile. The fuel tax rate is set at the current tax rate of 21,603 JPY/ton of CO_2. $|\Delta CS|$ represents the absolute value of the change in consumer surplus from the no-policy baseline.

their fuel economy, indicating that high-income households that drive long distances particularly react to the introduction of the fuel tax by purchasing fuel-efficient vehicles to save on driving costs. However, since low-income households already tended to purchase fuel-efficient vehicles before the introduction of the fuel tax, the improvement in average fuel economy in the low-income groups is relatively small. In contrast, the externality-equivalent product tax substantially decreases sales, particularly in the low-income class, and in turn reduces the distance traveled in that income group.

The figures on the bottom show approximately the same trends of the change in variables across the actual feebate and the externality-equivalent product subsidy; however, the amount of change differs. In particular, it is remarkable that while both policies increase the sales in any income class, the product subsidy significantly drives up sales in the low-income classes relative to the actual feebate. This is because the product subsidy is designed to provide fuel-efficient vehicles such as Kei-cars that households in the low-income class tend to purchase with substantial subsidies.

Table 3.7 reports that the change in consumer surplus as a percentage of CO_2 reduction and that as a percentage of income due to the implementation of the fuel tax and the product tax. The change in consumer surplus as a percentage of CO_2 reduction can be interpreted as a shadow cost of a policy. Table 3.7 shows that each of the policies burdens households in the lowest-income group with a shadow cost of approximately 97,000 JPY and 170,000 JPY to reduce a ton of CO_2 on average for the fuel tax and the product tax, respectively. Here, the shadow cost of the fuel tax indicates a larger value than the fuel tax rate of 21,603 JPY/ton of CO_2. This can be attributed to the fact that the fuel tax causes households not only to control their driving demand but also to forgo the purchase of a car to reduce a ton of CO_2. In addition, the result suggests that in terms of the shadow costs, the fuel tax is 1.7 times less costly than the product tax in all income classes.

Furthermore, Table 3.7 shows that the shadow costs of the two policies fall with the income level. I find that because low-income households already own fuel-efficient vehicles and drive shorter distances before the imposition of taxes, the additional costs for CO_2 abatement are high for low-income households. In contrast, high-income households have greater potential to abate a ton of CO_2 than low-income households, and thus the shadow costs are relatively low for high-income households.

Table 3.7 also shows that the changes in consumer surplus as a percentage of income are larger for the lower-income classes under each of the two policies. Specifically, I find that both the fuel tax and the product tax are regressive until the fourth quintile and become progressive in the highest income group. Comparing the regressivities between the two policies, the product tax is slightly more regressive than the fuel tax (see also Figure 3.A.1 in the Appendix).

3.6.4 Decomposition of CO_2 Emissions

I conduct a decomposition analysis to identify the sources of environmental externalities arising under each policy scenario. Through the decomposition analysis of CO_2 emissions, it is evident which factor contributes to the change in CO_2 emissions and particularly the extent to which the rebound effect estimated in the previous section affects the externality.

Following D'Haultfœuille et al. (2014), I define some potential variables for the decomposition analysis. Let $d \in \{0, 1\}$ denote a policy indicator that equals zero before policy introduction (a policy status that corresponds to the baseline scenario) and one after policy introduction. Denoting $\mathrm{CO}_{2,t}(d)$ as the potential total CO_2 emissions arising from driving cars purchased in year t with policy status d, the variation in CO_2 emissions in year t due to the introduction of a policy Δ_t is written as

$$\Delta_t = \mathrm{CO}_{2,t}(1) - \mathrm{CO}_{2,t}(0),$$

where

$$\mathrm{CO}_{2,t}(d) = \int \int \sum_{j=1}^{J_t} e_{jt} M_{ijt}(d) N_t s_{ijt}(d) \, dF(D_i) \, dG(v_i).$$

In the expression, $M_{ijt}(d)$ is the annual distance traveled by car j purchased by household i in year t with policy status d, and $s_{ijt}(d) = s_{ijt}(r_t(d))$ is a choice probability evaluated at equilibrium rental prices r_t. In what follows, to control for the impacts of vehicle attributes other than e_{jt} on CO_2 emissions, I separate vehicles into K groups of $\{\mathcal{J}_1, \ldots, \mathcal{J}_K\}$ based on vehicle attributes x_{jt} and calculate Δ_t by summing the changes in CO_2 emissions by group.[37]

[37] In practice, I form 100 groups $\{\mathcal{J}_1, \ldots, \mathcal{J}_{100}\}$ based on vehicle attributes x_{jt}.

I decompose the change in CO_2 emissions Δ_t into the following four components:[38]

$$\Delta_t = \sum_{k=1}^{K} \int\int \Bigg[\underbrace{Q_{k,it}(0) \sum_{j \in \mathcal{J}_k} (e_{jt} - \bar{e}_{k,t}) M_{ijt}(1) \Delta s_{ijt}^{inside}}_{\text{Composition effect}} + \underbrace{Q_{k,it}(0) \bar{e}_{k,t} \sum_{j \in \mathcal{J}_k} (M_{ijt}(1) - \bar{M}_{k,it}(1)) \Delta s_{ijt}^{inside}}_{\text{Rebound effect}}$$

$$+ \underbrace{N_t \sum_{j \in \mathcal{J}_k} e_{jt} (\Delta M_{ijt}) s_{ijt}(0)}_{\text{Fuel cost effect}} + \underbrace{N_t \left(\sum_{j \in \mathcal{J}_k} e_{jt} M_{ijt}(1) s_{ijt}^{inside}(1) \right) \sum_{j \in \mathcal{J}_k} \Delta s_{ijt}}_{\text{Fleet size effect}} \Bigg] dF(D_i)\, dG(v_i),$$

where

$$Q_{k,it}(0) = N_t \sum_{j \in \mathcal{J}_k} s_{ijt}(0), \quad s_{ijt}^{inside}(d) = \frac{s_{ijt}(d)}{\sum_{j \in \mathcal{J}_k} s_{ijt}(d)}, \text{ and}$$

$$\Delta V = V(1) - V(0),\ V \in \{M_{ijt}, s_{ijt}, s_{ijt}^{inside}\}.$$

Additionally, $\bar{e}_{k,t}$ and $\bar{M}_{k,it}(d)$ represent the average CO_2 emissions per kilometer e_{jt} and the average travel distance $M_{ijt}(d)$ in group k, respectively. The first term in the above expression refers to a composition effect, which captures an expected decrease in CO_2 emissions caused by the change in the sales mix when one assumes that driving distance remains unchanged following policy introduction. If the elasticity of driving distance with respect to a policy change is assumed to be zero, CO_2 emissions should decrease in response to the introduction of the fuel tax or the feebate; they are expected to encourage households to buy fuel-efficient cars. As such, the composition effect will be negative when the expected policy effect is sufficiently large.

In practice, however, the driving distance will change with policy status. There are two channels through which a policy change affects driving distance. The first channel is when a household changes its car choice depending on policy status d. The effect through the first channel refers to the rebound effect. In the above expression, the rebound effect captures a correlation between the deviation of $M_{ijt}(1)$ from the mean value and the change in market share within the inside options Δs_{ijt}^{inside}. The second channel arises when a household purchases the same car in either policy status $d = 0, 1$. The effect through the second channel, which I call the fuel cost effect, is the direct effect of the change in the fuel cost on driving distance. Since the feebate does not directly change the fuel cost when a household purchases the same car in either policy status, the fuel cost effect comes to zero. On the other hand, a fuel tax directly affects driving demand. This direct effect of the fuel

[38] The transformation for the CO_2 decomposition used in this study is slightly different from that proposed by D'Haultfœuille et al. (2014). In the decomposition of D'Haultfœuille et al. (2014), the composition effect and the rebound effect contain a part of the fleet size effect because the difference between market shares before and after policy introduction, $s_{ijt}(1) - s_{ijt}(0)$, that appears in their transformation includes not only the relative changes in market shares within the inside options $s_{ijt}^{inside}(1) - s_{ijt}^{inside}(0)$ but also the change in the aggregate market share $\sum_{j=1}^{J_t}(s_{ijt}(1) - s_{ijt}(0))$. As shown below, I modify their transformation to separate these effects.

Table 3.8: CO_2 Decomposition

	Fuel tax		Actual feebate	
	Δ_t	%	Δ_t	%
Total	-697.2	-100.0	654.6	100.0
Composition effect	-12.6	-1.8	-43.1	-6.6
Rebound effect	1.5	0.2	2.9	0.4
Fuel cost effect	-118.3	-17.0	0.0	0.0
Fleet size effect	-567.8	-81.4	694.9	106.1

Note: This table reports the changes in CO_2 emissions from the no-policy baseline and the contribution rate (%) of the four effects calculated using the 2012 sample. The unit of Δ_t is 1,000 tons of CO_2. The rate of the fuel tax in the first column is set at the current tax rate of 21,603 JPY/ton of CO_2.

tax is captured by the fuel cost effect. Finally, the fourth effect, the fleet size effect, captures the change in CO_2 emissions arising from a change in the number of cars owned by households due to the introduction of a policy. The fleet size effect here is obtained by the expected CO_2 emissions arising from driving a car multiplied by the change in the sales of automobiles.

Table 3.8 shows the results of the decomposition analysis.[39] The table reports changes in CO_2 emissions from the no-policy baseline scenario and the contribution ratios of the four effects. As expected, the composition effect contributes to reductions in the CO_2 emissions in the actual feebate policy and fuel tax scenarios since each policy introduction changes the fleet composition and shifts sales toward fuel-efficient cars. Moreover, in both the policy scenarios, the reductions in CO_2 emissions from the composition effect are partially offset by the increases in the CO_2 emissions resulting from the rebound effect. In particular, the actual feebate scheme results in a larger rebound effect than in the fuel tax scenario. The rebound effect induced by the feebate contributes to the increase in the CO_2 emissions and cancels out approximately 7% of the decrease in emissions resulting from the composition effect.

In contrast, the fuel tax succeeds in controlling the rebound effect. Table 3.8 confirms that the

[39] One point should be noted when interpreting the results in Table 3.8. The analysis here focuses only on the policy impacts on new vehicles purchased in the corresponding year. I expect the estimates of the fuel cost effect and the fleet size effect to change when considering the impacts on vehicles already owned by households who choose the outside option in a given year. Because the fuel tax impacts not only the mileage of vehicles purchased in the year but also the mileage of vehicles already owned, the fuel cost effect becomes larger than that reported in Table 3.8. Additionally, the magnitude of the fleet size effect decreases because policies are expected to reduce CO_2 emissions from old fuel-inefficient vehicles by replacing them with new fuel-efficient vehicles. For these reasons, I here focus only on the estimates of the composition effect and the rebound effect.

increase in CO_2 emissions due to the rebound effect is offset by the decrease in emissions due to the fuel cost effect. Finally, Table 3.8 suggests that the reduction in CO_2 emissions in the fuel tax scenario is driven primarily by the fuel cost effect and the fleet size effect.

3.7 Discussion and Conclusions

This study examines the welfare effects of the fuel tax and feebate policies in the Japanese new car market. To answer the empirical questions posed in the introduction, I evaluate the performance of feebate policy as a green economic stimulus program and the regressivity of the two policies, with emphasis on efficiency and distributional equity. I employ a model with two decisions—on car ownership and utilization—on the demand side and identify model parameters by using both micro-level data from a household survey and macro-level aggregate data. Hence, with respect to methodology, this study is in line with a strand of the micro BLP literature, such as Petrin (2002), Berry et al. (2004), and Goolsbee and Petrin (2004), in which a method is developed that allows for more robust identification of parameters by adding moment conditions formed by micro-level data to those established using aggregate data.

