Three Essays on the Effects of Government Taxation and Incentive Policies on Consumers New Vehicle Purchase Behavior

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Thesis submitted to the Faculty of Graduate and Postdoctoral Studies in partial fulfillment of the requirements for the degree: Doctorate in Philosophy Economics

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Abstract

Chapter 1.—This chapter aims to find the effects of financial point of sales incentives on the sales of electric vehicles across the Canadian provinces from September 2012 to December 2016. The findings of my study indicate that purchase incentives cause the sales of new electric vehicles to increase by 8 percent on average due to a $1000 increase in incentives. I find that 47% of electric vehicle sales across the rebating provinces (Ontario, Quebec, and British Columbia) are attributed to the purchase incentives. Results of my counter-factual simulations imply that the cost of eliminating one tonne of carbon emissions across the provinces that offer incentives over the years of my study is, on average, \$216/tonne CO_2.

Chapter 2.—In light of the rapid increase in Canadian gasoline prices from 2000 to 2010, this chapter focuses on the relationship between gasoline price and demand for vehicle fuel efficiency across the Canadian forward sortation areas (FSAs) over this period. I find that consumers respond to variations in gasoline price when deciding the fuel efficiency of their new vehicle; increases in gasoline price result in shifts in demand toward more fuel efficient vehicles and therefore improve the average fuel efficiency of the new vehicle fleet. I find that the elasticity of fuel economy with respect to gasoline price for new vehicles sold across the Canadian forward sortation areas (FSAs) from 2000 to 2010 is -0.06 to -0.16. Results of further analyses imply that consumer are more responsive to rising and constant gasoline prices than falling prices, and that urban residents are slightly more responsive to variations in gasoline price compared to residents of suburb regions.

Chapter 3.—This chapter investigates the effect of the carbon tax policy implemented by the Canadian Province of British Columbia on households' new vehicle purchase decisions. I dis-aggregate the effects of gasoline price into two effects: carbon tax and carbon tax-exclusive gasoline price. These effects are both measured along the extensive margin of replacing a fuel inefficient vehicle with a fuel efficient vehicle. The results indicate that there is a significant negative relationship between both effects and fuel efficiency substitutions. However, vehicle fuel economy is more sensitive to changes in the carbon tax than to equivalent changes in the carbon tax-exclusive gasoline price. I find that the elasticity of fleet fuel economy with respect to the carbon tax ranges from -0.22 to -0.26 whereas this elasticity changes between -0.1 and -0.15 with respect to gasoline price (net of the carbon tax). I obtain consistent results when estimating the effect of both factors on fleet fuel economy conditional on fleet composition, indicating that almost all vehicle segments respond more strongly to changes in the carbon tax component of gasoline price than other components. Results also imply that, among all segments, the fuel consumption of compact sport utility vehicles (SUVs), minivans, and luxury high-end cars respond the most to the carbon tax.

Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

Acknowledgments

It is my pleasure to acknowledge the roles of several individuals who were instrumental for the completion of my doctoral dissertation. First and foremost, I would like to express my most sincere gratitude and appreciation to my co-supervisor, Professor Nicholas Rivers, for his excellent guidance in all steps of my thesis preparation. He provided me with many insightful suggestions and helped sharpen my skill set. He was always welcoming to discuss ideas and answer my questions. Without his guidance and persistent help this dissertation would not have been possible. It was an honor for me to work with him and learn from him. I would also like to offer my sincere appreciation to my supervisor, Professor Louis Hotte, who not only broadened my knowledge in Environmental Economics but supported me throughout my Ph.D. whenever I needed encouragement and support.

Special thanks to my committee members, Professor David Gray, Professor Maya Papineau, Professor Anthony Heyes, who have provided me with invaluable advice and helpful comments. Many thanks to my external examiner, Professor Philippe Barla, the Director of Undergraduate Programs in Economics at University of Laval, for his constructive comments and suggestions. I would also like to express my gratitude to my former co-supervisor, Professor Brandon Schaufele, for his valuable supervision through the initial steps of my Ph.D. thesis as well as in the preparation of my first workshop.

Thank you to the entire department at the University of Ottawa; all of the faculty and staff who I met throughout my program were wonderful people. I am grateful to the following professors and friends in the department of economics: Jason Garred, Catherine Deri

Armstrong, Forough Seifi, Golnaz Sedigh, Fatemeh Saberian, Soodeh Saberian, Steve Martin, and David Stambrook for their unfailing support and assistance in my graduate studies. I would like to give warm thanks to Irene Pare and Diane Ritchot for their constant help. I also benefited greatly from academic discussions with my fellow schoolmates especially Wessel Vermeulen, Miroslav Kljajic, Mirna Abourizk and many more who have become great friends. There is no doubt that completing my Ph.D. was impossible without the unconditional love and consistent support of my beloved friends Sepideh Sanaei, Mona Rezaei, Arash Nouri, Ghazal Memartolouei. And finally, last but by no means least, I would like to thank my mother, Farideh Hamidi, whose unconditional love and support have always been with me in whatever I pursue. Thank you so much for always being my fuel for life and listening, offering me advice, and supporting me through my life.

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General Introduction

In line with the growing global concern about climate change, many countries began to undertake significant efforts to reduce emissions. Canada was one of the 195 countries that signed the Paris Agreement in 2015 and made commitments to reduce greenhouse gas emissions 30% below 2005 levels by 2030. To meet these obligations, the federal and provincial governments developed a framework to mitigate climate change through various policy proposals targeting several sectors in Canada's economy. The energy and transportation sectors are Canada's largest sources of emissions. In the transportation sector, emissions are mostly from passenger vehicles and freight trucks. Therefore, deep reductions in emissions from on-road vehicles are required to meeting national and provincial reduction targets.

The governments in different provinces implemented a variety of regulations on the vehicle market. It is essential to understand whether the current policies have been effective in reducing fuel consumption and consequently emissions from vehicles. My thesis evaluates the effectiveness of some of the provincial policies implemented to reduce emissions in the recent years in Canada. The three provinces of Ontario, British Columbia, and Quebec have implemented incentive programs to induce the purchase of electric vehicles since 2010; I evaluate the cost-effectiveness of financial purchase incentives offered by these provinces to encourage demand for electric vehicles in chapter 1. As another important determinant in new vehicle purchase behavior, in chapter 2, I investigate the effect of variations in gasoline price on the fuel efficiency of new vehicle purchases. Finally, British Columbia implemented a unique carbon tax policy on the consumption of all fossil fuels; chapter 3 aims to address the effect of this policy on consumer vehicle purchase decisions.

Chapter 1 adds to the growing literature examining the relationship between purchase incentives, fuel savings, and electric vehicle purchases. In this chapter, I investigate whether the financial purchase incentives offered by the provinces of British Columbia, Ontario, and Quebec encourage consumers to replace conventional gasoline cars with electric vehicles. I also evaluate whether gasoline prices affect consumers' willingness to purchase electric vehicles by calculating the dollar value savings from driving one kilometer in an electric vehicle compared to driving one kilometer in an average gasoline vehicle. Using sales and incentive amount data for individual electric vehicle models across all Canadian provinces from September 2012 to December 2016, I employ a differentiated products demand approach to estimate changes in the market share of electric vehicles in response to the purchase incentives and fuel cost savings.

This chapter makes several contributions to the existing literature. First, variations in the presence and generosity of the incentive programs across provinces and time, as well as variations in the incentive amounts offered to various electric vehicle models within a given province and time, provide a solid ground to identify the incentive effects on electric vehicle sales. Second, the model-specific incentive data allow me to incorporate incentives into the estimations without having to make unnecessary assumptions on the calculation of incentives. Moreover, since the incentives are in the form of purchase incentives, as opposed to income or sales tax deductions/waivers, I do not require additional data on consumer income distribution or provincial sales tax. Finally, observing electric vehicle sales by model, province, and month allows me to control for other unobserved temporal and provincial factors, including other electric vehicle support programs, that may be correlated with the purchase incentives.

I find that the purchase incentives have been effective in shifting preferences from gasoline cars to electric vehicles such that a $1000 increase in rebates increases sales of electric vehicles by 8 percent. Results also suggest that on average, a 10-cents-per-liter increase in gasoline prices would result in a 2.8 to 6.1 percent increase in electric vehicle sales. Finally, I evaluate fuel consumption savings associated with the incentive programs by calculating the difference between aggregate sales-weighted fuel consumption in the presence and absence of the incentives. I then convert fuel savings into equivalent carbon emission savings to obtain the emissions saved as a result of the incentive programs. Results suggest that the lifetime (i.e., 10 years in my study) carbon emission reductions of the electric vehicles sold due to the incentive programs are 60,000 tonnes on average across the rebating provinces between 2013 and 2016. Furthermore, the governmental cost of eliminating one tonne of carbon emissions due to the incentives is estimated to be $216.

In chapter 2, I evaluate a consumer response to variations in gasoline prices when determining the fuel efficiency of their new vehicle choice. This chapter adds to the existing literature on gasoline prices and vehicle fuel economy in Canada, while also contributing to the literature in several ways. First, using vehicle registration data across the dis-aggregated forward sortation areas (FSAs) from 2000 to 2010, I obtain more-precisely-estimated effects of gasoline price variations on vehicle fuel economy than the estimates reported in the studies using aggregate provincial-level data. Second, following the methodology in Klier and Linn (2010a), I estimate changes in the market share of all new vehicle models in response to changes in the gasoline cost of driving the given models (per 100 kilometers) within each forward sortation area (FSA) over time. Moreover, the gasoline cost effects are identified by exploiting two sources of variation: variation in gasoline price within a forward sortation area (FSA) over years; and 2) variation in vehicle fuel consumption rating (in liters per 100 kilometers) due to minor vehicle redesigns over time.

Results of my analysis imply that consumers respond to variations in both gasoline price and vehicle fuel efficiency when purchasing a new vehicle. I find that an increase in gasoline costs, due to an increase in gasoline price or to worsened vehicle fuel efficiency, leads to larger reductions in the market share of fuel-inefficient vehicles relative to fuel-efficient vehicles, thus causing an improvement in overall fleet fuel economy. According to the results of my counter-factual calculations, the elasticity of vehicle fuel efficiency with respect to the gasoline price is estimated to be between -0.06 and -0.16 depending on the model specification. These estimates are in the range of those reported in the literature using Canadian vehicle data: Rivers and Schaufele (2017a) find elasticity estimates ranging from -0.08 to -0.13 (2000-2010), and Barla et al. (2009) report an elasticity of -0.1 (1990 to 2004). I also find that consumers tend to be more responsive to gasoline price increases than decreases, and that residents of suburb regions are more sensitive to increases in the gasoline price compared to the residents who live closer to city center points. Finally, results imply that variations in the gasoline price also affect fleet composition; sales of compact and sports utility vehicles (SUVs) increase, whereas sales of minivans, intermediate cars, and sport cars decrease, in response to an increase in gasoline prices.

In chapter 3, I evaluate the effect of British Columbia's carbon tax policy on the fuel efficiency of new vehicle purchases using sales and fuel consumption data for individual vehicles across the Canadian provinces from 2000 to 2010.

The contributions of this chapter to the literature are twofold. First, it adds to the small number of studies that empirically investigate the effect of gasoline prices (exclusive of taxes) on new vehicle fuel economy in a Canadian context. I find that consumers are responsive to changes in the carbon tax-exclusive gasoline price by shifting away from fuel inefficient vehicles when selecting the fuel efficiency of their new vehicle choice. Second, this chapter fits into the emerging literature that focuses on the saliency of gasoline taxes. As addressed in some existing studies such as Li et al. (2014), consumers are more responsive to changes in prices that are perceived as more permanent (such as taxes) than temporary changes due to market-driven fluctuations. As such, by evaluating the effect of an actual carbon tax policy, I examine whether consumers respond differently to changes in the carbon tax than to commensurate changes in the carbon tax-exclusive gasoline price when purchasing a new vehicle.

My empirical results suggest that the elasticity of fleet fuel economy with respect to the carbon tax-exclusive gasoline price averages to -0.15%, whereas this elasticity with respect to the carbon tax is -0.25%. According to the counter-factual results of my preferred estimation on model-level market shares, I find that a 0.01 dollar per liter increase in the carbon tax is associated with an eight times larger reductions in overall fuel economy than an equivalent increase in the carbon tax-exclusive gasoline price; 0.02 and 0.0026 liters per 100 kilometers reductions in each case. My results are consistent with the results of similar studies in this literature; Rivers and Schaufele (2017a) also use Canadian vehicle data from 2000 to 2010 and find that new vehicle fuel efficiency improves due to a change in excise tax by almost ten times as much as to an equivalent change in gasoline price due to other factors. Similarly, I compare the effect of various provincial taxes on vehicle fuel economy and find that the effect of the carbon tax on vehicle fuel efficiency is relatively equal to the effect of the excise and transit taxes in British Columbia; a one percent increase in provincial excise and transit taxes leads to a 0.23 percent reductions in fleet fuel efficiency. Finally, I address the observed changes in fleet fuel economy due to the carbon tax conditional on fleet composition and find that intermediate cars and minivans are the most responsive vehicle segments to changes in the carbon tax. Results of my additional analysis on fleet composition and fuel efficiency conditional on composition imply that all segments respond more strongly to changes in the carbon tax than to equivalent changes in the carbon tax-exclusive gasoline price.

Chapter 1

Assessment of Electric Vehicle Incentive Policies in Canadian Provinces

1.1 Introduction

In line with the Canadian federal government's action plan to mitigate climate change[1], the federal and provincial governments began to implement a series of policies to reduce greenhouse gas (GHG) emissions. The transportation sector, as the second largest contributor to GHG emissions[2], has been a major target for various policy initiatives across the Canadian provinces. Among various policies, the transition to electric mobility is likely to be a key component in achieving provincial and national emission targets.[3] Therefore, the provincial governments began to put in place a range of policy initiatives including electric vehicle (EV) purchase and private charger incentives, unrestricted access to high occupancy vehicle

[1] According to the 2015 Paris Accord, Canada set a target to reduce greenhouse gas (GHG) emissions 30% below 2005 levels by 2030.

[2] In Canada, the transportation sector was responsible for over 25% of emissions in 2016 (Environment and Climate Change Canada (2017)).

[3] Axsen et al. (2016) reports that "electric vehicles can reduce emissions by 45% to 98% compared to a gasoline vehicle with Canada's current electricity grid".

(HOV) lanes, public charging deployment, and carbon taxation and cap-and-trade policies, to promote demand for electric vehicles (EVs).

This study intends to estimate the impacts of financial purchase incentives, among other demand inducing factors, on electric vehicle sales using data on sales and incentive amounts by model, province and month from September 2012 to December 2016. I attempt to answer three questions: (1) Do financial incentives encourage consumers to switch away from conventional gasoline vehicles to electric cars? (2) Do changes in gasoline prices affect consumers' propensity to purchase electric vehicles? (3) Have the purchase incentive programs been cost-effective in reducing carbon emissions?

The differences in the presence and generosity of the incentive programs across provinces and time serves as an advantage to identify incentive effects in my study. Three provinces of Ontario, Quebec, and British Columbia offered incentives of differing values on the purchase/lease of new electric vehicles. Ontario and Quebec changed incentive generosity over time and at different points in time, and British Columbia stopped the incentive program in February 2014 and restarted as of April 2015. Also, the incentive amounts vary across electric vehicle models depending on the model attributes and price within each of the rebating provinces.

Other advantages of this study are explained as follows. First, unlike the rebate programs in the form of income (or sales) tax deductions/waivers, the calculation of Canada's incentive programs offered at the time of purchase does not require additional data (on income distribution or provincial sales tax, for example). I have access to model-specific incentive data which allow me to incorporate incentives into the models without having to make unnecessary assumptions on the calculation of incentives. Second, I am able to control for the potential correlations that exist between incentives and time-invariant unobserved preferences for each electric vehicle model using model-specific fixed effects. Finally, observing electric vehicle sales by month has made it possible to incorporate the changes in incentive programs in the exact months they occur, as well as to control for unobserved factors that vary by month within a particular year.

According to the results of my preferred regression, I find that a $1000 increase in rebates increases the sales of electric vehicles by 8 percent.[4] I also find changes in gasoline prices as another important factor in electric vehicle sales. My results suggest that on average, a 10-cents-per-liter increase in gasoline prices would result in a 2.8 to 6.1 percent increase in electric vehicle sales.

I calculate the number of electric vehicle sales caused by the incentive programs in each province and year using counter-factual sales in the presence of incentives versus a no incentive scenario. I find that incentives have been responsible for about 47% of electric vehicle sales in the rebating provinces from 2013 to 2016. This implies that almost half of the new electric vehicle buyers would still have purchased electric vehicles even if they had not been offered incentives. Therefore, a part of the government expenditures on incentives were allocated to the consumers who would have bought electric vehicles regardless of the rebates.

