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Essays in Industrial Organization: Financial Incentives on Adoption of New Products

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Essays in Industrial Organization:

Financial Incentives on Adoption of New Products

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by

Gyurim Kim

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ABSTRACT OF THE DISSERTATION

Essays in Industrial Organization:

Financial Incentives on Adoption of New Products

by

Gyurim Kim

Doctor of Philosophy in Economics

University of California, Los Angeles, 2023

Professor Simon Adrian Board, Chair

In this dissertation, I empirically examine the effectiveness of financial incentives on consumer adoption of new products. Specifically, I study the impact of two subsidies, which are federal tax credits and rebates, on electric vehicle sales in New York. The first chapter studies heterogeneity in the subsidy effect on electric vehicle adoption across two types of incentives. The second chapter develops a dynamic discrete choice model for demand of electric vehicles and compares the average impact of tax credits and rebates per spending through counterfactual simulations. The third chapter discusses the policy implication of revisions in federal tax credits and studies the impact of the protectionist policy on domestic and foreign-produced EV sales.

The first chapter investigates how each type of subsidy affects consumer adoption of EVs differently and how consumers dynamically optimize their consumption decisions in this market. There are two noticeable differences between rebates and tax credits. First, while consumers receive rebates directly at the point of sale by applying the amount to reduce the purchasing price of EVs, consumers have to wait to enjoy tax credits till the end of each tax year. Also, tax credits are non-refundable, so consumers who do not have any

tax liability cannot benefit from these credits. Due to these disparities, it is important to understand the effectiveness of each subsidy respectively to promote the adoption of EVs with a more efficient subsidy scheme in the future. This chapter provides descriptive evidence on the relative effectiveness of the two subsidies. The findings indicate that rebates are more effective in promoting EV sales than tax credits : for every thousand dollars, rebates lead to an $3.9 \sim 4.1\%$ increase in new EV purchases, while tax credits increase EV sales by only 1.3%. Moreover, I find that current EV sales are associated with an expected subsidies change in the future, implying that households dynamically optimize their consumption decisions in this EV market.

The second chapter takes a structural approach to conduct a more rigorous analysis on the impact of rebates and tax credits. Based on the empirical observations in the first chapter, I specify a dynamic demand model in which consumers are assumed to discount the financial benefits of tax credits. Along with coefficients of vehicle characteristics, I estimate the discount factor as well. In this context, the variation in EV sales in response to anticipated changes in subsidies and the difference between the variation in market shares with respect to tax credits and rebates provide sources for identifying and estimating the discount factor. Using the estimated coefficients and discount factor, I run counterfactual simulations to compare the effectiveness of each subsidy. Direct rebates result in promoting 918 additional EV purchases per $10 million, while tax credits only increase EV sales by 582 per $10 million. The results suggest that direct rebates are a more effective means to promote a wider adoption of EVs. Furthermore, at alternative levels of government spending, the average impact of rebates is still significantly higher than that of tax credits. This implies that with rebates only, the government could have saved 23% of the current subsidy costs to accomplish the same level of EV adoption.

In the third chapter, I study the recent major changes in federal tax credits for electric vehicles and further examine the impact of one controversial revision on EV sales. Under

the Inflation Reduction Act (IRA), there were four revisions on tax credits : the removal of the phase-out structure, the availability of tax credits at the point of sale, the MSRP requirement, and the final assembly plant requirement. I focus on the requirement of EVs to have undergone the final assembly in North America to qualify for tax credits. Using the estimated dynamic demand model in the second chapter, I quantify the impact of this requirement on domestic-produced and foreign-produced EV sales through counterfactual simulations. If EVs manufactured outside North America no longer qualify for tax credits, their sales decrease by 42.6%, while sales of EVs with final assembly in North American increase by only 1.2%. This implies that removing tax credits for foreign-produced EV models does not directly translate into consumers' adoption of domestic-produced EVs. Also, this requirement undermines the overall effectiveness of subsidies on EV adoption by 8.6%.

The dissertation of Gyurim Kim is approved.

John William Asker

Martin B. Hackmann

Aaron Tornell

Simon Adrian Board, Committee Chair

University of California, Los Angeles

2023

To my wife, family, and friends

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CHAPTER 1

Financial Incentives on Diffusion of Electric Vehicles : The Electric Vehicle Industry

1.1 Introduction

In many countries, electric mobility is rapidly becoming an essential part of the transportation industry to reduce greenhouse gas emissions from on-road vehicles[1]. In particular, in the U.S., the electric vehicle (EV) industry has significantly grown over the last 10 years, with annual sales increasing from only thousands in 2010 to more than 300,000 vehicles in 2020.[2] Also, the number of EV models grew to 48 models, and the average range of EVs more than doubled to 210 miles in 2020. However, EV prices are still high compared to fuel-powered vehicles and are thus one of the most significant barriers to broader adoption. To make EVs more affordable, the federal and state governments in the U.S. have implemented various financial incentives such as tax credits, rebates, or tax exemptions since 2010. Though these EV subsidies have a positive effect on EV adoption (Clinton and Steinberg, 2019, Xing, Leard, and Li, 2021), there is little consensus on the optimal policy design of these subsidies.

In this chapter, I empirically examine how each type of subsidy affects consumer adoption of EVs differently and investigate whether the current subsidy schemes can be improved in a dynamic framework. I focus on two financial incentives primarily implemented in the U.S.:

[1]The EPA reports that a substantial amount of transportation energy comes from gasoline and diesel, and consumption of petroleum-based fuels by the transportation sector accounts for 28% of the total U.S. greenhouse gas emissions.

[2]Annual electric vehicle sales by country can be found in EV Data Center in EV-Volumes.

tax credits and rebates. A rebate affects consumers' demand by reducing the purchasing price of EVs directly at the point of sale. However, consumers enjoy discounted financial benefits from tax credits since credits are received at the end of each tax year. Also, tax credits are non-refundable, so consumers who do not have any tax liability cannot benefit from these credits. Because of these dissimilarities between rebates and tax credits, consumers may respond differently to each type of financial incentives. Thus, understanding the effectiveness of each subsidy is crucial for policymakers to promote the adoption of EVs more efficiently in the future.

This chapter studies consumer demand of electric vehicles and the entry and exit of subsidies in New York to address this policy question. The focus on the EV market in New York is driven by several advantages in quantifying the effect of the two financial incentives. First, consumers in this market could benefit from both federal tax credits (FTC) and state rebates, varying across different vehicle models. Between 2015 and 2020, I also observe variation in each type of incentive over time by the introduction of rebates in 2017 and the multi-step phase-out of federal tax credits for specific products in 2019. Examining consumer responses to this heterogeneity in each subsidy across products and time allows me to estimate the differential impact of the two subsidies.

Moreover, the availability of data on the universe of newly registered electric vehicles in New York on each date sheds light on the dynamic nature of consumers' decision-making processes. Because of the fine granularity of the New York registration data in time, I construct bi-weekly sales of each electric vehicle between 2015 and 2020. I exploit this level of detail in EV sales data to learn how the adoption pattern of consumers changes over time in response to their anticipation of new rebates or reduction in FTC. This enables me to explore whether consumers in New York are dynamically optimizing their purchasing decisions of electric vehicles.

Through a descriptive analysis, I examine how each type of financial incentive is related to EV sales and how a change in discounted future benefits affects current EV sales through regression approach. Initially, I regress EV sales of each vehicle on its net price adjusted by two subsidies, expected change of subsidies, vehicle characteristics, and a set of time and model fixed effects. To overcome the issue of price endogeneity, I take an IV-GMM approach to estimate the first equation, where BLP-style instruments, such as a sum of the characteristics of EVs produced by other firms, are used.[3] The initial IV regression results indicate that financial incentives have a positive and significant effect on EV consumer demand, with EV sales increasing by approximately $2.5 \sim 2.65\%$ for each thousand dollar. More importantly, a negative and significant relation between anticipated change in subsidy amount and EV sales shows that the timing of purchasing decisions depends on consumers' expectation about the future in this industry.

I augment this initial regression analysis by allowing the coefficients of the price (or rebate) and the tax credits to be different. That is, I investigate whether consumers' responses vary by different types of subsidies by estimating the impact of each subsidy on EV sales. To accomplish this, I regress EV sales on its net price adjusted by rebate only, federal tax credits, expected change of subsidies, vehicle characteristics, and a set of time and model fixed effects using the IV-GMM estimation method. Though both direct rebates and tax credits have a statistically significant positive impact on EV sales, I find that the two incentives are not equally effective in promoting EV adoption. Specifically, while a thousand dollar rebate increases new EV purchases by a $3.9 \sim 4.14\%$, a thousand dollar tax credit is associated with only a 1.3 % increase in EV sales. This finding strongly suggests that rebates are a more effective tool for promoting EV adoption than tax credits.

This chapter contributes to the literature that examines the impacts of financial incentives

[3]Muehlegger and Rapson (2022) finds that the rate of EV subsidy pass-through to consumers is almost 100% in California. Gulati et al (2017) also shows that a very high proportion of financial incentive is captured by hybrid electric vehicle consumers. Following this discussion, I assume here a complete pass-through of EV subsidies to consumers and thus do not use the amount of rebate or tax credits as instruments for price.

in the automobile market. Several recent studies focus on policies promoting the adoption of cleaner vehicles, such as plug-in EVs. DeShazo et al (2017) study California's plug-in electric vehicle (PEV) rebate program to assess the effectiveness of the status quo policy on EV adoption and find that the rebate program induces a 7% increase in EV sales. Muelegger and Rapson (2018) examine another subsidy program for EV purchases in California, the Enhanced Fleet Modernization Program (EFMP), which provides subsidies towards low- and middle-income consumers. Using a difference-in-difference approach, the authors find that the EFMP is associated with a 26% increase in the quantity of new EVs purchased. Li et al (2017) explore how the federal tax credit program promoted EV purchases in the U.S. between 2011 and 2013 and suggest that the tax credits contributed to 40% of new EV sales, which incorporates indirect network effects from expansion of charging stations.

This chapter also relates to the literature that investigates the relative effectiveness of each financial incentive for passenger vehicles. Gallegher and Muelegger (2011) suggest that more generous incentives induce higher sales of hybrid vehicles, and the effectiveness of these incentives varies depending on their type. According to their results, the effect of sales tax waivers on hybrid vehicle sales are found to be almost 10 times greater than that of tax credits. Similarly, Beresteanu and Li (2011) analyze the hybrid vehicle demand in the U.S. and compare the cost effectiveness of federal tax credits with direct rebates. They show that with direct rebates, the federal government could have saved almost 25% of the government spending to achieve the same level of average fuel economy. In this chapter, I provide new evidence for plug-in electric vehicles market in New York that direct rebates foster a greater consumer adoption of electric vehicles than tax credits.

1.2 Institutional Background and Data

In this section, I describe the industry setting on how the federal and state governments initiated supporting the adoption of hybrid or electric vehicles in the US passenger vehicle market. I discuss the structures of both the federal and state incentives for consumers of electric vehicles. Then, I provide a description of sales and characteristics data of electric vehicles in New York with summary statistics. I show how sales, prices, and vehicle characteristics changed over time in this EV market.

1.2.1 Federal Tax Credits for Electric Vehicles

In the early 2000s, there has been a nationwide effort to reduce the consumption of petroleum-based fuels from the transportation industry. As the major bottleneck in promoting wider adoption of cleaner vehicles was higher prices than conventional vehicles, the U.S. government started providing tax credits for hybrid or alternative fuel vehicles since the Energy Policy Act of 2005. This legislation included tax credits up to $3400 mostly for hybrid vehicles or diesel-powered vehicles.

To transform the transportation sector to be cleaner, the Congress passed the American Recovery and Reinvestment Act in 2009 to establish federal tax credits for plug-in hybrid electric vehicles or pure electric vehicles. For eligible vehicles[4], the tax credits vary between $2500 and $7500. Because electric vehicles are more expensive on average, these financial incentives are greater than those for alternative fuel vehicles in order to make them more price competitive. The objective was to encourage potential consumers to purchase electric cars so that more vehicle manufacturers would produce them in the passenger vehicle market.

For any eligible electric vehicle purchased, an individual can claim the federal tax credit to reduce one's tax liability when they file taxes. That is, the incentive cannot be collected at the point of sale, but at the end of the tax year. This implies that the consumer's utility from this subsidy depends not only on the amount, but also on the timing of the purchase because of a discounted value of the tax credit.

[4] To qualify, vehicles must be newly purchased after Dec 31st, 2009, have more than or equal to four wheels, and draw propulsion using a battery with at least 4 kWh that can be recharged from an external source of electricity

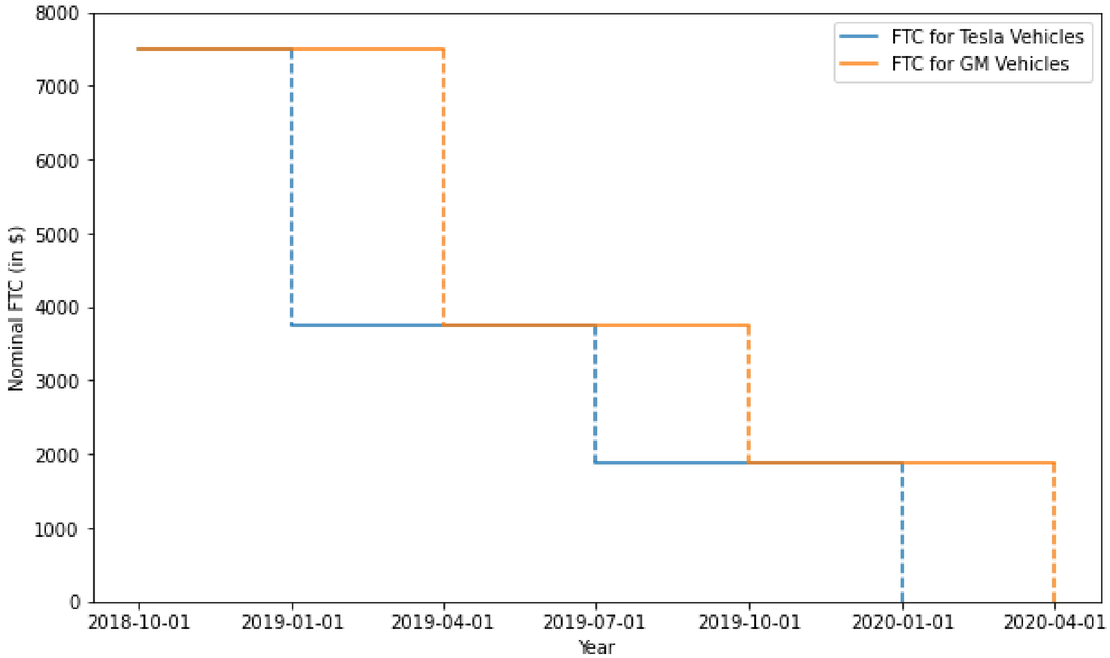
Similar to the tax credits for hybrid vehicles in 2005, the federal tax credit for electric vehicles had a predetermined phase-out structure for popular vehicle models. Once a vehicle manufacturer sells 200,000 qualifying vehicles, the credit for vehicle models produced by the manufacturer phases out starting in the second quarter after the 200,000 limit is reached. During the first 6 months of the phase-out period, the credit is reduced to 50% of the original credit amount. For the next 6 months, the credit reduces to 25% of the original credit amount. At the end of the phase-out period, the credit is completely phased out and remains zero afterward. Along with the variation in the amount of tax credits across different EVs, this phase-out scheme allows me to observe the variation in tax credits for the same vehicles across time.

For example, between 2015 and 2020, there were two auto manufacturers that reached these limits, Tesla and General Motors. In July 2018, Tesla became the first car manufacturer to deliver 200,000 electric vehicles to consumers, so the phase-out period of the federal tax credits for Tesla vehicles began in January 2019. Also, General Motors confirmed in November 2018 that the company passed 200,000 sales of plug-in vehicles. Thus, the full amount of tax credits for GM vehicles was available till March 2019 and gradually reduced to zero on April 1st, 2020. Figure 1.1 shows how federal tax credits for Tesla and GM products were completely phased out in this period.

1.2.2 New York State Rebate

Along with the financial incentive from the federal government, there are additional state-level subsidies, which consumers can also benefit from electric vehicle purchases. Since 2010, fifteen states have established their own incentive programs to lower the cost of EVs more. Each state has a separate list of eligible vehicles for its program and differs in how it distributes its incentive to consumers. There are three main types of incentives: tax credits,

Figure 1.1: Phase-Out of Federal Tax Credits for Tesla and GM Products



Notes: Tesla vehicles in this graph refer to Model 3, Model S, and Model X, and GM vehicles include Bolt EV, Volt, and Spark from Chevrolet and CT6 from Cadillac.

tax exemptions, or rebates. [5]

In April 2016, New York state announced its plan to introduce an electric vehicle rebate program in a year and successfully launched the Drive Clean Rebate program on March 21st, 2017. This program is open to all New York residents and offers direct rebates up to $2000 for new purchases of pure electric and plug-in hybrid vehicles. Unlike the federal tax credit, each rebate can be applied at the point of sale. That is, consumers can get a discount of the rebate amount from the retail price at the time purchases are made.

From New York State Energy Research and Development Authority (NYSERDA), I collect this rebate data for each eligible electric vehicle model. The rebate amount varies from 0 to $2000 with a standard deviation equal to $600.89. In addition to the variation in

[5]Colorado, Delaware, and Maryland offer tax credits. New Jersey and Washington offer tax exemptions. Ten states including California and New York provide rebates.

price across electric vehicle models, I use this variation in state rebate to identify a consumer's marginal utility of each dollar spent on electric vehicles. Moreover, as the rebate program was announced 1 year before the effective date, consumers observed how much discount they would receive for each electric vehicle in the future. I exploit this variation in future state rebates to identify a discount factor in the utility function.