The results obtained in my study have the following two implications. The first implication highlights the importance of accounting for the rebound effect in evaluating energy efficiency programs. Prior studies that analyzed the extent to which programs, such as an appliance replacement program, contribute to energy use reduction have found that realized energy savings were significantly lower than those projected by ex ante engineering analyses (e.g., Davis et al., 2014; Fowlie et al., 2018; and Levinson, 2016). In this study, I consider the rebound effect as a possible cause leading to such a gap between actual and anticipated energy use in the context of the feebate policy in the automobile market. Through a decomposition analysis, I find that the rebound effect induced by the feebate cancels out approximately 7% of the reduction in CO_2 emissions that would originally have been attained by the fuel economy improvement. Overall, counterfactual analyses show that the Japanese feebate policy stimulates demand but augments environmental externalities. These results suggest that the feebate policy alone fails to simultaneously achieve both economic and environmental goals.

The second implication relates to the efficiency and equity of a fuel tax and a product tax. The counterfactual analysis reveals that the fuel tax at the current tax rate in Japan is 1.7 times less costly than the externality-equivalent product tax and that there is no difference in terms of regressivity between the two policies. Currently, in Japan, there is discussion of simplifying the automobile-related taxes that determine the tax amounts according to a vehicle's weight and displacement. The results in my study suggest that social welfare could be increased without relatively increasing the tax burden on low-income households by substituting the existing product taxes, such as the tonnage tax and the automobile tax, for a revenue-neutral carbon tax.

I acknowledge some limitations to this study. First, I do not consider misperception of fuel costs by households in facing the vehicle choice. For example, Grigolon et al. (2018) assume the situation in which households, at the time of purchase, undervalue the future fuel cost savings obtained by purchasing fuel-efficient cars and evaluate the welfare effects of a fuel tax and a product tax, with the belief error being included. Although Grigolon et al. (2018) and other papers studying this issue show that there is little such undervaluation by households, if it is substantial, my study may underestimate the social welfare of the feebate policy. Second, I use static models on the demand and supply sides and particularly in the supply model, treat only prices as a variable that firms can manipulate endogenously. As such, the estimation results should be interpreted as short-term policy impacts. Designing a model to account for the dynamic responses of households and firms is required to analyze the long-term effects of the fuel tax and feebate. Finally, I need to undertake a more careful analysis of optimal policy for the automobile market and the fuel market targeted by the DCC model. A discussion of the optimal policy for the two markets is expected to become more complicated when the introduction of a policy designed to eliminate distortions in a market in turn produces distortions in the other market. I would like to make these points the subject of future work.

3.A Appendix

3.A.1 Institutional Background of the Japanese Feebate Policy

3.A.1.1 Automobile-Related Taxes

In this section, I outline automobile-related taxes relating to the feebate schemes. During the study period between 2006 and 2013, new car purchasers were obliged at the time of purchase to pay three types of automobile-related taxes: the acquisition tax, the motor vehicle tonnage tax, and the automobile tax.[40] Denoting the vector of the three automobile-related taxes as T_{jt}, the tax-inclusive price p_{jt} faced by a purchaser of car j in year t is expressed by the function p as follows:

$$\begin{aligned} p_{jt} &= p^e_{jt} + p\left(p^e_{jt}, T_{jt}\right) \\ &= \left(1 + \tau^{ex}\right) p^e_{jt} + T^{acquisition}_{jt} + T^{tonnage}_{jt} + T^{auto}_{jt}, \end{aligned}$$

where τ^{ex} represents the excise tax rate of 5%. The amount of the acquisition tax $T^{acquisition}_{jt}$ is proportional to the acquisition price of the purchased car.[41] Thus, the sum of the rates of excise tax and acquisition tax yields the ad valorem tax rate. The acquisition tax rates are 5% for ordinary

[40] While the acquisition tax involves a duty to pay only at the time of purchase, the tonnage tax and the automobile tax (or mini-vehicle tax for mini-vehicles) are payable by the owners every year after purchase. When an individual buys a new car, the first inspection is due three years after purchase. Thereafter, the vehicle must be inspected every two years. Regarding the tonnage tax, the amount of tax due each year is paid at the time of the vehicle inspection. Therefore, in practice, the purchaser of a new vehicle is obligated at the time of purchase to pay the tonnage tax for the three years until the next vehicle inspection.

[41] In practice, the acquisition price is approximately 90% of the tax-exclusive price p^e_{jt}.

passenger cars and 3% for mini-vehicles.[42] On the other hand, the amounts of the tonnage tax $T_{jt}^{tonnage}$ and automobile tax T_{jt}^{auto} are proportional to the curb weight and engine displacement, respectively. For example, until March 2010, the tonnage tax amount was determined by a tax rate of 6,300 JPY (4,400 JPY) per 0.5 tonnes for ordinary passenger cars (for mini-vehicles).[43] The amount of the automobile tax is shown in Table 3.A.1.

3.A.1.2 Feebate Scheme

The Japanese feebate scheme is a rebate program, consisting of tax incentive measures for automobile-related taxes and a subsidy program for fuel-efficient vehicles. Under the Japanese feebate scheme, the tax-inclusive vehicle price p_{jt} depends on the tax reduction rate tr_{jt} due to the tax incentive measures and the amount of subsidy ES_{jt}. As I explain below, the tax reduction rate and the subsidy amount are determined according to fuel economy standards and emission standards.

Tax Incentive Measures Table 3.A.2 shows the eligibility requirements for the tax incentive measures and the tax reduction rates tr_{jt} (or the deductible amounts) for target taxes during the sample period. As shown in Table 3.A.2, the reduction rates for three automobile-related taxes are determined according to the achievement rates for the fuel economy standards and the emission standards. See Table 3.A.3 for the target values of the fuel economy standards.[44] For example, for purchasers of a new car meeting the 2010 fuel economy standard by 20% or more during the period between 2007 and 2008, the acquisition tax was reduced by 300,000 JPY (in the case of hybrid vehicles, the tax was cut by 2.0% in 2007 and 1.8% in 2008), and the automobile tax was cut by 50%. In 2009, the system of the tax incentive measures were changed and substantially expanded as one of the Green New Deal programs.[45] Table 3.A.2 shows that, in the period 2009–2011, hybrid vehicles were exempt from their acquisition tax and tonnage tax regardless of their fuel economy achievement level.

Subsidy Program In addition to the tax incentives, a subsidy program for fuel-efficient cars has been implemented since 2009. During the sample period, the subsidy program had two phases. The first and second terms ran from April 2009 to September 2010 and from January 2012 to September

[42] The acquisition tax is not imposed when the acquisition price of a vehicle is less than 500,000 JPY.

[43] The tonnage tax rate was revised twice during the study period: 5,000 JPY (3,800 JPY) from April 2010 to April 2012 and 4,100 JPY (3,300 JPY) from May 2012 was added for every 0.5 tonnes for ordinary passenger cars (mini-vehicles).

[44] Fuel economy standards have been revised many times since they were first established in 1979. For ordinary passenger cars, the 2010 and 2015 target values were established in March 1999 and in March 2006, respectively. Each of the target values is used during the sample period. In particular, the 2010 target values are used in the first term and the 2015 target values in the second term to select vehicles for tax reduction.

[45] The tax incentives implemented until 2008 were intended to reduce the acquisition tax and the automobile tax (or the mini-vehicle tax) for low-emission vehicles, comprising the following three schemes: the green tax scheme, the special scheme for fuel-efficient vehicles, and the acquisition tax incentive for clean-energy vehicles.

2012. During the first term, purchasers of a car achieving the 2010 fuel economy standard by 15% or more received a subsidy ES_{jt} of 100,000 JPY (50,000 JPY for mini-vehicles), and in the second term, purchasers of a car achieving the 2010 fuel economy standard by 25% or more or achieving the 2015 fuel economy standard received a subsidy of 100,000 JPY (70,000 JPY for mini-vehicles).

3.A.2 Derivation of the Direct Utility Function

I derive the direct utility function under the indirect utility specified in this chapter. By solving the following optimization problem, I can obtain the direct utility function for household i conditional on purchasing car j in year t (Varian, 1992):

$$\begin{aligned} \min_{p_{jt}^M, p_t^X} \quad & \alpha_i \left(\frac{y_i - r_{jt}}{p_t^X} \right) + \lambda \exp\left(x_{jt}'\beta + h_i'\gamma - \rho_i \frac{p_{jt}^M}{p_t^X} \right) + w_{jt}'\psi + \xi_{jt} + \varepsilon_{ijt} \\ \text{subject to} \quad & p_{jt}^M M_{ijt} + p_t^X X_{it} = y_i - r_{jt} \end{aligned}$$

Note that the price of the Hicksian composite good p_t^X explicitly appears in the functions, although p_t^X is set to one by the normalization in the main body of this chapter. The Lagrange function with its multiplier μ takes the following form:

$$\mathcal{L} = \alpha_i \left(\frac{y_i - r_{jt}}{p_t^X} \right) + \lambda \exp\left(x_{jt}'\beta + h_i'\gamma - \rho_i \frac{p_{jt}^M}{p_t^X} \right) + w_{jt}'\psi + \xi_{jt} + \varepsilon_{ijt} - \mu \left(y_i - r_{jt} - p_{jt}^M M_{ijt} - p_t^X X_{it} \right).$$

Then, the optimization problem yields the first-order conditions:

$$\begin{aligned} & -\frac{\lambda \rho_i}{p_t^X} \exp\left(x_{jt}'\beta + h_i'\gamma - \rho_i \frac{p_{jt}^M}{p_t^X} \right) + \mu M_{ijt} = 0 \\ & -\frac{\alpha_i (y_i - r_{jt})}{\left(p_t^X\right)^2} + \frac{\lambda \rho_i p_{jt}^M}{\left(p_t^X\right)^2} \exp\left(x_{jt}'\beta + h_i'\gamma - \rho_i \frac{p_{jt}^M}{p_t^X} \right) + \mu X_{it} = 0 \\ & p_{jt}^M M_{ijt} + p_t^X X_{it} = y_i - r_{jt} \end{aligned}$$

Arranging these conditions, I have the direct utility function as follows:

$$\alpha_i X_{it} + \left\{ 1 + \log\left(\frac{\lambda \rho_i}{\alpha_i} \right) + x_{jt}'\beta + h_i'\gamma - \log M_{ijt} \right\} \frac{\alpha_i M_{ijt}}{\rho_i} + w_{jt}'\psi + \xi_{jt} + \varepsilon_{ijt}.$$

Note here that the second term in the expression is proven to be concave in driving demand M_{ijt}.

3.A.3 Computation of Equilibrium Prices

In this section, I describe the computation of equilibrium prices by the method of Morrow and Skerlos (2011). First, I divide the Jacobian matrix $\partial s_t(r_t)/\partial r_t$ into the following two matrices:

$$\frac{\partial s_t(r_t)}{\partial r_t} = \Lambda_t - \Gamma_t$$

where Λ_t is a $J_t \times J_t$ diagonal matrix and Γ_t is a $J_t \times J_t$ matrix with the following elements:

$$\Lambda_{jj,t} = \int\int(-\alpha_i)s_{ijt}\,dF(D_i)\,dG(v_i), \quad \Gamma_{jk,t} = \int\int(-\alpha_i)s_{ijt}s_{ikt}\,dF(D_i)\,dG(v_i).$$

Substituting these matrices into the pricing equations defined in (3.5), I have the following:

$$p_t^e = \widehat{mc}_t + \zeta_t, \quad \text{where} \;\; \zeta_t = \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*)(p_t^e - \widehat{mc}_t) - \Lambda_t^{-1}s_t^e(r_t). \tag{3.A.1}$$

Then, I iterate function $\widehat{mc}_t + \zeta_t \mapsto p_t^e$ until $\|\Lambda_t(p_t^e - \widehat{mc}_t - \zeta_t)\|_\infty < \epsilon^{tol}$ is satisfied and define the convergence points as the new equilibrium prices.