I then evaluate fuel savings associated with the incentive programs by calculating the aggregate sales-weighted fuel consumption (using counter-factual sales and other data on vehicle fuel efficiency and average kilometers traveled) in the presence of incentives, and comparing that with fuel consumption of other conventional cars which would have replaced electric vehicles if incentives had not been offered. The fuel savings are then converted into equivalent carbon emission savings using the emissions produced from electricity and gasoline in each province and year. Overall, the lifetime (i.e., 10 years in my study) carbon emission reductions of the electric vehicles sold as a result of the incentive programs are estimated to be 60,000 tonnes on average across the rebating provinces between 2013 and 2016.

Finally, carbon emission savings are divided by the government expenditures on incentives to construct the cost of emissions displaced due to the incentive programs. The cost of carbon emissions reduced is estimated to be on average $216 per tonne across the rebating

[4]Note that the econometric specifications in this study estimate changes in the market share of electric vehicles, instead of quantities sold, in response to changes in incentives. Since incentives do not affect aggregate new vehicle sales, the percent changes will be the same for both quantities sold and market shares.

provinces over this period. This calculation accounts for the emissions produced by electricity generation. Overall, my counter-factual analysis only takes into account the governmental costs of reducing one tonne of carbon emissions, and does not include other social externalities (such as network, learning, and information externalities) associated with using EVs. As a result, my results can not be used to provide an answer for the overall cost-effectiveness of the incentive programs.

Throughout the paper, I first review the growing literature on different federal and state-level incentive programs to promote the sales of more fuel-efficient vehicles in Section 1.2. In Section 1.3, I present a summary of the incentive programs by Canadian provincial governments from 2012 to 2016. Data and summary statistics are presented in Section 1.4 followed by the identification strategy and econometric specifications in Section 1.5. Section 1.6 presents the results. In Section 1.7, I address the extensive margin effects of the incentives. Section 1.8 provides the results of the counter-factual simulations. Section 1.9 concludes.

1.2 Literature Review

Several researchers and scholars have directed their attention to the factors that impact the adoption of hybrid and electric vehicles in the last decade. They address many socioeconomic and policy variables, such as financial and non-financial supports by governments, gasoline prices and fuel costs, consumers' willingness to adopt fuel-efficient technologies, and hybrid and electric vehicles' characteristics and prices as the key determinants of hybrid and electric vehicle adoption. In this section, I will briefly explain the methodology and findings of some of the studies that focus on the impacts of financial incentives and gasoline price on hybrid and electric vehicle sales and summarize their findings in Table 1.1.

Beresteanu and Li (2011), Diamond (2009), and Gallagher and Muehlegger (2011) investigate the effects of rising gasoline prices and tax rebates, in the form of income tax deductions/credits or sales tax waivers, on hybrid vehicle sales using different empirical analyses over the same period (2000 to 2006) in the USA.

Beresteanu and Li (2011) conduct simulations to address the effects of rising gasoline prices and federal income tax deductions/credits on hybrid vehicle sales in 22 US Metropolitan Statistical Areas (MSAs). Following Berry et al. (2004), they use a structural method to estimate the demand and supply determinants of hybrid vehicle sales in the US automobile market by taking advantage of both household-level and aggregate market-level sales data. Then, using estimates of the structural model, they perform simulations to compare the cost-effectiveness of different support schemes.[5]

Diamond (2009) evaluates the effectiveness of government incentives (including federal tax credits, state-specific incentives, and other non-financial supports) and other socioeconomic factors (such as gasoline prices and annual miles traveled) on market shares of three hybrid vehicle models.[6] He estimates several models: cross sectional regressions on annual state-level market shares, and panel regressions using fixed, between, and random effects for each hybrid model separately. In addition, he evaluates state-specific responses to financial incentives using monthly sales data in nine individual states where a significant incentive policy was implemented.

Gallagher and Muehlegger (2011) address the affects of various forms of state incentives on the adoption of hybrid vehicles using quarterly sales data in US. They examine the effect of both the magnitude and form of different state incentives on hybrid adoption by utilizing within-state$*$model variation in incentives and gasoline prices.

All the above studies conclude that rising gasoline prices have greater effects on hybrid vehicle sales than federal tax incentive schemes from 2000 to 2006 in the USA. As shown in Table 1.1, the magnitude of the incentive and gasoline price effects, however, differ across these studies. As argued by Beresteanu and Li (2011), one of the important reasons for the

[5]They perform simulations on the sales of five hybrid models: Ford Escape Hybrid, Honda Civic Hybrid, Honda Accord Hybrid, Toyota Highlander Hybrid, Toyota Prius, separately, as well as on the total sales of all hybrid vehicles in each year from 2000 to 2006.

[6]Honda Civic Hybrid, Toyota Prius, and Ford Escape.

larger effects of gasoline price is associated with the substantial increases in gasoline price (from $1.75 in 1999 to $2.60 in 2006), which explain 37% of the increase in hybrid vehicle sales over this period. This effect occurred while tax incentives were found more effective in the final year of their study (i.e., in 2006) when more generous tax incentives were in effect; subsidies across the five hybrid models, on average, increased from $460 in 2005 to $1860 in 2006. These studies also attribute the greater impacts of gasoline price to (1) consumers' perception of gasoline price as the most visible signal in fuel savings, and (2) willingness to purchase hybrid vehicles over conventional cars to avoid the uncertainty and volatility of future gas prices in the calculation of future fuel costs. Finally, they show that financial incentives given at the time of purchase have shown greater impacts on hybrid sales than future income tax credits (up to ten times larger effects by sales tax waivers according to Gallagher and Muehlegger (2011)).

In Canada, Chandra et al. (2010) estimate hybrid vehicle sales in response to variations in rebates (sales tax reductions or waivers) over years, across provinces, and across hybrid vehicle models within each province from 1989 to 2006. They find, in their most comprehensive specification, that provincial rebates increase market share for hybrid vehicles by 31-38% whereas the gasoline price has no significant impacts on vehicle shares over this period. They attribute the insignificant effects of the gasoline price to the correlations between fuel costs and various year and model-specific fixed effects in their regressions.[7]

In addition to the studies on hybrid vehicle sales, many of the recent studies examine policies to promote the purchase of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) across the US states. Narassimhan and Johnson (2014) and Clinton et al. (2015) perform similar analyses to estimate the effects of state-level monetary incentives and other demand stimulating factors on EV model registrations (per capita) prior to 2014. Using random effects models on both BEV and PHEV registrations (per capita) from 2008

[7]They use hybrid model-specific fuel costs as a measure to exploit gasoline price variations over time and across provinces and vehicles and therefore find perfect correlation between fuel costs and various year and model-specific fixed effects.

to 2014, Narassimhan and Johnson (2014) find purchase rebates and income tax credits to have significant positive effects on BEV purchases only, not PHEVs. Clinton et al. (2015) find similar impacts of tax credits on BEV purchases (after excluding Tesla BEV from the analysis) using fixed effects regressions on BEV registrations (per capita) from 2011 to 2014. Unlike the findings in Clinton et al. (2015), gasoline prices appear to have increased both BEV and PHEV purchases over the period of analysis in Narassimhan and Johnson (2014).

Regarding the effect of other EV support programs, Narassimhan and Johnson (2014) find heterogeneous effects of high occupancy vehicle (HOV) exemption on BEV and PHEV purchases. Their findings indicate that HOV exemptions have no statistically significant impacts on BEV sales, whereas they lead to a 0.31% higher PHEV sales. Clinton et al. (2015) find no statistically significant effects of HOV exemptions and charging infrastructure on BEV sales due to lack of variation in these support programs over this period.

In the previously mentioned studies in the USA, where incentives mostly take the form of income or sales tax deductions/waivers, the calculation of rebates is dependent on the vehicle price or the distribution of income. This adds more complications to the analysis and may require additional assumptions on the calculation of incentives. In the current study, however, the incentives offered to electric vehicles are in the form of point-of-sale subsidies (up-front purchase price reductions off the pre-tax vehicle list price for eligible EV models purchased/leased) rather than tax deductions/waivers. Another advantage over some studies that only perform cross sectional analysis (for example, Beresteanu and Li (2011)), this study allows for time-series and cross sectional analysis using variations in the timing and generosity of the incentive programs across the rebating provinces. This allows for the isolation of the effect of this incentive program after eliminating the effects of many unobserved regional and temporal factors that may affect EV purchase decisions. While there may still be some unobserved factors influencing EV sales, the identification in my analysis relies on weaker assumptions as compared to the identification in the cross sectional analyses in other studies.

This study, to the best of my knowledge, is the first to address the effects of Canadian provincial point-of-sale incentives on electric vehicle sales. It is most closely related to Chandra et al. (2010). However, my approach is novel in several ways. First, using monthly sales data allows me to more precisely incorporate the timing of the incentive policies in each of the provinces that implemented the incentive programs. For example, British Columbia ceased the incentive program between February 2014 and April 2015, and thus changes in sales in response to this policy change can be precisely evaluated using monthly sales. Second, I observe the list of electric vehicle models eligible for incentives as well as the corresponding incentive amounts associated with each electric vehicle model in each of the treated provinces.[8] This is advantageous since it allows me to use the exact incentive amount offered to each electric vehicle model without having to make questionable assumptions on the calculation of incentives. Finally, I use various combinations of fixed effects to control for the unobserved provincial and temporal factors, including other EV support programs, that may influence electric vehicle sales.

1.3 Electric Vehicles and An Overview of Provincial Incentives Programs

Plug-in electric vehicles (PEVs), which are usually referred to simply as electric vehicles (EVs), consist of two subgroups: battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). BEVs only operate on electricity and do not require gasoline as a fuel source at all. The batteries are rechargeable when plugged into an electric vehicle charger and, depending on the model and battery size, they can travel anywhere between 100 to 500 kilometers on one charge. PHEVs, on the other hand, operate on both electricity and gasoline.[9] Again, depending on the make and mode of the PHEV, they run the first 20 to 60

[8] My data is obtained directly from the ministries of each of the rebating provinces and covers the electric vehicle models eligible for incentives and the corresponding incentive amount associated with each model.

[9] PHEVs, similar to traditional hybrid electric vehicles (HEVs), use two propulsion methods, a combustion engine and an electric motor. HEVs usually draw their power from the electric motor at low speeds and

kilometers on electricity on a single charge and then switch to using gasoline if they run out of charge. For the rest of the paper, EV will be used to point to any type of electric vehicle regardless of its fuel type (i.e., whether it is a BEV or PHEV).

Following the introduction of new policy initiatives towards reducing carbon emissions in Canada after 2010,[10] provincial governments put into effect new policies to promote EV adoption. A short list of the programs that have been offered to induce demand for EVs and facilitate their use includes point-of-sale rebates on the purchase/lease of a new EV as well as financial incentives on private charging stations, non-financial incentives (such as unrestricted access to lanes for high occupancy vehicles and free parking), public charging stations, carbon pricing policies (i.e., carbon tax and cap-and-trade policies) to increase the price of gasoline, regulating policies to reduce the price of low-carbon electricity, and finally developing educational campaigns to raise public awareness about EVs.[11] Table 1.2 presents the demand-based policies that were in place across Canadian provinces from 2012 to 2016. Over the period of this study, public-charging deployment was the only demand-focused policy effective in all ten provinces.[12] Although all provinces began to provide infrastructure to facilitate EV adoption, the three provinces of Ontario, British Columbia, and Quebec engaged in more comprehensive policies to accelerate demand for EVs, each at different points in time, after 2010.[13]

As the first Canadian province that regulated an Electric Vehicle Incentive Program

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switch to the internal combustion engine to generate power at high speeds. PHEVs, however, use their electric motor to power all aspects of propulsion and will continue to operate until battery runs out of charge. PHEVs are essentially electric vehicles that require gasoline to extend driving range. With PHEVs, energy savings are much more substantial than HEVs (Electric Vehicle News (2012)).

[10] According to Axsen et al. (2016), the goal of 40% new electric vehicle market share is defined as an excellent EV policy progress to meet Canada's long-term plan to reduce greenhouse gas emissions.

[11] There also exist many supply-based incentives that support the research and development of EVs and provide incentives for manufactures and suppliers to increase production and sales. Zero emission vehicle mandates, vehicle emission standards, and low-carbon fuel standards are also examples of supply-based policies. The analysis of the supply-side factors is out of the scope of this study.

[12] In 2015, there were 20, 168, 49, 71, 28, 51, 260, 49, 146, 29 public charging stations in AB, BC, MB, NL, NB, NS, ON, PEI, QUE, and SK.

[13] According to the Axsen et al. (2016), the number of direct and indirect EV supportive policies varies across Canadian provinces with Quebec (32 policies), Ontario (26 policies), and British Columbia (19 policies) taking the lead in having implemented the largest number of policies, respectively.

(EVIP), Ontario started offering financial point-of-sale incentives for the lease or purchase of new EVs in December 2010. According to the EVIP program, a rebate of $3000 to $8500 was applied to the lease or purchase price of each eligible EV after all applicable taxes and costs have been applied. The rebate amount varies across new EVs depending on the make, model, fuel type (whether they are BEVs or PHEVs), and the electric battery capacity, model year and year of acquisition. Ontario also offered up to $1000 rebate for private charging stations at the time. Among non-financial incentives, in July 2010, Ontario Ministry of Transportation (MTO) launched Green License Plate Program, which granted access to high occupancy vehicle (HOV) lanes on 400 series of highways. Under this program, vehicle charging stations are also eligible for rebates of up to $1000 or 50% of the total purchase and installation cost, whichever is lower. In November 2015, greater Green Investment Funds were granted to support more charging stations across Ontario. In February 2016, EVIP increased the rebate amount granted to EVs to cover between $3000 to $13000 of the lease or purchase price. The rebate amount increases as the battery size and passenger capacity of an electric vehicle rises.[14]

British Columbia announced the Clean Energy Vehicle (CEV) program in November 2011 to encourage the adoption of clean-energy vehicles. The CEV program was designed to increase sales of battery and plug-in electric, compressed natural gas, and hydrogen fuel cell vehicles.[15] This program consisted of two phases. Phase 1 of the program that ran between December 2011 to February 2014 provided a rebate of $2500 to $5,000 (depending on the make, model, battery size and net weight of each vehicle) on the pretax Manufacturer's Suggested Retail Price (MSRP) of a newly purchased or leased eligible EV. Since 2011, the province also introduced other EV support programs, such as unrestricted access to HOV lanes and incentives for replacing older vehicles with EVs. Moreover, British Columbia's carbon tax policy sets the highest price on carbon emissions in Canada, which stayed at $30/tonne during this period. The provincial government stopped the rebate program for

[14] A part of these information are obtained from Power (2016).

[15] Hydrogen fuel cell vehicles were not available to the public throughout the CEV program.

over a year between February 2014 to April 2015 as the full budget allocated for 2013/2014 fiscal year had been depleted. The second phase of the program began in April 2015 with the same incentive amount but on a broader range of EV models. The CEV Infrastructure Deployment Program also provides funding for EV charging stations and upgrading existing hydrogen fueling stations, general infrastructure design, academic research, curriculum development, and outreach on clean energy vehicles and infrastructure.

In January 2012, the province of Quebec implemented a purchase or rental rebate from \$500 to \$8000 to individuals, businesses and municipalities willing to purchase a new EV. In November 2013, the purchase or lease rebate amount ranged from 4500\$ to 8000\$ for new EVs, and a \$1,000 rebate was also available for low-speed EVs. Like the other two rebating provinces, Quebec also provides EVs with privileged access to reserved lanes where carpooling is authorized. In addition, Quebec launched the largest charging network system in Canada, called Electric Circuit, to improve access to public and private charging infrastructure and provided a rebate of up to \$600 for purchasing and installing private charging stations. Besides the Drive Electric Program, a cap-and-trade policy was adopted to impose tax on carbon in 2013. Once again, the rebate amount varies across vehicle models depending on the vehicle's selling price, electric battery capacity, model year, year of purchase, and so on. Later in 2015, Quebec launched a Transportation Electrification Action Plan offering a series of policies designed to increase the availability of electric public transportation. Several major initiatives were undertaken by this action plan, including the electric public transportation and school buses plans, supporting pilot projects for the electrification of taxi fleets, installation of several more public and private charging stations along main roads, multi-unit residential buildings, new office buildings, and for on-street parking, research and innovation activities to support projects related to transportation electrification, and education and awareness programs to promote the use of EVs. Table 1.3 shows the average rebates (in dollar values) offered to an EV in each of the provinces that offered purchase incentives in this period.