1.2.3 Main Data

I collect data on sales and characteristics of electric vehicles in New York from two main sources, New York State Energy Research and Development Authority (NYSERDA) and the WARD's Automotive Yearbook. The NYSERDA provides a panel of all electric vehicle registration data in New York from 2011 to 2020. While registration records up to 2014 are provided on an annual basis, I observe daily snapshots of all EV registration records from February 2015 to February 2020. Each observation includes information on its 17-digit vehicle identification number (VIN), registration date, brand, and model. Since this data contains registration records from both new and used purchases, I drop duplicates of VINs to focus on new EV sales. Using the registration dates, I count the number of new vehicle registrations every two weeks to compute the biweekly sales of each EV model.

The WARD's Automotive Yearbooks contains a panel of electric vehicle models sold in the U.S. during the observed time period. Each observation provides product characteristics and the price of an EV model available each year. Product characteristics include size (defined as length times width), horsepower, weight, electric range, fuel economy, battery capacity, and battery type. As I do not observe transaction prices for each EV registration, I use the MSRP for the price variable. I express all prices in 2011-equivalent dollars by deflating them with the Consumer Price Index.

I merge the product characteristics data with EV sales data at the model level. I assume that vehicles of the upcoming model year are available in the market since October of the previous calendar year. For example, GM started selling a 2018 Chevrolet Volt in October 2017 and continued to sell it till September 2018.[6] Thus, product characteristics of a 2018 Chevrolet Volt are assigned to all observations of the Chevrolet Volt model between October 2017 and September 2018. Each market is defined by a bi-weekly time period (t), and the unit of observation is defined by vehicle model (j) and time period (t). For the final dataset, I exclude "exotic" models from each market, which had extremely low sales for three consecutive time periods.

Along with data on federal tax credits and state rebates, I gather additional data to complete the final dataset. First, I obtain data on the monthly average retail price of electricity in New York from the Energy Information Administration to calculate the cost of driving an EV, which is miles per dollar.[7] Also, data on monthly CPI in New York is collected from the Bureau of Labor Statistics and used to deflate prices. Lastly, I obtain data on the number of households in New York each year from the American Community Survey to measure the market share of each EV model in each market.

Table 1.1 summarizes the key variables used in this paper. It includes summary statistics of biweekly sales, price (in $1000 units), the ratio of horsepower to weight, size, the number of miles one can drive with $1 worth of electricity, the range an EV can travel on a single charge, battery capacity, federal tax credit, and state rebate. Table 1.2 provides how these variables in the electric vehicle market in New York change over time and illustrates some interesting trends. First, there is a clear upward trend in the number of models. The number of available vehicle models in New York increased from 17 in 2015 to 34 in 2019. Figure 1.A.1 clearly shows that both the number of models and brands nearly doubled in five years.

Also, the market exhibits strong trends in sales and important factors affecting the de-

[6]Traditionally, most of new model year vehicles debut in the fall of the previous year. Also, from the registration data, I find that the average month a new model year was first registered across all vehicle models is 9.32.

[7]Miles per dollar is computed as $\frac{\frac{MPG_e}{33.7}}{\text{electricity price}}$

Table 1.1: Descriptive Statistics

Variable	Mean	Std.Dev.
Sales	408.400	228.966
Price ($1000)	51.680	24.287
HP/Weight (hp/lb)	0.066	0.020
Size (1,000 in^2)	14.211	16.302
Miles/$	17.989	3.807
Range (mi)	131.059	126.550
Battery Capacity (kWh)	37.977	33.460
Tax Credit ($1000)	5.574	1.886
Rebate ($1000)	1.045	0.740

Note: The table above covers the summary statistics for all observations between 2015 and 2020. For sales, the average and standard deviation of biweekly sales in the observed time period are presented. For the rest of the variables, the sales weighted mean and standard deviation are presented.

mand of electric vehicles, such as price and range. New EV sales grew by 500% during the observed time period, while the sales-weighted average price decreased by 20%. What's even more striking is the huge increase in the sales-weighted range from 94 miles in 2015 to 169 miles in 2019. Figure 1.2 illustrates aa similar trend in the average price and range of EVs over time. This suggests that quality-adjusted price has significantly fallen in this period, leading EVs to be more affordable by lowering barriers in price and range.[8] This nature of changing products, product characteristics, and sales in the data illustrates that the electric vehicle market in New York was evolving rapidly in this period.

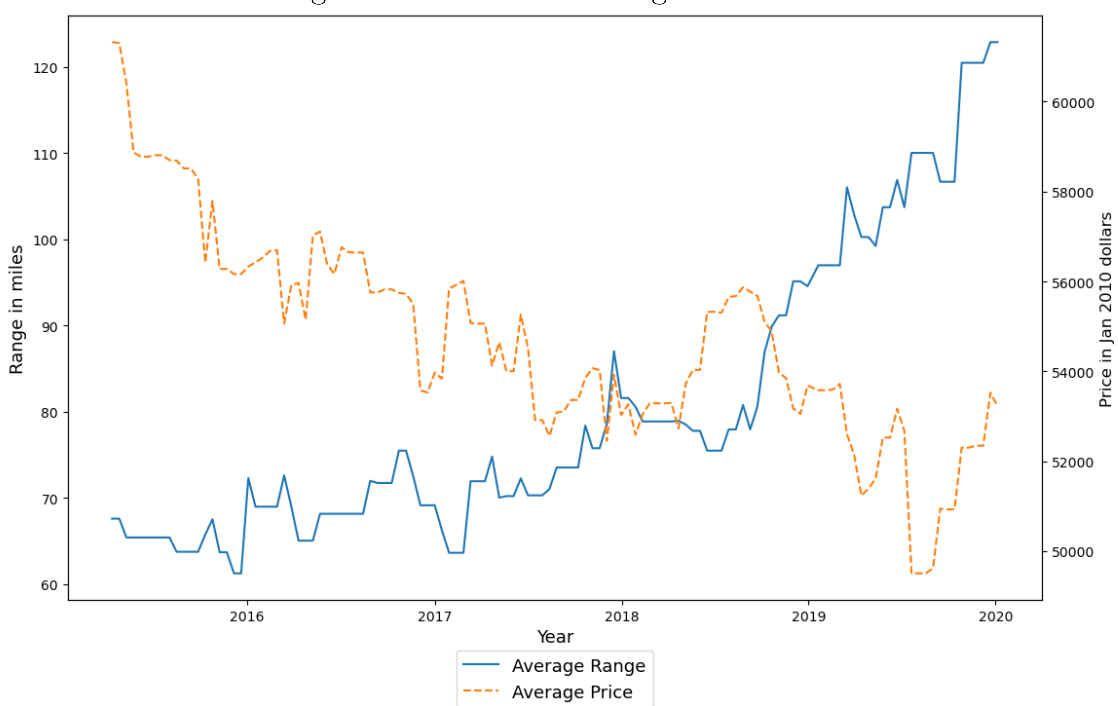
[8]While the ratio of horsepower per weight remains fairly stable, fuel efficiency and battery capacity increase quite sharply over time.

Table 1.2: Descriptive Statistics

Year	No.of Models	Sales	Price	HP/Wt	Size	Miles/$	Range	Capacity
2015	17	3,273	60.946	0.069	12.988	15.611	94.108	29.279
2016	21	5,916	55.815	0.070	13.551	16.197	101.674	32.705
2017	30	11,193	50.753	0.066	13.824	17.654	104.075	33.620
2018	34	16,203	51.396	0.070	14.789	18.080	142.493	40.493
2019	34	14,500	49.131	0.060	14.575	19.109	168.877	46.233

Note: The table above illustrates the yearly summary statistics of the key variables used for the empirical analysis. For the price and vehicle characteristics, the sales weighted means are presented.

Figure 1.2: Prices and Ranges over Time



1.3 Stylized Facts

This section provides evidence on two empirical facts. First, I show descriptive evidence that purchasing decisions of consumers in this electric vehicle market depend on their expectation about the future. I use both graphical and regression approaches to illustrate how households react dynamically to a predetermined exit or entry of subsidies. Second, I present suggestive evidence that there is heterogeneity in the subsidy effect on EV adoption based on the type of financial incentive.

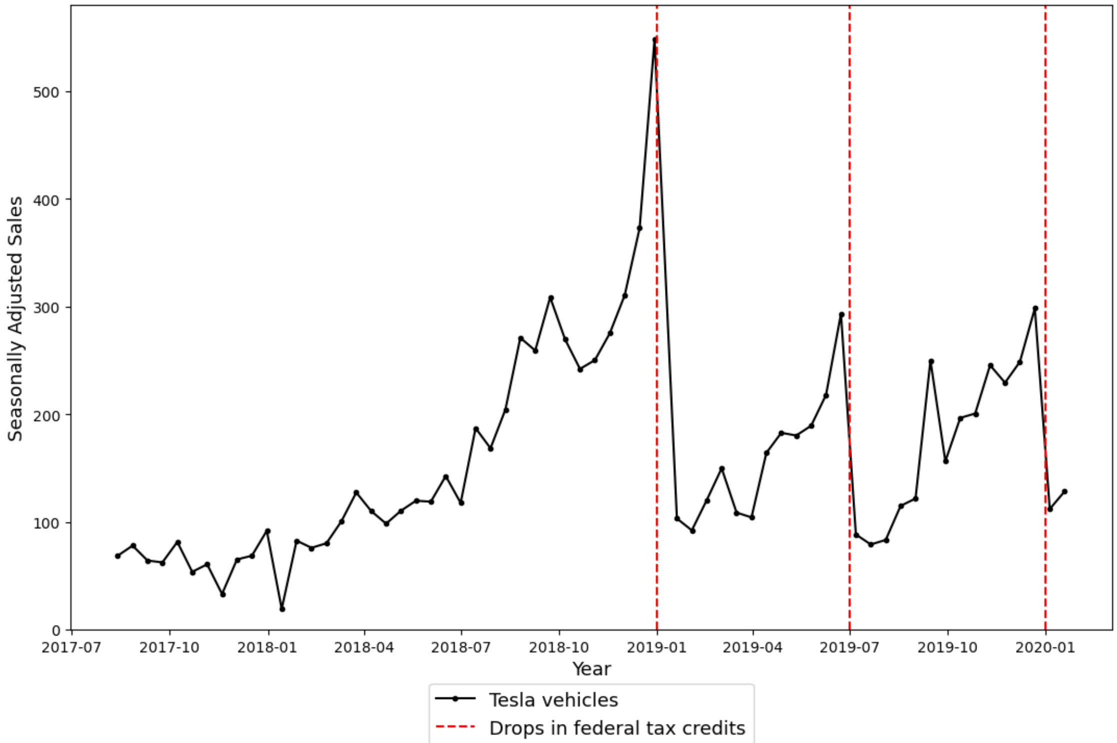
1.3.1 Descriptive Analysis of Dynamically Optimizing Consumers

The relationship between EV sales and an expected subsidies change in the future illustrates how households dynamically optimize their consumption decisions. If new subsidies are anticipated to be implemented, postponing the purchase of an EV can be an optimal choice. Hence, EV sales in the current period will decrease (or increase) in response to a pre-announced entry (or exit) of subsidies in the future.

Based on this intuition, new sales of electric vehicle models, whose monetary incentives such as tax credits are expected to decrease in the future, will rise before the predetermined date of the change in incentives. As discussed in the previous section, federal tax credits were phased out in three steps for all Tesla and General Motors vehicles in 2019. To visualize the change in the adoption pattern of Tesla vehicles during this period, I control for the seasonal patterns of biweekly sales data using the ratio-to-moving average method (RMA). The trend-cycle component of raw sales data is first estimated by a year-wide centered moving average. Then, I divide the raw data by the estimated MA series to compute a de-trended series, and seasonal factors are estimated by averaging this de-trended series. These seasonal indices are used to derive the seasonally adjusted series of EV sales.

Figure 1.3 shows the evolution of the seasonally adjusted sales of Tesla products over time near the three dates of the phase-out. The dotted red lines refer to these dates when federal tax credits were reduced for all Tesla vehicles. The plan for this phase-out was first announced in July 2018. Since then, new sales of Tesla vehicles have risen quite sharply till the peak just before the first announced drop in January 2019. Similarly, the repeated

Figure 1.3: Seasonally Adjusted Sales of Tesla Vehicles over Time



Notes: In July 2018, Tesla announced that it sold 200,000 qualifying EVs, and the federal tax credits would start to phase out on January 1st, 2019.

pattern of increases and peaks was observed before the second and the third drop in tax credits. Moreover, the magnitude of the surge in the adjusted sales is the highest in the first phase-out. This may be because only Tesla vehicles purchased before 2019 could receive the full tax credit, and the amount of reduction in tax credits, which was $\$3,750$, is the largest in the first drop.

To examine whether this trend in Figure 1.3 is caused by other macroeconomic (or exogenous) variables, which would affect all electric vehicle models, I show how the seasonally adjusted sales of other vehicles[9] were changing in the same time period. Figure 1.A.2 illustrates that the pattern of sudden increases is missing near the red lines. The sales of other

[9]These vehicles exclude all EVs manufactured by Tesla and GM.

vehicles rather decreased right before January 2019 and January 2020. The adjusted sales were increasing before the second phase-out, but continued to grow even after July 2019. Such difference in the evolution of adjusted sales in this period indicates that consumers anticipate the decrease in the expected utility of postponing the purchase of Tesla vehicles due to the phase-out of tax credits in the future. This is also evident in Figure 1.A.3. Before the announced drops in tax credits, the adjusted sales of Chevrolet vehicles increase to reach a peak and thus show the similar pattern as in Figure 1.3.

Additionally, I employ a regression approach to measure how consumers' current decisions depend on the anticipated change in subsidies and assess the impact of subsidies on EV adoption. I model the logarithm of new electric vehicle sales as a function of the price, two financial incentives, a set of vehicle characteristics, and a set of time and model fixed effects. That is, for each electric vehicle model j at time t, I model its log of sales ($\ln S_{jt}$) as follows:

$$\ln(S_{jt}) = \alpha - \beta_1 p_{jt}^{net} + \beta_2 X_{jt} + \beta_3 \Delta Subsidies_{jt+2} + \gamma_j + \delta_t + \epsilon_{jt} \tag{1.1}$$

The set of vehicle characteristics, X_{jt}, includes the ratio of horsepower to weight, size, fuel efficiency, and range. p_{jt}^{net} is the net price consumers pay to purchase vehicle j after receiving both rebates and tax credits, which is equal to $p_{jt} - \text{Rebate}_{jt} - \text{FTC}_{jt}$. The state rebate in New York is discounted directly from the price at the point of sale, so I set the coefficients of the price and the rebate to be equal. In equation 1.1, I make an assumption that the effects of rebates and tax credits on EV sales are equivalent and thus restrict the coefficients to be the same as well.[10] $\Delta Subsidies_{jt+2}$, which is one of the key variables of interest, refers to the expected change of subsidies for vehicle j within the next month.[11]

[10] I relax this strong assumption in the next section to allow for the unequal impact of each subsidy.

[11] Note that each period here represents a bi-week. For example, as it was pre-announced that federal tax credits would decrease from \$7,500 to \$3,750 for Tesla Model 3 on January 1st, 2019, $\Delta Subsidies_{jt+2}$ for Tesla Model 3, where t is in December 2018, is equal to -\$3,750. Also, since the plan of the electric vehicle rebate program in New York was predetermined and announced 1 year before April 2017, $\Delta Subsidies_{jt+2}$ for Ford Focus Electric, where t is in March 2017, is equal to \$1,700.

Due to potential endogeneity issues with prices, I address this concern by taking an instrumental variable (IV) approach. To account for the possible correlation between prices and unobserved demand characteristics, I estimate the above equation using the Generalized Method of Moments (GMM).[12] For instrumental variables for the price, I use exogenous vehicle characteristics and the sum of each characteristic of other EV models in the same market. These instruments vary a lot across vehicles in the sample because there is sufficient variation in the choice set across time.

Table 1.4 presents the IV-GMM regression results. All estimation results here include the full set of fixed effects. Column (1) reports the regression as in equation 1.1. Column (2) contains all the same regressors, but alters $(\Delta Subsidies)_{jt+2}$ to $(\Delta Subsidies)_{jt+4}$, which is the expected change of subsidies for product j within the next two months. In both cases, net price is negatively correlated with lower sales of EVs, implying that the impact of federal tax credits and tax rebates on EV adoption is positive and statistically significant. The point estimates in Table 1.4 suggest that each thousand dollar of financial incentive is associated with an increase in new EV sales by approximately $2.5 \sim 2.65\%$. This finding indicates that monetary incentives are effective in promoting EV purchases. However, there is a potential concern that the strong assumption on the same coefficients of both direct rebates and tax credits might have diluted the degree of the price (or rebate) coefficient. I address this concern by allowing different coefficients and quantify the impact of each incentive in the next section.

More interestingly, the reduced form analysis finds that an anticipated change in the amount of subsidies in the near future is significantly and strongly related to new EV sales in the current market. The first specification shows that holding all others constant, the

[12]The IV-GMM estimator and its robust standard errors are computed as follows.

$$\hat{\beta}_{GMM} = (X'Z\hat{S}Z'X)^{-1}X'Z(\hat{S}^{-1})Z'y, \; V(\hat{\beta}_{GMM}) = (X'Z\hat{S}^{-1}Z'X)^{-1}$$

where $\hat{S}$ is a consistent estimator of the covariance matrix of the moment conditions.