Derivation of Equation (3.A.1) Replacing the marginal costs mc_t in (3.5) with the estimates $\widehat{mc}_t$ yields

$$p_t^e = \widehat{mc}_t + \Omega_t^{-1}s_t^e(r_t).$$

Then, I transform the second term by following matrix algebra and obtain the desired result.

$$\begin{aligned}
p_t^e &= \widehat{mc}_t + (S_t \odot \Omega_t^*)^{-1}s_t^e(r_t)\\
&= \widehat{mc}_t + (-\Lambda_t + \Gamma_t \odot \Omega_t^*)^{-1}s_t^e(r_t)\\
&= \widehat{mc}_t + \left[-\Lambda_t^{-1} + \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*)\left\{E - \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*)\right\}^{-1}(-\Lambda_t)^{-1}\right]s_t^e(r_t)\\
&= \widehat{mc}_t - \Lambda_t^{-1}s_t^e(r_t) + \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*)\left[-\Lambda_t\left\{E - \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*)\right\}\right]^{-1}s_t^e(r_t)\\
&= \widehat{mc}_t - \Lambda_t^{-1}s_t^e(r_t) + \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*)(p_t^e - \widehat{mc}_t),
\end{aligned}$$

where E denotes an identity matrix. In the transformation above, note that $\Lambda_t \odot \Omega_t^* = \Lambda_t$ as Λ_t is a diagonal matrix and the diagonal elements of the ownership matrix Ω_t^* are all ones. Additionally, I apply the Woodbury formula to obtain the third equation.

3.A.4 Additional Figures and Tables

Table 3.A.1: Automobile Tax Amounts

displacement (ℓ)	tax amount (JPY)	displacement (ℓ)	tax amount (JPY)
<1.0	29,500	3.5-4.0	66,500
1.0-1.5	34,500	4.0-4.5	76,500
1.5-2.0	39,500	4.5-6.0	88,000
2.0-2.5	45,000	>6.0	111,000
2.5-3.0	51,000	Kei car	7,200
3.0-3.5	58,000		

Table 3.A.2: Eligibility Requirements for the Tax Incentive Measures (2006-2013)

Requirements	Acquisition Tax	Tonnage Tax	Automobile Tax
Panel A. Year 2006			
2010 FE target values +10% and ES 4 stars	150,000 JPY (2.2%)	-	25%
2010 FE target values +20% and ES 4 stars	300,000 JPY (2.2%)	-	50%
Panel B. Years 2007–2008			
2010 FE target values +10% and ES 4 stars	150,000 JPY	-	25%
2010 FE target values +20% and ES 4 stars	300,000 JPY (2.0%, 1.8%)	-	50%
Panel C. Years 2009–2011			
2010 FE target values +15% and ES 4 stars	50% (100%)	50% (100%)	25%
2010 FE target values +25% and ES 4 stars	75% (100%)	75% (100%)	50%
Panel D. Years 2012–2013			
2015 FE target values and ES 4 stars	50%	50%	25%
2015 FE target values +10% and ES 4 stars	75%	75%	50%
2015 FE target values +20% and ES 4 stars	100%	100%	50%

Source: JAMA (2006, 2007, 2008, 2009, 2012).

Note: The table presents the eligibility requirements for the tax incentive measures from 2006 to 2013. In the requirements shown in the table, the 2010 (2015) FE target values refer to the 2010 (2015) fuel economy target values, and the ES 4 stars represent the emission-standard four stars, awarded to vehicles whose emission values represent a reduction of at least 75% from the 2005 regulatory levels (JAMA, 2006). The monetary amounts are what is deductible from the purchase price, and figures in percentage terms represent the reduction rates for each automobile-related tax. The tax reduction rates for hybrid vehicles are reported in parentheses. The light vehicle tax was not targeted by the tax incentive measures between 2009 and 2013.

Table 3.A.3: Fuel Economy Standards

2010 Standard		2015 Standard			
curb weight (kg)	target value (km/ℓ)	curb weight (kg)	target value (km/ℓ)	curb weight (kg)	target value (km/ℓ)
<703	21.2	<601	22.5	1531-1651	13.2
703-828	18.8	601-741	21.8	1651-1761	12.2
828-1016	17.9	741-856	21.0	1761-1871	11.1
1016-1266	16.0	856-971	20.8	1871-1991	10.2
1266-1516	13.0	971-1081	20.5	1991-2101	9.4
1516-1766	10.5	1081-1196	18.7	2101-2271	8.7
1766-2016	8.9	1196-1311	17.2	>2271	7.4
2016-2266	7.8	1311-1421	15.8		
>2266	6.4	1421-1531	14.4		

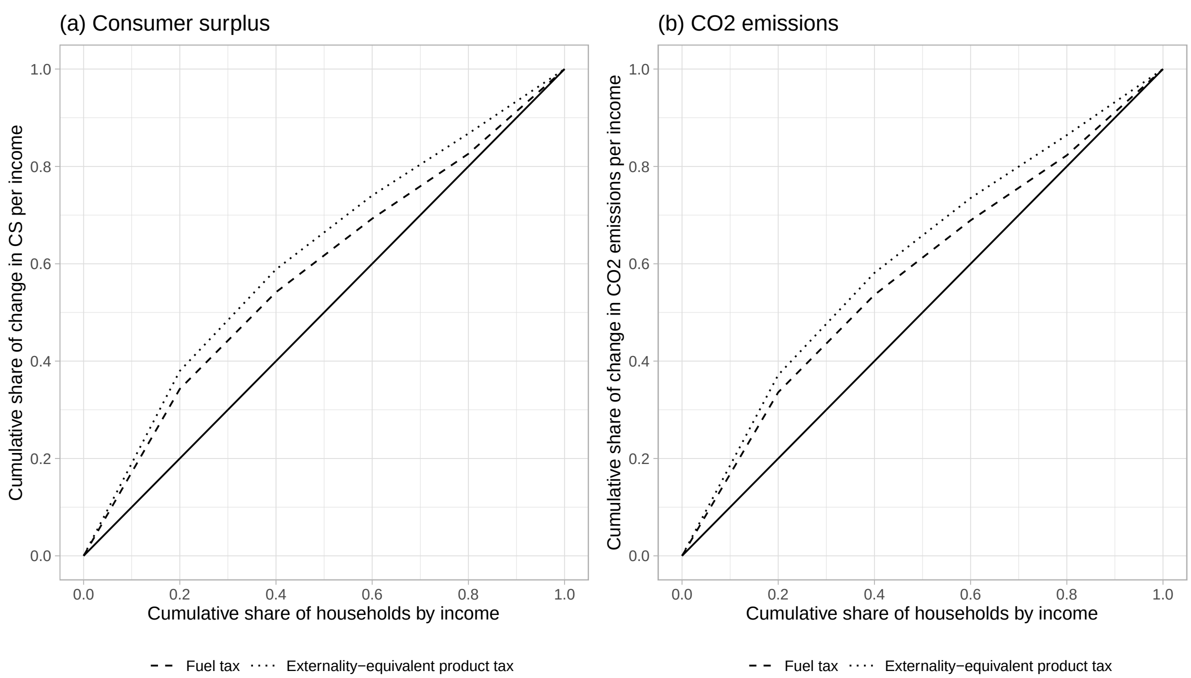

Figure 3.A.1: Regressivity of the Fuel tax and Product Tax

Note: The figures show the Lorenz curves obtained under the scenarios for the fuel tax at the current tax rate in Japan and the externality-equivalent product tax, along with the 45-degree line. The left and right figures take the cumulative shares of consumer surplus and CO_2 emissions as the vertical axes, respectively. The 45-degree line indicates the situation in which households in each income class incur the tax burden or emit CO_2 evenly.

Chapter 4

Causal Effects of the Tokyo Emissions Trading Scheme on Energy Consumption and Economic Performance*

4.1 Introduction

To efficiently reduce greenhouse gas (GHG) emissions, emissions trading schemes (ETSs) have attracted attention globally as one of the main climate policy instruments. In fact, to combat climate change, introducing ETSs at the national level is becoming a global movement. For example, in February 2021, China launched the largest ETS to date in a single country. Accordingly, many empirical studies have begun to quantify the policy impacts of existing ETSs, mainly focusing on the emissions trading scheme in the EU (EU ETS) and the Regional Greenhouse Gas Initiative (RGGI) in the United States. An ETS at the national level has not yet been introduced in Japan, where ETSs remain at the regional level. One reason for the delay in introducing a national Japanese ETS is strong concern regarding a possible negative impact of ETS introduction on the national economy, a concern that is particularly pronounced in the industry sector. Accumulating empirical evidence regarding the consequences of ETSs, emissions mitigation and economic activity is crucial for regulatory design to decrease its potential impacts on regulated objects.

The Tokyo ETS is the first regional ETS in Japan and the first worldwide to cover the commercial sector. In 2010, Tokyo established its own emissions trading market ahead of the rest of the country. Following Tokyo, Saitama Prefecture, which is a prefecture adjacent to Tokyo, introduced its own scheme in 2011 in collaboration with Tokyo. There is a large difference between the two regional schemes. That is, the Tokyo ETS imposes a penalty if regulated business establishments cannot comply with the regulation, while the Saitama ETS scheme involves no penalization, which implies that it only asks its regulated business establishments to abate their CO_2 emissions on a

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voluntary basis (Hamamoto, 2020). This difference implies that the Tokyo scheme is the only ETS in Japan with a specified economic incentive for regulated business establishments to reduce CO_2 emissions from their economic activities. More specifically, the Tokyo ETS includes both the manufacturing sector and the commercial sector as regulatory targets, an approach that is completely different from schemes in which only energy-intensive sectors are regulatory targets, such as the EU ETS and RGGI. Since nonenergy-intensive commercial business establishments are concentrated in Tokyo, many regulated entities belong to the commercial sector (Arimura and Abe, 2021).

Although the Tokyo ETS commenced its third phase in April 2021, to date, no studies have examined its impact on economic activity. Moreover, few studies have examined the effect of the Tokyo ETS using panel data with a sufficiently long pretreatment period, i.e., the period prior to policy implementation. Prior studies have focused on the short-run effect of the ETS on energy consumption during its first phase. In contrast, here, I attempt to estimate the policy impacts of the Tokyo ETS on the energy consumption and economic activity of regulated business establishments during the first phase of the scheme (2010–2014) and the first four years of its second phase (2015–2018) using business establishment-level panel data from 2007 to 2018.

This chapter focuses on the Tokyo ETS for two reasons. First, as mentioned above, the Tokyo ETS's regulatory targets differ from those of other schemes. Thus, focusing on the Tokyo ETS enables me to examine the impact of an ETS on a nonenergy-intensive sector, i.e., the commercial sector. Second, because the literature using long-term panel data has been dominated by research on the EU ETS and RGGI, I believe that my empirical analysis of the Tokyo ETS contributes to increasing our understanding of ETS regulatory impacts in a different region. Although recent studies have attempted to quantify the policy impact of other ETSs, such as China's pilot ETS and the Korea ETS, further empirical research on other regions is required if I am to properly validate ETSs.