In this study, I will focus on the demand-side factors that influence new EV purchases, with a particular attention to financial purchase incentives. I am unable to assess the effect of other demand-inducing factors such as HOV-lane access, charging stations, and private charging incentives. I do not have data on the number of charging stations,[16] and there are no variations in incentives on private charging stations and HOV-lane access over time in the rebating provinces.[17] Failure to account for the effect of these policies may result in omitted variable bias. In Section 1.5, I will discuss how I take advantage of different identification techniques and various combinations of fixed effects to account for the effect of these additional incentive programs.

1.4 Data

In order to address the effects of financial incentives on new EV purchases, data from various sources are combined together. The EV sales data is obtained from IHS Automotive Canada and is made accessible by Green Car Canada. This data-set includes monthly sales of new EVs by make and model from September 2012 to December 2016. Therefore, markets are defined as province-year-month in my analysis. The IHS Auto data does not include non-EV sales and also does not dis-aggregate sales within the model by fuel type or battery capacity or other vehicle characteristics. As such, I use monthly sales reports from Green Car Canada to disaggregate sales by fuel type, which defines whether the vehicle is a BEV or PHEV. Green Car Canada also reports dis-aggregated estimates for monthly sales of EV models: Toyota Prius, Ford C-Max and Ford Fusion, where both hybrid and plug-in hybrid variants exist.[18]

[16] The number of charging stations across the rebating provinces are only publicly available for 2016.

[17] In British Columbia, the monetary incentives on private charging stations were renewed in April 2015 in conjunction with the EV purchase incentives (after the cease of the incentive program for over a year as of February 2014).

[18] Green Car Canada estimates the number of electric Ford Fusion and C-Max sales there have been in Canada by taking the sales numbers from Quebec (which are reported in provincial registration numbers periodically) and applying a best-guess of what the nationwide monthly numbers are. For example, for Toyota C-Max PHEV, Green Car Canada estimates monthly Canadian sales assuming Quebec represents 2/3 of electric market in Canada and 2/3 of Quebec C-Max's are plug-in electric.

In addition to EV sales data, I obtain the total automobile unit sales (including the sales of passenger cars and trucks separately) in each province and month from Statistics Canada.[19] Aggregate monthly sales data allows me to find the market share of each EV model from the total vehicles sold in each market.

The list of all eligible EV models as well as the corresponding incentive amounts (in dollar value terms) offered to each model are directly collected from the Ministry of Transportation in Ontario and British Columbia and from the Ministry of Energy and Natural Resources in Quebec.[20] Using the exact incentive amounts allocated to each particular EV model allows me to capture incentive effects without having to make unnecessary assumptions to calculate incentive values. As an alternative way to incorporate incentives into the analysis, I use the ratio of incentives to vehicles' list prices by utilizing the Manufacturer Suggested Retail Prices (MSRPs) data available online at MSN AUTO for each model-year generation.[21] This alternative measure is used to provide insights about the relative incentive effects across different EV models with differing prices. The challenge associated with using vehicle list prices, rather than transaction prices, is that list prices do not account for the dealers' and manufacturers' incentives and the negotiations between the dealer and buyer at the time of purchase. I will discuss this challenge and explain how this might bias the incentive estimates in my models in 1.5.

To account for the effect of gasoline prices, I calculate dollar value savings from driving 1 km in an EV compared to driving 1 km in an average gasoline vehicle using: $\text{FuelSavings}_{jpt} = (FE_{pt}^{Gasoline} * GasolinePrice_{pt}) - (FE_{jpt}^{EV} * ElectricityPrice_{pt})$. The dollar value savings (FuelSavings_{jpt}, measured in ¢/km) is the cost incurred by driving 1 km of average gasoline vehicle k (i.e., the first term) minus the cost incurred by driving 1 km in EV j (i.e., the

[19] Statistics Canada, CANSIM, Table 079-0003, New motor vehicle sales, Canada, provinces and territories, annual. 2015.

[20] In each of the rebating provinces, EV manufacturers must apply for the eligibility of every model they desire to qualify for incentives to the Ministry of Transportation and re-apply for each vehicle model and trim already in the program every year.

[21] I account for year-to-year changes in their list price in my data except for a number of EV models whose list prices did not change over time.

second term) in province p and year t. The fuel costs of driving 1 km in a vehicle is the product of its fuel efficiency rating (denoted by FE) and the price of fuel consumed by the given vehicle (i.e., electricity price (in ¢/kWh) for EVs and gasoline price (¢/L) for gasoline cars in my calculation). Natural Resources Canada (NRCan) provides data on fuel efficiency ratings of all EV models (in kWh/100 km) and the fuel economy of an average non-EV model (estimated to be 10.7 (L/100 km)).[22]

I obtain the average tax-inclusive retail gasoline price from Kent Group Ltd.'s survey for retail gasoline, diesel and automotive propane pump collected daily from gas stations in 70 urban cities in Canada. Since Kent Group only reports gasoline price data for major urban cities, I take the average gasoline price of the cities that belong to each province to account for monthly provincial averages in my analysis.[23] Monthly electricity price data are available at Statistics Canada's consumer price index series (Statistics Canada, CANSIM, Table 326-0020).[24]

Finally, I control for provincial demographic and labor market trends over months and years using Statistics Canada's surveys. To capture monthly variations in income, I use real labor income calculated from seasonally adjusted wages, salaries and employers' contributions (in 1000 dollars) from the survey of "Estimates of Labor Income". I also control for monthly variations in unemployment rate, as well as annual variations in the fraction of female population, the percent of adults (between 20 and 65 years of age) with a college diploma, and the median age in each province using Statistics Canada's CANSIM database.[25] All nominal dollar values are converted to real terms based on the 2002 prices to account for inflation.

[22]As documented by Rivers and Schaufele (2017a), I assume that the fuel consumption rating of an average gasoline vehicle stays relatively unchanged over time.

[23]I follow this procedure for all provinces except for Ontario and Quebec, for which, Kent Group Ltd. provides monthly average prices in their survey.

[24]I also perform my estimations using alternative electricity price data from "Comparative Index of Electricity Prices", residential consumers (in cents per kWh), using HydroQuebec reports: "Comparison of Electricity Prices in Major North American Cities" (2017).

[25]These data are collected, respectively, from the seasonally adjusted labor force of working age (15 years and over) that are unemployed (Table 282-0087), the Standard Geographical Classification (SGC) reports (2016), Table 477-0019, and Table 051-0001 of CANSIM database.

Table 1.4 presents the summary statistics for the EV sales data, provincial incentives, gasoline prices, and socioeconomic measures. Accounting for EV model-level data in addition to province-month data, there are a total of 5644 observations, corresponding to 10 provinces, 52 months, and an average of 10 EV models in each province and month. As shown in the table, there are on average 91 EV sales, with a low of 0 and a high of 649 sales, in each market, with BEVs comprising about 42% of total EV sales. The average sales-weighted incentive value across the three rebating provinces over the years of study is $2786, with a minimum of zero dollars offered in BC between February 2014 to April 2015, and a maximum of $7973 in Ontario in 2014. Excluding the period in BC where incentive programs were inactive, the average sales-weighted incentive value across the rebating provinces becomes larger ($6296), with a minimum of $2465 in BC in 2015. Also, the incentives offered to BEVs are, on average, two times greater than those offered to PHEVs.

1.5 Identification Strategy and Econometric Specifications

In this section, I will discuss the identification and empirical strategy used to estimate changes in EV market shares in response to the presence and variations in purchase incentives and gasoline prices across provinces and over time. I will also explain how the effects of other observed and unobserved temporal and provincial factors, including other support programs (such as public charging infrastructure, access to HOV-lanes, and monetary incentives on private charging stations, and etc.) are accounted for in my analysis.

Figure 1.1 shows the trends for EV sales and gasoline prices in Canada from September 2012 to December 2016. The number of new EVs sold, and the real average tax-inclusive retail gasoline price ($/L), across provinces and months are presented.[26] According to this

[26] As mentioned in Section 1.4, retail tax-inclusive gasoline prices are deflated based on the 2002 price index.

graph, monthly EV sales are, on average, growing substantially over time, starting from below 500 sales per month in 2012 to above 1250 in 2016. On the other hand, gasoline price levels are high, but they are on average decreasing during this period, changing from high rates of around \$1.1/L at the beginning of this period to lower rates of about \$0.8/L towards the end. It is hard to explain the relationship between monthly gasoline prices and EV sales only based on visual observations of movements during this period. In my regressions, I will precisely estimate the effects of changes in gasoline price on EV sales.

I also provide Figure 1.2 to show the aggregate trends in EV market shares of total vehicle sales across provinces during the period of study. The vertical axis shows the market share of all EVs of total sales of all vehicles sold in the rebating provinces against the rest of Canada in each month. I include all the provinces that don't offer incentives in one group:"Rest of Canada", to avoid overcrowding the graph. As is visually clear in the graph, the trends in the three provinces where EV incentive policies are in effect show substantially higher market shares versus the rest of Canada. The divergence in trends in the treated provinces from the trends in other provinces during 2012, which is the time when rebates were effective in all three treated provinces, is apparent. In the three leading provinces, EV market share trends start at rates lower than 0.01 in 2012 but increase in the following months, with Quebec and British Columbia continuing to increase at higher rates than Ontario. The trends in Quebec and British Columbia rise at approximately the same pace during 2013 and 2014, but in the last two years, British Columbia outpaces Quebec by accelerating EV market shares. This can be attributed to the fact that British Columbia restarted its Clean Energy Incentive policy in April 2015 after it was stopped for more than a year from February 2014.

I intend to capture variations in EV market share trends across provinces and over time, as portrayed in Figure 1.2, as part of my empirical analysis. However, besides the visual representation of the changes in EV shares across provinces, which can partially be attributed to the incentive programs, there may be other time and province-specific factors that may influence new EV purchases and are not visible in the graph. Later in this section, I will explain the fixed-effect estimation used in my empirical analysis to control for the unobserved temporal and provincial factors that may be correlated with the purchase incentives.

Overall, there are four sources of variation across provinces, over time, and across EV models which allow me to identify incentive effects. The first source is associated with the number of provinces that implemented incentive programs; only three provinces offered purchase incentives to EVs. The second source is related to the generosity of the incentive programs across the rebating provinces in any given year, as these provinces differ in the incentive amounts they offer to most EV models. Third, the incentive amounts vary across different EV models within a given province-year. And finally, there are variations in the incentive amounts offered to a particular EV model within a given province over time (except in Quebec).

Quebec is the only province whose rebate treatment did not change from 2012 to 2016, and therefore the incentive amounts offered to most eligible EV models remained unchanged for the duration of my data.[27] There were only a number of EV models whose incentive treatments underwent slight changes over this period. For example, the rebates offered to a Mitsubishi i-MiEV were \$7731 in 2012, \$7731 in 2013, \$8000 in 2014, no incentives in 2015, and \$8000 in 2016. Another example is the Toyota Prius (PHEV), which was offered \$4607.60 in 2012, \$500 in 2013, \$4000 in 2014, \$500 in 2015, and no incentives in 2016.[28] Due to these small changes in the incentive treatments designed for particular EV models, the mean value of incentives will also vary slightly over time (see Table 1.3), allowing me to capture average incentive effects in Quebec as well.[29]

[27] I was unable to obtain data on provincial EV sales prior to the implementation of incentive programs and therefore can not perform a comparison analysis on the pre versus post effects of incentives on EV sales.

[28] A potential reason for these differential treatments can be attributed to the eligibility process. As mentioned previously, manufacturers must register the EV models they desire to qualify for incentives every year. The provincial governments then decide if the registered EV models meet the requirements to receive purchase incentives. For example, an incentive of \$4000 was allocated to Porsche 918 only in 2015 and to Panamera only in 2014, whereas Porsche Cayenne received the same amount of incentive in two consecutive years (2015 and 2016).

[29] I attempt to estimate all models once by including Quebec and another time by eliminating it from the analysis; the results are statistically significant across all models and the magnitude of the effects do not change significantly across models. Additionally, I estimate a model using Quebec as the only treated province (versus non-treated provinces) and find that incentives still have positive significant effects on EV

The empirical strategy used in my analysis follows the conventional discrete choice model of demand for differentiated products. Assume that there are K models in each market (province-time), and the price of model k is p_{kpt} ($k \in 1, 2, \ldots, K$). The utility that individual i will obtain from purchasing a new vehicle in each market can be expressed as:

$$U_{ikpt} = \alpha_i(Y_{ipt} - p_{kpt}) + \beta_i X_k + \epsilon_{kpt} + \lambda_i F_{kpt} + \varepsilon_{ikpt}, \tag{1.1}$$

where Y_{ipt} represents individual i's income, and therefore α_i captures the marginal utility of income. β_i captures vehicle k's observed (by consumers) attributes (X_k), ϵ_{kpt} accounts for the unobserved attributes of the given model, F_{kpt} is an index of fuel cost for vehicle k, and finally ε represents the mean zero stochastic term that captures individual i's unobserved preferences for a particular vehicle. Indexes p and t represent province and time, respectively, and time is defined as month-year in this model.

I incorporate incentives into the analysis by decomposing a vehicle's price into two components: a model-year specific mean (p_{kt}) and a province-time-specific incentive associated with a particular model (Incentive_{kpt}). More precisely, I assume that the price of a particular model consists of a list price that is constant across provinces and an incentive associated with province-specific rebate policies towards purchasing electric vehicles. The price of a particular vehicle can therefore be defined as:

$$p_{kpt} = p_{kt} - \text{Incentive}_{kpt}, \tag{1.2}$$

where $\text{Incentive}_{kpt} = 0$ for a non-electric vehicle.

I now rewrite the utility function after substituting in the vehicle price components:

$$U_{ikpt} = \alpha_i Y_{ipt} - \alpha_i(p_{kt} - \text{Incentive}_{kpt}) + \beta_i X_k + \epsilon_{kpt} + \lambda_i F_{kpt} + \varepsilon_{ikpt} \tag{1.3}$$

Instead of purchasing a new vehicle, individual i may choose to purchase an outside good

shares, but with smaller magnitude compared to the specifications that include all three treated provinces.

and spend their income on other goods than vehicles. I define $U_{i0pt} = \alpha_i Y_{ipt}$ as the utility obtained from purchasing the outside good, as I assume that consumers will choose one unit of the good (a new vehicle or an outside good) that provides the highest utility. Suppose that j denotes a particular EV model ($j \in 1, 2, \ldots, K$). Then, the probability that consumer i will purchase EV j among all $k \in 1, 2, \ldots, K$ and the outside good is:

$$P_{ijpt} = Pr(U_{ijpt} > U_{ikpt}) \quad \text{for} \quad k \in 0, 1, 2, \ldots, K, j \in 1, 2, \ldots, K, \text{and} \quad j \neq k \tag{1.4}$$

By decomposing preferences into deterministic and random components ($U_{ikpt} = V_{ikpt} + \varepsilon_{ikpt}$),[30] I allow the probability of choosing a particular EV model to be derived from the differences between utilities from the available alternatives (rather than the absolute values of individuals' utility, i.e., $P_{ijpt} = Pr(V_{ijpt} - V_{ikpt} > \varepsilon_{ikpt} - \varepsilon_{ijpt}) \quad \text{for} \quad j \neq k$.

The aggregate market shares for EV j (s_{jpt}) can then be found by integrating over preferences of all individuals in each market:

$$s_{jpt} = \int_{\varepsilon} I(V_{ijpt} - V_{ikpt} > \varepsilon_{ikpt} - \varepsilon_{ijpt} \quad \text{for} \quad j \neq k) f(\varepsilon) d\varepsilon, \tag{1.5}$$

where I is an index that takes a value of one if the condition in Equation 3.5 is satisfied and zero if otherwise.

I assume that for all individuals in my analysis, $\alpha_i = \alpha$, $\beta_i = \beta$, and $\lambda_i = \lambda$, meaning that there is no systematic heterogeneity across individuals' preferences, and the only source of heterogeneity is in the mean zero stochastic term. Assuming that the error term ε_{ikpt} for all individuals is distributed independently and identically multivariate type-I extreme value, there is a closed form solution for the integral in 3.5 that yields the standard logit model: $s_{jpt} = \frac{e^{V_{jpt}}}{\sum_K e^{V_{kpt}}}$, where s_{jpt} is the market share of EV j from total vehicle sales in each

[30]The deterministic component V_{ikpt} captures consumers' observable attributes as well as vehicles' observable and unobservable attributes, and the random term ε_{ikpt}, captures consumers' unobservable preferences over their vehicle choice.

market.