Table 1.4: Empirical Analysis of Financial Incentives and Consumers' Forward-Looking Behaviors

Dependent Variable:	log(Sales)	
	(1)	(2)
Net price (\$1,000)	-0.0265^{*}	-0.0249^{*}
	(0.0142)	(0.0145)
Expected change of subsidies	-0.3039^{***}	
within a month (\$1,000)	(0.0472)	
Expected change of subsidies		-0.2052^{***}
within two months (\$1,000)		(0.0427)
Model FE	Y	Y
Time FE	Y	Y
Observations	2798	2798
R^2	0.66	0.66
Adjusted R^2	0.65	0.65

Note: Robust standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The table above reports the IV-GMM coefficient estimates and standard errors from the descriptive analysis of EV incentives and consumers' dynamic behaviors. The dependent variable is log of new electric vehicle sales. Net price here is equal to price minus the sum of all subsidies, which are rebates and tax credits. All regressions include time and model fixed effects.

expectation of a \$1,000 decrease in any type of financial incentive within the next month is associated with a 30.4% increase in current EV purchases. Even in the second specification where the term of the near future is extended to two months, I find a statistically significant, negative relationship between an expected change of subsidies and EV sales. If consumers anticipate that EV subsidies will increase by $\$1,000$ within the next two months, it is estimated that current EV sales will decrease by 20.5%. These results provide evidence on the dynamic nature of households' consumption problem in this EV market.

To check the robustness of the analysis, I run additional reduced form regressions in which there is a variation in the fixed effects. I keep the same explanatory variables as in equation 1.1. Columns (1) and (2) in Table 1.B.1 report these estimation results of the key variables. First, all specifications show a negative and statistically significant correlation between net price and EV sales. That is, both tax credits and rebates are positively correlated with EV sales. However, the coefficient ranges from 0.88% to 2.65%. Along with the strong assumption on the coefficients of tax credits and rebates, this suggests that a more thorough investigation is needed to evaluate the effectiveness of each subsidy better. Table 1.B.1 also shows that the expected decrease in subsidies within a month is strongly associated with an increase in EV sales in all specifications. As the effect of such anticipation on current EV sales is estimated to be at least 27.8% per thousand dollars, it implies that consumers are dynamically optimizing their purchasing decisions. In short, a change in the expected utility of purchasing an EV in the future affects consumers' current decisions on whether to adopt an EV or postpone it.

1.3.2 Descriptive Analysis of Incentive Effects by Each Type

This section studies whether consumers' responses differ depending on the type of financial incentive. As discussed before, there are two major differences between direct rebates and tax credits. Unlike rebates, monetary benefits from tax credits are not collected right away at the time of purchase. Also, consumers do not receive the total amount of available tax credits when their tax liabilities are less than credits. Hence, consumers may have a different perception of the value of $\$1,000$ in rebates compared to $\$1,000$ in federal tax credits.

Based on the empirical evidence of consumers' dynamic responses, I estimate the effect of each subsidy on EV sales using the same set of control variables, including the expected change of subsidies in the near future. In the following equation, I differentiate between the two financial incentives by allowing the coefficients of the price (or rebate) and the tax credits to be distinct.

$$\ln(S_{jt}) = \alpha - \beta_1 p_{jt}^{net} + \beta_2 FTC_{jt} + \beta_3 X_{jt} + \beta_4 (\Delta Subsidies)_{jt+2} + \gamma_j + \delta_t + \epsilon_{jt} \tag{1.2}$$

X_{jt} refers to the same set of vehicle characteristics. p_{jt}^{net} here represents the net price consumers actually pay at the point of sale, which is calculated by subtracting the rebate from the original price p_{jt}, and FTC_{jt} is the amount of federal tax credits eligible for vehicle j. To avoid concerns about the possibility of a correlation between prices and unobserved characteristics, I estimate equation 1.2 with the IV-GMM estimation with the fixed effects as before.

Table 1.5 reports the GMM estimates of the key variables in the above equation. Column (1) presents the results of the regression using $(\Delta Subsidies)_{jt+2}$, while Column (2) presents those using $(\Delta Subsidies)_{jt+4}$. It is noteworthy that the expected change of subsidies in the near future still has a significantly and strongly negative correlation with new EV sales in these regressions. According to the estimation, EV sales in the current period is expected to rise by 28.4% (or 18.2%) when consumers anticipate a $\$1,000$ decrease in EV subsidies in the next month (or two months). This reiterates that in the EV market, consumers are forward-looking and take into account changes in future benefits when making their current purchase decision.

The first two coefficients in Table 1.5 present the results of the impact of subsidies broken down by each financial incentive type. The estimates for the effect of direct rebates on EV sales are statistically significant and positive. They suggest that for every thousand dollars of rebates, there is a $3.9 \sim 4.1\%$ increase in new EV purchases. I also find a significant and positive effect of tax credits. However, the effect is much smaller than that of rebates. On average, a $\$1,000$ increase in federal tax credits is associated with only a 1.3% increase in EV

Table 1.5: Empirical Analysis of Financial Incentives by Incentive Type and Consumers' Forward-Looking Behaviors

Dependent Variable:	log(Sales)	
	(1)	(2)
Net price ($1,000)	-0.0412^{***}	-0.0394^{***}
	(0.0138)	(0.0141)
Tax credits ($1,000)	0.0128^{***}	0.0127^{***}
	(0.0019)	(0.0019)
Expected change of subsidies	-0.2844^{***}	
within a month ($1,000)	(0.0480)	
Expected change of subsidies		-0.1820^{***}
within two months ($1,000)		(0.0408)
Model FE	Y	Y
Time FE	Y	Y
Observations	2798	2798
R^2	0.67	0.67
Adjusted R^2	0.66	0.66

Note: Robust standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The table above reports the IV-GMM coefficient estimates and standard errors from the descriptive analysis of EV incentives and consumers' dynamic behaviors. The dependent variable is log of new electric vehicle sales. Net price here is equal to price minus rebate. All regressions include time and model fixed effects.

sales. This aligns with my intuition that consumers view the same amount of dollars from rebates and tax credits differently, leading to different responses to each policy. Furthermore, consistent with the literature (Gallagher and Muehlegger, 2011)[13], my findings indicate that rebates provided at the point of sale are more successful in promoting EV sales, as opposed to tax credits given at the end of the tax year. There are two potential reasons behind this empirical evidence that consumers are more responsive to direct rebates than tax credits. First, while direct rebates are immediately enjoyed at the point of the sale, tax credits are claimed in the future so that consumers might discount the value of the tax incentive. Second, whereas all consumers enjoy the full value of direct rebates, consumers might not be able to collect the full value of tax credits depending on the status of their tax liability.

Table 1.B.2 presents the outcome of supplementary IV regressions with different fixed effects. In all specifications, both types of incentives have a positive correlation with EV sales, but the impact of rebates is estimated to be larger than that of tax credits. This reduced form analysis thus provides concrete evidence both for the positive correlation between financial incentives and EV adoption and the varying impacts of subsidies based on their type. To further assess and compare the effectiveness of each financial incentive at alternative government budget levels, I take a structural approach in the next chapter. I build a dynamic demand model for electric vehicles, taking into account the key characteristics of the EV market in New York highlighted in this section. I use this model to conduct counterfactual simulations to recover the impact of each financial incentives by changes in the number of EV sales and government spending in each scenario.

[13]Gallagher and Muehlegger find that a type of tax incentive which has an immediate effect, such as tax waivers, is more effective than tax credits in the hybrid vehicle market.

APPENDIX

1.A Figures

Figure 1.A.1: Number of Models and Brands over Time

Figure 1.A.2: Seasonally Adjusted Sales of Other Vehicles over Time

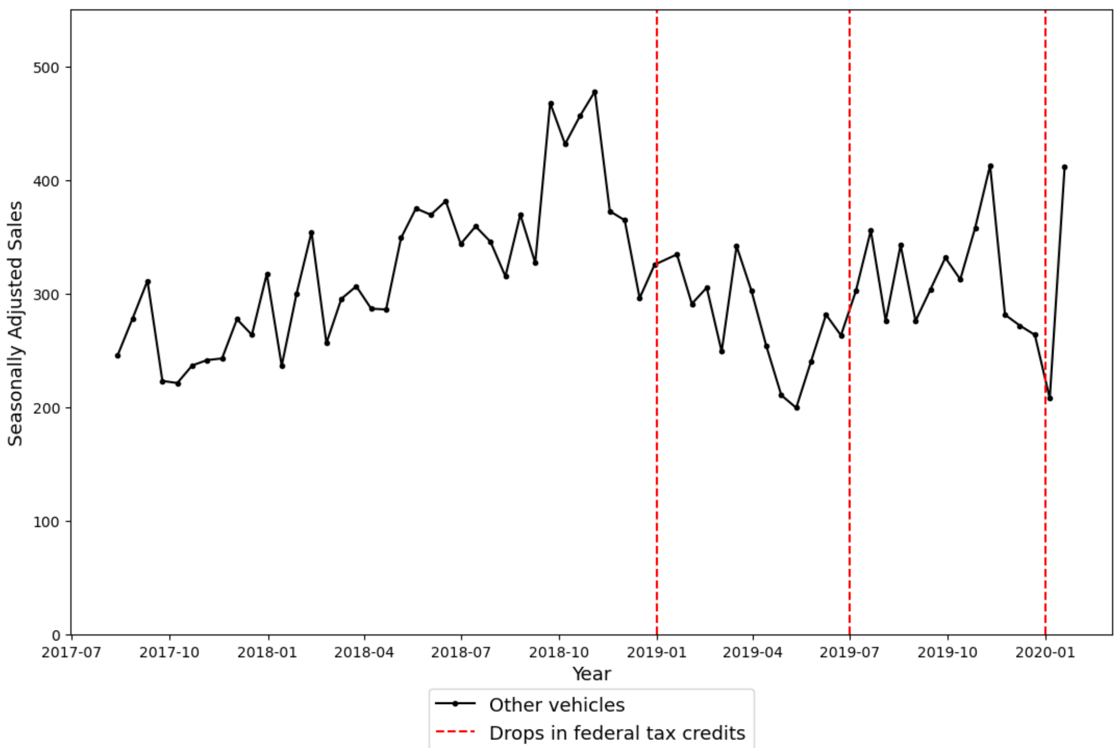
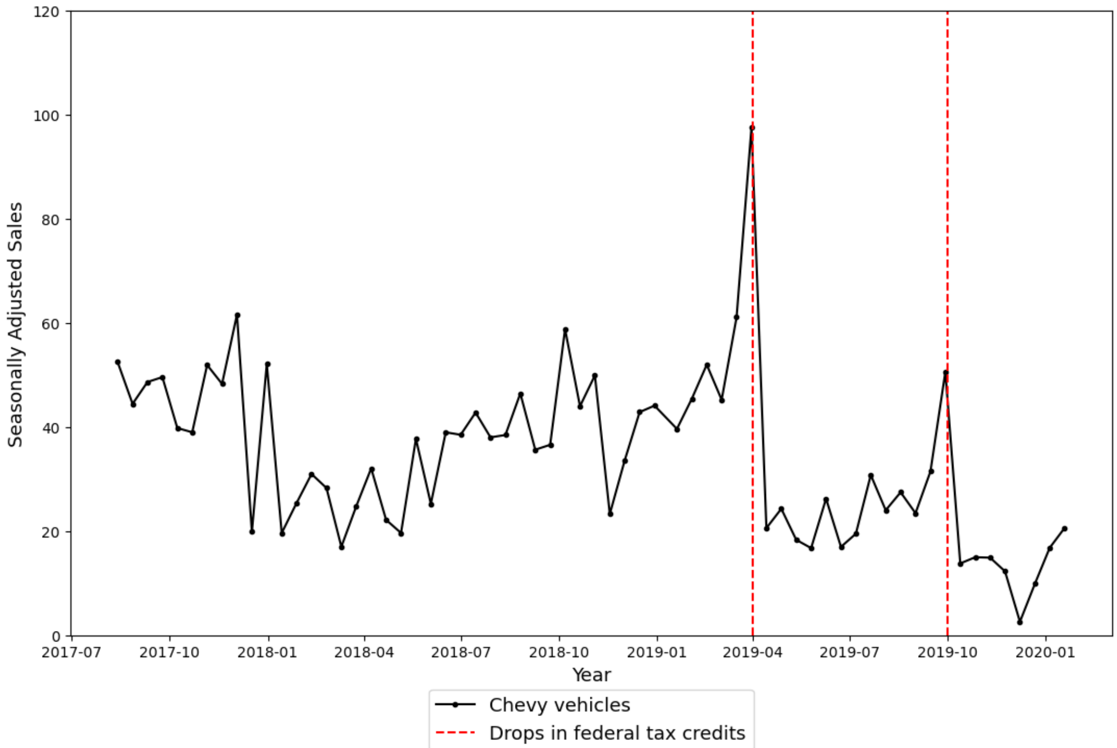


Figure 1.A.3: Seasonally Adjusted Sales of Chevrolet Vehicles over Time



Notes: In Nov 2018, GM announced that it sold 200,000 qualifying EVs, and the federal tax credits would start to phase out on April 1st, 2019.

1.B Tables

Table 1.B.1: Robustness Check : Different Specifications

Dependent Variable:	log(Sales)		
	(1)	(2)	(3)
Net price ($1,000)	-0.0088^{***}	-0.0139^{**}	-0.0265^{*}
	(0.0041)	(0.0066)	(0.0141)
Expected change of subsidies	-0.2784^{***}	-0.3739^{***}	-0.3039^{***}
within a month ($1,000)	(0.0577)	(0.0633)	(0.0472)
Model FE	Y	N	Y
Time FE	N	Y	Y
Observations	2798	2798	2798
R^2	0.51	0.43	0.66
Adjusted R^2	0.51	0.42	0.65

Note: Robust standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The table above reports the IV-GMM coefficient estimates and standard errors from the descriptive analysis of EV incentives and consumers' dynamic behaviors. The dependent variable is log of new electric vehicle sales. Net price here is equal to price minus the sum of all subsidies, which are rebates and tax credits. All regressions include time and model fixed effects.

Table 1.B.2: Robustness Check : Different Specifications

Dependent Variable:	log(Sales)		
	(1)	(2)	(3)
Net price ($1,000)	-0.0147^{***}	-0.0335^{***}	-0.0412^{***}
	(0.0042)	(0.0097)	(0.0138)
Tax credits ($1,000)	0.0080^{***}	0.0019	0.0128^{***}
	(0.0019)	(0.0027)	(0.0019)
Expected change of subsidies	-0.2862^{***}	-0.3179^{***}	-0.2844^{***}
within a month ($1,000)	(0.0588)	(0.0650)	(0.0480)
Model FE	Y	N	Y
Time FE	N	Y	Y
Observations	2798	2798	2798
R^2	0.51	0.39	0.67
Adjusted R^2	0.50	0.38	0.66

Note: Robust standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The table above reports the IV-GMM coefficient estimates and standard errors from the descriptive analysis of EV incentives and consumers' dynamic behaviors. The dependent variable is log of new electric vehicle sales. Net price here is equal to price minus rebate. All regressions include time and model fixed effects.

CHAPTER 2

Financial Incentives on Diffusion of Electric Vehicles: Dynamic Discrete Choice Model

2.1 Introduction

In the previous chapter, I find descriptive evidence that direct rebates have a greater impact on consumer behavior in the New York EV market than tax credits. This implies that direct purchase subsidies could be a more effective means of promoting EV sales than tax credits. However, the effectiveness of these incentives may vary at different levels of government spending. Therefore, it is necessary to conduct a more rigorous analysis of the impact of rebates and tax credits at alternative spending levels through counterfactual simulations. In this chapter, I employ a structural approach to empirically quantify the disparity in the impact of each subsidy.

Additionally, in Chapter 1, I find that consumers' purchasing decisions not only depend on their valuation of electric vehicle attributes, such as price, driving range, and subsidies, but also on consumers' expectation about the future. Also, during the sample period, as illustrated in Table 1.2 and Figure 1.2, the EV market has experienced rapidly changing prices and quality, such as the EV battery range. Given such nature of the EV industry, using the dynamic demand model to analyze the impact of different subsidies is crucial. In this market, forward-looking consumers' purchasing decisions depend on both the characteristics of available products and the expectations about future choice sets and characteristics. If prices are expected to fall and ranges are likely to improve in the future, consumers have incentives to delay their adoption of EVs. Then, a static model, which does not account for dynamic behaviors, might underestimate the price elasticity and thus the impact of each subsidy.

Moreover, there were revisions of financial incentives in the EV industry, which include pre-announced entry of rebates and phase-out of tax credits. When consumers know beforehand about an exit of a subsidy, forward consumers might decide to purchase EVs earlier. In this case, the static model might overestimate the price elasticity and subsidy impact. Thus, if consumers are forward-looking, a dynamic demand model is essential for evaluating subsidy policies. To capture these decision-making processes, I develop a dynamic discrete choice model for the demand for electric vehicles in New York. Quantifying how the market outcomes change with different levels of subsidies in counterfactual scenarios first requires recovering estimates of consumer taste and a discount factor in this structural model.

In the dynamic model, consumers may either choose to purchase one of the available electric vehicle models or to wait in each period. I model the purchasing decision as a terminating action,[1] where consumers receive flow utility of the chosen vehicle model as in a typical random coefficients discrete choice model (Berry et al, 1995). Following the fact that monetary benefits from tax credits are delayed till the end of the tax year, I assume that consumers discount the benefits from tax credits. On the other hand, not adopting provides consumers with the flow utility of outside options and the option value of adopting EVs in the future. As consumers form expectation about future states to evaluate this option value of waiting, I specify this expectation as a Markov process. In the specification of the main model, consumers expect that the value of future purchases depends on the value of current purchases and the anticipated changes in subsidies in the future.