The contribution of this study is threefold. First, I measure the effect of the Tokyo ETS on the economic activity of regulated business establishments relative to unregulated business establishments using panel data over the first and second phases of the scheme. Among the various variables of economic activity, I use employment to represent economic performance because, compared with other variables such as sales, employment is less likely to reflect business establishment-level demand heterogeneity, which is independent of regulation. Thus, focusing on employment enables me to evaluate the policy effect, with external shocks being ruled out. Furthermore, employment has been widely used as an economic performance indicator in the empirical literature. Therefore, by availing myself of the commonly used variable of employment, I can compare the effect of the Tokyo ETS with that of ETSs in other counties.

Second, I estimate the long-term impacts of the ETS on emissions reduction. In this study, I use a panel data set including information on the energy consumption and economic activity of business establishments nationwide. Using nationwide panel data enables me to identify the impact of the Tokyo ETS on actual energy use and the scale of economic activity specific to each business establishment. Moreover, by comparing the situation of regulated and unregulated business establishments before and after policy introduction, it is possible to draw causal inferences regarding policy effects. To more precisely quantify such effects, following Fowlie et al. (2012) and subsequent studies, I adopt a difference-in-differences (DID) approach combined with a matching method.

Third, this study contributes to the discussion on ETSs in Asia, where other countries are considering the adoption of such schemes. Tokyo's ETS is the first to target the urban service sector, including office and commercial buildings. Many ASEAN countries can expect an emissions increase from urban areas with many commercial buildings. Therefore, the experience in Tokyo will benefit ASEAN countries where the introduction of ETS is being considered.

I obtain two main findings from the empirical analysis. First, business establishments regulated by the Tokyo ETS clearly decreased their electricity consumption during my sample period, and unregulated business establishments also decreased their electricity consumption by an equal amount. As will be clear later, the reduction in energy use achieved by regulated business establishments is comparable to that achieved by business establishments in other regions. This result suggests that the reduction in energy use observed in phase I may have been mainly caused by exogenous events, such as the 2011 earthquake. Meanwhile, my result remains the same for phase II, during which exogenous shocks were moderated. Summarizing these findings, I note that the emissions caps set by the ETS for phases I and II were not sufficiently demanding to bring about a statistically significant difference in energy use reductions between regulated and unregulated business establishments. This possibility is supported by the fact that the permit prices have been decreasing since 2011, as shown in Figure 4.2 in Section 2. Figure 4.2 and my estimation results indicate that regulated business establishments have had substantial excess emissions reductions, and thereby, there was little demand for credit. Second, I find little evidence that regulated business establishments reduced their numbers of employees relative to unregulated business establishments through phases I and II.

The empirical literature on ETSs has focused on the EU ETS and the RGGI. In particular, the number of empirical studies using panel data at the micro level has recently increased. For instance, Chan et al. (2013) examined the impacts of the EU ETS on the competitiveness of firms using firm-level panel data over the 2001–2009 period. They found no evidence that regulation caused job losses or negatively affected the competitiveness of firms in energy-intensive industries. Furthermore, many researchers have attempted to evaluate the causal impact of the EU ETS using multiple indicators (e.g., Petrick and Wagner, 2014; Marin et al., 2018; Colmer et al., 2022). They have examined the emissions reduction effect and the influence on economic performance in phase I and phase II from multiple perspectives by using the DID strategy with a matching method. Significant findings from these studies include that the EU ETS caused regulated firms to reduce their emissions relative to unregulated firms and did not have a negative impact on the economic performance of regulated firms over the two phases. Regarding the RGGI, many empirical studies have examined the effects of the regulation on CO_2 emissions mitigation from coal-fired plants and carbon leakage using plant-level or state-level panel data (e.g., Murray and Maniloff, 2015; Fell and Maniloff, 2018; Huang and Zhou, 2019).

Empirical studies focusing on policy evaluation of China's ETS have recently been increasing. In China, a pilot ETS was introduced in seven provinces in 2013, ahead of the introduction of a national ETS. Several researchers have conducted ex post analyses to quantify the effects of the pilot ETS (e.g., Zhang et al., 2019; Gao et al., 2020; Yi et al., 2020; Feng et al., 2021). For instance, Gao et al. (2020) found that the pilot ETS contributed to mitigating production-based CO_2 emissions and that regional regulations resulted in carbon leakage from regulated provinces to other areas.

As shown in the preceding discussion, previous empirical studies have come to different conclusions regarding the effects of regulation, and a consensus on the effectiveness of ETSs has not been reached. This state of affairs inspired me to accumulate new findings based on empirical analysis. My study aims to provide empirical evidence associated with the policy effect of the Tokyo ETS, focusing especially on the scheme's emissions mitigation effect and its influence on economic performance. The objective of my empirical study is in line with the literature discussed above. My study is one of the first to examine the economic impact of an ETS in Asia.

The remainder of this chapter is organized as follows. Section 4.2 describes the institutional background of the Tokyo ETS. Sections 4.3 and 4.4 explain the data set and estimation approaches adopted in the study. Section 4.5 presents my estimation results. Finally, Section 4.6 discusses policy implications and concludes.

4.2 Regulatory Background

Ahead of all other prefectures in Japan, Tokyo's Metropolitan Government launched emissions trading in 2010. The Tokyo ETS is the first cap-and-trade program in Asia with CO_2 emissions as its regulatory target.[1] The ETS was established to reduce the CO_2 emissions of large-scale business establishments in Tokyo. An energy consumption of 1,500 $k\ell$ of crude oil equivalent per year was set as the compliance threshold. If a business establishment exceeds the threshold for three consecutive years, it must comply with the ETS regardless of its industrial category. Therefore, compared to

[1] Even before Tokyo introduced an ETS, ETSs have been used to address other environmental issues in Asia, such as local air pollution problems. For example, Taiyuan City in China introduced an ETS for sulfur dioxide (SO_2) in 2002 and extended it into a pilot program in 11 provinces in 2007 (Ren et al., 2020). In 2011, India launched a pilot ETS with a focus on particulates, such as SO_2, nitrogen oxide, and small particulate matter, in the states of Gujarat, Maharashtra, and Tamil Nadu. These three states were chosen because they have the highest number of manufacturing facilities in the country (Arimura et al., 2022).

other ETSs, the industrial composition of this regulation is unique. Since many business offices are located in Tokyo, the commercial sector accounts for approximately 80% of regulated business establishments.

The Tokyo ETS has already experienced two compliance periods, a first phase (2010–2014) and a second phase (2015–2019), and currently, the Tokyo ETS is in its third phase (2020–2024). The reduction target has gradually been tightened. The reduction target for business establishment i in phase τ is determined as follows:

$$\sum_{t \in T_\tau} \text{emissions}_{it} \leq \text{reference emissions}_i \times (1 - \text{reduction rate}_\tau) \times |T_\tau|$$

where emissions_{it} and $\text{reduction rate}_\tau$ denote the amount of CO_2 emissions of business establishment i in year t and the reduction rate set by the Tokyo ETS for phase τ with compliance period T_τ, respectively. The reduction rates differ across sectors. In phase I, the reduction rates for the industrial sector and the commercial sector were 6% and 8%, respectively, which means that business establishments subject to the Tokyo ETS were required to reduce their CO_2 emissions by at least 6% or 8% of their reference level for the entire compliance period.[2] The reference level for each business establishment is defined by the level of emissions in periods prior to the announcement of the introduction of the regulation.[3] Therefore, the reference level is designed to be unaffected by behaviors after the announcement. The reduction rates increased to 15% and 17% in phase II and further increased to 25% and 27% in phase III for the industrial sector and the commercial sector, respectively.

The Tokyo Metropolitan Government reports the amounts of emissions by regulated business establishments. Figure 4.1 shows the transitions of reported emissions of Tokyo ETS business establishments and all business establishments in Japan. The emissions described in Figure 4.1 are calculated by fixing CO_2 emission factors set by the Tokyo Metropolitan Government for each phase.[4] Figure 4.1 suggests that energy consumption and reported emissions consistently decreased during phases I and II, whereas the two graphs appear to move in parallel after 2011.[5] These energy use trends provide evidence for the external validity of my empirical results shown in later sections.

[2] These reduction rates are not annual rates but for the entire compliance period for each phase. The Tokyo Metropolitan Government does not ask regulated business establishments to comply with the reduction target for each year. As a result, regulated establishments try to reduce total emissions over the compliance period to below the target value. This also applies to the second and third phases.

[3] For each business establishment, the reference levels were defined as the average CO_2 emissions for three consecutive years, and each regulated business establishment could freely choose these three consecutive years from the period between 2002 and 2007.

[4] In phases I and II, the ETS requires business establishments to fix the emission factors for electricity at 0.382 and 0.489 tons of CO_2 per 1000 kWh in reporting their emissions.

[5] Appendix Figure 4.A.1 shows the transitions of emissions that are calculated by varying emission factors every year. Figure 4.A.1 confirms that actual emissions after 2011 increased compared with 2010 due to an increase in the emission factors, while actual emissions from business establishments regulated by the ETS and in all Japan present parallel trends as shown in Figure 4.1.

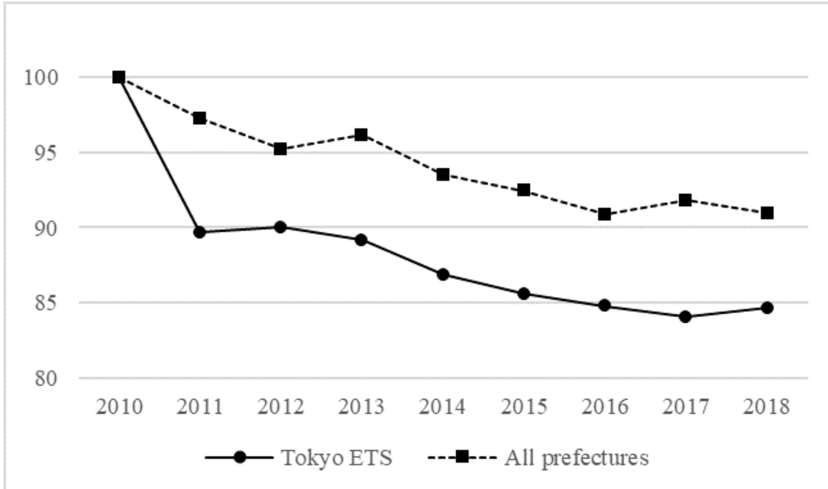

Figure 4.1: Comparison of transitions of reported emissions under the Tokyo ETS

Source: Tokyo Metropolitan Government Bureau of Environment (2020) and the FY2019 Comprehensive Energy Statistics from the Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry.
Note: This figure plots emissions from business establishments regulated by the Tokyo ETS and those of all Japan. The emissions are calculated by fixing emission factors of 0.382 and 0.489 tons of CO_2 per 1000 kWh set by the ETS for phases I and II, respectively. The graphs are drawn by setting the levels in 2010 to 100.