Finally, I divide the share of EV j by the share of the outside good (s_{0pt}) and estimate the log odds ratio of purchasing a new EV relative to the outside good as a function of product characteristics using the following standard logit specification:[31]

$$\log(\frac{s_{jpt}}{s_{0pt}}) = \alpha p_{jt} - \alpha \text{Incentive}_{jpt} + \beta X_j + \lambda F_{jpt} + \epsilon_{jpt}, \tag{1.6}$$

where p_{jt} is the list price of EV model j (i.e., the manufacturer's suggested retail price (MSRP)), Incentive_{jpt} in the province-time specific incentive amount offered to each EV model, X_j and ϵ_{jpt} are EV j's observed and unobserved attributes, respectively, and finally F_{jpt} is defined as the dollar-value savings (in ¢/km) from driving one kilometer in an EV compared to driving one kilometer in an average vehicle.

The coefficient of interest, α, captures the effect of incentives (in dollar values) on the log odds ratio of purchasing a new EV relative to an outside good in a given market. More specifically, it indicates a shift in preferences from the outside good (i.e., not purchasing a new vehicle at all) to purchasing a new EV due to incentives. This implies that the consumers who would not have purchased any new vehicle in the absence of incentives would choose to buy a new EV when offered incentives. If this has happened, the total number of new vehicles sold in a given market must have increased in response to incentives. To test whether this has happened, I estimate the extensive margin effects of incentives on total vehicle sales in each market after eliminating the provincial and temporal unobserved factors and find that incentives have no significant impacts on aggregate sales.[32] As a result, for the rest of the models in my study, I will use model-specific market shares (as opposed to the odds ratios) as the dependent variable. I will further explain the details of incentive effects on total vehicle sales in Section 1.7.

[31] Note that dividing the equation by s_{0pt} and taking logs will cancel out Y_{ipt} and ε_{jpt} from the equation.

[32] Many studies in the literature also find it unlikely that financial incentives would affect total vehicle sales in a given market. For example, Chandra et al. (2010) find no evidence that tax rebates would influence consumers to shift preferences from not buying a vehicle at all into buying a new hybrid vehicle.

The challenge with estimating Equation 3.6 is that the unobserved EV attributes are likely correlated with EV prices and potentially with other EV observed attributes and therefore may create biased estimates. As such, all estimating equations include EV-model fixed effects to control for all the observed (X_j) and unobserved model attributes that only change across EV models but are constant over time and across provinces.[33]

As mentioned previously, I do not have EV transaction price data and therefore can only control for vehicle list prices in my models. Although the model-specific fixed effects will capture the observed and unobserved vehicle attributes (including vehicle prices), they may not fully control for vehicle transaction prices and the negotiation between the dealer and buyer at the time of purchase. It is likely that manufacturers and dealers respond to incentives by changing transaction prices to offset EV purchase costs. In any case, this is not problematic in my study, since I intend to estimate the reduced-form impact of incentives on EV shares, therefore, α captures the average equilibrium impact of incentives on EV shares that include both consumer and manufacturer response to the incentives. I believe that this is the desired estimate for evaluating the incentive programs.

Moreover, several time-varying and provincial factors, in addition to purchase incentives, can influence EV purchases. I employ various combinations of fixed effects to account for these unobserved factors that are correlated with the incentives and might affect EV sales. The fixed effects used in my estimations define the source of identification. In specifications without vehicle-province fixed effects, the identification is cross sectional. The challenge with the cross sectional model is that I am unable to differentiate between unobserved preferences by province and by vehicle, since changes in preferences over time can either be attributed to vehicle characteristics or to provincial attributes. As such, I apply the highest resolution of fixed effects: EV-model-province, EV-model-year-month, and province-year-month fixed effects, in the preferred specification. Including EV-model-province fixed effects allows me

[33] The unobserved attributes refer to the first component included in ϵ_{jpt} that do not vary by time and province: $\epsilon_{jpt} = \epsilon_j^1 + \epsilon_{jpt}^2$. Some examples of the observed and unobserved attributes are make, model, engine type, fuel economy, battery size, number of cylinders, interior and exterior design, performance, and the time and province invariant component of the vehicle retail price (excluding rebates).

to identify the incentive effects based on variations in individual EV model shares within a given province over time in response to the presence and variations in incentives.

EV-model-time (denoted by ϕ_{jt}, with time referring to a year-month) and EV-model-province (denoted by ω_{jp}) fixed effects capture the unobserved time-varying and provincial preferences for individual EV models, respectively. EV-model-time fixed effects control for national time-varying unobserved factors that might influence EV sales; year-specific demand shocks, federal regulations and taxation on the vehicle market, and other federal environmental regulations on fuels are examples of such factors. EV-model-province fixed effects are designed to capture the unobserved provincial characteristics that are more consistent with the use of particular EVs. Some examples of these time-invariant provincial factors are climate, geography, density, road structures, culture, and make up of the population, popularity of a given EV in a particular region, perception of the population about environmentalism, etc. In addition to these unobserved factors, the province fixed effects (interacted with each EV model) also control for the effect of other time-invariant provincial incentive programs that are correlated with the purchase incentives. As mentioned earlier in the paper, I am unable to assess the effect of HOV-lane access and monetary incentives on private charging stations, as they do not vary over the period of my analysis.[34] EV-model-province fixed effects absorb the effect of these factors as well. Finally, province-time fixed effects (denoted by κ_{pt}) capture the unobserved preferences across EV models within a given province and year. These unobserved factors also include time-varying provincial regulations in the vehicle market that occur in conjunction with the purchase incentives and therefore might affect EV sales. Regulations such as public charging infrastructure[35] and the extensive policies

[34]It is also worthwhile to add that some empirical evidence in the literature find smaller impacts of support programs, such as HOV-lane access and public charging stations on EV sales relative to monetary incentives. Axsen et al. (2016) estimate that HOV-lane access and public charging deployment have an overall impact of 0.57% and 7.8%, respectively, on market shares in the Canadian EV market by 2040. However, financial purchase incentives are estimated to have a market share impact of 10% by 2040. Some other empirical evidence are explained in the Literature Review.

[35]The programs to deploy public charging infrastructure in the rebating provinces are: the Green Investment Funds Program in Ontario (launched in November, 2015), CEV Infrastructure Deployment Program in British Columbia (launched in November 2011, updated in April 2015), and the Electric Circuit Program in Quebec (launched in November 2013).

and funding to support more public charging stations over time, the cap and trade policy to impose tax on carbon in Quebec in 2013, the Transportation Electrification Action Plan to provide electric public transportation in Quebec in 2015, and so forth.

Including the EV-model-time (time refers to a year-month), EV-model-province-, and province-time fixed effect combination into the model leaves the error term with a mean zero component that varies by time and province (μ_{jpt}) in the following estimation:

$$\log s_{jpt} = \alpha \text{Incentive}_{jpt} + \lambda F_{jpt} + \omega_{jp} + \phi_{jt} + \kappa_{pt} + \mu_{jpt} \tag{1.7}$$

α is expected to be positive and can be treated as the percent change in the market share of a particular EV model due to a \$1000 increase in incentives. For example, assuming that α is 0.09, the market share of a Chevrolet Volt, with an average share of about 0.00059 in Ontario over the period of study, increases to 0.00063 [0.0.00059 + (0.00059*0.09) = 0.00064] due to a \$1000 increase in incentives. As mentioned previously, I also use incentive to the EV's base price ratio as an alternative measure for incentives in my models. λ captures the effect of fuel cost savings associated with driving an EV (compared to a gasoline vehicle) (used as logs and measured in ¢/km) on EV shares, and measures the percent change in EV market shares due to a one percent increase in fuel cost savings. Linear regression with fixed effects is applied to estimate Equation 3.7, and the standard errors across all the specifications are clustered by province$*$class to allow the unobserved characteristics of particular EV classes within a province to have serial correlations with one another over time.[36] There are 80 clusters, accounting for 8 EV classes and 10 provinces, in each regression. The EV classes defined in my data are subcompact, compact, compact SUV, mid-size, full-size, two-seater, and station wagon.

It is important to address an issue that arises upon the transformation of the dependent variable to logarithm in the above equation. As there are many zero sales observations in

[36]For example, compact EVs that are within a given province are more likely to undergo similar province-specific changes over time (due to the geography of the region, the make up of the population in that region and etc.) than compact EVs across provinces.

the data (3223 out of 5620 observations), the log transformation of EV shares creates several missing observations. I take advantage of a number of methods suggested in the literature to overcome this problem and explain them in greater details in the next section (i.e., Section 1.5.1).

1.5.1 Alternative Specifications and Zero Sales Observations

In this section, I explain a few approaches that I use to address the problem associated with the substantial zero sales observations contained in my data following the methods suggested in the literature. In Figure 1.3, I provide the histogram of individual EV shares from total vehicle sales in each market in levels and in logarithms to show the relevant influence of the mass of observations at zero compared to the rest of the sample. The left panel shows a right-skewed distribution for EV market shares with a mean and standard deviation of 0.0001 and 0.0004, respectively. The extensive tail of this distribution reaches to 0.007, which corresponds to the maximum market share level in the sample. The density distribution of the transformed shares (to logarithm) shown on the right panel, however, is closer to normal distribution and clearly has a higher minimum and average (0.0003 and 0.006, respectively) as it corresponds to a smaller sample including only positive shares. Although this sample represents an approximately normal distribution, it is clearly observed that lots of zero-share observations are omitted from the sample. In the following subsections, I will explain the methods used to overcome the challenge with the zero market share observations.

Linear versus Generalized Linear Regressions

In my first attempt to deal with zero market shares, I estimate a standard linear regression using market shares (in levels) as the dependent variable. While a standard linear regression is a practical and reasonable approach, and the transformation of market shares is not necessary due to the nature of the variable (as ratios), using shares imposes a few problems on the estimation: it would ignore the zero lower bound and therefore would not take account of the decisions of not buying an EV, it predicts non-positive values for market shares, and more importantly the relationship between the dependent and independent variables is not linear due to the large number of observations at zero. As a result, for these specifications, as suggested by Papke and Wooldridge (1996), I take another approach and use Generalized Linear Models (GLM) with a binomial distribution and a logit link function.[37] I only present the GLM results (instead of the results of the standard linear regressions, which I present in the appendix) and apply the different combination of fixed effects (on all market shares including zeros) explained previously to allow for comparison across models with different identification and unobserved controls. These models are also used as a benchmark for comparison with the rest of the methods discussed in this section in dealing with zero share observations.

Another common practice that is widely used in the literature is to add an arbitrary constant that is smaller than the smallest observed positive share (0.000001, in my analysis) to all market share observations to avoid missing data after log transformation. For this specification, I use the same independent variables as in Equation 3.7 and only apply the combination of fixed effects in my preferred model (i.e., EV model-year-month, EV model-province, and province-year-month fixed effects). However, as argued by Gaudry et al. (2009) and many other scholars in this literature, this method may imply drastic changes to the data since the results depend on the choice of the arbitrary constant, and there is no reason to prefer one value over the others;[38] this can create large negative outliers, especially when we are dealing with too many zeros in the data. Having mentioned this, I choose a constant that doesn't significantly change the magnitude of the log shares before and after this modification and also test this model using arbitrary constants of differing values to check the robustness of the results. I find that the magnitude and significance of the results are largely unaffected. I only include this model to show the consistency of the estimates

[37]I try other potential family and link functions including inverse Guassian and log-gamma as well but only include the results of the binomial-logit model as it shows to be the best fit among all regressions.

[38]For example, the natural logarithm of 0.01 equals to -4.6 whereas for 0.0001, it equals to -9.21.

of the main coefficient based on this approach, but will present the results in the Appendix (due to the disadvantages of this model).

Aggregate Regressions

In the next three specifications, I attempt to reduce the number of zero observations by aggregating sales according to the following approaches. First, I aggregate sales by EV model, province, and year and apply a GLM regression using the same model as in Equation 3.7 except that the dependent variable is the share of each EV model from aggregate auto sales in a given province (p) and year (t) (i.e., time refers to a given year, rather than a year-month). Similar to the previous models, the effect of gasoline price is captured by using fuel cost savings (in ¢/km) for each EV model; the difference between the cost of driving a given EV and the cost of driving a conventional gasoline car in each province and year. I control for EV-model-province and EV-model-year fixed effects and cluster standard errors by province∗class. From the total of 507 observations (corresponding to 10 provinces, 5 years and an average of 10 EV models), there are only 82 observations with zero market shares.

Next, I aggregate EV sales by province and month and estimate the effects of province-wide mean incentives using:

$$s_{pt} = \alpha \text{Mean Incentive}_{pt} + \gamma Z_{pt} + \delta_p + \sigma_t + \xi_{pt} \tag{1.8}$$

where s_{pt} is EV monthly shares (from aggregate provincial vehicle sales),[39] Z_{pt} are time varying provincial characteristics, including log sales-weighted fuel cost savings from driving EVs rather than non-EVs (in ¢/km) in a given province and month,[40] log real per capita labor income and log unemployment rate, and δ_p and σ_t are province and time (i.e., year-

[39] I once divide EV monthly sales by total passenger cars in a given market and another time by total vehicle sales (including passenger cars and trucks) and find that results are not affected by the choice of this variable.

[40] The sales-weighted fuel cost savings of driving EV j in province p and time t is calculated using: $\frac{\sum_j^J (Sales_{jpt} * FuelSaving_{jpt})}{\sum_j^J Sales_{jpt}}$, which is the product of model-specific sales and fuel cost savings, aggregated over all EVs in a given market and divided by aggregate EV sales in that market.

month) fixed effects, respectively. The total number of observations in this particular model is 520 (10 provinces and 52 months) with only 50 observations corresponding to zero shares. Finally, I bootstrap standard errors using wild cluster bootstrapped t-statistics (WCBSTs).[41]

In the last aggregated regression, I divide provinces into four groups: Ontario, Quebec, British Columbia, and "Rest of Canada" and estimate the changes in each of the rebating provinces against the "Rest of Canada". The dependent and independent variables and fixed effects are the same as in Equation 1.10 except that for the "Rest of Canada", I use aggregate EV shares over the provinces included in this group and the averages of each of the independent variables across the given provinces. Since a large number of EV models with zero sales in the data correspond to the provinces with no incentive programs, this level of aggregation leads to no zero share observations. Therefore, there are 280 observations for 4 groups of provinces and 52 months in this regression.

For both of the aggregate models by month, I perform additional estimations using log average tax-inclusive gasoline prices (measured in ¢/L) and log average electricity prices (measured in ¢/kWh), instead of sales-weighted fuel cost savings, to capture the effects of changes in gasoline and electricity prices on EV purchases. I find that including these variables do not affect the magnitude and significance of the incentive estimates. As such, I only include the results of these models in the Appendix.

Moreover, the advantage of aggregation by province and month is that, in addition to reducing the number of missing observations by a large number, these models evaluate the shifts in preferences from non-EVs to EVs in response to incentives and other determining factors in each market. With respect to other factors that likely induce EV purchases (versus non-EVs), a number of demographic variables (in addition to EV support programs and charging infrastructure) are found to be effective in some of the studies in the literature.

[41] I also attempt to estimate the regressions by bootstrapping standard errors using pairs cluster bootstrapped t-statistics (PCBSTs) and cluster-adjusted t-statistics (CATs), but find that WCBSTs performs better in my panel data analysis. PCBSTs are more effective in controlling the size of hypothesis tests with serially correlated panel data for a moderate number of clusters (not very few clusters, like in my data), and CATs cannot be estimated when a key independent variable doesn't vary within the cluster (Esarey and Menger (2017)).

For example, Narassimhan and Johnson (2014) find that median age and the percent of college graduates have positive impacts on PHEV sales, and the average residential energy consumption has positive impacts on BEV sales. My data allow me to account for the following annual demographic variables: median age, the fraction of females from total population, and percent of adults (i.e., 24 years above) with a college diploma. I include these variables in the monthly regressions reported in the appendix in addition to gasoline and electricity prices. These additional variables do not have statistically significant impacts on EV sales (versus non-EVs), which is likely due to the small variations in these variable over the years of my data.