[1] According to the Bureau of Transportation Statistics, the average age of all light vehicles is 11.7 years, and the percentage of vehicles older than 5 years is 85.05%. This implies that a majority of consumers in this industry will choose not to replace their old vehicle with a new vehicle model within 5 years, which is the duration of time in this paper.

To estimate this BLP-style demand model within the dynamic framework, I follow a similar estimation procedure in Gowrisankaran and Rysman (2012). I use a GMM estimation method in which the GMM objective is constructed with unobserved quality and instrumental variables to deal with a potential endogeneity issue of price. The key distinction from Gowrisankaran and Rysman (2012) is an estimation of a discount factor. Along with coefficients of consumer tastes for EV characteristics, this paper estimates a discount factor additionally. Past literature on the dynamic structural model emphasizes the difficulty in identifying the discount factor (Manski, 1993, Rust, 1994, Magnac and Thesmar, 2002). The discount factor could be identified in a setting where consumer valuations change in response to variation that affects future utilities only, not current utilities. In this chapter, large variations in biweekly EV sales on dates before the entry of rebates or multi-step exit of tax credits in our data give the source of identification of the discount factor. This source allows me to estimate a statistically significant discount factor using the estimation method above.

In the estimation procedure, I examine several specifications of the model, such as a static model, two dynamic discrete choice models with different equations of consumer expectation, and the main model explained above. The estimation results provide important implications. First, the estimated price coefficient in the dynamic framework is significantly different from that in the static framework. When consumers are optimizing their choices dynamically, this implies the possibility of bias in static estimates of price elasticity, which could result in an incorrect evaluation of the impact of purchase subsidies. Another implication is that the annual discount factor in the main model is estimated to be 0.8244, which differs significantly from 1. The value of the estimated discount factor is different in the two dynamic models with different specifications of consumer expectation. In those two models, I specify consumers to form predictions of the value of purchases still based on the current value but not on the expected change in future subsidies. This result highlights the importance of making a realistic specification of consumer expectation for estimating the discount factor in the dynamic discrete choice model. Since the descriptive evidence illustrates that consumer demand largely reacts to changes in available subsidies in the future, I choose the specification of consumer expectation in the main model.

With the estimated dynamic demand model, I study the impact of two financial incentives on EV adoption in New York between 2015 and 2020. I first conducted simulations of three hypothetical scenarios, each of which removed either tax credits or state rebates entirely. Then, I compare total EV sales and government spending in each scenario to assess the average impact of tax incentives and rebates respectively. The results of these simulations demonstrate that due to the difference in government spending on each subsidy, tax credits alone would have led to an increase of 15206 EV sales, while rebates alone would have only resulted in an increase of 3088 EV sales. However, when considering the average impact of each incentive per million dollars spent, direct rebates were found to be significantly more effective than tax credits. Specifically, direct rebates resulted in promoting an additional 918 EV purchases per $10 million, while tax credits only led to an increase of 582 EV sales per $10 million.

In the second set of simulations, I compare the impact of the two subsidies at alternative government spending levels. Based on the simulation results, the difference in the average effectiveness between rebates and tax credits decreases at higher spending levels, but direct rebates are still more effective than tax credits at alternative levels. This implies that the government could have saved their budget and accomplished the same level of EV adoptions in New York by focusing a more effective policy tool, direct purchase subsidies. The simulations estimate that 23% of the current subsidy costs would have been saved. This finding is largely due to the fact that consumers tend to undervalue the future benefits of tax credits and discount them with an annual implicit interest rate of 21.30%, leading to a smaller impact on EV sales than direct rebates, which provide an immediate reduction in the cost of purchase.

This chapter relates to the vast discrete choice literature that models consumer decisions for differentiated products, such as Berry et al (1995). Specifically, this study contributes to literature using dynamic discrete choice models for durable goods. Gowrisankaran and Rysman (2012) estimate a dynamic demand model of digital camcorders with model-level data. I use a similar estimation method with the assumption of inclusive value sufficiency to estimate the dynamic demand of electric vehicles. This allows me to account for the timing dimension of consumers' EV purchase decisions and evaluate the policies of EV subsidies in the dynamic framework. The dynamic model here additionally estimates the discount factor along with the coefficients. Bollinger (2015) and De Groote and Verboven (2019) demonstrate in their studies of green technology adoption that variation in current choice decisions in response to regulations that only affect their future expenses can provide a source of identification in discount factor. In my setting, to identify the discount factor, I exploit large variations in consumer responses to anticipated changes in future financial incentives over time, which only affects future utilities.

This chapter also contributes to the literature that examines the impact of environmental government policies in the automobile market using the structural approach. Based on the estimation of a static, discrete choice model, Xing, Leard, and Li (2021) investigate the effectiveness of federal tax credits on promoting electric vehicle sales in the U.S. between 2010 and 2014. Springel (2021) studies the impact of financial incentives in the two-sided structural framework with network externalities using data on the Norwegian EV market. While these previous studies assume that the type of incentives has no effect on EV sales, I account for descriptive evidence (from Chapter 1) that demonstrates the difference in the effectiveness of subsidies on EV purchases between rebates and tax credits. This follows the discussions in Gallagher and Muelegger (2011) and Beresteanu and Li (2011), which emphasize importance on the types of monetary incentives as well. Using the estimated discount factor in the dynamic discrete choice model, this chapter thus studies the impact of rebates and tax credits respectively to compare the cost-effectiveness of each policy.

2.2 Model

In this section, I develop a dynamic model of consumer preferences for electric vehicles. In each period, a consumer chooses either to purchase a new EV among the available vehicle models or to delay the purchase. If the consumer chooses not to purchase any EV in the current period, she has an option to purchase in the next period. Though the consumer discounts the future, this option allows her to purchase at a later period when prices decrease, qualities improve, or subsidies increase. I specify a purchasing decision as a terminating action. That is, a consumer neither has multiple holdings of EVs nor replaces an old EV with a new EV.[2]

Along with the discrete choice model of demand for EVs, I specify how consumers expect the states of the industry to evolve in the future. Based on the assumption that consumers are on average correct about the future states, I model consumers' belief on the evolution of the future states as a linear autoregressive equation. This specification enables the computation of expected ex-ante value function for consumers and subsequently, the estimation of parameters in the dynamic demand model.

2.2.1 Conditional Indirect Utility

At time $t = 0$, a consumer i holds the outside good. In each time period $t \geq 1$, a consumer may choose to buy one of the available alternatives, $j = 1, ..., J_t$ or not purchase any model, $j = 0$. If the consumer chooses one of the alternatives j at time t, she obtains a utility of $u_{ijt} = v_{ijt} + \varepsilon_{ijt}$ where v_{ijt} is the conditional value for consumer i choosing alternative j at

[2]Based on 2017 National Household Travel Survey (NHTS) from the U.S. Department of Transportation, a percentage of households holding multiple electric vehicles in the U.S. is less than 1%.

time t, and ε_{ijt} is a random taste shock with a type I extreme value distribution. I assume that ε_{ijt} is independent and identically distributed across alternatives and time periods so that it represents random taste variations each consumer experiences for j at time t.

Since I assume that purchasing any EV model is a terminating action, I formalize the conditional value of purchasing j as follows:

$$v_{ijt} = X_{jt}\alpha_i^x - \alpha_i^p p_{jt}^{net} + \xi_{jt}, \quad j = 1, ..., J_t \tag{2.1}$$

where X_{jt} is a vector of the observed product characteristics of vehicle model j at period t; p_{jt}^{net} is the net price after subtracting state rebates and discounted federal tax credits; ξ_{jt} is the unobserved product characteristic. X_{jt} contains the ratio of horsepower to weight, size, fuel efficiency, and range. The net price p_{jt}^{net} is defined as a function of the product price p_{jt}, the state rebates s_{jt}^{Rebate}, the federal tax credits s_{jt}^{FTC}, and the biweekly discount rate β.

$$p_{jt}^{net} = p_{jt} - s_{jt}^{Rebate} - \beta^{E_t - t} s_{jt}^{FTC} \tag{2.2}$$

where E_t is the time period indicating the end of the tax year. As the rebates are deducted from the vehicle price at the point of the sale, I subtract the rebates directly from p_{jt}. On the other hand, consumers would have to wait till the end of the tax year to enjoy the financial benefits from federal tax credits, so I include the discounted future benefits from tax credits.[3]

Decomposing individual-specific taste coefficients on product characteristics and the net price, I can rewrite equation (2.1) as follows:

$$v_{ijt} = X_{jt}\alpha^x - \alpha^p p_{jt}^{net} + \xi_{jt} + X_{jt}\sigma^x z_i^x - \sigma^p p_{jt}^{net} z_i^p \tag{2.3}$$

$$= F_{jt} + X_{jt}\sigma^x z_i^x - \sigma^p p_{jt}^{net} z_i^p \tag{2.4}$$

(z_i^x, z_i^p) are unobserved individual characteristics that interact with product characteristics and price and are assumed to follow a standard multivariate normal distribution. F_{jt} is the mean utility that any household enjoys from consuming j at time t.

[3]A more general structural model would be to set different coefficients for rebates and tax credits respectively. This would account for other potential factors on how consumers value two incentives differently, such as reduction in benefits from tax credits depending on tax liability.

Even if a consumer does not purchase any EV model at time t, she has an option to delay and purchase an EV in future. That is, the conditional value of not purchasing is the sum of the flow utility in period t, F_{0t}, and the option value of waiting:

$$v_{i0t} = F_{0t} + \beta E[\bar{V}_i(M_{t+1})|M_t] \tag{2.5}$$

where M_t is the market state at time t, and $\bar{V}_i(.)$ is the ex-ante value function before the realization of random taste shocks. M_t includes all variables influencing consumers' purchasing decisions at time t, such as the number of available models J_t, prices p_{jt}, product attributes X_{jt}, subsidies, and any other factors affecting the future vehicle characteristics such as changes in subsidies in the future.[4] $\bar{V}_i(M_{t+1})$ thus represents the continuation value the consumer i expects to receive when she makes optimal decisions from period $t+1$ onward given the information about M_{t+1}. Lastly, since I assume that consumers do not replace their old products with new products here, all potential consumers at t hold the outside good initially, implying that F_{0t} can be normalized to zero.

2.2.2 Consumer Dynamic Optimization Problem

Given the industry state M_t and realized taste shocks $\{\varepsilon_{jt}\}_{j=0}^{J_t}$, the consumer's problem in each period t is to maximize her indirect utility by choosing the optimal choice among $J_t + 1$ options. Using the indirect utilities derived in the previous section, I specify the Bellman equation that states this consumer problem as follows:

$$V_i(M, \{\varepsilon_j\}_{j=0}^{J}) = \max_j \{\beta E[\bar{V}_i(M')|M] + \varepsilon_0, \max_{j=1,\dots,J}\{F_j + X_j\sigma^x z_i^x - \sigma^p p_j^{net} z_i^p + \varepsilon_j\}\} \tag{2.6}$$

where t subscript is dropped, and M' denotes the industry state in the next period. Since $\bar{V}_i$ captures the value that consumer i expects to enjoy before the unobserved taste shocks are

[4] Figure 1.A.1 and Figure 1.2 in Chapter 1 show how prices, ranges, and the number of models were changing quite rapidly in the New York EV market during the sample period.

realized, I obtain this ex-ante value function by integrating equation (2.6) with respect to $\vec{\varepsilon}$.

$$\bar{V}_i(M) = \int \max_j\{\beta E[\bar{V}_i(M')|M] + \varepsilon_0, \max_{j=1,...,J}\{F_j + X_j\sigma^x z_i^x - \sigma^p p_j^{net} z_i^p + \varepsilon_j\}\}g(\vec{\varepsilon})d\vec{\varepsilon} \quad (2.7)$$

$$= \ln[\exp(\beta E[\bar{V}_i(M')|M]) + \sum_{j=1}^{J} \exp(F_j + X_j\sigma^x z_i^x - \sigma^p p_j^{net} z_i^p)] \quad (2.8)$$

where $g(.)$ is the joint density function of $\vec{\varepsilon}$. Under the assumption of the i.i.d. type I extreme value distribution of ε_js, I derive the closed form solution of the ex-ante value function as equation (2.8).

In the spirit of Gowrisankaran and Rysman (2012), I use the definition of the logit inclusive value to reduce the dimensionality of this dynamic problem. Let δ_i denote the logit inclusive value, which is equal to

$$\delta_i(M) = \ln(\sum_{j=1}^{J} \exp(F_j + X_j\sigma^x z_i^x - \sigma^p p_j^{net} z_i^p)) \quad (2.9)$$

This represents the ex-ante value of purchasing the electric vehicle model that gives the highest indirect utility to consumer i.[5] Then, I can rewrite equation (2.8) as follows

$$\bar{V}_i(M) = \ln[\exp(\beta E[\bar{V}_i(M')|M]) + \exp(\delta_i(M))] \quad (2.10)$$

Equation (2.10) shows that current values of δ_i and predictions of future values of δ_i are sufficient statistics to determine the ex-ante value function.[6] Finally, to further simplify the state space, I introduce the inclusive value sufficiency assumption.

Assumption 1 *Inclusive Value Sufficiency (Gowrisankaran and Rysman (2012))*
If $\delta_i(M) = \delta_i(\tilde{M})$, then $g_{\delta_i}(\delta_i(M')|M) = g_{\delta_i}(\delta_i(\tilde{M}')|\tilde{M})$ where $g_{\delta_i}(.)$ is the density of the logit inclusive value.

This assumption implies that if two market states provide the same logit inclusive value, then a consumer expects the same distribution of future logit inclusive values from those

[5] $\int \max_{j\geq 1}\{F_j + X_j\sigma^x z_i^x - \sigma^p p_j^{net} z_i^p + \varepsilon_j\}g(\vec{\varepsilon})d\vec{\varepsilon} = \ln(\sum_{j=1}^{J} \exp(F_j + X_j\sigma^x z_i^x - \sigma^p p_j^{net} z_i^p))$

[6] The proof is provided in the appendix of Gowrisankaran and Rysman (2012).

market states. That is, the consumer would receive the same ex-ante value $\bar{V}_i$ from the two states. Thus, equation (2.10) can be simplified as:

$$\bar{V}_i(\delta_i) = \ln[\exp(\beta E[\bar{V}_i(\delta_i')|\delta_i]) + \exp(\delta_i)] \tag{2.11}$$

I discuss consumer's rational expectation on how the logit inclusive value evolves in the next section. Given the specification of the rational expectation, I can compute the option value of waiting and thus the ex-ante value V_i. Then, with the assumption of the type I extreme value distribution for ε_js, the choice probability of product $j = 1, ..., J$ by consumer i is given as follows:

$$s_{ij}(\delta_i, F_j, X_j, p_j^{net}) = \frac{\exp(F_j + X_j\sigma^x z_i^x - \sigma^p p_j^{net} z_i^p)}{\exp(\bar{V}_i(\delta_i))} \tag{2.12}$$

And the probability of not purchasing any product is given as:

$$s_{i0}(\delta_i, F_j, X_j, p_j^{net}) = \frac{\exp(\beta E[\bar{V}_i(\delta_i')|\delta_i])}{\exp(\bar{V}_i(\delta_i))} \tag{2.13}$$

2.2.3 Consumer Expectation

I assume that consumers form rational expectation about how the industry state will evolve over time. During the early stages of the electric vehicle industry, it was common for consumers to anticipate that prices would decrease and driving ranges would increase with time. Given that these advancements have indeed occurred in the EV industry, as discussed in Chapter 1, I assume that consumer's expectations for future progress in the industry is on average accurate. However, to be more realistic, I acknowledge the limited capacity of consumers to predict the state of the industry in the future.

Additionally, I assume that consumers' projections for the value of the industry in the next period are based not only on its current value, but also on expected changes in subsidies, such as the introduction of new rebates or the elimination of existing tax credits in the future. This consideration takes into account the fact that changes in subsidy policies are often announced well in advance, allowing consumers to be aware of such changes beforehand. If a consumer anticipates an increase in subsidies in the future, it is rational to believe that the logit inclusive value in the next period will also increase.

Therefore, for the baseline model, I formulate consumer's rational expectation as follows:

$$\delta_{it+1} = \gamma_{i1} + \gamma_{i2}\delta_{it} + \gamma_{i3}ES_t + \eta_{it+1} \tag{2.14}$$

where η_{it+1} is consumer i's prediction error about the future state, and ES_t is the weighted sum of anticipated changes in subsidies. η_{it+1} is assumed to follow the normal distribution with mean 0 to reflect that consumers are correct on average. Additionally, I acknowledge that the expected increase (or decrease) in subsidy for a popular EV model, such as a Tesla product, will impact consumers' predictions differently compared to the expected increase (or decrease) in subsidies for less popular models. To account for this, I utilize the weighted sum of expected changes in subsidies for each product j, where the weights are based on their respective market shares. While it would be more ideal to include the anticipated change in subsidy for each product as a predictor in equation (2.14), I use ES_t in order to make estimation tractable.[7]

This formulation of consumer perceptions about the future enables the calculation of the ex-ante value function, thereby allowing for the solution and computation of each consumer's optimal choice in this dynamic optimization problem.

[7]I examine two additional linear specifications of consumer expectations and later compare the estimation results later to assess the significance of a realistic specification. The first specification assumes that the future logit inclusive value depends solely on its current value, while the second specification substitutes ES_t with $ln(J_t)$ from equation (2.14).