In phase I, there was little active trading in the market for various reasons. According to a Tokyo Metropolitan Government report, regulated business establishments reduced their CO_2 emissions by a total of approximately 25% during phase I relative to the reference emissions levels, and nearly the entire amount of this reduction was achieved by the internal abatement efforts of each business establishment. Specifically, 91% of the regulated business establishments reached their reduction targets independently without making use of emissions trading in phase I. While the number of trades gradually increased in phase II, 85% of regulated business establishments still achieved their reduction obligations through their emission reduction efforts in phase II. The fact that the cap was not set at a particularly challenging level in phases I and II may be considered one reason for this outcome. In addition, regulated business establishments may have engaged in borrowing for the next phase because there was uncertainty regarding the level of the cap in the phases following phase I.[6]

The market price of permits is not directly observed in the scheme because all the trading was bilateral, and the price was hidden. However, the Tokyo Metropolitan Government reports a

[6] In practice, "banking" for the next phase was undertaken in phases I and II. However, a large fraction of the banking came from excess emissions reductions that resulted from the occurrence of exogenous shocks, such as the earthquake in 2011. Since this statement holds for unregulated business establishments as well and nevertheless a large amount of banking occurred, it is likely that banking did not lead to a statistically significant difference in emission reductions between regulated and unregulated business establishments, as shown by my empirical results.

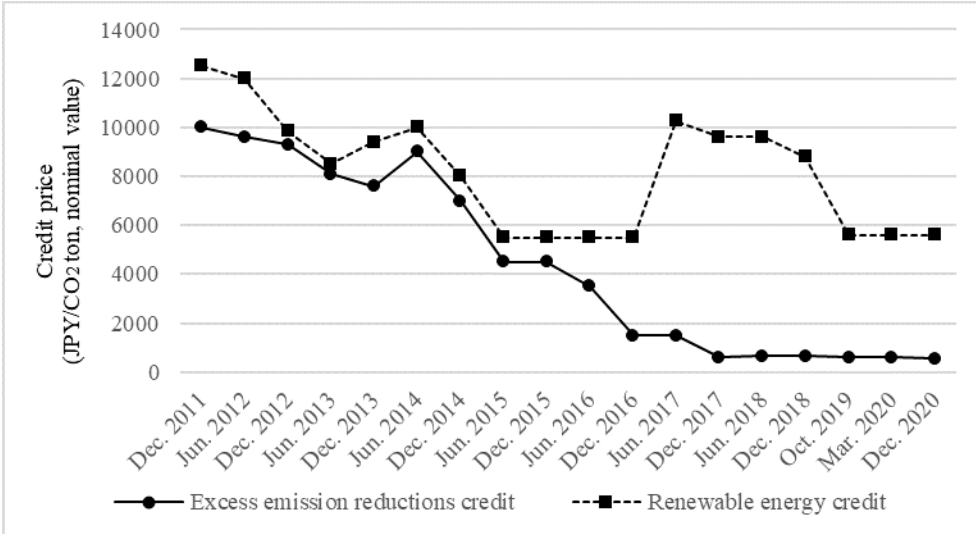

Figure 4.2: Permit prices

Source: Fujitsu Research Institute (2020), https://www.kankyo.metro.tokyo.lg.jp/climate/large_scale/trade/past_information.files/sateikakaku20201202.pdf (accessed June 22, 2022) (in Japanese).
Note: This figure shows the changes in the prices of two credits, the excess emission reductions credit and the renewable energy credit, between December 2011 and December 2020.

weighted average price of trades for every year based on interviews about each transaction. Figure 4.2 plots the reported prices of two credits available in the ETS. For example, the price of the excess emission reductions credit, which is the most traded credit under this scheme, started at 10,000 JPY per ton of CO_2 in December 2011 and then decreased to 540 JPY in December 2020. Overall, I find that the permit prices exhibit decreasing trends during phases I and II.[7]

4.3 Data

The main data source used in this study is the Statistical Survey of Energy Consumption (SSEC), which includes information on energy usage and the characteristics of business establishments. The SSEC is a unique nationwide survey in Japan, where there exists no comprehensive nationwide survey on the energy consumption of business establishments. The Agency for Natural Resources and Energy (ANRE), which has conducted the survey since 2007, requires approximately 180,000 business establishments over a certain scale level to complete the questionnaire every year. In this study, the SSEC enables me to construct panel data including information from 2007 to 2018. Thus, these panel data cover the three years prior to policy implementation (2007–2009), the period of

[7] The impact of the market permit price on other objects is thought to be limited. It is unlikely that permit prices affect the electricity price because most power plants are located outside Tokyo, and thus, the Tokyo ETS does not cover most of the generation sector. However, the Tokyo ETS may have affected the rental price of office buildings in Tokyo although I cannot be certain because I lack empirical evidence.

Table 4.1: Summary Statistics

	# of facilities	Q25	Q50	Mean	Q75
Panel A. Electricity consumption (1,000 kWh)					
Regulated business establishments	176	7,074	10,909	16,012	20,136
Unregulated business establishments	8,112	1,077	2,968	7,836	8,059
Panel B. Number of employees					
Regulated business establishments	68	129.8	400.0	697.8	900.0
Unregulated business establishments	8,690	83.0	137.0	227.1	240.0

Note: The unregulated business establishments exclude those in Saitama prefecture since it has its own ETS.

phase I (2010–2014), and the first four years of phase II (2015–2018); therefore, these panel data enable me to infer the policy impacts of the Tokyo ETS based on a DID approach. Moreover, I identified the business establishments regulated by the ETS by using a list of the names of the business establishments regulated by the ETS that the Tokyo Metropolitan Government offers to the public.

The SSEC data include information on the attributes and energy consumption of each business establishment. As the attributes of the business establishments, the SSEC has the address of the establishment and the number of employees. Regarding energy consumption, the SSEC has information on the consumption of all the types of energy that each business establishment uses for its economic activity. Therefore, I can investigate the impact of the ETS on both the economic activity and the energy use of regulated business establishments.

The SSEC is characterized by the inclusion of not only large-scale business establishments but also small and medium-sized business establishments within the survey. In Japan, such a survey is quite rare because most Japanese surveys aim to investigate only large-scale business establishments. Furthermore, the SSEC covers all industrial sectors. Thus, the survey's features suit the purpose of my empirical study.

Table 4.1 presents summary statistics. Panels A and B in the table show the distributions of electricity consumption and number of employees, respectively. I find that in terms of the scale of energy consumption and average employment, the business establishments regulated by the Tokyo ETS are larger than those not regulated by the ETS. Moreover, I realize that simply comparing the levels of these outcomes between the two groups may be meaningless because there are large differences in the levels of outcomes across the two groups. This finding from the descriptive statistics leads me to estimate the causal policy impacts of the regulation based on a DID approach.

4.4 Estimation Strategy

The aim of this study is to estimate the causal policy impacts of the Tokyo ETS. More specifically, to identify the effects of regulation on the energy use and economic activity of regulated business establishments, I focus on electricity consumption and the number of employees in the SSEC data. Using this information, I compare the outcome values of the regulated business establishments with counterfactual outcomes achieved if these establishments did not comply with ETS regulation, both of which outcomes are evaluated for a treatment period. I let a potential outcome of business establishment i at time t when the business establishment is not subject to regulation be denoted by $Y_{it}(0)$, and I let a potential outcome when the business establishment is subject to regulation be denoted by $Y_{it}(1)$. In my setting, time $t = 0, 1$ corresponds to the pretreatment period (i.e., the period before policy implementation) and the treatment period (i.e., phases I and II), respectively. Then, I estimate the average treatment effect on the treated (ATT):

$$E[Y_{i1}(1) - Y_{i1}(0) | X_i, ETS_i = 1],$$

where X_i is a vector of the time-invariance characteristics of business establishment i, and ETS_i is a binary variable that takes the value of one if business establishment i complies with the Tokyo ETS and zero otherwise. Note that the difference in the above equation is taken at time $t = 1$ and evaluated only for regulated businesses ($ETS_i = 1$).

When I estimate the ATT with the above equation, a certain problem always arises: The ATT cannot be estimated without a parallel trends assumption in the pretreatment period between the treatment group and control group because the variable $Y_{i1}(0)$ in the definition of the ATT is not observed in the real world. Therefore, under the parallel trends assumption, the validity of which I verify later, I conduct DID estimation, which is a widely used econometric method for drawing causal inferences when panel data are available.

Following Fowlie et al. (2012) and the subsequent literature, I adopt two estimation strategies: parametric DID estimation and semiparametric DID estimation with a matching strategy. The reason I adopt these two estimation strategies is to maintain robustness since the functional form assumed in the parametric estimation can significantly influence the estimation results. Parametric DID estimation indicates the linear regression of the equation as follows:

$$y_{it} = \alpha + \sum_{\tau=1}^{2} \beta_\tau 1(i \in I_1) \cdot 1(t \in T_\tau) + \gamma 1(i \in I_1) + \sum_{\tau=1}^{2} \delta_\tau 1(t \in T_\tau) + x'_{rt}\theta + c_i + \lambda_t + \xi_{rt} + \varepsilon_{it}$$

On the left-hand side of the equation, the dependent variable y_{it} is the natural logarithm of either the electricity consumption or the number of employees of business establishment i in year $t = 2007, \ldots, 2018$. On the right-hand side of the equation, the function $1(\cdot)$ is an indicator function. I_1 is a set of business establishments regulated by the Tokyo ETS. Sets T_1 and T_2 correspond to the treatment periods of phase I and phase II, respectively. The variable x_{rt} is a vector of explanatory variables, such as the regional GDP of region r in year t. In addition, I add several fixed effects in the equation: c_i is an individual fixed effect for business establishment i, λ_t is a year fixed effect, and ξ_{rt} is a region-year fixed effect. Finally, I have an idiosyncratic error, ε_{it}.

The estimates of coefficients β_1 and β_2 are my primary interest. One advantage of the parametric specification is that the interpretation of its estimates is straightforward because the coefficient of the interaction term indicates the treatment effect that I am trying to estimate. Therefore, the parametric DID specification enables me to interpret the estimates of parameters β_1 and β_2 as the treatment effects of the ETS in phase I and phase II, respectively. I estimate the preceding equation using a sample chosen by a matching method. I explain the matching procedure in detail below.

The second approach to estimating the ATT is semiparametric DID estimation combined with the matching approach developed by Heckman et al. (1997, 1998). The estimate is written as follows:

$$\frac{1}{N_1}\sum_{i\in I_1}\left\{(Y_{i1}-Y_{i0})-\sum_{j\in I_0} w_{ij}(Y_{j1}-Y_{j0})\right\}$$

Again, note that $t = 0, 1$ indicates the pretreatment and treatment periods, respectively. In the above equation, Y_{it} is an observed value of an outcome variable for business establishment i at time t. For the period prior to policy implementation $t = 0$, I have $Y_{i0} = Y_{i0}(0)$ because no business establishments were subject to regulation at $t = 0$ and the observed value always equals the potential outcome. In period $t = 1$, I have the relationship $Y_{i1} = ETS_i \cdot Y_{i1}(1) + (1 - ETS_i) \cdot Y_{i1}(0)$ because the ability to observe the potential outcomes depends on whether business establishment i is subject to regulation. Finally, N_1 is the number of business establishments regulated by the Tokyo ETS, $N_1 = |I_1|$, and I_0 is a set of business establishments not regulated by the Tokyo ETS.