Across all aggregate regressions, I apply GLM regressions (rather than log-linear or log-log regressions) as GLM shows to be a better model fit and produce economically meaningful estimates (both in terms of the coefficients' magnitude and statistical significance) in the aggregate models.[42]

Olsen and Schafer Two-part Model

Finally, I employ the model in Olsen and Schafer (2001) for repeated measurement of semi-continuous data, which is an extension of the two-part model of Duan et al. (1983) to longitudinal data, to take account of the disproportionately large frequencies of zeros. I choose this model over the other methods proposed in the literature to deal with zero observations (such as the Tobit model, the sample selection model of Heckman, and the compound Poisson exponential dispersion model) because of its appealing properties. Unlike the Tobit and Heckman models, this model doesn't assume an underlying normal distribution for idiosyncratic terms, especially when zero observations represent actual response outcomes (instead of censored or missing values), has a well-behaved likelihood function, and finally allows for more appropriate interpretations when zeros are true values. The model consists of two parts: the first part is a logistic regression (logit estimation in my analysis)

[42] The results of the log-linear or log-log regressions of the same model are similar to the GLM results due to the lower number of zero shares in the aggregate models.

for a dichotomous variable R that takes a value of zero if market shares are zero, and one, if shares are greater than zero.[43]. The second part involves a log-normal regression involving some parameters, defined as β_2 in the second stage, that measure the expected value $E[sharejpt|share_{jpt} > 0]$ conditional on market shares being positive (i.e., R=1).[44] The expected value of the dependent variable, EV model share, then consists of two parts: $E[share_{jpt}] = P(share_{jpt} > 0) \times E[share_{jpt}|share_{jpt} > 0]$. I use the log of fuel cost savings and incentives (in $1000) as explanatory variables in each stage of the model. I also include EV-model-province, EV-model-year-month, and province-year-month fixed effects to control for the unobserved factors that vary by province, time, and by the interaction of the two and are correlated with the incentives.[45] Finally, as it is assumed that $E[\epsilon_2|share_{jpt} > 0, X_2] = 0$, the unconditional expectation can be given by $E[share_{jpt}] = \phi(\beta_1 X_1) \times \beta_2 X_2$.

1.5.2 Nested logit analysis

As mentioned previously, in logit models, the error term is assumed to be distributed identically and independently (iid) Type I extreme value. The Independence of Irrelevant Alternatives (IIA) property implicit in the logit model is the product of iid structure of the random shock. The IIA property imposes restrictions on the ratios of probabilities and/or on the cross-elasticities of probabilities and therefore can create unrealistic own and cross-attribute (including price) elasticities. For example, in my analysis, the IIA implies that the ratio of choice probabilities between two EV models j and h only depends on the systematic

[43]R = 1, if $share_{jpt} = \beta_1 X_{1jpt} + \epsilon_1 > 0$, and R = 0, if $share_{jpt} \leq 0$, with X_1 serving as a vector of explanatory variables as included in Equation (7).

[44]$E[share_{jpt}|R = 1, X_2] = E[share_{jpt}|share_{jpt} > 0, X_2] = \beta_2 X_{2jpt} + E[\epsilon_2|share_{jpt} > 0, X_2]$, with X_2 again serving as the determinants of EV shares as included in Equation (7).

[45]As the model allows using different explanatory variables in each stage of the model, I try different combinations of independent variables for each part. For example, in the first stage, I include log labor income per capita, log median age, log percent females, and log percent college graduates in the population, as additional explanatory variables to control for the factors that vary by province and time and can influence EV purchase decisions. For this specification, I only include EV-model-province and EV-model-time fixed effects. I find that none of these additional variables add much explanatory power to the estimation and the inclusion of these variables do not substantially affect the estimates for the key variables. As such, I include province-time fixed effects instead of these additional variables (in addition to EV-model-province and EV-model-time fixed effects) to account for the unobserved provincial and temporal factors in the main regressions.

utility of the two EV models (i.e., $\frac{P_{ij}}{P_{ih}} = \frac{e^{Vij}}{e^{Vih}}$) and is independent of the characteristics of other alternatives. As such, the probability of choosing a particular EV model over other EV alternatives is invariant to the number of alternatives as well as to the introduction or elimination of alternatives. It also means that substitutions across EV models depend only on their market shares and not on vehicle attributes. This is particularly important from a policy perspective, as it may result in the misprediction of incentive effects. I make the following example (in the context of incentives offered to an EV) to explain the kind of misprediction that likely arises in logit models when a change in the attribute of an alternative can cause unrealistic substitutions across the available alternatives. Suppose that there are only three models in a vehicle market: a Toyota Corolla (a non-EV), a Nissan Leaf (an EV), and a Ford Focus Electric (also an EV which compares to Nissan Leaf in many regards). The probabilities that a consumer will choose each of these models (which are, in fact, equal to their aggregate market shares) are assumed to be 0.66, 0.33 and 0.01, respectively. Now suppose that the government decides to offer financial incentives to Ford Focus Electric buyers only, and the incentive amount is sufficient to increase the probability of buying a Ford Focus by 0.09 (i.e., from 0.01 to 0.10). This incentive program results in a change in the final price of Ford Focus relative to the other two alternatives. The logit model would predict the probability of each of the other two alternative models to drop by the same percentage. The probability for Toyota Corolla would drop by 10% (from 0.66 to 0.60) and for Nissan Leaf would drop by the same 10% (from 0.33 to 0.30). This means that the increased probability of Ford focus is predicted by the logit model to be allocated twice as much from Toyota Corolla (0.06) away from Nissan Leaf (0.03). This substitution pattern is unrealistic since Nissan Leaf is a closer substitute to Ford Focus (as they are both EVs and have many common attributes), and a change in the price of Ford Focus is expected to have a significant impact on the choice probability for the Nissan, but next to no effect on the choice probability for the Toyota. Therefore, the IIA property implies that a change in the attributes of an alternative changes the probabilities for all the other alternatives in proportion to their market shares (regardless of their attributes).

To overcome the IIA, a few alternative models have been suggested in the literature. For example, Nevo (2001) suggests using nested logit and random parameter logit models. I use a nested logit specification to partially relax the IIA assumption. According to Nevo (2001), by grouping differentiated products into exhaustive and mutually exclusive nests in a way that products with similar attributes fall into one nest, we are allowing the within-nest products to have closer cross attribute elasticities with one another than with products from other nests.[46] For the nested logit specification in my analysis, I group all the EVs sold in each province and month in one nest to allow for more reasonable substitution patterns between EVs as compared to the simple logit model. This means that, in each market, in the first stage of purchasing a new vehicle, consumers decide whether they will buy a new EV or non-EV (rather than choosing between buying or not-buying a new vehicle).[47] Then, in the second stage, they choose which of the EV models, among all EV alternatives, they are willing to purchase. I choose this grouping as it allows all EVs to have closer substitutions with one another than with non-EVs, which is reasonable since EVs have similar attributes.[48] The nested logit equation can be characterized as follows:

$$\log(\frac{s_{jpt}}{s_{kpt}}) = \alpha \text{Incentive}_{jpt} + \pi \log(S_{j/J})_{pt} + \lambda F_{jpt} + \phi_{jt} + \omega_{jp} + \kappa_{pt} + \mu_{jpt} \tag{1.9}$$

The dependent variable is the logs odds ratio of purchasing an EV relative to a non-EV.[49] All the independent variables and indexes, as well as the combination of fixed effects, are the

[46]However, the nested logit model only partially relaxes the IIA assumption, because the IIA assumption still applies to the unobserved attributes between products within each nest.

[47]As explained previously, incentives have not caused shifts in preferences along the extensive margin channel. As such, in my nested logit analysis, I will only account for purchase decisions along the intensive margin channel and use model-specific shares in a given market as the dependent variable (rather than the odds ratio of purchasing a vehicle).

[48]I also try grouping EVs by price, make, class, and engine type (BEV or PHEV) and check the robustness of the results based on these additional classifications as well. I find that the incentive effects do not substantially vary across models with different classifications.

[49]The denominator of this term, which I call the share-out variable, shows the fraction of the non-EV sales in each market and equals to (Total Vehicle Sales - Total EV Sales) / Total Vehicle Sales) , and the numerator defines the share of each EV model from total vehicle sales multiplied by (1 - share-out) in each market.

same as Equation 3.7. There is only one additional independent variable that is added to the equation: log of within-nest shares, $\log(S_{j/J})_{pt}$. This variable represents the share of an EV model from all EVs sold in a given market. Therefore, π captures the substitutability of EV models with one another and ranges between zero and one, with one showing the highest substitutions between EVs within a given market. The within-nest share variable, however, is endogenous since any increase in the share of an EV model compared to a non-EV model in a given market will necessarily increase its share compared to other EV alternatives in that market. Therefore, I use instrumental variables (IVs) to account for the endogeneity of within-nest shares. Moreover, similar to the previous models, since there are several zero value observations for EV model shares as well as within-make shares in the nested logit model, using log shares will result in the loss of many observations. I then use a GMM regression on EV shares and within-make shares (both in levels rather than in logs) after accounting for the endogeneity of the within-make share variable using IVs. Following Berry et al. (1995), I use the sum of characteristics of other EVs in the same market as EV j as instruments, because these characteristics are correlated with within-nest shares but unlikely to be correlated with the EV to non-EV relative shares and the consumers' valuation of EV j. The consumers' valuation of EV j (relative to non-EVs) is only a function of EV j's own characteristics. Three characteristics of other EVs in the same market as EV j — motor horse power, the recharge time (hours needed to recharge an EV), and the fuel efficiency (both in liter equivalent and kWh per 100 km) are considered as potential IVs for EV model j.

1.6 Results

I present the results of the models described in Section 1.5. I find that incentives have statistically significant positive impacts on EV market shares; relative change in EV market shares is between 5 to 8 percent due to a \$1000 increase in incentives (depending on the fixed effects used in the estimations). In Section 1.6.1, I discuss the findings of the regressions on market shares when various combination of unobserved factors are controlled for. Then I move to the rest of the models discussed previously to deal with zero sales observations. Finally, Section 1.6.2 reports the results of the nested logit specification.

1.6.1 Main Results

Table 1.5 presents the results of the GLM regressions on market shares using different configurations of fixed effects. The application of GLM, as explained previously, will take into account zero EV sales and the non-linear relationship between the dependent and independent variables (unlike linear regressions). In all models, the dependent variable is the market share of a new particular EV model (out of total auto sales)[50] in a given market. Columns 1 to 6 show the effect of incentives (in \$1000) and log-fuel-cost savings (i.e., the cost of fuel saved due to driving 1 km in a given EV rather than a conventional gasoline car (in ¢/km)) on individual EV market shares using various combinations of fixed effects. Columns 5, 6, and 7 present the results of the specifications with the highest resolution of fixed effects (i.e., EV-model-year-month, EV-model-province, and province-time fixed effects). Column 5 presents incentive effects (in \$1000), column 6 captures the differential effects of incentives on BEVs and PHEVs separately, and column 7 reports the incentive effects relative to a given EV's MSRP. As mentioned earlier, I exploit two sources of identification by changing the fixed effect strategy. Columns 1 and 2 report the results of the cross-sectional specifications. The combination of fixed effects in the specifications in columns 5, 6, and 7 allows the identification to rely on within-province variations in EV market shares.

Column 1 displays the most parsimonious specification that only includes EV-model fixed effects. In column 2, I add time (year-month) fixed effects to capture national time-varying preferences that are correlated with the incentives. In column 3, I raise the resolution of fixed effects and add province fixed effects to column 2 to capture the unobserved preferences that

[50]Using the total passenger car sales instead of total auto sales (which includes all passenger cars and trucks) doesn't significantly change the results.

vary by province. Province fixed effects control for time-invariant unobserved factors that are specific to each province; factors such as climate, geography, density, culture and make up of the population, as well as other EV support programs, such as HOV-lane access and incentives on private charging stations. Column 4 includes province-time controls in addition to EV-model fixed effects. Province-time fixed effects capture the unobserved preferences that change by time, province, and by both. Examples of such factors are the number of charging stations and new provincial regulations and taxation on the vehicle market. Finally, columns 5, 6, and 7 report the most comprehensive specifications that include EV-model-province, EV-model-year-month, and province-year-month fixed effects. Identification in the preferred models comes from within-province variations in individual EV shares over time in response to the presence and variations in incentives and fuel cost savings.

It is evident that the effects of incentives on the market share of a particular EV model across these specifications are consistent in sign and statistical significance. The magnitude of the incentive effects does not substantially change as I raise the resolution of fixed effects across models. This is in particular true across the specifications that include province fixed effects. This indicates that the effect of other unobserved provincial and temporal factors, including other EV support programs (as stated above), have small impacts on the magnitude of the incentive estimates. This leads me to conclude that the omitted variable bias has minimal threats to the identification. The result of the most comprehensive model (in column 5) indicates that on average, a $1000 increase in the incentive offered to a particular EV in a given market is associated with a 8 percent increase in the market share of the given EV once EV-model-province, EV-model-time, and province-time unobserved factors are eliminated.[51] Results in column 6 suggest that the incentives have similar impacts on sales of BEVs and PHEVs, causing about 5 percent increase in sales of both EV types due to a $1000 increase in incentives. By performing a Wald test for the hypothesis that the coefficients for BEVs

[51] It is important to mention that the results of the standard linear regression of these models (reported in Table 1.10 in the Appendix) indicate smaller effects (and inconsistent statistical significance) compared with the GLM results because of misrepresenting a linear relationship between incentives and EV shares and not taking into account the effect of zero share observations.

and PHEVs are equal, I find that I can not reject the equality hypothesis. Therefore, the incentive effects appear to be similar on BEV and PHEV sales. Column (7) suggests that an increase in incentives by one percent of an EV's base price leads to a 3.8 percent increase in its market share.[52]

Regarding the effects of fuel cost savings, the sign and statistical significance are not consistent across the columns. In column 2, since time and EV-model fixed effects are included, only variations in gasoline and electricity prices across provinces are identified by the fuel cost savings variable. As such, the differential effects of cross sectional variations in fuel savings on various EV models (depending on their fuel efficiency (in kWh/km) are captured. The coefficient estimate implies that a one percent increase in the fuel cost savings from driving a particular EV model (compared to a non-EV model) leads to a 0.24 percent increase in the share of the given model, all else equal. However, the model is cross sectional and therefore does not account for province-specific factors that might be correlated with the fuel savings. In column (3), province fixed effects are added and therefore the differential effects of fuel savings over various EV models within a given market is captured. As opposed to the previous model, the coefficient estimate is not statistically significant. In the last four columns, variations in gasoline and electricity prices (as components of fuel cost savings) are highly correlated with province-time fixed effects, and the fuel cost savings do not have statistically significant impacts on EV shares. Overall, none of the specifications with the highest resolution of fixed effects (i.e., EV-model-province, EV-model-year-month, and province-year-month) show statistically significant effects of fuel cost savings on EV shares.[53] In Table 1.6, I will show that fuel cost savings have significant positive impacts on

[52]Following a comment from the examiners in my thesis evaluation reports concerning the degree of variability that is contained in the incentive variable after eliminating the fixed effects, I estimated an additional regression on the incentives with the preferred combination of the fixed effects as the only explanatory variables in the model. The R-squared from this additional regression allows me to capture how much variation in the incentives are being explained by the fixed effects, and consequently how much variation is contained in the incentive variable once the fixed effects are eliminated. I find that the fixed effects explain about 80% of the variation in the incentives, and as a result, the coefficient for the incentives explain about 9% of the variability that is contained in the incentives after removing the fixed effects.

[53]Lack of statistical significance across the estimations on individual model shares can partly be due to the high correlations between energy prices (i.e., gasoline and electricity prices) and different fixed effects

EV market shares in the aggregate regressions.

In Table 1.6, I summarize the results of the remaining models discussed previously to overcome the problem associated with zero share observations. Column 1 reports the incentive and fuel cost savings effects on EV shares aggregated by model, province, and year. Results indicate that a \$1000 increase in model-specific incentives is associated with a 5 percent increase in the given model's market share. The costs of fuels saved due to driving 1 km in an EV (compared to a non-EV) have statistically significant impacts on EV market shares, indicating that a one percent increase in the fuel savings of an EV (compared to a gasoline car) is associated with a 0.26 percent increase in its market share. This implies that a 10 cents per liter increase in gasoline price on average would result in a 2.9 percent increase in EV sales.[54]

Columns 2 and 3 present the results of the aggregate EV sales by province and month across all provinces and across each of the rebating provinces versus the "Rest of Canada", respectively. For these two specifications, variations in the monthly share of EVs from total vehicle sales across provinces in response to changes in average province-wide incentives (in both measures) and log of aggregate sales-weighted fuel cost savings and other controls (i.e., log real labor income and log unemployment rate) are considered.[55] Consistent across both columns, a \$1000 increase in average province-wide incentives causes a 7 percent increase in EV shares relative to non-EV shares (in the rebating versus non-rebating provinces).[56] Fuel cost savings (in ¢/km) has significant positive impacts on EV shares in both specifications.

in my models. The fuel economy of an EV is highly correlated with EV-model fixed effects, and gasoline price is correlated with province and time fixed effects. Chandra et al. (2010) also find that gasoline prices do not have statistically significant impacts on hybrid vehicle sales across the Canadian provinces due to similar reasons (i.e., correlations between gasoline costs and various province and time fixed effects). It can also be in part due to the small variation that is retained in the fuel cost savings variable after eliminating the effects of other province-specific and time-varying factors.