2.3 Estimation and Identification

2.3.1 Identification

In this section, I discuss the source of identification for the structural parameters $\{\alpha^x, \alpha^p, \sigma, \beta\}$ in the dynamic discrete choice model. For identification, I assume that the observed vehicle attributes X_{jt} are exogenously determined by technological progress so that X_{jt} is uncorrelated with the unobserved characteristics ξ_{jt}. Under this exogeneity assumption, the mean coefficient of vehicle characteristics α^x is identified through the variation in market shares in response to the variation in the observed vehicle attributes. To account for the potential correlation between price and the unobserved characteristic, I construct instrumental variables, which provide exogenous variation in price. Following the standard practice in the static discrete choice models, I include the following variables as instruments: exogenous characteristics, the sum of each characteristic of electric vehicle models by the manufacturer and by competing manufacturers in the same period, and the number of available vehicle models by the manufacturer and by competing manufacturers.[8] Since these variables measure the degree of competition in characteristic space in each period, they are assumed to be correlated with price and thus help identify α^p. Along with those instrumental variables, the variation in purchase probabilities corresponding to changes in the choice sets over time identifies the heterogeneity parameters σ.

Magnac and Thesmar (2002) and Abbring and Daljord (2020) show that identification of the discount factor β requires additional exclusion restrictions. If there exists a state that affects future utilities or state transitions but not current utilities, and the state has at least two dimensions, β can be identified. In my context, there is substantial variation in EV sales in response to anticipated changes in subsidies, as evidenced by the seasonally adjusted sales

[8]Since information on the location of each electric vehicle's assembly plant can be extracted using the identified 17-digit VIN number, data on cost-side shifters, such as unit labor costs, can be obtained to include additional instrumental variables for future research.

figures presented in Chapter 1. I formulate consumers' rational expectations as equation (2.14) to take account of the observation that their expectation of subsidy changes solely influences the option value of delaying a purchase, not current utility. I exploit this observed variation in choice responses as an intuitive source of identification on time preference.[9] Moreover, as federal tax credits are future financial benefits, the variation in market shares resulting from differences in tax credits across products and time, relative to rebates and vehicle prices, provides an additional source of identifying β.

2.3.2 Estimation

To summarize, the set of structural parameters that solve the dynamic discrete choice model is $\theta = \{\alpha^x, \alpha^p, \sigma^x, \sigma^p, \beta\}$ where $\alpha = (\alpha^x, \alpha^p)$ is the mean of consumer tastes for vehicle characteristics and price, $\sigma = (\sigma^x, \sigma^p)$ is the standard deviation of consumer taste, and β is the biweekly discount factor. Here, we estimate all parameters including the discount factor. Even though it might be challenging, Magnac and Thesmar (2002) demonstrate that the discount factor in dynamic discrete choice models can be identified if there exists a state variable that impacts only state transitions and not current utilities. This paper employs the anticipated change in subsidies, which influences only future utilities, to identify and estimate the discount factor.

I estimate θ following the standard practice of estimation methods for discrete choice models. I find parameters that minimize the following GMM criterion function subject to

[9] Bollinger (2015) and De Groote and Verboven (2019) discuss a similar identification strategy, which uses variation in choices in response to variation that shifts expected discounted future utilities only.

the equilibrium conditions:

$$\min_{\theta} \quad (Z'\vec{\xi}\,)'W(Z'\vec{\xi}\,)$$

$$\text{s.t.} \quad \delta_{it} = \ln(\sum_{j=1}^{J_t} \exp(F_{jt} + X_{jt}\sigma^x z_i^x - \sigma^p p_{jt}^{net} z_i^p)) \quad \forall i, t \tag{2.9}$$

$$\bar{V}_i(\delta_i) = \ln[\exp(\beta E[\bar{V}_i(\delta_i')|\delta_i]) + \exp(\delta_i)] \quad \forall i \tag{2.11}$$

$$\delta_{it+1} = \gamma_{i1} + \gamma_{i2}\delta_{it} + \gamma_{i3}ES_t + \eta_{it+1} \quad \forall i, t \tag{2.14}$$

$$\xi_{jt} = F_{jt} - (X_{jt}\alpha^x + \alpha^p p_{jt}^{net}) \quad \forall j, t \tag{2.15}$$

$$s_{jt} = \hat{s}_{jt}(\vec{F}, \theta) \quad \forall j, t \tag{2.16}$$

where Z is a matrix of instrument variables, W is a weight matrix, $\vec{\xi}$ is a vector of unobserved product characteristics, s_{jt} is the observed market shares in data, and $\hat{s}_{jt}$ is the predicted market shares from the model. As shown in equations (2.15) and (2.16), ξ_{jt} is the value of the unobserved characteristic which results in the predicted share of model j at time period t matching the observed share.

To compute the GMM criterion function for a given θ, I recover $\vec{\xi}$ that solves the equilibrium conditions above. Here is the procedure for solving $\vec{\xi}$. First, with initial guesses of F_{jt}, σ, and β, and random draws of $z_i = (z_i^x, z_i^p)$[10], I compute conditional values of purchasing each product, v_{ijt}, and logit inclusive values, δ_{it}. Next, I use OLS estimation to estimate the γ_i coefficients in equation (2.14), which allows me to create a transition probability matrix for δ_{it}.[11] Then, I solve the ex-ante value function in equation (2.11) using the standard value function iteration method. Once the logit inclusive values and the values of $\bar{V}_i(\delta_i)$ are obtained, the predicted market share of each model at each time period is calculated as

[10] Importance sampling is used to derive these draws of unobserved individual characteristics.

[11] Details on the discretization of δ_{it} and the corresponding transition matrix are provided in the appendix.

follows:

$$\begin{aligned}\hat{s}_{jt}(\vec{F},\sigma,\beta) &= \frac{1}{N}\sum_{i=1}^{N} h_{it-1}Pr_{it}(j)\\ &= \frac{1}{N}\sum_{i=1}^{N}\{\prod_{k=0}^{t-1}(1-\frac{exp(\delta_{ik})}{exp(V_i(\delta_{ik}))})\}\frac{exp(F_{jt}+X_{jt}\sigma^x z_i^x-\sigma^p p_{jt}^{net}z_i^p)}{exp(\bar{V}_i(\delta_{it}))}\end{aligned} \tag{2.17}$$

where h_{it-1} is the share of consumers of type i holding the outside option till $t-1$, and $Pr_{it}(j)$ is the conditional probability of purchasing j at time t given that a type i consumer holds the outside option till $t-1$.

Since I need to solve for $\vec{F}$ that satisfies equation (2.16), I use the contraction mapping in BLP:

$$F_{jt}^{n+1} = F_{jt}^{n} + (ln(s_{jt}) - ln(\hat{s}_{jt}(\vec{F}^n,\sigma,\beta))) \quad \forall j,t \tag{2.18}$$

I iterate the procedure of computing predicted market shares using the updated $\vec{F}$ and keep updating $\vec{F}$ until $||\vec{F}^{n+1}-\vec{F}^{n}||$ falls below a specified threshold. Lastly, using this $\vec{F}(\sigma,\beta)$ derived from the contraction mapping, I recover $\vec{\xi}$ from equation (2.15). With observed instrument variables, I build the GMM objective function and search for θ that minimizes it. Following Nevo (2000, 2001), I use analytical first-order conditions to solve for the linear parameters α, thereby reducing the search time.[12] The remaining parameters (σ,β) are estimated using a non-linear search algorithm. In the appendix, I provide additional information regarding the estimation algorithms.

2.4 Results

Table 2.4.1 shows the parameter estimates obtained from estimating the structural models using the GMM estimation. The first column (1) represents the full dynamic structural model discussed in the previous section. In this model, the consumer's rational expectation is employed as described in (2.14). On the other hand, the second column (2) illustrates

[12]The optimal α is estimated as a function of (σ,β), $\hat{\alpha} = (X'ZWZ'X)^{-1}X'ZWZ'\vec{F}(\sigma,\beta)$.

the standard static discrete choice model in which the discount rate term in the net price variable is retained. This reflects the fact that consumers does not benefit from tax credits at the point of purchase. To compare the parameter estimates on taste coefficients, I set the discount factor in this static model equal to the estimated value from the first column (1) and use equation (2.1) as the static utility flow each household receives for purchasing an EV.[13] Both specifications account for consumer heterogeneity in taste coefficients on the constant term, price, and range.

The first specification (1) reveals that the estimated coefficient for the mean valuation of price is negative and statistically significant, indicating that customers, on average, prefer lower prices for electric vehicles. Additionally, the estimated standard deviation of consumer taste for price is 2.975. The magnitude of this standard deviation relative to the mean coefficient suggests that there is a significant heterogeneity in consumer preference for price. The positive mean coefficient for the driving range of an electric vehicle is consistent with the intuition that consumers prefer vehicle models with longer ranges. The estimate for standard deviation on the range, however, suggests that there is little variation on consumers' taste for range.[14]

While the static model also estimates a statistically significant and negative price coefficient, the magnitude of this coefficient is considerably smaller than that of the mean price coefficient in the dynamic model. As discussed in Gowrisankaran and Rysman (2012), in industries where the prices of durable goods are decreasing or financial incentives vary over time, the static model may produce biased estimates of the price coefficient. The difference in the price coefficients between the two specifications can be attributed to the static

[13]The standard BLP estimation (IV-GMM method) is utilized to compute the estimates of the static model.

[14]Using the estimated mean and standard deviation coefficients in the first specification, Table 2.B.1 reports a sample of indirect utility and logit inclusive values for individuals with different random coefficients. The average of indirect utility across products and logit inclusive values ($\delta_i t$) are negative for three samples including an individual with all random coefficients at the 75th percentile.

Table 2.4.1: Empirical Results

Variable	Dynamic	Static
	(1)	(2)
Discount Factor	0.9926***	
	(0.048)	
Mean		
Constant	−9.380***	−11.504*
	(0.025)	(5.951)
Price	−7.294***	−2.330***
($10,000)	(0.745)	(0.843)
Range	0.354***	0.174*
(100 mi)	(0.0672)	(0.090)
Miles/$	−0.604***	0.273
(10 mi/$)	(0.013)	(0.308)
Size	0.270***	0.117
(1000 in^2)	(0.024)	(1.497)
HP/Weight	1.097	1.111
(hp/lb)	(1.011)	(1.767)
Standard deviation		
Constant	2.763*	0.255
	(1.618)	(2.724)
Price	2.975***	0.772**
($10,000)	(0.239)	(0.335)
Range	0.016	0.193
(100 mi)	(0.135)	(1.413)

Note: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. For the dynamic model, I assume ξ_{jt} to be correlated over products within each period and to be heteroskedastic across time periods. Both models include brand and time fixed effects.

model's inability to account for consumers' intertemporal substitution. Moreover, several of the estimated coefficients in the static model are not statistically significant.

In the baseline dynamic model, it is estimated that the biweekly discount factor is 0.9926, which implies that consumers annually discount future benefits by 0.8244. The estimated annual implicit interest rate from this discount factor is 21.30%,[15] which is considerably higher than the market interest rates for new vehicle loans observed during the sample period. Between 2015 and 2020, the annual interest rates for car loans were between 4.14 and 5.39%.[16] The high implicit interest rate indicates that consumers in the electric vehicle industry considerably discount future financial benefits, such as tax credits. This implies that consumers may value two types of EV subsidies differently. In the following section, I conduct counterfactual simulations to assess the relative effectiveness of each financial subsidy in the New York EV industry.

As a robustness check, Table 2.B.2 in the Appendix shows the results of estimating the dynamic discrete choice model using various specification choices. The first column (1) is the estimation result of the baseline dynamic model discussed in Table 2.4.1. The second column considers the dynamic model in which consumer heterogeneity in preferences is limited to the constant and price terms, while the third column considers the dynamic model with an additional random coefficient for energy efficiency. In the last column, I consider a specification without the brand dummy variables. The estimation results remain qualitatively very similar across all specifications. The estimated discount factor vary only slightly between 0.9896 and 0.9926. The mean price coefficients are all negative and statistically significant. Also, the estimated standard deviations for the price range from 1.012 to 3.852 and is statistically significant in all specifications, indicating a substantial variation in consumer heterogeneity for taste in price.

[15] Annual implicit interest rate $= \frac{1}{\beta^{26}} - 1$

[16] Information regarding the interest rates for new car loans is obtained from the Board of Governors of the Federal Reserve System (US).

Additionally, I consider two specifications under different assumptions of consumer expectation. The first column in Table 2.B.3 in the Appendix reports the estimated parameters under an assumption that consumers predict the future logit inclusive values based on the current values only. The second column estimates a model in which consumers predict the future logit inclusive values with current values and the log of number of EV models.[17] That is, in these two specifications, I do not account for the observed variation in electric vehicle sales from expected changes in future subsidies and examine how the estimation results are sensitive to the assumptions on the evolution of δ_{it}. First, the estimation results across the two specifications in Table 2.B.3 are very similar. The signs, magnitudes, and statistical significance of the estimates remain consistent in both specifications. This implies that adding the number of vehicle models in the specification of consumer expectation about future does not influence the estimation results. On the other hand, compared to the baseline model, the annual discount factor is estimated to be higher in both specifications. Specifically, the annual implicit interest rate ranges between 10.18% and 11.26%, whereas the implicit interest rate is 21.30% in the baseline model. This difference suggests that the variation in expected changes in subsidies provides an additional source for identifying the discount factor in the baseline model, while the discount factors in Table 2.B.3 are majorly sourced from the variation in future benefits (tax credits) only. As the descriptive evidence from Chapter 1 illustrates that in New York, current consumer demand of electric vehicles largely reacts to anticipated changes of subsidies in future, I choose the specification of consumer expectation as equation (2.14) for the baseline model.

Using the estimated coefficients of the baseline dynamic model in Table 2.4.1, I compute own- and cross-price elasticities that provide insight into substitution patterns between EV models in New York during the sample period. Table 2.4.2 provides a sample of these price

[17] In the first column, the evolution of logit inclusive values follows $\delta_{it+1} = \gamma_{i1} + \gamma_{i2}\delta_{it} + \eta_{it+1}$. In the second column, the evolution of logit inclusive values is equal to $\delta_{it+1} = \gamma_{i1} + \gamma_{i2}\delta_{it} + \gamma_{i3}\ln(J_t) + \eta_{it+1}$, where J_t is the number of available models in each period.

elasticities in the median period in my data, which is September 2017. I estimate these elasticities by simulating how EV sales of each model changes with respect to a permanent 1 percent change in the price. The price increase is assumed to be unexpected before, and consumers realize that the price increase is permanent right at the time.[18]

Table 2.4.2: Sample of Own- and Cross-Price Elasticities

EV Model	i3 REx	Bolt EV	Fusion Energi	Soul EV	B Class	Leaf	Model S	Prius Prime
BMW i3 REx	-4.2952	0.0053	0.0051	0.0054	0.0049	0.0054	0.0000	0.0054
Chev Bolt EV	0.0068	-4.4526	0.0117	0.0125	0.0111	0.0124	0.0001	0.0128
Ford Energi	0.0051	0.0093	-4.1270	0.0096	0.0086	0.0096	0.0000	0.0099
Kia Soul EV	0.0054	0.0101	0.0098	-4.3156	0.0093	0.0105	0.0000	0.0106
Mercedes B-Class	0.0024	0.0053	0.0051	0.0054	-4.4527	0.0054	0.0000	0.0054
Nissan Leaf	0.0050	0.0094	0.0092	0.0098	0.0086	-4.3331	0.0000	0.0100
Tesla Model S	0.0018	0.0044	0.0042	0.0044	0.0040	0.0044	-1.9667	0.0043
Toyota Prime	0.0096	0.0171	0.0168	0.0181	0.0157	0.0180	0.0000	-4.3753

Note: This table reports a sample of own- and cross-price elasticities. Each cell entry (i, j) , where i denotes a row and j denotes a column, gives the percentage change of EV sales of model j with respect to a 1 percent change in the price of model i.

The estimated own-price elasticities of EV models in the sample period range between -1.86 and -4.58. Compared to the previous studies on automobiles that focus on traditional gasoline or hybrid vehicles, such as Berry et al (1995), Beresteanu and Li (2011), and Li (2012), these own-price elasticities are somewhat smaller in magnitude. However, they are much more consistent with the average own-price elasticities found in the electric vehicle literature, such as Li et al (2017), Muehlegger and Rapson (2022), Xing, Leard, and Li (2021), and Springel (2021). The reported own-price elasticties in these studies are approximately

[18]Since the price increase is unknown and unexpected before it is realized at a certain time period, I use the realized δ_{it} with the same estimates of γ_{i1}, γ_{i2}, and γ_{i3}.

between -1.3 and -3.9.

One obvious observation from Table 2.4.2 is that an expensive model, such as Tesla Model S, has much a lower magnitude of the own-price elasticity. For instance, in September, 2017, a permanent 1 percent increase in the price of Tesla Model S results in diminishing sales of Model S by only 1.97%, while a permanent 1 percent increase in the price of Chevy Bolt EV leads to a decrease in sales of Bolt EV by 4.45%. Other expensive models, such as BMW 740e Plug-In, Volvo XC90 Plug-In, or Porsche Cayenne SE Hybrid, have much lower price elasticities as well, which ranges between -1.86 and -2.92. Moreover, it is also recognizable that substitution toward similar EV models are larger than dissimlar models when price changes. For example, the cross-price elasticities of Chev Bolt EV implies that consumers are more likely to substitute to Kia Soul EV or Nissan Leaf when the price of Bolt increases, and there will be almost no substitution towards Tesla Model S. These estimates of own- and cross-price elasticities give insights on the effectiveness of financial incentives on consumer adoption of EVs. In the next section, I further investigate the relative effectiveness of each type of price subsidy using counterfactual simulations.