In the equation for the semiparametric DID, I have the function w_{ij} to implement matching. Here, I term this function a weight function. Following Fowlie et al. (2012) and relevant subsequent studies, I conduct k-nearest neighbor (k-NN) matching. To make comparable pairs through the matching approach, I take several steps. First, I conduct exact matching based on the industrial sector code. Second, within a sample chosen by the first process, I conduct k-NN matching based on the outcome level in 2007, which is the initial year in my sample. In fact, Fowlie et al. (2012) suggest that the outcome level in the pretreatment period should be used as a covariate for the matching because it is a proxy that well captures the scale of business establishments. Let me now denote M neighbors of business establishment i chosen using the above procedure by $j_1(i), \ldots, j_M(i)$, assuming that index $j_1(i)$ represents business establishment i's closest neighbor chosen from among business establishments not regulated by the Tokyo ETS (Abadie and Imbens, 2006). Defining set $\mathcal{J}_M(i)$ as $\mathcal{J}_M(i) = \{j_1(i), \ldots, j_M(i)\}$, I write the weight function as follows:

$$w_{ij} = \begin{cases} \frac{1}{M} & \text{if } j \in \mathcal{J}_M(i), \\ 0 & \text{otherwise.} \end{cases}$$

This function gives the same weights to all neighbors chosen by the matching. In the estimation, I examine estimates by changing the number of neighbors M to check the robustness of my estimates.

4.5 Empirical Results

In this section, I present my empirical results using the models specified above. To ensure the robustness of the estimation results, I estimate the ATT with different control groups. In the estimation, I consider three geographical areas as control groups: (i) areas outside the three major metropolitan areas, (ii) three major metropolitan areas except the Kanto region, and (iii) the Kanto region.[8] In the first control group, I exclude prefectures with socioeconomic demographics similar to those of Tokyo because I suspect that ETS regulation has an indirect effect on neighboring prefectures, such as a spillover effect (positive effect) or carbon leakage (negative effect).[9] If I ignored this effect of the ETS on the neighboring areas, including them in the control group would result in a biased estimate of the treatment effect of regulation. To estimate the treatment effect without bias, I must satisfy the stable unit treatment value assumption (SUTVA). If the indirect effect is local, I can obtain the unbiased ATT from the estimation with area (i) being set as the control group. Meanwhile, areas (ii) and (iii) correspond to areas near Tokyo from socioeconomic and geographical perspectives, respectively. By comparing these estimation results with groups (ii) and (iii) as control groups with the results obtained by specification (i), I can confirm whether the Tokyo ETS has indirect effects on other areas and whether my estimation results are robust to the specifications.

Tables 4.2 and 4.3 report the parametric and semiparametric DID estimation results. Each column in each table shows the estimation results for the different control groups defined above. Regarding the electricity consumption results, which are shown in Panel A in Tables 4.2 and 4.3, I find that no estimate indicates statistical significance regardless of the definition of the control group. Therefore, combined with the findings in Figure 4.3, I can conclude that although regulated business establishments clearly reduced their electricity consumption over phases I and II, unregulated business establishments also decreased their electricity consumption to the same extent. Regarding the number of employees in Panel B in Tables 4.2 and 4.3, for phase II, I have a statistically significant ATT estimate with a negative sign when the control group consists of business establishments in prefectures outside the three major metropolitan areas. The number of employees in unregulated business establishments increased through phase II, while the number of employees in regulated business establishments remained constant or decreased slightly during the

[8] The three metropolitan areas belong to prefectures in the Kanto, Kansai and Chubu regions, that is, Tokyo, Saitama, Kanagawa, Chiba, Osaka, Kyoto, Hyogo, Shiga, Nara, Wakayama, Aichi, Gifu, and Mie. Of these prefectures, the first four belong to the Kanto region.

[9] In fact, the direction of the expected bias depends on that of the indirect effects on outcomes for the neighboring areas.

Table 4.2: Parametric matching-based DID estimation results

Control group:	(1) Prefectures outside the 3 major metropolitan areas		(2) Prefectures in the 3 major metropolitan areas except the Kanto region		(3) Prefectures in the Kanto region	
	Coeff.	Std. Dev.	Coeff.	Std. Dev.	Coeff.	Std. Dev.
Panel A. Dependent variable: ln(electricity consumption)						
$1(i \in I_1) \cdot 1(t \in T_1)$	-0.047	(0.034)	-0.034	(0.032)	-0.032	(0.026)
$1(i \in I_1) \cdot 1(t \in T_2)$	-0.012	(0.068)	-0.051	(0.043)	-0.058	(0.040)
$1(t \in T_1)$	-0.275	(0.080)	-0.096	(0.029)	-0.100	(0.036)
$1(t \in T_2)$	-0.333	(0.082)	-0.141	(0.050)	-0.134	(0.054)
business establishment FE	Yes		Yes		Yes	
year FE	Yes		Yes		Yes	
region-year FE	Yes		Yes		–	
R^2	0.160		0.173		0.154	
observations	274		271		266	
Panel B. Dependent variable: ln(employment)						
$1(i \in I_1) \cdot 1(t \in T_1)$	-0.066	(0.050)	-0.011	(0.074)	-0.021	(0.045)
$1(i \in I_1) \cdot 1(t \in T_2)$	-0.233	(0.093)	-0.036	(0.083)	-0.068	(0.079)
$1(t \in T_1)$	0.228	(0.115)	-0.035	(0.072)	-0.120	(0.068)
$1(t \in T_2)$	0.057	(0.074)	-0.039	(0.092)	-0.201	(0.117)
business establishment FE	Yes		Yes		Yes	
year FE	Yes		Yes		Yes	
region-year FE	Yes		Yes		–	
R^2	0.057		0.022		0.020	
observations	116		115		115	

Note: These parametric estimation results were obtained by one-to-one matching.

same period. However, in the estimation results in the second and third columns, the statistical significance of the ATT estimates disappears for both phase I and phase II. To verify the robustness of my estimation results, I estimated the same specifications with different numbers of neighbors M in the weight function, obtaining the same conclusions. For details regarding the robustness check, see Appendix 4.A.1.

4.5.1 Parallel Trends Assumption

In this subsection, I examine the validity of the parallel trends assumption. Figures 4.3 and 4.4 show the trends of electricity consumption and of the number of employees by group, in which the control groups consist of areas outside the three major metropolitan areas. I find that my matching strategy is likely to succeed because the trends of the treatment group (the solid line

Table 4.3: Semiparametric matching-based DID estimation results

Control group:	(1) Prefectures outside the 3 major metropolitan areas		(2) Prefectures in the 3 major metropolitan areas except the Kanto region		(3) Prefectures in the Kanto region	
	Coeff.	Std. Dev.	Coeff.	Std. Dev.	Coeff.	Std. Dev.
Panel A. ln(electricity consumption)						
ATT in phase I	-0.041	(0.023)	-0.037	(0.020)	-0.010	(0.022)
ATT in phase II	-0.058	(0.039)	-0.021	(0.035)	-0.029	(0.038)
treated observations	154		158		147	
Panel B. ln(employment)						
ATT in phase I	-0.023	(0.037)	-0.028	(0.039)	-0.008	(0.042)
ATT in phase II	-0.155	(0.066)	-0.100	(0.072)	-0.111	(0.079)
treated observations	62		62		61	

Note: These semiparametric estimation results were obtained by one-to-one matching. The numbers in parentheses are standard errors based on Abadie and Imbens (2006).

with circles) and the matched control group (the dotted line with triangles) move in parallel during the pretreatment period, i.e., from 2007 to 2009. However, the unmatched control group displayed trends during the pretreatment period that were different from those of the above two groups. More specifically, the decrease in electricity consumption between 2008 and 2009 was larger than that of the other groups. One possible explanation is the financial crisis of 2008. Although the Lehman Shock exerted a substantial effect on the Japanese economy, the degree of impact is considered to vary by industry. Notably, the impact on the manufacturing sector was larger than on other sectors. Because of the small number of manufacturing firms in Tokyo, the decrease in 2009 was moderate compared to other prefectures. This fact suggests the importance of conducting exact matching on the sector code.

During the treatment period, both the treatment group and the matched control group exhibited decreasing electricity consumption trends over time. The decrease was considerably large in 2011. In fact, the Great East Japan Earthquake in 2011 triggered several quantitative regulations and behavioral changes to save energy, and these regulations and changes contributed to the sharp reduction in electricity use after 2011.

Figures 4.5 and 4.6 show the ATTs estimated year by year with the same model, and they help me verify in more detail whether the parallel trends assumption is satisfied. These figures present the ATTs for each year, which are calculated based on comparison with the outcomes in 2007. The ATTs between 2008 and 2009 are not statistically significant, which implies that the outcome trends for both the treatment and matched control groups moved in parallel in the pretreatment period. This result indicates the reliability of my DID estimates. Moreover, I find that to make

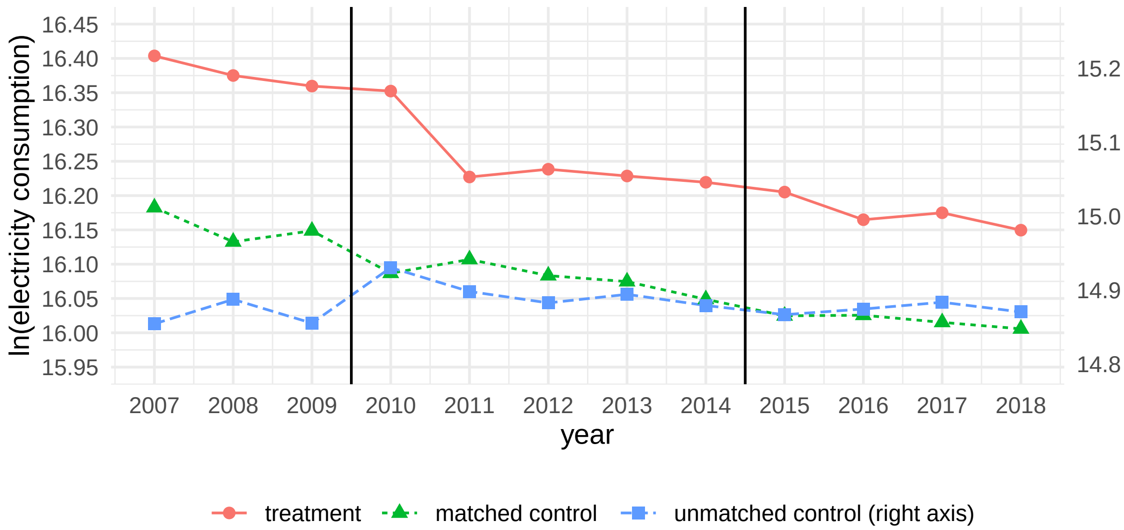

Figure 4.3: Transition of electricity usage (natural logarithm) by group

Note: The control group in this figure consists of business establishments outside the three major metropolitan areas. The matched controls were chosen by one-to-one matching.

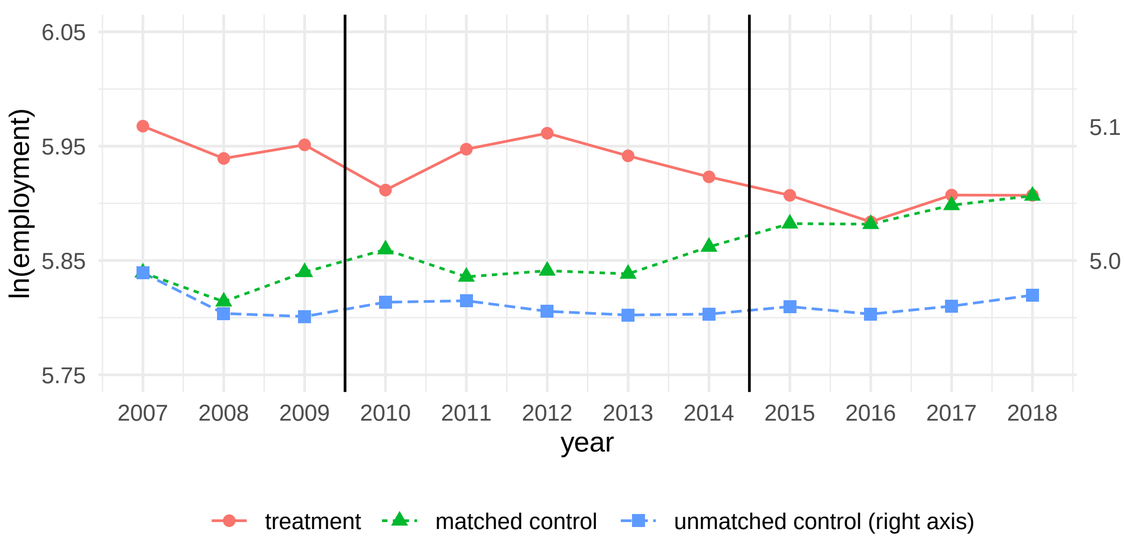

Figure 4.4: Transition of employment (natural logarithm) by group

Note: The control group in this figure consists of business establishments outside the three major metropolitan areas. The matched controls were chosen by one-to-one matching.

the outcome trends of the two groups in the pretreatment period parallel, the matching method is essential.