[54] A 10 cents per liter increase in gasoline price is equal to 11% increase when compared with the mean value of gasoline price over this period (i.e., 90 cents per liter), and therefore would lead to a 2.9% ($0.26 \times 0.11 = 2.9$) increase in EV sales.

[55] In column 3, the monthly averages of fuel cost savings, real labor income, and unemployment rate in each of the rebating provinces and the "Rest of Canada" as a whole are considered.

[56] Using EV shares from total passenger car sales (rather than total auto sales) doesn't change the magnitude or statistical significance of the main coefficient.

The coefficient estimates imply that a one percent increase in the fuel savings associated with driving 1 km in EVs (compared to non-EVs) in a given market leads to a 0.41 to 0.55 percent increase in EV market shares. In other words, a 10 cents per liter increase in gasoline price on average would lead to a 4.5 to 6.1 percent increase in EV sales.

Finally, columns 4 and 5 report the results of the two-part model in Olsen and Schafer (2001) for longitudinal data. Both models find the effects of the incentives (in $1000) and log-fuel-cost savings on individual EV model shares once EV-model-province, EV-model-time, and province-time fixed effects are accounted for. These fixed effects control for all the unobserved factors that vary by province, year, and by both that can affect EV purchase decisions. Column 4 presents the results of the first part of the model using a logit regression to estimate the probability of purchasing an EV (relative to a non-EV) due to the incentives and log-fuel-cost savings. The first part of the model defines the probability of observing a zero versus positive market share. As observed in the results, incentives do not have statistically significant effects on the probability of purchasing an EV. Column 5 presents the second part of the model using OLS regression on the log of individual EV shares conditional on a positive market share. The effect of incentives is consistent with the estimates in the other specifications in the table, implying an 8 percent increase in the market share of a given EV model due to a $1000 increase in incentives conditional on buying an EV (significant at the 1% level). Fuel cost savings, similar to other estimations on individual model shares, do not have statistically significant impacts on EV purchases in neither of the stages of the two-part model, although they are positive in sign and close to the other fuel savings estimates in magnitude.

Overall, across all the specifications in both tables, incentives show positive significant effects on EV market shares ranging from 6 to 17 percent (due to a $1000 increase in incentives) depending on the level of aggregation and the configurations of fixed effects. Results of the most flexible specification indicate an 8 percent increase in EV sales due to a $1000 increase in incentives. The results of my analysis are consistent with the results of some of the studies in the literature. For example, Gallagher and Muehlegger (2011) find that a tax incentive of \$1000 value increases hybrid sales by 5%, while a tax incentive of mean value (using a tax incentive dummy as alternatives to the value of the tax incentive across the US states offering incentives) results in 22% increase in sales. Narassimhan and Johnson (2014) shows that monetary incentives (in the form of purchase rebate, tax credit, or sales tax waiver) only have significant impacts on BEV purchases rather than PHEV purchases. They find that a \$1000 purchase rebate leads to a 9% increase in BEV purchases. Chandra et al. (2010) also show in their most comprehensive model (with model-specific rebates) that a \$1000 increase in the tax rebates increases the share of sales of new hybrid vehicles by 34%. The results of my analysis show smaller effects for incentives on EV shares relative to the incentive effects found by Chandra et al. (2010). I believe that the smaller impacts of incentives in my analysis compared to their results are due to the following reasons: (1) the relative influence of British Columbia's incentive program over the course of my study, compared to the other two rebating provinces, as well as the cease of the incentives for more than a year in this province, (2) lack of comparable variations in incentives over time in Quebec against the other two rebating provinces despite the high incentive rates offered in this province, and (3) as the price difference between EVs and gasoline vehicles are much larger than that of between hybrid and gasoline vehicles, a \$1000 incentive would have much larger impacts on hybrid vehicle sales (than EV sales).

Lastly, my findings imply that the fuel cost savings associated with driving EVs compared to non-EVs also have significant impacts on EV demand. I find that a one percent increase in fuel cost savings leads to a 0.26 to 0.55 percent increase in EV shares in a given market. This is equivalent to a 2.9-6.1 percent increase in EV sales due to a 10 cents per liter increase in the real average price of gasoline over the period of study (i.e., 90 ¢/L as shown in Table 1.4). These effects are consistent with the estimates reported in other studies: Gallagher and Muehlegger (2011) find positive correlations between gasoline price and hybrid vehicle sales using US hybrid vehicle sales data from 2000 to 2006; Narassimhan and Johnson (2014) find variations in gasoline price to be an effective factor in increasing Gallagher and Muehlegger (2011) estimate that the cross price elasticity of demand for hybrid vehicles with respect to gasoline price is 0.86. Narassimhan and Johnson (2014) find that a 1% increase in gasoline price leads to a 1.3% and 2.8% increase in PHEV and BEV purchases, respectively.

1.6.2 Nested Logit Results

As explained in the nested logit analysis, I employ an alternative specification to partially relax the IIA assumption implicit in the standard logit model defined in Equation (7). According to this model, I classify all EVs sold in each market into one nest because of the similar attributes that exist between EVs in a given market, and account for substitutions between EVs in that market by including the share of each EV model from total EV sales as an additional variable in the regression. The effects of incentives (in dollar values and relative to the EV's base price) and fuel cost savings (¢/km) of driving an EV compared to a gasoline vehicle are then measured on the market share of a given EV model (of total vehicle sales in each market) after accounting for the share of that EV model from total EV sales in the given market. Results are presented in Table 1.7. The robustness of the results presented in Table 1.7 with the results of the specifications in Section 1.6.1 is evident. The coefficient of interest implies that a one percent increase in the incentive to the base price ratio is associated with a 2.9 percent increase in the share of sales of a particular EV model in each province and month after accounting for substitutions between all EVs in that market. This effect is equivalent to a 6 percent increase in EV shares due to a \$1000 increase in the amount of incentives. The coefficient π indicates the substitutability between EVs within each nest and indicates that the EVs within each market are allowed to have higher substitutions with one another than non-EVs in that market. This coefficient is also significant and positive and indicates that the degree of substitutability between EVs with the same make is 37%. Finally, in line with the results of the previous models of individual market shares, the variable of fuel cost savings does not have statistically significant impacts on EV market shares.

1.7 Extensive Margin Effects

As discussed in Section 1.5, a conventional differentiated products demand model suggests a closed-form solution for the aggregate demand of a particular vehicle model. According to Equation 3.6, the market share of a given EV is considered relative to the market share of the outside good (i.e., any product other than vehicles). As such, a positive coefficient for incentives would imply that any increase in incentives causes an increase in the probability of purchasing a new EV (relative to not purchasing any vehicle at all). As has been argued in the literature (for example by Chandra et al. (2010)), it is unlikely that rebates would cause shifts in preferences from not buying any vehicle at all into buying a new EV. In this section, I will investigate the extensive margin effect of incentives on new EV purchases and find whether total new vehicles sold in a given market have changed due to the incentives. I estimate the following equation:

$$\log \text{Sales}_{pt} = \alpha \text{Mean Incentive}_{pt} + \gamma Z_{pt} + \delta_p + \sigma_t + \xi_{pt} \tag{1.10}$$

where $Sales_{pt}$ is the total number of new vehicles sold in province p and time (year-month) t, incentives are province-wide averages (in \$1000), and Z_{pt} includes other time-varying provincial controls. Some of these controls change by province and month: log real gasoline price (inclusive of all taxes), log real labor income, and log unemployment rate, and some change by province and year: log median age, log fraction of females from total population, and log percent of adults (i.e., 24 years above) with a college diploma. δ_p and σ_t are province and time fixed effects, respectively.[57] I estimate this regression using aggregate auto sales, as well as passenger car sales. Across all models, linear regression with fixed effects is applied and standard errors are bootstrapped using wild cluster bootstrapped t-statistics (WCBSTs).

[57]Time fixed effects consist of year and month dummies, respectively, as follows: $\sigma_t = \sigma_y + \sigma_m$.

Results are presented in Table 1.8. The estimates listed in columns 1 and 2 are based on aggregate auto sales, while those presented in columns 3 and 4 are based on aggregate passenger car sales. Columns 1 and 3 only include mean incentives as the explanatory variable and no other provincial controls are included. The specifications in columns 2 and 4, however, capture the effects of other provincial controls in addition to the incentive effects. I apply linear regressions with province and time (year-month) fixed effects, and bootstrap standard errors using wild cluster bootstrapped t-statistics (WCBSTs), across all specifications. Consistent across all models, incentives do not show any statistically significant effects on aggregate vehicle sales. This means that the incentive programs have no implications on the extensive margin and only cause shifts in preferences along the intensive margin channel (i.e, from non-EVs to EVs). I believe that the following reasons explain why incentives didn't affect total vehicle sales: (1) although EV sales are growing, they still constitute a very small share in the Canadian vehicle market with an average of about 0.34 of all vehicles sold across provinces in Canada, (2) EVs are normally more expensive than their non-EV counterparts, which also offer similar characteristics, and (3) the average incentives across provinces over this period only cover a very small portion of the price of a new EV. It is now reasonable to conclude that the incentive coefficient in the logit model implies that a fraction of the people who were willing to purchase a new vehicle regardless of the incentives decided to shift their preferences away from non-EVs to EVs due the incentives in the treated provinces versus non-treated.

According to the coefficients of the estimates of other provincial controls, real labor income and percent females from total population appear to have homogeneous effects on passenger and total vehicle sales. I find that a 1% increase in real labor income causes a 1.6% and 1.7% increase in all vehicle and passenger car sales, respectively, and are statistically significant at the 5% level in both models.[58] Also, a 1% increase in the fraction of females from total population is associated with a 20% and 68% increase in total auto and passenger

[58] I find similar results when I use real labor income per capita, but use real labor income instead, since this variable seems to be a better fit for both models in terms of the level of significance.

car sales, respectively. The remaining variables show heterogeneous effects on total and passenger car sales. Median age only has significant negative impacts on passenger car sales, whereas the real gasoline price and unemployment rate only have significant negative impacts on total vehicle sales (all at a 10% significant level). A 1% increase in the real gasoline price and the unemployment rate leads to 0.52% and 0.21% decreases in total vehicle sales, respectively.

1.8 Counter-factuals Simulations

In this section I use the results of the most preferred nested logit estimation presented in Table 1.7 to calculate counter-factual market shares and the number of EV sales that were induced by incentive programs in each province and month. I will then evaluate the cost-effectiveness of the incentive programs by calculating the total amount of CO_2 emissions (in tonnes) displaced, and the dollar value of emissions saved, due to the incentives.

First, I calculate the fitted market shares using the estimated α from Equation 1.10 to find the predicted shares in the presence of incentives (s^*_{jpt}). Analogously, I calculate the fitted shares after setting incentives to zero to find the predicted shares in the absence of incentives($\hat{s_{jpt}}$).[59] The predicted number of EV sales induced by the incentives (i.e., Sales^*_{jpt}) can then be measured using: $(s^*_{jpt} - \hat{s_{jpt}}) \times \text{Sales}_{pt}$, where Sales_{pt} is the total number of vehicles sold in each market.

I obtain the lifetime fuel consumption of each EV model using the predicted sales of the given model (i.e., Sales^*_{jpt}) multiplied by its fuel efficiency, average kilometers traveled, and the vehicle lifespan.[60] Natural Resources Canada (NRCan) provides data on fuel efficiency ratings of all BEV and PHEV models.[61] I use data on the annual ve-

[59]Note that I take the exponential of the predicted share values since the dependent variable is in logarithmic form. Moreover, the estimation is on the share of sales of an electric vehicle from total auto sales in each province and month, therefore, the sum of predicted shares do not have to add to one.

[60]I assume for simplicity that an EV, like a conventional gasoline car, will stay on the road for 10 years.

[61]The fuel economy data for PHEVs reflect fuel consumption when operating on electricity (in kWh/100 km) and gasoline (in L/100 km) and also take into account the potential amount of gasoline usage while

hicle miles traveled (VMT) collected from thousands of North American Ford BEV and PHEV owners from a survey reported in the EVS29 Symposium in Canada in 2016.[62] For all the PHEVs in my data, I take the average VMT and electric VMT (eVMT) for C-MAX and Fusion from this study and calculate their lifetime fuel consumption as follows: $[(\text{eVMT}_j \times \text{fuel-economy}_j^{electricity}) + (\text{VMT}_j \times \text{fuel-economy}_j^{gasoline})] * 10$. And for all BEVs, I use the annual eVMT for Ford Focus Electric and only account for electricity consumption.[63]

Next, I measure the total emissions produced in the presence and absence of incentives and calculate the amount of CO_2 emissions displaced as a result of the incentive programs. The carbon emission savings (in tonnes) are obtained from the difference between the aggregate emissions over all the predicted BEV and PHEV sales in my data (i.e., Sales^*_{jpt}) and the emissions generated by the conventional gasoline cars which would have replaced EVs if no incentives had been offered. For BEVs, only the emissions generated from electricity are considered after the carbon intensity of electricity generation in each province is accounted for.[64] And for PHEVs, I use the emissions generated from a mix of electricity and gasoline-only operation following: $[\text{fuel consumption}_j^{electricity} * \text{carbon intensity}_{pt}] + [\text{fuel consumption}_j^{gasoline} * 2.3]$, where 2.3 is the amount of CO_2 emissions produced by a liter of gasoline (NRCan (2017)).[65]

In order to compare the lifetime emissions from EVs with emissions from the conventional gasoline vehicles which would have replaced EVs in the absence of incentives, I use the same

operating on electricity.

[62] Haugneland et al. (2016) measure average trip length and distance traveled by day, month, and year by the owners of Ford Focus Electric, Ford C-MAX Energi PHEV, and Ford Fusion Energi PHEV from Canada, California, the Northeast Zero Emission Vehicle (ZEV) mandate member states, and the remaining of the states in US from 2013 to 2016. I choose the results of this study because: (1) they take into account the weather and geographical conditions in Canada versus the other regions in their study and (2) the period of their study matches perfectly with the period of my analysis.

[63] The results of this study indicate that PHEV owners drive more kilometers than conventional vehicle owners (11,284 and 10,295 miles for Fusion and C-Max, respectively, with 34% eVMT), whereas BEV owners tend to drive less than their conventional and PHEV counterparts (i.e., 8,491 miles or 13,700 km).

[64] CO_2 Intensity is calculated as follows: CO_2 Intensity (kg/kWh)= CO_2 emissions (kg)/Electricity Generation (kWh), and varies by province as each province uses different sources of fuels (such as coal, natural gas, nuclear, hydro, steam from waste heat, and etc).

[65] It is important to note that as the electricity emissions from charging an EV varies depending on the time of day a vehicle is being charged, an average measure of the carbon intensity of electricity by province may over- or under-estimate the related emissions.

annual distance traveled for EVs and their gasoline counterparts in my calculations. This means that, the lifetime emissions from the PHEVs sold during this period are compared with the emissions from their gasoline counterparts with the same annual distance traveled as an average PHEV (i.e., 17,300 km as suggested in Haugneland et al. (2016)). Similarly, I compare the lifetime emissions from the BEVs sold and the emissions from their gasoline counterparts with the same annual distance traveled as an average BEV (i.e., 13,700 km).[66]

It is important to note that my counter-factual calculations are based on the following two assumptions: the total vehicle sales in each market are assumed to stay unchanged in response to incentives, and that there are no rebound effects on driving.[67] The emission savings (in tonnes) can then be converted into dollar value savings when divided by the government expenditures on incentives in a given market. I find the government expenditure by aggregating the incentive amounts over all the EV models sold in each province and year.

The results of the counter-factual calculations are presented in Table 1.9. Columns 1 and 2, respectively, report the actual number of EVs and BEVs sold in each province and year, column 3 reports the percentage of EV sales induced by the incentives based on the counter-factual results, column 4 is the CO_2 emission reductions (in tonnes) over the lifetime (i.e., 10 years in my study) of the EVs sold in each year,[68], and finally column 5 displays the cost of emissions saved over the lifetime of the EVs sold due to the incentive programs (in dollars per tonne). I only present the annual (rather than monthly) calculations to avoid overcrowding the table.

According to the results of Table 1.9, the actual number of EV sales across the three

[66]I also perform an alternative approach; I compare the emissions from EVs and emissions from their gasoline counterparts using the annual distance traveled of an average gasoline vehicle (i.e., 15,300 km according to Statistics Canada (2017)) for each EV sold over this period. However, for PHEVs, I take into account the 34% annual eVMT in my emission calculations (i.e., 5200 km driving on electricity and 10,100 km driving on gasoline). I find that the results are relatively unchanged between the two methods, so I only present the results of the first approach.