2.5 Counterfactual Analysis

Based on two stylized facts identified in Chapter 1, namely dynamically optimizing consumers and varying effectiveness of each subsidy, I develop and estimate the structural dynamic discrete choice model in the previous sections. Using the estimated parameters on mean and standard deviation of consumer preferences and the discount factor, I simulate counterfactual scenarios to examine the impact of each type of financial incentives in this section. In each scenario, I first change the level of each EV subsidy to an alternative level. Then, the estimated parameters are used to compute the market shares of each vehicle model in each time period, which satisfy the equilibrium conditions (2.9), (2.11), (2.14), and (2.15). Since the supply side is not explicitly modeled, I assume a complete pass-through of EV subsidies to consumers to derive the equilibrium market shares.[19] Also, I assume that vehicle models arrive according to some exogenous process, and vehicle characteristics evolve exogenously. Lastly, I compute total government spending in EV subsidies with the predicted number of EV sales and the counterfactual level of subsidies.

In the first analysis, I study the relative effectiveness of federal tax credits and direct rebates in promoting electric vehicle sales. In the second part of this section, I conduct a series of simulations to explore how the impact of each subsidy varies with different levels of government expenditure. This enables me to discuss policy implications, such as possible budgetary savings, resulting from a more effective design of the two financial incentives in the New York EV market.

2.5.1 Impact of Federal Tax Credits vs Direct Rebates

Three counterfactual policies are simulated to measure the average impact of each incentive per dollar. The first scenario assumes zero financial subsidy, meaning that there is no rebate or tax credit for electric vehicle purchases. The second scenario assumes that consumers receive the same amount of federal tax credits for each vehicle model as previously, but without any direct rebates. The last scenario assumes that consumers receive direct rebates as before, but not tax credits. Then, I evaluate the simulation outcomes of the second and the third policies against the first policy to assess the per dollar impact of each incentive. The simulated outcomes include the estimated sales of each vehicle model in each period and total amount of financial incentives distributed to EV consumers, which is calculated as follows

[19] Using data on electric vehicle sales and a subsidy program in California, Muehlegger and Rapson (2022) find that the rate of subsidy pass-through to consumers is almost 100%. Similarly, Gulati et al (2017) finds that hybrid electric vehicle consumers capture a very high proportion of financial incentive, and Sallee (2011) also shows a similar evidence from tax incentives for Toyota Prius.

$$TS = \sum_t \sum_{j=1}^{J_t} \hat{s}_{jt} \cdot N_t \cdot (Rebate_{jt} + FTC_{jt}) \tag{2.19}$$

where $\hat{s}_{jt}$ is the predicted shares of vehicle model j at time t, N_t is the number of potential customers at time t, and $Rebate_{jt}$ and FTC_{jt} denote the amount of each subsidy for model j at time t.

Table 2.5.1 summarizes the simulation results of the three counterfactual scenarios and the current subsidy policy. First, the difference between the current subsidy policy and the first counterfactual implies that the combination of tax credits and rebates increased the total EV sales by 21655 in New York during the sample period 2015 - 2020. The total amount of spending on direct rebates is approximately \$56.62 million, and the total spending on tax credits is \$297.91 million. That is, the simulated results indicate that the two EV subsidies together promoted an additional 611 electric vehicle purchases per \$10 million. Table 2.B.4 in the appendix provides a comprehensive breakdown of the impact of financial incentives on various automakers. It is evident that the average impact of subsidies is considerably smaller for brands that offer more expensive electric vehicle models. For instance, the two subsidies encourage 271 $\sim$ 367 additional EV adoptions per \$10 million for costly brands, such as Audi, BMW, and Tesla, while the incentives promote around 801 $\sim$ 945 additional purchases for Hyundai, Kia, and Toyota.

To compare the effectiveness of each subsidy, I measure the impact of each incentive separately by taking the difference between the respective counterfactual and the first scenario. As can be see in the second column, federal tax credits alone would have resulted in increasing EV sales by 15206.[20] Since the total spending on tax credits is almost 9 times that on direct rebates[21], I find that rebates alone would only increase EV sales by 3088.

[20]Xing et al (2021) find that removing federal income tax credits reduces EV sales by 28.8% in the U.S. in 2014. Comparing the first and the second scenario in Table 2.5.1, I find that the percentage decrease in EV sales is similar, amounting to 31.98% when tax credits are eliminated.

[21]Note that the amount of tax credits per vehicle model is much larger on average than the amount of

Table 2.5.1: Impact of Tax Credits and Rebates

	No Subsidy	Only Tax Credits	Only Direct Rebates	Current Subsidy
ΔEV sales	0	15205.76	3087.86	21655.23
ΔTotal spending (million \$)	0	261.315	33.638	354.537
$\frac{\Delta\text{EV sales}}{\Delta\text{Total Spending}}$		58.189	91.796	61.080

Note: The table summarizes the impact of tax credits and rebates on EV sales per million \$. The change in total EV sales in each column represents the increase in EV sales from the first simulation (no subsidy) in which both tax credits and rebates are removed. Similarly, the change in government spending is computed by taking the difference of total spending between each simulation and the first simulation.

However, the average impact of rebates per million dollar is significantly greater than that of tax credits. Direct rebates result in promoting 918 additional EV purchases per \$10 million, while tax credits only increase EV sales by 582 per \$10 million. The findings indicate that on average, tax credits is not as effective as rebates in promoting a wider adoption of EVs.

2.5.2 Impact of Subsidies at Alternative Spending Level

The previous results on the estimated impact of each incentive have an important policy implication. If direct subsidies to purchase prices are more effective than tax incentives for EV consumers at all levels of government spending, it implies that the government could have achieved the same level of current EV sales with much lower spending by replacing tax credits with direct rebates. However, the finding in Table 2.5.1 that the average impact of rebates per million dollars is significantly higher than that of tax credits may be attributed to the substantially lower total spending on rebates. The marginal impact on EV sales could

rebates. Also, direct rebates were initially implemented in April, 2017, while tax credits were available from the initial time period.

be much higher at a lower level of government spending. Therefore, in this section, I conduct a series of simulations to compare the impact of tax credits and direct rebates at multiple, equivalent levels of government spending.

For each counterfactual simulation, I consider a setting in which only one of the two financial incentives is distributed, and the spending on the other is set to zero. I assume the timing of the initial implementation for each subsidy is the same as in the current subsidy plan.[22] In order to adjust the spending on each subsidy to different levels, I modify the amount of financial incentive allocated to each vehicle model during a specific time period in proportion to the levels in the current policy design. Then, in each scenario, I compute the predicted number of EV sales and the average impact of subsidy at the alternative level of spending.

Table 2.5.2 shows the impact of tax credits and rebates separately in alternative subsidy levels. In Panel A, the simulation results for EV sales are presented when government spending on tax credits is increased to 50, 100, 150, 200, and 250 million dollars. Panel B shows a similar table when government spending on rebates is increased to those same levels. In all spending levels, I find that the average impact of rebates per million dollars is more effective than tax credits. When government spending on EV incentives is at the 50 million dollar level, direct rebates would encourage the purchase of 316 more EVs per 10 million dollars compared to tax incentives. While the difference in average effectiveness between the two incentives diminishes at higher spending levels, direct rebates remain significantly more effective, even at the 250 million dollar level.

It is important to highlight that the finding of rebates having a greater impact on EV sales is attributed to consumers undervaluing the future benefits of tax credits. In other words, consumers tend to discount the value of a tax credit that they will receive in the

[22] For counterfactuals in which tax credits are non-zero, I assume that tax credits exist from the initial time period. For counterfactuals in which direct rebates are non-zero, I assume that consumers start to receive rebates starting in April, 2017.

Table 2.5.2: Impact of EV Subsidies at Alternative Spending Level

Panel A : Tax Credits					
ΔSpending (million $)	50	100	150	200	250
ΔEV sales	2971.84	5943.64	8876.30	11756.95	14575.73
$\frac{\Delta EV Sales}{\Delta Spending}$	59.438	59.430	59.177	58.781	58.304
Panel B : Rebates					
ΔSpending (million $)	50	100	150	200	250
ΔEV sales	4552.77	8818.22	12793.34	16539.99	20099.88
$\frac{\Delta EV Sales}{\Delta Spending}$	91.054	88.170	85.288	82.693	80.340

Note: The table summarizes the average impact of tax credits and rebates on EV sales at a given level of government spending. In panel A, the change in total EV sales in each column represents the increase in EV sales if government spending on tax credits increase from zero to the stated amount, and spending on direct rebates remains zero. In panel B, the change in total EV sales in each column represents the increase in EV sales if government spending on direct rebates increase from zero to the stated amount, and spending on tax credits remains zero.

future with annual implicit interest rate of 21.30% in the baseline model, as opposed to a direct rebate the provides a reduction in the cost of purchase at the time of purchase. As a result, the potential future benefit of tax credits may not be enough to change a consumers' decision in the present.[23]

Given the greater impact on promoting EV sales by direct purchase subsidies, it is natural to ask how much the government could have saved their budget if all financial incentives were given as rebates. Through a series of simulations, I investigate the amount of government

[23]The primary factor that distinguishes the simulation results in this analysis is the observation that tax credits are claimed in the future, whereas direct rebates provide immediate financial benefits. However, it's important to consider other factors that could affect the impact of the incentives on consumer behavior. One such factor is the fact that all consumers can enjoy the full value of direct rebates, whereas some consumers may not be able to collect the full value of tax credits, depending on their tax liability. This could affect the attractiveness of tax credits to certain consumers and lead to differences in the effectiveness of the incentives.

spending necessary for each financial incentive to attain the same level of current EV total sales. In the appendix, Figure 2.B.1 and Figure 2.B.2 illustrate the impact of increased government spending on tax credits and rebates respectively. First, as can be seen by comparing the slope of the two lines, I find that the marginal impact of rebates is greater than that of tax credits at all levels of government expenditure till 400 million dollars. More importantly, from the red dots in the figures, I find that the government would have spent approximately $380.4 million on tax credits to achieve the current EV sales, while it would have spent only $272.6 million on rebates. That is, the government could have attained the same level of EV adoption and saved $81.9 million (23% of the current subsidy costs) in its budget if the current combination of rebates and tax credits were fully replaced with rebates only.

Overall, the results of the counterfactual analysis indicate that direct purchase rebates are a more efficient and effective policy tool for increasing EV adoption than tax credits. This finding can be largely derived from the high implicit interest rate estimated in our baseline model, which suggests that consumers are more likely to respond to immediate benefits, such as rebates, rather than to delayed benefits, such as tax credits. Therefore, by offering rebates instead of tax credits, the government can achieve the same level of EV sales while spending less. This conclusion has important implications for policymakers seeking to maximize the impact of government incentives for EV adoption while minimizing costs.

2.6 Conclusion

Though many studies have examined the positive impact of financial incentives for electric vehicles, there has been little progress in analyzing how subsidies should be designed to be more effective in promoting consumer adoption of EVs. This research thus makes a contribution to the empirical understanding of the optimal design of EV subsidies by highlighting the significance of subsidy type.

This chapter uses a panel data on all electric vehicle registrations and two types of subsidies available in New York to study the question on the relative effectiveness of rebates and tax credits. I first find descriptive evidence that rebates are more effective in promoting EV sales than tax credits. To further evaluate the effectiveness of each incentive at alternative government budget levels, I take a structural approach, developing a dynamic demand model for electric vehicles. Through counterfactual simulations, I recover the average impact of each subsidy on EV sales per government spending.

I find that direct rebates result in promoting 918 additional EV purchases per $10 million, while tax credits only increase EV sales by 582 per $10 million. Even, at alternative, equivalent levels of government spending, tax credits are not as effective as rebates in encouraging EV adoption. This implies that the government could have achieved the same level of current EV sales with much lower spending by replacing tax credits with direct rebates. It is estimated that the government could have saved 23% of the current subsidy costs. That is, the government could maximize the impact of financial incentives for EV adoption with lower spending by focusing more on incentives provided at the point of sale, such as rebates.

APPENDIX

2.A Details on estimation algorithms

To solve the ex-ante value function in equation (2.11), I discretize the state space δ_i for each possible value of ES_t and compute the transition probability matrix for each individual i and ES_t. Then, I apply the standard value function iteration with a convergence threshold set to $1e^{-6}$. I allow the state space of δ_i to cover a range of 20% below the minimum and 20% above the maximum of realized δ_is. More precisely, the computation of the value function involves a grid with 50 points for δ_i, and the model considers seven discrete states of ES_t. The seven states of ES_t correspond to five anticipated reductions in tax credits, an expected entry in rebates, and a state where subsidies are not expected to change in the near future. I assume that consumers have perfect foresight regarding ES_t because they have prior knowledge of these future values due to preannouncement by the government. For a given value of ES_t, I calculate the transition probability matrix of δ_i using equation (2.14).

Following BLP, I employ importance sampling to draw unobserved individual characteristics in order to minimize the simulation error in Monte Carlo integration when estimating market shares. That is, I sample draws, z_i, from the following distribution:

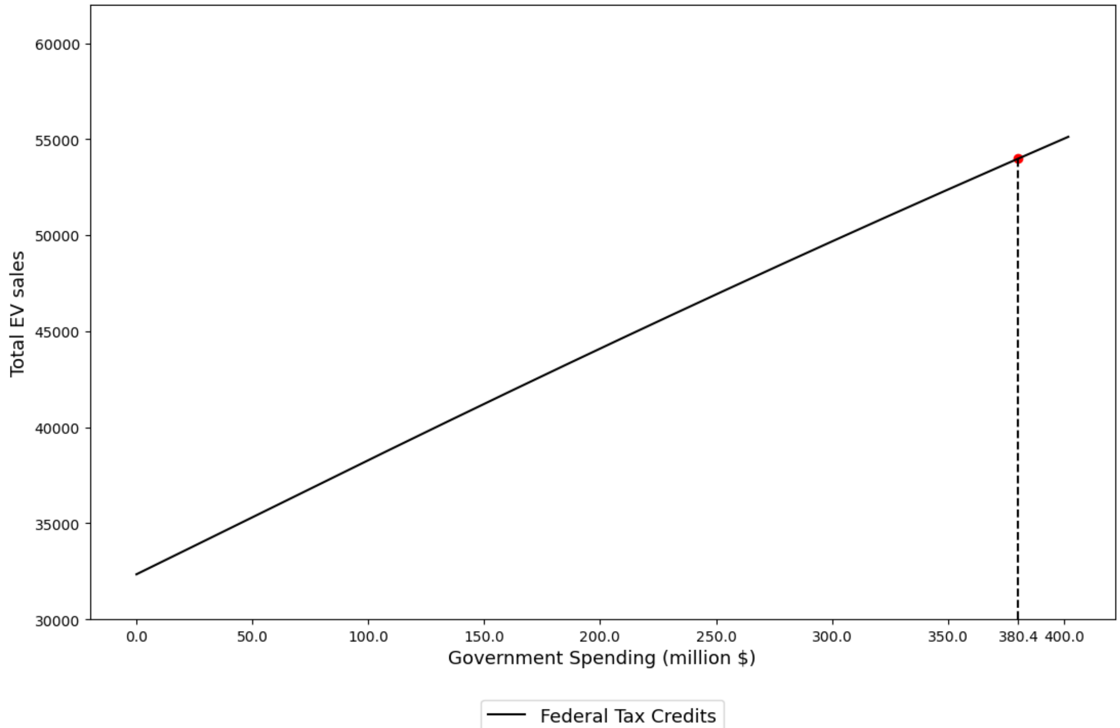
$$h(z_i) = \frac{\hat{s}(z_i, \vec{F}, \sigma, \beta)\phi(z_i)}{\int \hat{s}(z, \vec{F}, \sigma, \beta)\phi(z)dz} \tag{2.20}$$

where $\hat{s}(z_i, \vec{F}, \sigma, \beta)$ is the probability of purchasing any EV for an individual i given σ, β, and the corresponding $\vec{F}$. In practice, the first step is to calculate the denominator, which is the probability of purchasing any EV. This integral is computed only once, so I use a large number of draws from the standard normal distribution to approximate the integral as $\hat{s}(\vec{F}, \sigma, \beta)$. The next step is to draw from the density $h(.)$ by an accept-reject procedure. I take random draws of u_i and z_i from the uniform distribution and the standard normal distribution and keep z_i only if $u_i \leq \hat{s}(z_i, \vec{F}, \sigma, \beta)$. Then, I weight this draw with $\frac{\hat{s}(\vec{F},\sigma,\beta)}{\hat{s}(z_i,\vec{F},\sigma,\beta)}$.

I repeat the process above until 50 draws are sampled. Here, I use the initial consistent estimate of (σ, β), which were computed simply with the standard normal draws.