Furthermore, I find that the decrease in electricity consumption of business establishments

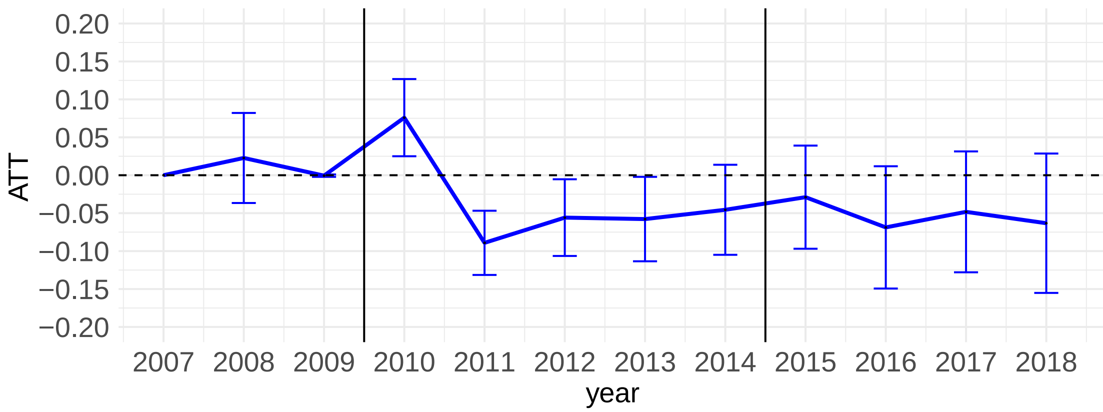

Figure 4.5: ATTs of the Tokyo ETS on electricity consumption over time

Note: The calculations of the ATTs for each year are based on comparisons of the outcome for each year with that for the reference year in my analysis, i.e., 2007. The control group in this figure consists of business establishments outside the three major metropolitan areas. The matched controls were chosen by one-to-one matching.

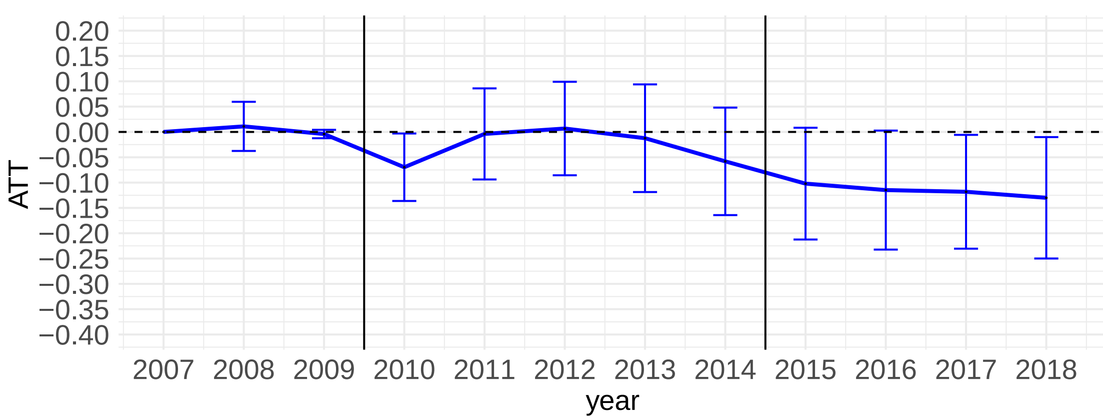

Figure 4.6: ATTs of the Tokyo ETS on employment over time

Note: The calculations of the ATTs for each year are based on comparisons of the outcome for each year with that for the reference year, i.e., 2007. The control group in this figure consists of business establishments outside the three major metropolitan areas. The matched controls are chosen by one-to-one matching.

regulated by the Tokyo ETS was statistically significant in 2011. This finding implies that in phase I, for business establishments regulated by the Tokyo ETS, the main driver of the decrease in energy usage was the Great East Japan Earthquake and the behavioral changes that followed. This result for phase I is consistent with the finding of Wakabayashi and Kimura (2018). While the ATTs display negative signs through phase II, they are not statistically significant. In addition, over phase I, the ATTs for employment shown in Figure 4.6 are not statistically significant, while after 2015, I detect a slight decline in employment in business establishments regulated by the Tokyo

ETS.

4.6 Conclusions and Policy Implications

In this study, I quantitatively analyzed the effects of the Tokyo ETS on the energy usage and employment of regulated business establishments over the first phase of the scheme (2010–2014) and the first four years of its second phase (2015–2018) using business establishment-level panel data from 2007 to 2018. My estimation results suggest that business establishments regulated and unregulated by the Tokyo ETS clearly decreased electricity consumption through phases I and II, whereas there was no statistically significant difference in the degree of decrease in electricity consumption between the two groups. In addition, I found little evidence that regulated business establishments reduced their number of employees relative to unregulated business establishments through phases I and II. Similarly, Wakabayashi and Kimura (2018) find no evidence that the Tokyo ETS affected the energy usage of regulated business establishments relative to unregulated business establishments during phase I. They conclude that the decreases in energy use observed in Tokyo were mainly driven by the Great East Japan Earthquake in 2011. While this conclusion is plausible, I can consider another interpretation, i.e., that the Tokyo ETS may have indirectly affected neighboring areas. This view suggests that the ETS has a spillover effect, and my estimation results do not rule out this possibility. In fact, when I included areas geographically near Tokyo in the control group, I confirmed that the estimated policy impacts decreased in magnitude and statistical significance. Sadayuki and Arimura (2021) also confirm that CO_2 emissions decreased in neighboring prefectures as well as in Tokyo and Saitama during phase I.

In addition, my study suggests that the ETS is a useful policy tool for the commercial sector. As demonstrated by my analysis and by reports from the Tokyo Metropolitan Government, emissions significantly decreased after the introduction of the ETS. However, in my analysis of the Tokyo ETS with respect to commercial business establishments, I did not find a significant negative economic impact due to the regulation. My finding is consistent with those of previous studies on the manufacturing sector under the EU ETS (e.g., Chan et al., 2013; Rammer et al., 2017; Marin et al., 2018). Instead of reducing employment, business establishments may have invested in energy savings to implement the reduction. Onuma and Arimura (2020) conducted a survey and provided descriptive statistics, showing that office buildings in Tokyo were more likely to invest in relatively expensive energy efficiency equipment than buildings in other regions. My study did not find incremental emissions reduction arising from such investments with statistical significance, suggesting that the investments observed by Onuma and Arimura (2020) were not large enough to lead to a difference in emissions reduction between regulated and unregulated business establishments. This point requires further research.

In many countries, there are many objections to the introduction of ETSs due to concerns over negative economic impacts (Rammer et al., 2017). My findings suggest that such concerns are unfounded in the case of the Tokyo ETS, which mainly covers commercial business establishments. Therefore, the ETS can be an effective policy instrument in the commercial sector without causing severe economic damage.

Furthermore, my study hints that ETSs can be an important component of climate policy even when the allowance price is modest. In practice, a modest carbon price can have an influence that extends beyond the direct impact of the price incentive. For example, ETSs are expected to act as a signal of commitment to climate policy goals to innovators, investors, and businesses to help them plan for the future. Moreover, ETSs can help firms develop mechanisms for accounting and enforcement, mechanisms to encapsulate the price in other market prices, and mechanisms for allowance distributions. ETSs can also provide regulated firms with opportunities to learn about the climate policy program and make them more comfortable with their reporting responsibilities.

I also note that ETSs with auctions can generate revenue that can be used for compensation, research, investment in clean technology, or other purposes or that can be kept within the industry through a free output-based allocation. In addition, ETSs can complement other regulations by improving cost-effectiveness and compensating for areas where regulators may lack information. By collecting data, regulators can design and implement other policies and strengthen the program over time. Finally, ETSs can be a signal to other jurisdictions of that jurisdiction's willingness and commitment to climate policy goals.

I acknowledge several limitations to my study. The foremost is the lack of data on electricity prices. In contrast to Arimura and Abe (2021), my study uses a data set that covers a period commencing after the deregulation of the electricity power market, which occurred in 2016 in Japan. Since deregulation, business establishments have been free to choose their suppliers and contracts. However, because such contract information is private, it is unavailable to researchers.

Second, because of data limitations, my study focuses only on electricity consumption. If information on all forms of energy consumed in economic activity had been available, I would also have been able to investigate changes in emissions and the substitution patterns among the forms of energy that business establishments used. However, to the best of my knowledge, because there are no comprehensive and accurate data on the use of all energy types in Japan, I could not calculate the emissions amount by aggregating all energy use.

Third, the number of observations in my analysis was limited due to many errors and missing values in the information reported in the SSEC data set. To construct balanced panel data over twelve years from 2007 to 2018, I first excluded business establishments with errors and missing values during the period. Because my sample did not detect any difference in the trend of the missing data between business establishments regulated and unregulated by the Tokyo ETS, I believe that the missing values do not cause systematic biases in my estimates.

Finally, I acknowledge a limitation related to my use of employment to reflect economic performance. In fact, facing the ETS, regulated business establishments are less likely to quickly adjust employment in the short term compared with other variables, such as sales. Therefore, it remains possible that the use of employment to represent economic performance may underestimate the effect of regulation on economic performance. Moreover, it would be better to investigate policy effects over a longer period using multiple measures. Future research should address these shortcomings.

4.A Appendix

4.A.1 Robustness Check

To verify the robustness of my main estimation results, I estimated the same specifications while changing the number of neighbors M in the weight function. Tables 4.A.1 and 4.A.2 report the parametric and semiparametric DID estimations with one-to-three matching ($M = 3$).