[67]This means that EV owners are assumed not to increase driving due to lower fuel costs of driving per kilometer. If a rebound effect exists, the marginal cost of driving an EV per kilometer, and consequently the emissions produced, will be higher which will result in lower fuel savings associated with the incentive programs as compared with the counter-factual results of my analysis.

[68]An approximation of the emission reductions for each year (rather than the emission reductions over ten years of using EVs) can be obtained by dividing the numbers in column 4 by 10.

rebating provinces are increasing over the years, with Quebec experiencing larger sales than the other two provinces.[69] In Ontario, incentives seem to have induced EV sales more than in the other two provinces, which is likely due to the higher population in that province (see Table 1.3). Overall, incentives explain 60%, 30%, and 52% of EV sales in Ontario, British Columbia, and Quebec, respectively, over these four years. While this implies that the incentive programs have been successful in increasing EV sales, they have been offered to many consumers who would have purchased EVs (or other fuel-efficient vehicles) regardless of the incentives.

In addition to higher EV sales in Ontario and Quebec compared to British Columbia, these two provinces have larger reductions in carbon emissions over the lifetime (10 years in my study) of the EVs sold during this period. The larger carbon emission reductions can be due in part to the larger proportion of BEVs from all EV sales and the fact that BEVs on average produce lower carbon emissions than PHEVs. I believe that the incentives in British Columbia has been less effective due to the following reasons: (1) lower incentive rates offered over this period, (2) the cessation of the incentive program for more than a year from February 2014 to April 2015 (which, as shown in Table 1.9, has caused the incentive-induced EV sales and fuel savings to decrease in 2014), (3) insufficient financial and infrastructural support on charging stations until the start of the CEV program in April 2015, and finally the fact that residents of British Columbia have already been using fuel-efficient vehicles over the past decade and therefore didn't shift preferences into buying EVs in comparison with the residents of Ontario and Quebec. Overall, the lifetime carbon emission reductions of the EVs sold as a result of the incentive programs are estimated to be 60,000 tonnes across the rebating provinces between 2013 and 2016.

The cost of emissions saved (per tonne of carbon dioxide) due to the incentive programs varies across the rebating provinces, with an average of $260 in Ontario, $80 in British

[69]Note that the year 2012 is not included in the table as I only have data for four months in 2012 (from September 2012).

Columbia, and $251 in Quebec over this period.[70] Over the same time period, the cost of purchasing a liter of gasoline ranges from the highest rate of $1.18/L in 2013 in British Columbia to the lowest rate of $0.68/L in Ontario in 2016 (based on the 2002 adjusted tax-inclusive gasoline prices). Across these three provinces over this period, on average, $216 was spent to displace a tonne of CO_2, which is equivalent to 434 liters of gasoline given that a liter of gasoline produces 2.3 kg CO_2).

Overall, my counter-factual analysis only takes into account the governmental costs of reducing one tonne of carbon emissions associated with the financial purchase incentives. This means that my cost-benefit analysis does not include other externalities (such as local pollution externalities, network and information externalities, and learning externalities and so forth) associated with using EVs. Therefore, the overall cost-effectiveness of the incentive programs require a comprehensive cost-benefit analysis that includes all the social and environmental costs and benefits associated with using EVs. As a result, my counter-factual results can not be used to provide an answer for the overall cost-effectiveness of the incentive programs.

1.9 Conclusion

Three provinces of Ontario, Quebec, and British Columbia offered financial incentives of differing values on the purchase/lease of EVs at different times after 2010. The characteristics of the incentive policies provide a great opportunity to evaluate the effects of provincial rebates on EV adoption due to the variations in the number, timing, and generosity of the incentive programs across the Canadian provinces between 2012 and 2016. This paper investigates whether consumers shift preferences from purchasing a non-EV to an EV in response to incentives. It also evaluates whether the incentive policies have been cost-effective in reducing carbon emissions over this period.

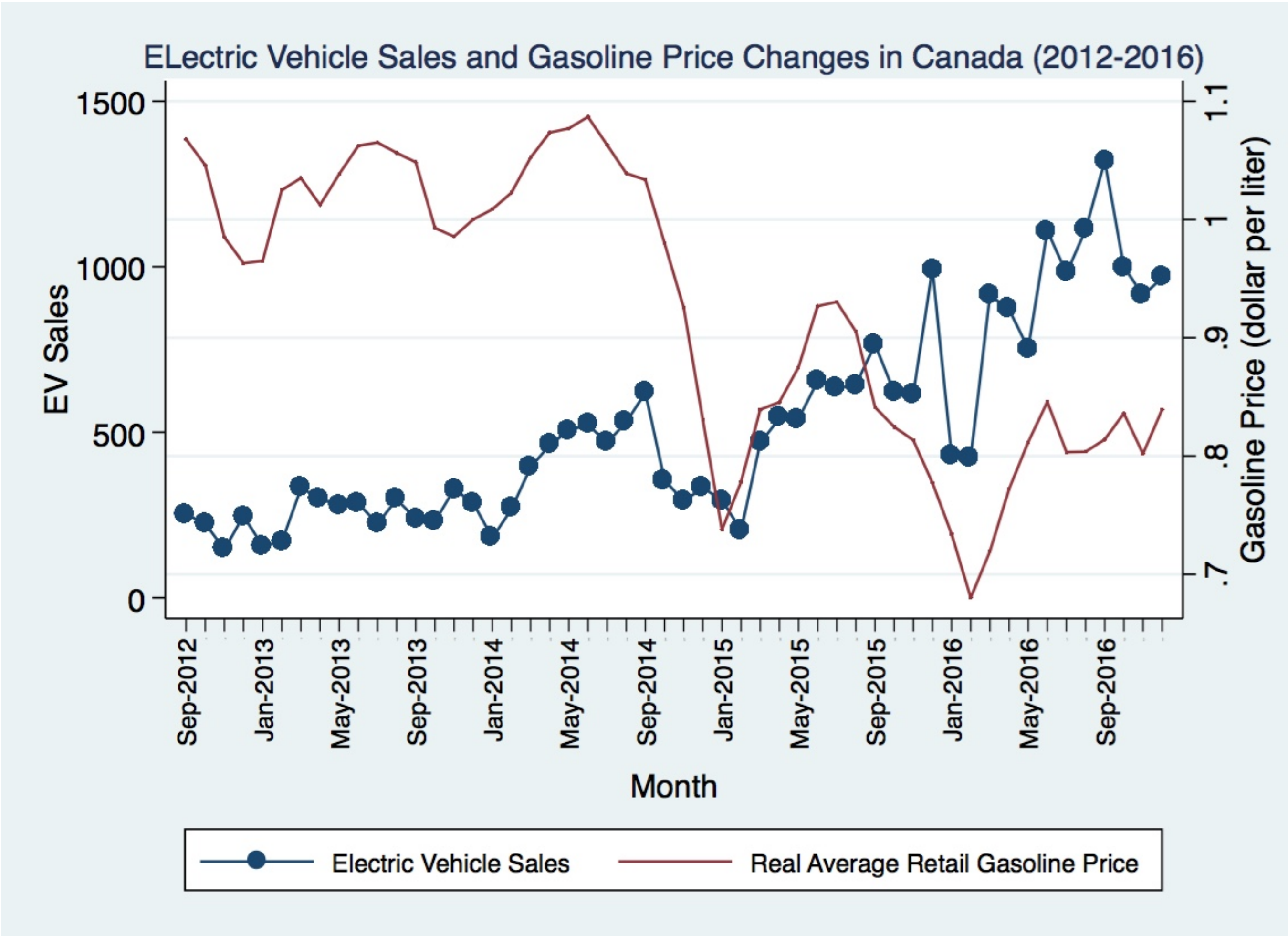
[70] Note that the small value of fuel savings in British Columbia in 2014 is due to the fact that the incentive programs were only available in the beginning of 2014; the provincial government stopped the incentive program from February 2014 to April 2015.

Using monthly sales data on all new EVs sold across the Canadian provinces, along with the incentive amounts offered to each EV model in each of the rebating provinces over time, incentive programs appear to have increased EV purchases by an average of 8 percent due to an incentive increase of $1000. This corresponds to about 4 percent increase in EV sales due to an increase in incentives by one percent of a given EV's base price, in the rebating versus non-rebating provinces.

The results of the counter-factual estimations on fuel savings and carbon emission reductions associated with the incentive programs indicate that incentives contributed to reducing carbon emissions by an average of 60,000 tonnes over the life-time (10 years in my study) of the EVs sold in the rebating provinces. However, the results on the costs of fuel savings indicate that incentives have not been cost-effective in reducing carbon emissions. The average cost of emission reductions across the provinces that offer incentives is $216 per tonne (over ten years of using EVs sold during the period of study). Overall, my counter-factual analysis only takes into account the governmental costs of reducing one tonne of carbon emissions, and does not include other social externalities associated using EVs. As a result, my results can not be used to provide an answer for the overall cost-effectiveness of the incentive programs.

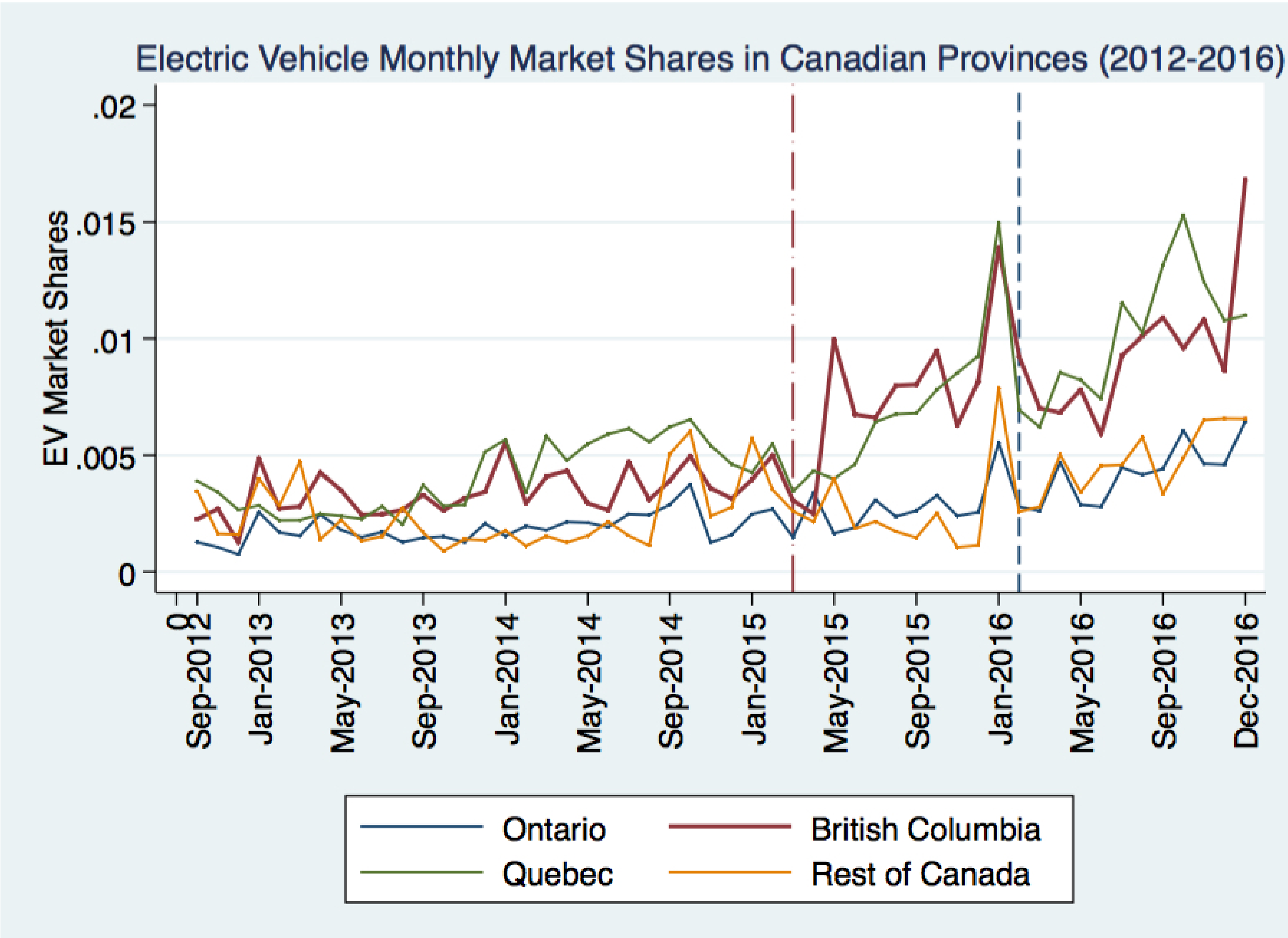
1.10 Figures

Figure 1.1: Electric Vehicle Sales and Gasoline Price, 2012-2016



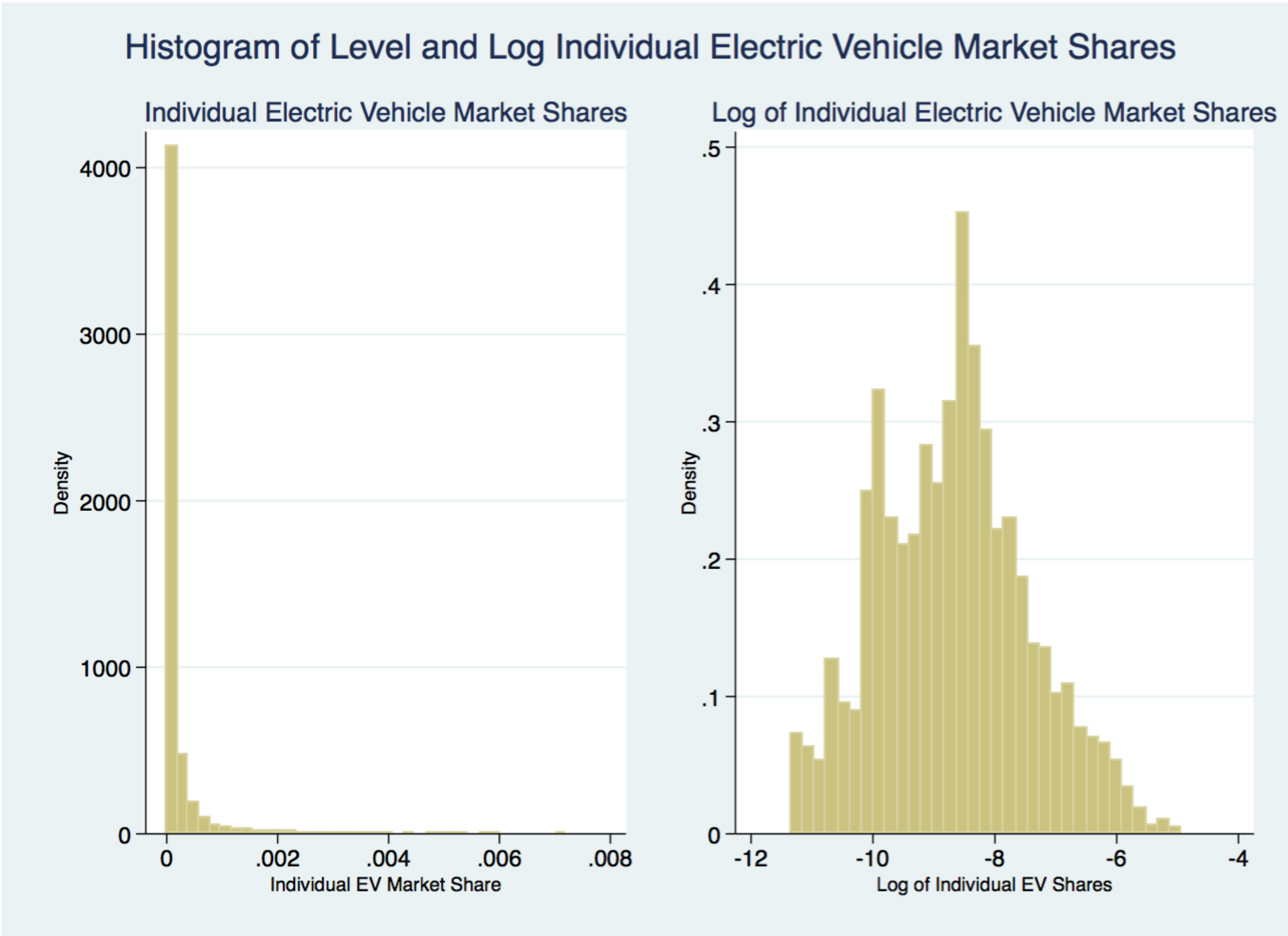
This figure plots national monthly EV sales and gasoline prices. Note that EV monthly sales are presented on the primary axis and the 2002 adjusted gasoline prices inclusive of all taxes (in \$/L) are shown on the secondary axis.