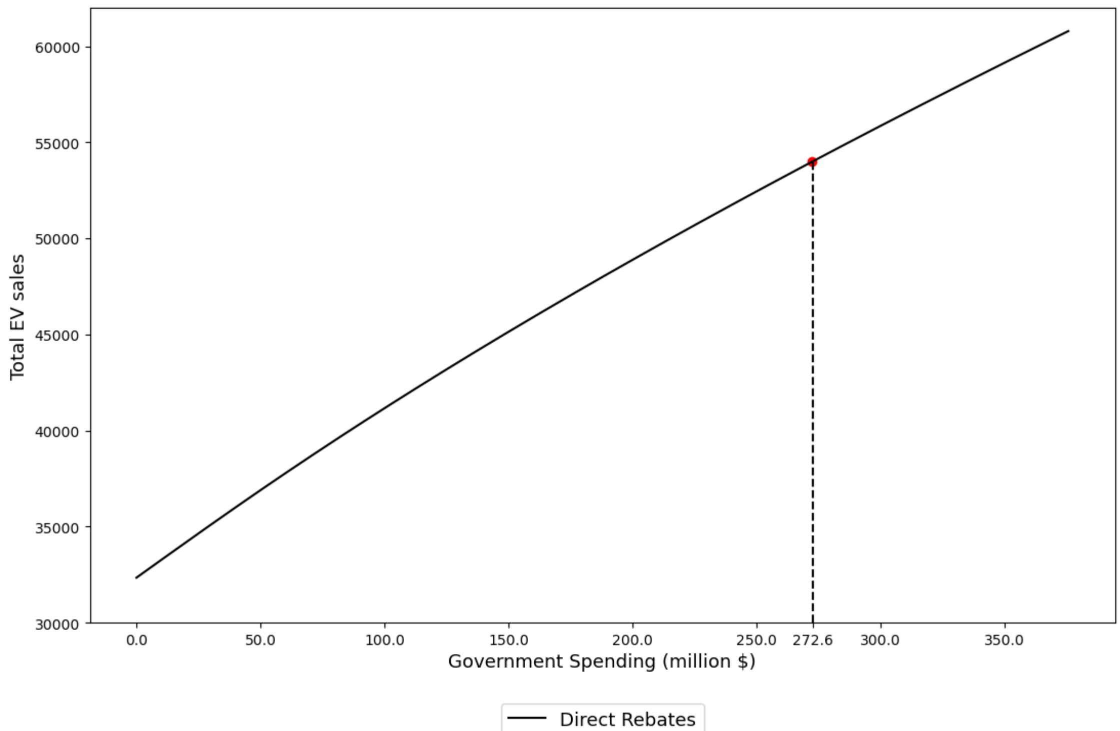
2.B Figures and Tables

Figure 2.B.1: Total EV Sales and Spending on Tax Credits



Notes: The figure above illustrates the simulation outcomes on how total EV sales change as government spending on tax credits increases, while no direct rebates are given to consumers. The red dot represents the amount of spending on tax credits needed to attain the current level of EV sales.

Figure 2.B.2: Total EV Sales and Spending on Direct Rebates



Notes: The figure above illustrates the simulation outcomes on how total EV sales change as government spending on rebates increases, while no federal tax credits are given to consumers. The red dot represents the amount of spending on rebates needed to attain the current level of EV sales.

Table 2.B.1: Sample of Indirect Utility (v_{ij}) and Logit Inclusive Value (δ_i)

	25th percentile	**50th percentile**	**75th percentile**
Average of v_{ij} across j	-48.46	-34.81	-28.83
δ_i	-26.25	-19.48	-15.80

Note: The table shows the average of indirect utilities and logit inclusive values for a sample of three households in the median period (September 2017). I draw three samples who have random coefficients of constant, price, and range at 25th percentile, 50th percentile, and 75th percentile and compute the average of indirect utility and logit inclusive value for each sample using the baseline dynamic model.

Table 2.B.2: Robustness : Different Specifications

Variable	Dynamic (1)	Dynamic (2)	Dynamic (3)	Dynamic (4)
Discount Factor	0.9926***	0.9902***	0.9919***	0.9896***
	(0.048)	(0.026)	(0.141)	(0.076)
Mean				
Constant	−9.380***	−14.139***	−8.391***	−6.941***
	(0.025)	(0.008)	(0.299)	(0.001)
Price	−7.294***	−7.859***	−4.162***	−7.670***
($10,000)	(0.075)	(0.003)	(0.752)	(0.001)
Range	0.354***	0.571***	0.032***	0.450***
(100 mi)	(0.007)	(0.002)	(0.009)	(0.001)
Miles/$	−0.604***	−0.922***	−0.971***	−1.158***
(10 mi/$)	(0.013)	(0.004)	(0.119)	(0.087)
Size	0.270***	0.349***	0.153	0.056***
(1000 in^2)	(0.024)	(0.008)	(0.249)	(0.002)
HP/Weight	1.097	2.992***	1.726	−3.904***
(hp/lb)	(1.011)	(0.943)	(10.55)	(0.046)
Standard deviation				
Constant	2.763*	7.408***	1.817	6.587***
	(1.618)	(1.120)	(2.981)	(0.631)
Price	2.975***	3.263***	1.012***	3.852***
($10,000)	(0.239)	(0.159)	(0.022)	(0.510)
Range	0.016		0.111	1.069*
(100 mi)	(0.135)		(2.102)	(0.647)
Miles/$			0.011	
(10 mi/$)			(1.041)	

Note: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. For all models, I assume ξ_{jt} to be correlated over products within each period and to be heteroskedastic across time periods.

Table 2.B.3: Different Specifications of Consumer Expectation

Variable	Dynamic	Dynamic
	(5)	(6)
Discount Factor	0.9963***	0.9959***
	(0.015)	(0.012)
Mean		
Constant	−5.041***	−7.877***
	(0.007)	(0.001)
Price	−11.764***	−10.525***
(\$10,000)	(0.023)	(0.004)
Range	0.573***	0.395***
(100 mi)	(0.002)	(0.004)
Miles/\$	−0.857***	−0.695***
(10 mi/\$)	(0.004)	(0.001)
Size	0.319***	0.265***
(1000 in^2)	(0.007)	(0.002)
HP/Weight	3.242***	1.968***
(hp/lb)	(0.311)	(0.162)
Standard deviation		
Constant	4.922***	3.285***
	(0.248)	(0.234)
Price	6.138***	4.275***
(\$10,000)	(0.066)	(0.022)
Range	0.032*	0.022
(100 mi)	(0.018)	(0.015)

Note: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. For all models, I assume ξ_{jt} to be correlated over products within each period and to be heteroskedastic across time periods.

Table 2.B.4: Impact of Tax Credits and Rebates across Automakers

Brand	**ΔEV Sales**	**ΔSpending (million \$)**	$\frac{\textbf{ΔEV Sales}}{\textbf{ΔSpending}}$
Audi	61.23	2.257	27.12
BMW	916.43	24.966	36.71
Chevy	3558.16	47.149	75.47
Chrysler	320.31	4.868	65.80
Ford	2512.10	27.976	89.79
Hyundai	1082.61	13.343	81.14
Kia	932.53	11.639	80.12
Mercedes-Benz	122.32	2.755	44.40
Nissan	904.22	11.834	76.41
Subaru	142.53	1.651	86.35
Tesla	3762.58	115.723	32.51
Toyota	4446.76	47.02	94.56

Note: The table summarizes the impact of subsidies on EV sales per million $ across a sample of automakers. The change in total EV sales represents the increase in EV sales when both tax credits and rebates are provided. Similarly, the change in government spending is the difference in total spending when both tax credits and rebates are provided.

CHAPTER 3

Financial Incentives on Diffusion of Electric Vehicles: Policy Implications

3.1 Introduction

In Chapter 2, I investigate the relative effectiveness of tax credits and direct purchase subsidies in promoting electric vehicle demand. Specifically, I quantify the average impact of each subsidy type on EV sales per dollar and compare the two effects to determine which subsidy policy is a more effective tool for a wider EV adoption. The counterfactual analysis shows that direct rebates have a greater impact on increasing EV sales at various government spending levels, and that the government could have saved approximately 23% of the current spending costs on EV subsidies with a policy using rebates only. Recent discussion and revision on the mechanism of federal tax credits also supports these results. The U.S. government modified the way federal tax credits are distributed to consumers. Starting in 2024, consumers could enjoy the benefit of federal tax credits right at the point of the sale by directly applying the subsidies to the transaction prices.

Along with the redesigned method for receiving EV tax credits, the government made additional changes to federal tax credits. One of the controversial modifications is that tax credits are now restricted to EVs that are manufactured in North America. That is, the new policy prefers domestically produced EVs over foreign-manufactured EVs. Though not explicitly stated, the intention of this policy is clearly to promote sales of domestically produced electric vehicles in the short-run and push foreign automakers to eventually produce all their EV models within North America in the long-run.

In this chapter, I thus study more about the changes in federal tax credits for electric vehicles and analyze the controversial requirement for tax credits in detail. After discussing the four major revisions on tax credits under the Inflation Reduction Act (IRA), I focus on the requirement of EVs to be produced in North America to qualify for tax credits. I first identify the final assembly plant of each electric vehicle model and provide summary statistics on the percentage of EVs in New York that would no longer be eligible for tax credits under this revision. Then, utilizing the estimated dynamic demand model in the previous chapter, I quantify the impact of this requirement on domestic-produced and foreign-produced EV sales through counterfactual simulations. Through this analysis, I examine whether eliminating tax credits for foreign EVs is effective in promoting the sales of domestically manufactured EVs.

3.2 Institutional Background and Data

This section presents a comprehensive overview of the new federal regulations on tax credits for electric vehicles. I discuss the major revisions on eligibility criteria for EV models to qualify for tax credits. Then, I provide descriptive statistics on the proportion of EV sales in New York that could have been affected by the new rules. This allows us to gain a better understanding of the policy implication for various automakers.

3.2.1 Inflation Reduction Act of 2022 (IRA)

The Inflation Reduction Act, which was signed into law on August 16th, 2022, includes several amendments of federal tax credits for electric vehicle purchases. Given the importance of financial incentives in promoting wider adoption of electric vehicles, the IRA modified the existing tax credits in various aspects. While some of the changes aim to expand the scope of tax credits available for potential consumers, other changes impose a more strict eligibility criteria so that the benefits of these tax credits are more enjoyed by specific groups of consumers or car manufacturers.

The first major revision is the elimination of the phase-out structure of tax credits for popular EV models. That is, each automaker can now sell more than 200,000 electric vehicles, and additional sales of EV models produced by the same automaker can still qualify for tax credits. Prior to this change, Tesla and General Motors reached the 200,000 limit in 2019, and consumers who purchased their electric vehicle models afterward could not receive any tax credits. However, under the IRA, consumers who purchase Chevy Bolt or Tesla Model 3 can once again enjoy tax credits. As more automakers, such as Toyota, were reaching the 200,000 cap, this change allows consumers to benefit from tax credits on a greater number of products in the EV market.

In addition, the IRA made a notable change on the method consumers can collect tax credits for their EV purchases. Before the enactment of this new regulation, individuals can claim the tax credits when they file taxes. In other words, consumers have to wait till the end of the tax year to enjoy the incentives and may not receive the total amount of available tax credits depending on their tax liabilities. Beginning in 2024, consumers will be able to transfer the entire amount of available tax credits to dealers at the point of sale, implying that tax credits can be used directly to reduce the purchase price. Similar to direct purchase subsidies, this ensures that all consumers can enjoy the full amount of tax credits, without any discounts in the incentive amount.

In contrast to the two revisions discussed above, the federal government imposed a few additional requirements for electric vehicles to qualify for tax credits. First, there are price caps for each type of electric vehicles to be eligible for tax credits. For vans, sport utility vehicles and pickup trucks, the manufacturer suggested retail price (MSRP) should not exceed $\$80,000$, while sedans and other vehicles should have the MSRP less than or equal to

$55,000 to eligible. This enforces tax credits not to subsidize expensive electric vehicles that are primarily consumed by high-income households. Rather, this change targets households for whom the tax credits would provide valuable financial support in their decisions to purchase EVs.

Lastly, the IRA added one more restriction on the eligibility of tax credits, which led to a heated controversy. Since August 17th, 2022, imported EVs are no longer qualified for tax credits. Specifically, electric vehicle models should have undergone final assembly in North America to be eligible for tax credits. The purpose of the provision is to promote consumption of domestic vehicles over imported vehicles in the first few years so that automakers would shift their manufacturing process to North America. It violates General Agreement on Tariffs and Trade (GATT) Article III of the World Trade Organization (WTO), as it enforces a law that favors domestic products over imported products and thus affects the sales of imported vehicles. However, the impact of this provision across automakers is not clear. Some foreign auto manufacturers, such as Toyota and Honda, are known to build a portion of their vehicles in the U.S, while domestic automakers, such as Jeep and General Motors, manufacture a part of their vehicles outside North America. To study how this restriction will affect domestic and foreign automakers, it is crucial to identify the final assembly plants for each electric vehicle sold to analyze which EV models are eligible for the tax credits.

This chapter studies how the last revision of the federal tax credits in the IRA would have heterogeneous impacts across auto manufacturers and thus discuss the policy implications on consumption of domestic-produced and foreign-produced vehicles in the short-run.[1]

[1] Note that in Chapter 2, I discuss in detail on how immediate financial incentives have a greater impact on EV sales. This analysis indicates that enabling the tax credits to be applied at the point of sale will be a more efficient method to promote EV sales than the previous implementation method.

3.2.2 Main Data

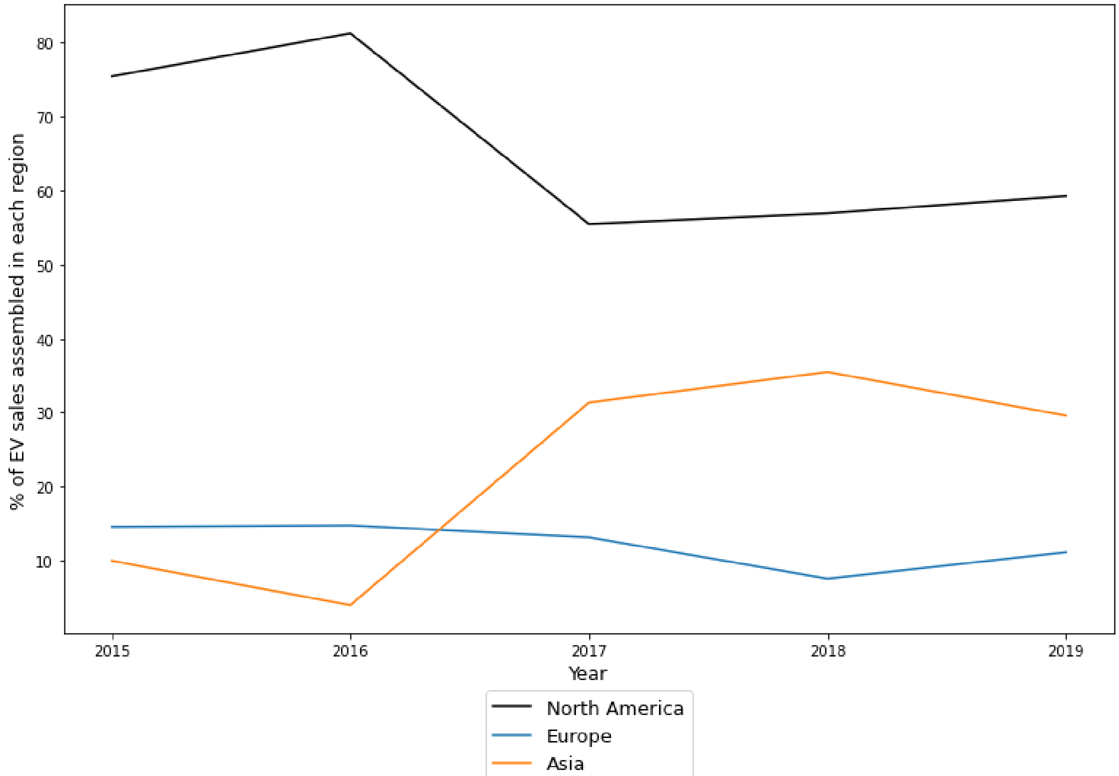
I first use the same data from Chapter 1 and 2, which contains sales and characteristics (including the MSRP) of all electric vehicles in New York from February 2015 to February 2020. As I observe the 17-digit vehicle identification number (VIN) of each EV sold during the sample period, I additionally collect information on the final assembly plant of each observation. Using the National Highway Traffic Safety Administration's VIN Decoder tool, I extract data on the build plant and country of each EV sold.

Figure 3.2.1 presents how much of EV sales in each year were produced in each region. In the first two years of the sample period, more than 70% of EV sales in New York had final assembly in North America, with a peak of 80.72% of EVs sold in 2016 being produced in North America. The percentage of domestically produced EV sales (North America) sharply declines to 55.40% in 2017 and remains at the similar level in the following two years. On the other hand, the proportion of EV sales that were produced in Asia increase significantly from 4.21% in 2016 to 35.50% in 2018. Throughout the sample period, the proportion of European-produced EV sales is relatively stable around $11 \sim 15\%$.

Table 3.A.1 in the appendix provides a more detailed breakdown of the percentage of EV sales produced in each region over time. During the observed period, there was an approximately 8% and 10% decrease in the proportion of EV sales produced in the U.S. and in Mexico respectively. Still, 49.93% of EV sales in 2019 were manufactured in the U.S., but only 7.70% were produced from Mexico. Conversely, the substantial increase in EV sales that were produced in Asia is largely attributed to the surge in EV sales produced from Japan and South Korea. The percentage of EV sales from Japan increases from 9.56% to 20.05%, while the proportion of South Korean EV sales rises from 0.28% to 9.21%.