Table 4.A.1: Parametric matching-based DID estimation results

Control group:	(1) Prefectures outside the 3 major metropolitan areas		(2) Prefectures in the 3 major metropolitan areas except the Kanto region		(3) Prefectures in the Kanto region	
	Coeff.	Std. Dev.	Coeff.	Std. Dev.	Coeff.	Std. Dev.
Panel A. Dependent variable: ln(electricity consumption)						
$1(i \in I_1) \cdot 1(t \in T_1)$	-0.081	(0.030)	-0.025	(0.029)	-0.040	(0.021)
$1(i \in I_1) \cdot 1(t \in T_2)$	-0.072	(0.048)	-0.076	(0.037)	-0.074	(0.035)
$1(t \in T_1)$	-0.146	(0.049)	-0.108	(0.023)	-0.100	(0.026)
$1(t \in T_2)$	-0.206	(0.052)	-0.120	(0.035)	-0.121	(0.041)
business establishment FE	Yes		Yes		Yes	
year FE	Yes		Yes		Yes	
region-year FE	Yes		Yes		–	
R^2	0.160		0.173		0.154	
observations	274		271		266	
Panel B. Dependent variable: ln(employment)						
$1(i \in I_1) \cdot 1(t \in T_1)$	-0.040	(0.045)	-0.050	(0.055)	-0.019	(0.038)
$1(i \in I_1) \cdot 1(t \in T_2)$	-0.124	(0.067)	-0.077	(0.065)	-0.075	(0.059)
$1(t \in T_1)$	0.009	(0.098)	0.047	(0.044)	-0.048	(0.038)
$1(t \in T_2)$	-0.041	(0.098)	0.075	(0.060)	-0.050	(0.064)
business establishment FE	Yes		Yes		Yes	
year FE	Yes		Yes		Yes	
region-year FE	Yes		Yes		–	
R^2	0.057		0.022		0.020	
observations	116		115		115	

Note: These parametric estimation results were obtained by one-to-three matching.

Table 4.A.2: Semiparametric matching-based DID estimation results

Control group:	(1) Prefectures outside the 3 major metropolitan areas		(2) Prefectures in the 3 major metropolitan areas except the Kanto region		(3) Prefectures in the Kanto region	
	Coeff.	Std. Dev.	Coeff.	Std. Dev.	Coeff.	Std. Dev.
Panel A. ln(electricity consumption)						
ATT in phase I	-0.033	(0.017)	-0.041	(0.018)	0.009	(0.018)
ATT in phase II	-0.034	(0.031)	-0.048	(0.031)	-0.020	(0.030)
treated observations	143		144		139	
Panel B. ln(employment)						
ATT in phase I	0.036	(0.041)	-0.025	(0.035)	-0.020	(0.039)
ATT in phase II	0.013	(0.061)	-0.069	(0.056)	-0.071	(0.055)
treated observations	61		61		60	

Note: These semiparametric estimation results were obtained by one-to-three matching. The numbers in parentheses are standard errors based on Abadie and Imbens (2006).

4.A.2 Additional Figure

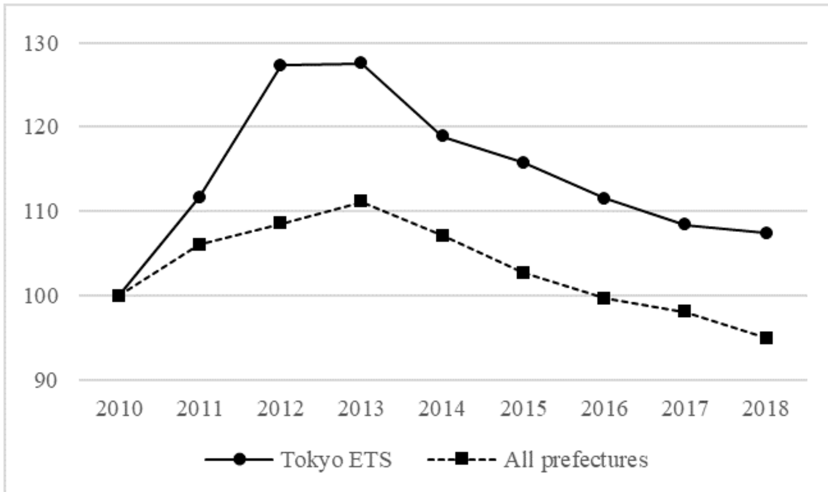

Figure 4.A.1: Comparison of emissions transitions

Source: Tokyo Metropolitan Government Bureau of Environment (2020, 2021) and the FY2019 Comprehensive Energy Statistics from the Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry.

Note: This figure plots emissions from business establishments regulated by the Tokyo ETS and those of all Japan. The annual growth rates of emissions of the Tokyo ETS business establishments are calculated by adding the growth rates of the emission factor varying every year to those of emissions reported in Figure 4.1. The graphs are drawn by setting the emissions levels in 2010 to 100.

Chapter 5

Conclusion

This thesis examines the impacts of market-based policy instruments for climate change, including a carbon tax, a feebate, and an ETS. I first analyze the economic and environmental consequences of the carbon tax and the feebate policy introduced in Japan. Existing empirical literature confirms that energy efficiency programs such as feebates give rise to a rebound effect that refers to an unintended increase in energy consumption. Chapter 2 then demonstrates the rebound effect of automobiles using household-level cross-sectional survey data, showing that there is substantial interregional heterogeneity in the rebound effect in Japan. Based on the results of Chapter 2, Chapter 3 builds a model of decisions of households and firms and examines the efficiency and distributional equity of the carbon tax and the feebate in the Japanese automobile market by combining household-level cross-sectional data and market-level panel data. Finally, Chapter 4 conducts causal inference to assess the extent to which the ETS implemented in Tokyo contributes to a decrease in energy use and influences the economic activities of regulated business establishments using nationwide business establishment-level panel data.

I obtain the following two policy implications from my empirical studies. The first implication is associated with the automobile taxation system. In Japan, every automobile owner must pay an annually imposed weight tax and automobile tax during the ownership duration. The result of Chapter 3 shows that a carbon tax dominates a product tax, including the weight tax and the automobile tax, on efficiency and distributional grounds while reducing the same amount of environmental externality. This result implies that replacing the existing automobile-related taxes with a carbon tax would improve social welfare without increasing the tax burden on low-income households.

Currently, there is a discussion to revise automobile-related taxes with the aim of stabilizing tax revenues under a situation where zero-displacement electric vehicles become popular, car sharing becomes widespread, and the number of vehicles owned by households declines in the future. In the discussion, a taxation system proportional to miles traveled is considered one of the most promising alternatives to the existing automobile-related taxes. The tax imposition for miles traveled would be an effective means for reducing negative externalities, including traffic accidents, congestion, local pollutants, and damage to the road (IEA, 2019; Van Dender, 2019). On the other hand, I consider that a tax on fuels, such as a fuel tax and a carbon tax, should also be used since a vehicle miles traveled (VMT) tax does not incentivize individuals to choose fuel-efficient vehicles. Taxing fuel consumption and mileage could improve the fuel economy of the nation's automobile fleet and reduce environmental and other externalities while ensuring stable financial resources over the long run.

I note that the abovementioned policy implication necessitates that the following point be discussed separately. Because Japanese automobile-related taxes include national and local taxes, a problem arises as to how tax revenues should be allocated to local regions when automobile-related taxes are integrated into a carbon tax or a VMT tax. The analysis of how changes in the allocation and use methods of tax revenues impact market outcomes is beyond the scope of my thesis. I consider that the careful discussion of this matter based on additional analyses is needed.

The second policy implication relates to the emissions caps set by the Tokyo ETS for the first and second phases. As indicated in Chapter 4, the reduction in energy use of regulated business establishments has been comparable to that of unregulated establishments since 2012. This result suggests that the emissions caps may not have been set at a sufficiently stringent level to induce regulated business establishments to implement additional energy-saving practices. Indeed, there has been little emissions trading during the first and second phases, and the price of credits has been declining since the onset of the regulation.

While ETSs are an effective instrument for ensuring stable emissions reductions, the following points should be noted when implementing an ETS nationwide. Under an ETS, for firms with high carbon abatement costs, purchasing allowances in a trading market from firms with low carbon abatement costs can be an efficient abatement measure in the short run. However, in the long run, this reduction measure may discourage investment in the introduction of low-carbon technologies and innovation. I then consider it necessary to narrow down the target industries in an appropriate way to encourage such investments in innovation in ETS firms and to impose a carbon tax on non-ETS subject industries to reduce carbon emissions cost-efficiently. In selecting target industries and setting emissions caps, it is crucial to capture the carbon abatement potential of each firm prior to the introduction of the ETS. I plan for future research to estimate the marginal abatement cost of carbon for individual firms based on the structural parameters of firms' production.

I acknowledge some limitations in my studies. First, in Chapter 2, I failed to correct the potential source of sample selection bias associated with the estimate of the rebound effect due to data availability. The target of the household survey used in the analysis is limited to those who purchased at least one vehicle during the sample period; thus, I do not account for households who do not own any vehicles when estimating rebound effects. A sample selection issue would arise in the estimation when unobserved household characteristics differed across households with and without vehicles. For example, some households that own fuel-efficient vehicles may be either more or less environmentally conscious, whereas most households that own fuel-inefficient vehicles may be less environmentally conscious because environmentally conscious households would rather choose not to buy a vehicle at all than to buy a low fuel economy vehicle. If this is the case, this leads to a positive correlation between the unobserved environmental consciousness and the fuel economy of vehicles owned by households, which is an explanatory variable in the regression equation. As a result, the estimated rebound effect would be biased downward because the environmental consciousness would be negatively correlated with the driving distance, a dependent variable. Hence, the estimate of the rebound effect obtained in Chapter 2 may suffer from selection bias, although I believe that there is no such concern in rural areas in which the rebound effect is estimated with statistical significance because almost all households in rural areas own vehicles.

Second, I acknowledge that careful discussion and additional analysis are needed to interpret the welfare consequences of the feebate policy. The results of Chapter 3 show that the feebate significantly increases social welfare compared with the no-policy baseline scenario. I consider that this is because the feebate policy mitigates the market distortion caused by high price-cost margins of automobiles and the imposition of automobile-related taxes; thus, whether the policy intervention by tax breaks is an optimal option in such a market requires a separate discussion, even if that policy intervention is welfare-improving. Additionally, because I take into account only environmental externalities as the source of negative externalities that result from car driving, negative externalities account for just a small fraction of social welfare. It should thus be noted that the welfare consequence of the feebate will change with the consideration of other externalities, such as traffic accidents, congestion, local pollutants, and damage to the road. Furthermore, the result of Chapter 3 suggests that the government can increase the total surplus in the automobile market by borrowing from future generations and providing tax breaks for eco-friendly cars. This means that the feebate improves the social welfare of the current generation at the expense of future generations, noting that the feebate policy is also problematic from the perspective of intergenerational equity.

In Chapter 3, I do not examine the influence of the feebate on the choice of product characteristics available to each automobile manufacturer. The feebate policy targeted in Chapter 3 determines the amount of tax reduction according to achievement levels of fuel economy standards set for each vehicle weight; currently, the structure itself has not changed. Chapter 3 shows that consumer welfare could be improved by a system change from the current attribute-based feebate scheme to a feebate scheme that determines the tax cut amount based only on vehicle energy efficiency while focusing on the equilibrium effect of the feebate policy through sales shifting by changing automakers' pricing strategies. Under the attribute-based feebate scheme, however, automakers have the incentive to change vehicle attributes other than fuel economy, such as weight, to benefit from tax reductions or subsidies (Ito and Sallee, 2018). Hence, I need to model the endogenous choice of product characteristics to consider the supply-side response to the feebate in more detail. This is a subject for future research.

Finally, there are limitations on the treatment effects of the Tokyo ETS estimated in Chapter 4. My matching-based DID estimation detects no statistically significant effects of the ETS on the energy use and employment of the regulated relative to the unregulated. However, this result may be attributable to the fact that the SSEC dataset used for the analysis described in Chapter 4 contains information on only a subset of business establishments with respect to Tokyo ETS establishments. This might lead to large standard errors associated with the ATT estimates; consequently, the treatment effects of the ETS might not be estimated with statistical significance. I consider that future research that uses a dataset covering a large portion of regulated business establishments is required to evaluate the policy impacts of the ETS with more accuracy.

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