Additionally, in Table 3.2.1, I provide information on the percentage of EV sales with final assembly in each region for each automaker. The table gives us a better understanding of where domestic and foreign automakers are sourcing their EV supply in New York and

Figure 3.2.1: Percentage of EV Sales Assembled in Each Region over Time



Notes: The graph is drawn by identifying the build country of each EV sold in New York during the sample period. The black line corresponds to the proportion of EVs that would still have been eligible for tax credits if the IRA had been in effect.

provide insights into how each brand would be affected differently by the IRA. Between 2015 and 2020, almost 100% of EVs sold from domestic auto manufacturers, such as Chevrolet, Chrysler, Ford, and Tesla, were produced from North America. In contrast, foreign automakers, except BMW, Mercedes-Benz, and Nissan, supplied EVs exclusively from outside North America.[2] During this period, Nissan supplied all EV sales from North America. For BMW, the proportion of EV sales produced from North America is 32.27%. This stems from the fact that BMW assembles each electric vehicle model in different locations. For

[2]Some foreign automakers, such as Honda, Mini, or Toyota, sold really few EVs (less than 1% of their total sales) that were produced from North America, and more than 99% of their sales in New York were from foreign countries.

example, the final assembly plant for BMW X5 is located in South Carolina, U.S, while the build plant for BMW i3 is in Leipzig, Germany. Similarly, Mercedes have a specific EV model produced in the U.S., such as GLE55e. In Table 3.A.2, I also provide a sample of the percentage of EV sales produced in different regions at the vehicle model level. With really few exceptions, I find that each electric vehicle model sold in New York during the observed period was consistently manufactured in a single region.

Table 3.2.1: Sample of Percentage of EV Sales Assembled in Each Region

Brand	**Region**		
	North America	Asia	Europe
Audi	0.00	0.00	100.00
BMW	32.27	0.00	67.73
Chevrolet	100.00	0.00	0.00
Chrysler	99.82	0.18	0.00
Ford	100.00	0.00	0.00
Hyundai	0.00	100.00	0.00
Kia	0.00	100.00	0.00
Mercedes-Benz	11.31	0.00	88.69
Nissan	100.00	0.00	0.00
Subaru	0.00	100.00	0.00
Tesla	99.97	0.02	0.01
Toyota	0.05	99.95	0.00

Note: For each brand, this table shows the percentage of EV sales in New York that had final assembly in different regions. Here I include a sample of popular brands which sold electric vehicles in New York between 2015 and 2020.

Furthermore, I collect the New York EV sales data for the years 2020 and 2021 to make a comparison and see if there has been any major change in the percentage of EV sales with final assembly in each region in recent years.[3] Table 3.A.3 clearly shows that the proportion of EV sales assembled in North America remains steady, similar to the levels observed from 2017 and 2019. Specifically, in 2020, 63.61% of EV sales were manufactured in North America, and in 2021, 56.30% were produced in North America. Also, during these two years, the proportion of Asian produced EV sales ranged from 30.06% to 35.72%, while the percentage of European-produced EV sales was between 6.33 and 7.98%. These figures are similar to those observed between 2017 and 2019.

In the next section, I investigate the short-run effect of the IRA on the demand for electric vehicles, especially domestic-produced EVs. I employ the structural dynamic discrete choice model developed in Chapter 2 and simulate counterfactual scenarios to examine the policy implications of the final assembly plant requirement. Specifically, I run two counterfactual simulations with and without the final assembly plant requirement and then compare the outcomes of each scenario to obtain insights on the policy impact on consumers' adoption of EVs.

3.3 Counterfactual Analysis

Using the estimated dynamic discrete choice model, I conduct two simulations to examine the impact of the requirement for final assembly plant on domestically manufactured electric vehicles and foreign-produced electric vehicles. In the baseline scenario, I maintain the subsidy amount for each EV model at the same level as observed in the data, except for GM and Tesla vehicles in 2019. According to the IRA, there is no limit on the number of EVs that each car manufacturer can sell in order to qualify for federal tax credits. This implies that

[3] As before, I gather all EV registration data in New York between January, 2020 and December, 2021. The NYSERDA publicly provides only monthly registration records now, which includes information upto 10-digit VIN. To determine the assembly plant location for each observation, I thus search for the first 11-digit VIN for each electric vehicle model in a database of all VINs, vininspect.com, and then use the NHTSA's VIN Decoder tool to identify the assembly plant location of all EV models between 2020 and 2021. Additionally, I collect the MSRP of each available EV model during this period from CarGurus.

tax credits for Tesla and GM products would not have phased out in 2019 under the IRA. Thus, in the baseline simulation, I assume that tax credits for Tesla and GM vehicles remain unchanged in order to eliminate any effect from the phase-out. In the second simulation, I set the amount of tax credits on EV models with final assembly outside North America to zero, while keeping the rest of subsidy amount for each EV model at the same level as the first simulation.[4] Lastly, I compare the equilibrium EV sales between two simulations to study heterogenous impacts across automakers in the short-run.

Table 3.3.1 presents how the final assembly requirement for tax credits would have affected EV sales differently for domestically manufactured and foreign-produced EVs. If EVs manufactured outside North America no longer qualify for federal tax credits, their sales decrease by 42.58%, whereas sales of EVs with final assembly in North America increase by only 1.15%. That is, if tax credits are eliminated for foreign-manufactured EVs, a significant portion of consumers who would have purchased foreign-produced EVs with tax credits substitute to the outside good[5], not to domestically produced EVs. This suggests that while the IRA policy of mandating the final assembly in North America would critically reduce the sales of foreign EVs, it may not be really effective in promoting the sale of domestic EVs.

In Table 3.3.2, I provide a sample of the percentage changes in sales for each auto manufacturer if the final assembly requirement were implemented during the study period. It is clear that the demand of brands that offer less expensive electric vehicle models, such as Hyundai or Toyota, experience a sharp decline in sales, ranging from 40.65 $\sim$ 52.44%. More expensive brands such as Audi or Mercedes, are less sensitive to the elimination of tax credits. Moreover, electric vehicle models produced by Chevrolet and Nissan, such as Chevy

[4]Similar to the steps in Chapter 2, I assume a complete pass-through of EV subsidies to consumers to derive the equilibrium market shares and that vehicle models and characteristics evolve exogenously.

[5]Since I have data only on electric vehicle sales in New York, the outside good here refers to the choice of not purchasing any EV, which includes the option of buying a gasoline vehicle. An interesting question for future research is to measure the substitution towards the gasoline vehicles from these foreign-produced EVs and the substitution towards not purchasing any vehicle at all.

Table 3.3.1: Impact of the Final Assembly Requirement under the IRA between 2015 - 2020

Vehicle Type	**FTC Change**	**Sales Change**	**%Δ in Sales**
Domestic-produced EVs	0	408.59	1.15%
Foreign-produced EVs	-$5735.38	-9109.41	-42.58%

Note: Domestic-produced EVs contain all electric vehicle models that had final assembly in North America, such as BMW X5, Chevy Bolt, Nissan Leaf, Tesla Model S, etc. Foreign-produced EVs indicate the models that had final assembly outside North America, such as Audi e-tron, BMW i3, Hyundai Ioniq EV, Volvo XC60 Plug-In, etc. FTC change refers to the change in the average of nominal federal tax credits across EV models in each type.

Bolt EV and Nissan Leaf, exhibit the largest percentage increase in sales, likely due to the similarity in characteristics of EV models between these domestic brands and the foreign brands that were heavily impacted by the policy, such as Kia Niro EV and Hyundai Ioniq EV. Also, the 1.1% increase in the percentage of sales in Tesla electric vehicles is primarily from the substitution toward its cheapest model, Model 3.

Additionally, in Table 3.A.4 in the appendix, I compare the average effectiveness of EV subsidies with the final assembly plant requirement to that without the requirement. This comparison allows me to evaluate the cost of this protectionism in terms of the average impact of subsidies on EV adoption. The first column in Table 3.A.4 implies that the two subsidies promote an additional 584 electric vehicle purchases per $10 million when both domestic and foreign-produced EVs qualify for federal tax credits. On the other hand, the average impact of financial incentives on EV sales is 534 additional adoptions per $10 million if federal tax credits are provided to domestic-produced EVs only under the IRA. Though the requirement for the final assembly plant to be in North America may result in a 1.15% increase in the sales of domestic-produced EVs in the short-run, it undermines the overall

Table 3.3.2: Sample of the Impact of the Final Assembly Requirement across Automakers

Brand	**FTC Change**	**%Δ in Sales**
Audi	-$6001.00	-17.23%
BMW	-$5355.00	-17.14%
Chevrolet	0	1.62%
Chrysler	0	1.04%
Ford	0	1.07%
Hyundai	-$6115.50	-49.04%
Kia	-$6115.50	-52.44%
Mercedes-Benz	-$6050.00	-21.14%
Nissan	0	1.84%
Subaru	-$4502.00	-40.65%
Tesla	0	1.11%
Toyota	-$3501.00	-43.96%

Note: For each brand, this table shows the change in the average of nominal FTC across EV models and the percentage change in sales. Except for BMW and Mercedes, each brand either produces all EV models either completely in North America or outside North America. BMW and Mercedes has one EV model respectively that are produced in North America, which are BMW X5 and Mercedes GLE55e.

effectiveness of subsidies on EV adoption, reducing it by almost 8.6%.

Based on the simulation results, the short-run effectiveness of the final assembly plant requirement under the IRA is brought into question. While the policy results in a slight increase in EV sales that were manufactured in North America, it implies that removing tax credits for foreign-produced EV models does not directly translate into consumers' adoption of domestic-produced EVs. There are, however, few caveats in this counterfactual analysis. First, this analysis is focusing on the impact of the policy on EV sales in New York. As this revision in federal tax credits is applied to all 50 states in the U.S., and substitution patterns among electric vehicles might vary across different markets, the aggregate impact of the IRA on domestic-manufactured EV sales in the U.S. can differ from the implication derived from the counterfactual simulation above. The other major caveat is that the analysis does not capture possible long-run adjustments by foreign auto manufacturers. To qualify for tax credits, foreign automakers may move their manufacturing process of electric vehicles within North America over the long-run. Though some foreign companies, such as Toyota and Honda, produce and assemble a significant portion of their gasoline vehicle models in the U.S., most of foreign-branded electric vehicles are now produced outside North America. The policy thus could incentivize these foreign carmakers to invest in building manufacturing plants for their EV models separately in the U.S.

3.4 Conclusion

This chapter studies the major revisions on federal tax credits in detail and discusses the policy implication of the domestic production requirement to qualify for tax credits. The Inflation Reduction Act (IRA) eliminated the phase-out structure of tax credits for popular EV models and plans to restructure tax credits to be distributed at the point of sale just like rebates starting in 2024. Also, the IRA placed new requirements for electric vehicles to qualify for tax credits, such as the MSRP requirement and the final assembly plant requirement. Among these revisions, I focus on the impact of the final assembly requirement on domestic-produced and foreign-produced vehicle sales in the short-run.

I gather additional data on the final assembly plant of each observation in the EV registration data in New York. This allows me to identify EV models that would not have received federal tax credits under the IRA between 2015 and 2020. I find that around 60% of EV sales were consistently manufactured in North America during the sample period. I also observe the percentage of domestic-produced EV sales to be similar levels even in recent years. Therefore, using the dynamic discrete choice model developed in the previous chapter, I study the short-run effect of the IRA on the demand for electric vehicles by simulating counterfactual scenarios in the sample period.

The simulation results indicate that mandating the final assembly in North America would substantially reduce the sales of foreign EVs by 42.6%, whereas sales of domestic-produced EVs increase only by 1.2%. That is, if foreign-manufactured EVs no longer qualify for tax credits, a significant portion of consumers substitute from foreign-produced EVs to the outside good, such as not purchasing any EV. Moreover, this protectionist measure comes at the cost of reducing the overall effectiveness of subsidies on EV adoption by 8.6%. Though the analysis in this chapter does not incorporate the long-run effect of the policy, such as the possibility of foreign automakers relocating the final assembly plant in North America, one may question whether the estimated short-run impact of the IRA on domestic-produced and overall EV sales aligns with the government's objectives.

APPENDIX

3.A Tables

Table 3.A.1: Percentage of EV Sales Produced in Each Country over Time (%)

Region	**Country**	**Year**				
		2015	2016	2017	2018	2019
North America	US	57.78	62.80	44.91	50.54	49.93
	Mexico	17.08	17.92	9.51	4.59	7.70
	Canada	0.00	0.00	0.97	1.53	1.46
Asia	Japan	9.56	2.91	25.37	32.72	20.05
	South Korea	0.28	1.30	5.77	2.57	9.21
Europe	Germany	13.66	11.55	7.45	6.28	7.99
	France	1.65	1.42	4.55	0.48	0.43
	Other	0.00	2.11	1.46	1.08	2.87

Note: This table reports the percentage of EVs sold in New York that had final assembly in each country for each year.

Table 3.A.2: Sample of Percentage of EV Sales Assembled in Each Region For Each Model

Brand	**Model**	**Region**		
		North America	Asia	Europe
Audi	e-tron	0.00	0.00	100.00
BMW	i3	0.25	0.00	99.75
BMW	X5	100.00	0.00	0.00
Chevrolet	Bolt EV	100.00	0.00	0.00
Chrysler	Pacifica	99.82	0.18	0.00
Ford	Fusion Energi	100.00	0.00	0.00
Hyundai	Ioniq EV	0.00	100.00	0.00
Kia	Soul EV	0.00	100.00	0.00
Mercedes-Benz	B-Class Electric	0.00	0.00	100.00
Mercedes-Benz	GLE55e	100.00	0.00	0.00
Nissan	Leaf	100.00	0.00	0.00
Subaru	Crosstrek Hybrid	0.00	100.00	0.00
Tesla	Model 3	99.95	0.03	0.02
Toyota	Prius Prime	0.05	99.95	0.00

Note: For each EV model, this table shows the percentage of EV sales in New York that had final assembly in different regions. Here I include a sample of representative EV models from popular automakers in New York between 2015 and 2020.

Table 3.A.3: Percentage of EV Sales Produced in Each Country over Time (%)

Region	**Country**	**Year**	
		2020	2021
North America	US	59.23	49.00
	Mexico	3.26	5.57
	Canada	1.12	1.73
Asia	Japan	17.58	25.42
	South Korea	12.40	9.86
Europe	Germany	2.54	3.38
	France	0.01	0.00
	Other	3.78	4.60

Note: This table reports the percentage of EVs sold in New York that had final assembly in each country for each year after the sample period.

Table 3.A.4: Comparison of the Impact of EV Subsidies

	All EVs	**Domestic only**
EV Sales without subsidy	32334.77	32334.77
EV Sales with subsidy	56908.42	48207.61
ΔEV Sales	24573.65	15872.84
ΔSpending (million \$)	420.202	297.188
$\frac{\Delta\text{EV Sales}}{\Delta\text{Spending}}$	58.481	53.412

Note: The table compares the average impact of financial incentives on EV sales between two scenarios. In the first column, EV sales with subsidy represents sales simulated under the scenario in which federal tax credits are provided to all electric vehicle models. Please note that this is equivalent to the baseline simulation mentioned in Chapter 3, where tax credits for Tesla and GM vehicles do not phase out in 2019. In the second column, EV sales with subsidy represents sales simulated under the scenario in which federal tax credits are only provided to domestic-produced EVs under the IRA requirement.

Bibliography

Abbring, Jaap H., and Øystein Daljord (2020). Identifying the discount factor in dynamic discrete choice models. *Quantitative Economics 11*(2), 471-501.

Beresteanu, Arie, and Shanjun Li (2011). Gasoline Prices, government support, and the demand for hybrid vehicles in the United States. *International Economic Review 52*(1), 161–182.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–890.

Bollinger, Bryan (2015). Green technology adoption: An empirical study of the Southern California garment cleaning industry. *Quantitative Marketing and Economics 13*(4), 319–358.

Clinton, Bentley C., and Daniel C. Steinberg (2019). Providing the spark: Impact of financial incentives on battery electric vehicle adoption. *Journal of Environmental Economics and Management 98*, 102255.

De Groote, Olivier, and Frank Verboven (2019). Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *American Economic Review 109*(6), 2137-2172.

DeShazo, J.R., Tamara L. Sheldon, and Richard T. Carson (2017). Designing policy incentives for cleaner technologies: Lessons from California's plug-in electric vehicle rebate program. *Journal of Environmental Economics and Management 84*, 18-43.

Gallagher, Kelly Sims, and Erich Muehlegger (2011). Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology. *Journal of Environmental Economics and Management 61*(1), 1-15.

Gowrisankaran, Gautam, and Marc Rysman (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy 120*(6), 1173–1219.

Gulati, Sumeet, Carol McAusland, and James M. Sallee (2017). Tax incidence with endogenous quality and costly bargaining: Theory and evidence from hybrid vehicle subsidies. *Journal of Public Economics 155*, 93-107.

Li, Shanjun (2012). Traffic safety and vehicle choice: Quantifying the arms race on American roads. *Journal of Applied Econometrics 27*(1), 34-62.

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou (2017). The market for electric vehicles: Indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists 4*(1), 89-133.

Magnac, Thierry, and David Thesmar (2002). Identifying dynamic discrete decision processes. *Econometrica 70*(2), 801-816.

Manski, Charles F. (1993). Dynamic choice in social settings: Learning from the experiences of others. *Journal of Econometrics 58*, 121-136.

Muehlegger, Erich, and David S. Rapson (2022). Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California. *Journal of Public Economics 216*, 104752.

Nevo, Aviv (2000). A practitioner's guide to estimation of random coefficients logit models of demand. *Journal of Economics and Management Strategy 9*(4), 513–548.

Nevo, Aviv (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica 69*(2), 307-342.

Rust, John (1994). Estimation of dynamic structural models: Problems and prospects part I: Discrete decision processes. *Proceedings of the 6th World Congress of the Econometric Society*(C. A. Sims, ed.), 119-171, Cambridge University Press, Cambridge.

Sallee, James M. (2011). The surprising incidence of tax credits for the Toyota Prius. *American Economic Journal: Economic Policy 3*(2), 189-219.

Springel, Katalin (2021). Network externality and subsidy structure in two-sided markets:

Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy 13*(4), 393-432.

Xing, Jianwei, Benjamin Leard, and Shanjun Li (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management 107*, 102432.