Figure 1.2: Monthly Changes in Electric Vehicle Market Shares, Rebating Provinces versus Rest of Canada, 2012-2016



This figure plots monthly provincial trends of EV market shares. Y axis shows the aggregate market share of EVs from total auto sales by month in each of the rebating province versus the rest of Canada. The vertical lines represent the timing of the change in the incentive programs; British Columbia in March 2015 and Ontario in February 2016.

Figure 1.3: Density Distribution of Electric Vehicle Market Shares by Month and Province, 2012-2016



The left panel shows the density distribution of individual EV market shares from total vehicle sales in each province and month and the right panel shows the density distribution of the logarithm of these market shares.

1.11 Tables

Table 1.1: Literature Review Summary

Study	**Country & Time Period**	**Gasoline Price Effects**	**Incentive Effects**
Beresteanu and Li (2009)	1999-2006, US	14% to 17% of overall hybrid sales	27% to 31% of overall hybrid sales
Diamond (2009)	2000-2006, US	11% to 50% increase in hybrid sales due to a 10% increase in gasoline price	No significant effects over the entire period
Gallagher and Muehlegger (2011)	2000-2006, US	27% of hybrid sales	6% of overall hybrid sales and 22% per mean value incentives
Chandra et al. (2010)	1989-2006, Canada	No significant impact	26% of all hybrid vehicle sales and 34% impact per 1000$ incentives
Narassimham and Johnson (2014)	2008-2014, US	13% and 28% increase in PHEV and BEV sales, respectively, due to a 10% increase in gasoline price	4% impact on BEV sales per 1000$ incentives
Clinton et al. (2015)	2011-2014, US	No significant impact	2% to 10% per 1000$ of incentives

Source: Author

Table 1.2: Demand-based policies for electric vehicles across Canadian provinces, 2012-2016.

Financial purchase incentives	Charging infrastructure subsidies	Carbon pricing	Public charging deployment	HOV-lane access
		AB	AB	AB
BC	BC	BC	BC	BC
			MB	
			NL	
			NB	
			NS	
ON	ON	ON	ON	ON
			PEI	
QUE	QUE	QUE	QUE	QUE
			SK	

Source: Author.

Table 1.3: Rebate Amount for an Average Battery Electric (BEV) and Plug-in Hybrid (PHEV) Over Years and Across Provinces, 2012-2016.

Province	Vehicle Type	2012	2013	2014	2015	2016
Ontario	BEV	8432.75	8432.75	8461.57	9237.00	9211.33
	PHEV	7243.66	6211.75	6927.14	5926.55	5957.75
British Columbia	BEV	5000	5000	0	5000	5000
	PHEV	2500	2500	0	2500	2500
Quebec	BEV	6346	6621	7000	6222	8000
	PHEV	6779	3566	3586	2722	3428

The rebate amounts in the table shows the average rebate that was paid to a BEV or PHEV over the period of analysis. In Ontario, PHEVs with a MSRP between $75000 and $150000 are eligible for a maximum rebate of $3000. PHEVs and BEVs with a MSRP equal to, or greater than $150000 are not eligible for an incentive. In British Columbia, the new EVs with a MSRP above $77000 are not eligible for an incentive. Chevrolet Volt, which is an extended range PHEV, is the only vehicle that was offered a rebate of $5000. In Quebec, a rebate of $3000 on the purchase or lease of new eligible BEVs with a MSRP between $75000 and $125000, and $8000 on new eligible BEVs with a MSRP less than $75000. For new eligible PHEVs with a MSRP less than 75000, the rebate amount varies between $500, $4000, and $8000 depending on the electric battery capacity.

Table 1.4: Summary statistics for sales, incentives, and socioeconomic data

Variable	**N**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Electric Vehicle-Province-Month Data					
Fuel efficiency rating (kWh/km)-BEV	2332	0.20	0.02	0.17	0. 27
Fuel efficiency rating (kWh/km)-PHEV	3312	0.26	0.07	0.13	0.43
Fuel cost savings (¢/km)	5644	8.7	2.2	1.1	13.8
Province-Month Sales and Incentive Data					
New EV sales	520	91.3	124	0	649
New EV sales per thousand people	520	0.01	0 .01	0	0.07
New BEV sales	520	55	66.2	0	311
New PHEV sales	520	36.3	64.8	0	338
EV purchase incentives	520	2086.4	3255.8	0	13000
BEV purchase incentives	520	3055.7	3868.5	0	13000
PHEV purchase incentives	520	1379.3	2496.8	0	10224
Province-Month Price and Demographic Data					
2002 adjusted gasoline price tax-inclusive (¢/L)	520	90.3	14.2	52.7	118.3
2002 adjusted electricity price (¢/kWh)	520	9.1	2.3	5.4	13.9
Labor income per capita (dollars×1,000)	520	1.9	0.4	1.4	3.1
Unemployment rate	520	7.9	2.5	3.3	15.2
Province-Year Demographic Data					
Labor income per capita (dollars×1,000)	50	28.2	0.5	27.3	28.8
Unemployment rate	50	7.3	0.12	7.1	7.4
Median household income (dollars×1,000)	50	78.9	8.8	65.9	10.07
Percent female	50	0.5	0.005	0.49	0.51
Percent of adults graduating college	50	0.008	0.002	0.005	0.015
Mean age	50	41.1	3.05	36	45.3

For all sales data, N is the number of all observations including the zero observations. There are 10 provinces, 52 months and average of about 10 EV models in each market. For vehicle-province-month data, N reports the total number of observations in my dataset (i.e., 5644). For provincial demographics, N reports the number of province-month and province-year observations, respectively. Fuel cost savings (¢/km) is the difference between the cost of driving 1 km in an EV and the cost of driving 1 km in an average gasoline vehicle. Labor income per capita represents "seasonally adjusted wages, salaries, and employer's contributions" per-capita, and is reported at both monthly and annual levels.

Table 1.5: Panel regression with Fixed Effects for New Electric Vehicle Market Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Incentive (in 1000$)	0.17***	0.16***	0.06*	0.06*	0.08***		
	[0.03]	[0.03]	[0.03]	[0.02]	[0.02]		
Incentive (in 1000$) * BEV						0.05**	
						[0.02]	
Incentive (in 1000$) * PHEV						0.04**	
						[0.02]	
Incentive to MSRP Ratio							3.84***
							[0.93]
Log Fuel Savings	0.24	2.47**	0.05	-0.17	0.19	0.19	0.18
	[0.25]	[0.79]	[0.29]	[0.29]	[0.29]	[0.29]	[0.29]
EV-model FE	Yes	Yes	Yes	Yes			
Time FE		Yes	Yes				
Province FE			Yes				
Province-time FE				Yes	Yes	Yes	Yes
EV-model-province FE					Yes	Yes	Yes
EV-model-time FE					Yes	Yes	Yes
N	5644	5644	5644	5644	5644	5644	5644
R^2	0.70	0.71	0.71	0.71	0.88	0.88	0.88

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the GLM results of the estimations on the market share of a particular new EV in response to variations in model-specific incentives and log fuel cost savings (from driving the given EV compared to driving an average gasoline car, in ¢/km) using various combination of fixed effects. I use the same dependent and independent variables across the models and only change the arrangement of fixed effects to control for unobserved factors that may influence the market share of a given EV. I start with EV-model generation fixed effects in column 1. Then, in column 2, I add time (i.e., year-month) fixed effects. Moving to column 3, province fixed effects are also added. Column 4 includes EV-model and province-time fixed effects. Columns 5, 6, and 7 present the results of the most comprehensive models and thus all control for EV-model-province, EV-model-time, and province-time fixed effects. Column 5 includes the dollar value of incentives (in 1000$) on the average EV, while column 6 shows the differential effects of incentives (in 1000$) on BEVs and PHEVs separately. Finally, column 7 reports the incentive effects relative to MSRPs. Standard errors are clustered by province-class across all models.

Table 1.6: Alternative Specifications and Aggregate Regressions

	1	2	3	4	5
Incentive (in 1000$)	0.05***	0.07***	0.07*	-0.002	0.08***
	[0.01]	[0.02]	[0.03]	[0.03]	[0.01]
Log Fuel Savings	0.26***	0.41***	0.55*	0.78	0.45
	[0.04]	[0.1]	[0.22]	[17.9]	[0.35]
EV-model-province FE	Yes			Yes	Yes
EV-model-year FE	Yes				
EV-model-year-month FE				Yes	Yes
Province FE		Yes	Yes		
Year-month FE		Yes	Yes		
Province-time FE				Yes	Yes
Other Controls		Yes	Yes		
N	507	520	208	2776	2421
R^2	0.80	0.80	0.80	0.80	0.89

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the results of the alternative specifications to deal with the problem associated with zero share observations. All the specifications estimate the average effects of incentives (in $1000) and log of fuel cost savings using different levels of aggregation and combination of fixed effects. Column 1 uses a GLM regression to estimate within province variations in EV-model specific incentives (in $1000) and fuel cost savings on aggregate market shares by EV-model, province, and year, using EV-model-province and EV-model-year fixed effects. Standard errors are clustered by province-class in this model. Columns 2 and 3 present the GLM results of aggregate EV shares by month across all provinces, and in each of the rebating provinces versus the "Rest of Canada", respectively, after controlling for province and month fixed effects. Both models also control for log fuel cost savings (i.e., log of sales-weighted fuel cost savings (in ¢/km) from driving EVs compared to driving non-EVs in a province and month) and additional controls, including log median labour income, log median age, log percent female and log percent college graduates from the population, and log unemployment rate. Standard errors are bootstrapped using wild cluster bootstrapped t-statistics (WCBSTs) for these specifications. Finally, the results of the two-part model are presented in columns 4 and 5. The first part (presented in column 4) defines the probability of purchasing an EV from all other vehicle alternatives in each market as a function of model-specific incentives (in $1000) and log fuel cost savings (using a logistic regression) and the second part (presented in column 5) defines the magnitude of the effects conditional on positive EV shares (using OLS regressions). Standard errors are clustered by province-class in the two part model.

Table 1.7: Nested Logit Results on Individual EV Market Shares

	(1)	(2)
Incentive ($1000)	0.06**	
	[0.01]	
Incentive to MSRP Ratio		2.96***
		[0.45]
Within-nest Shares	0.37***	0.37***
	[0.15]	[0.15]
Log Fuel Savings	0.19	0.19
	[0.29]	[0.29]
EV-model-province FE	Yes	Yes
EV-model-time FE	Yes	Yes
Province-time FE	Yes	Yes
N	5644	5644
R^2	0.91	0.91

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the IV regression results of the nested logit model on individual EV model shares. The dependent variable is the market share of sales of individual EV models from total vehicle sales in each market (province, year, and month) and the independent variables are incentives (in $1000 and relative to individual EV's base prices), within-nest EV shares, and log fuel cost savings associated with driving an EV compared to an average gasoline car. The within-nest share variable is the market share of each EV model from total EVs sold in each market. Three EV characteristics: horse power, the recharge time, and the fuel efficiency (both in liter equivalent and kWh per 100 km) are used as IVs for within-nest shares. I include EV-model-province, EV-model-time, and province-time fixed effects and cluster standard errors by province-class, in both models.

Table 1.8: Effect of Incentives on Total Vehicle Sales

	(1)	(2)	(3)	(4)
Mean Incentives (in $1000)	-0.005	-0.005	-0.012	-0.005
	[0.008]	[0.008]	[0.008]	[0.006]
Log real gasoline price		-0.52*		-0.43
		[0.17]		[0.28]
Log real labor income		1.66**		1.74**
		[0.45]		[0.49]
Log percent female population		20.48*		68.42***
		[8.19]		[12.86]
Log percent adults with college diploma		0.035		0.042
		[0.16]		[0.30]
Log median age		0.60		-6.77*
		[1.80]		[2.57]
Log unemployment rate		-0.21*		-0.11
		[0.08]		[0.09]
Province fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	520	520	520	520
R^2	0.99	0.99	0.99	0.99

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the extensive margin effects of incentive (in $1000) on the log of aggregate auto sales (columns 1 and 2) and the log of passenger car sales (columns 3 and 4) by province. In columns 1 and 3, only province and time (i.e., year-month) fixed effects are included (without any other provincial control), while in columns 2 and 4, other provincial controls are included in addition to province and time fixed effects. Controls contain log real gasoline price (in dollar per liter), log real labor income, log unemployment rate, log percent females from total population, log percent adults (24 years above) with college diploma, and log median age. Linear regressions with fixed effects are performed, and standard errors are bootstrapped using wild cluster bootstrapped t-statistics (WCBSTs), across all models.

Table 1.9: Counter-factual results: electric vehicles versus other vehicles

Province	Year	1	2	3	4	5
Ontario	2013	1090	618	0.44	31,266	270
	2014	1666	1088	0.52	48,885	271
	2015	2125	1492	0.63	63,457	253
	2016	3463	1590	0.81	92,427	249
British Columbia	2013	596	408	0.38	18,634	145
	2014	734	559	0.01	22,410	6
	2015	1563	1303	0.20	48,588	79
	2016	2063	1279	0.31	60,702	93
Quebec	2013	1243	526	0.56	37,052	241
	2014	2339	1052	0.58	67,259	262
	2015	3017	1753	0.48	94,248	234
	2016	4772	2084	0.48	134,827	269

This table summarizes the results of the counter-factual calculations for each of the rebating provinces in each year. Columns 1 and 2, respectively, show the actual number of EVs and BEVs sold in each province and year, column 3 is the percentage of EV sales induced by the incentive programs based on the counter-factual results, column 4 is the CO_2 emission reductions over ten years of using EVs (in tonnes), and finally column 5 is the cost of carbon emissions saved over the ten years of using EVs (in dollars per tonne of CO_2) are calculated.

1.12 Appendix

Table 1.10: Results of Linear Regressions with Fixed Effects on New Electric Vehicle Market Shares

	(1)	(2)	(3)	(4)	(5)	(6)
Incentive ($1000)	0.00004^{**}	0.00003^{**}	0.00003^{*}	0.00003^{*}	0.0000002	
	[0.00001]	[0.00001]	[0.00001]	[0.00001]	[0.000009]	
Incentive to MSRP ratio						0.00004
						[0.0002]
Log fuel cost savings	0.00005	0.0003^{*}	-0.00009	-0.0004^{+}	0.0002	0.0002
	[0.00003]	[0.0001]	[0.0001]	[0.0002]	[0.0001]	[0.0001]
EV-model FE	Yes	Yes	Yes	Yes		
Time FE		Yes	Yes			
Province FE			Yes			
Province-time FE				Yes	Yes	Yes
EV-model-province FE					Yes	Yes
EV-model-time FE					Yes	Yes
N	5644	5644	5644	5644	5644	5644
R^2	0.21	0.23	0.29	0.33	0.76	0.76

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the results of linear regressions on market share of a particular new EV in response to variations in model-specific incentives and log fuel cost savings (from driving the given EV compared to driving an average gasoline car, in ¢/km) using various combination of fixed effects. These models replicate the models in Table 5 but apply linear regressions on individual market shares rather than GLM estimations. I use the same dependent and independent variables across the models and only change the arrangement of fixed effects to control for unobserved factors that may influence the market share of a given EV. I start with EV-model generation fixed effects in column 1. Then, in column 2, I add time (i.e., year-month) fixed effects. Moving to column 3, province fixed effects are also added. Column 4 includes EV-model and province-time fixed effects. Columns 5 and 6 present the results of the most comprehensive models and thus control for EV-model-province, EV-model-time, and province-time fixed effects. Column 5 includes the dollar value of incentives (in 1000$) on the average EV, while column 6 reports the incentive effects relative to MSRPs. Standard errors are clustered by province-class across all models.

Table 1.11: Log-linear Results on Individual EV Market Shares Added by a Constant Value

	1	2
Incentive (in $1000)	0.08*	
	[0.03]	
Incentive to MSRP Ratio		2.72*
		[1.21]
Log Fuel Savings	0.18	0.18
	[0.29]	[0.29]
EV-Model-Province FE	Yes	Yes
EV-Model-Year-month FE	Yes	Yes
Province-time FE	Yes	Yes
N	5644	5644
R^2	0.71	0.71

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the regression results of the one of the alternative practices to overcome the challenge with zero share observations where I add a constant to EV individual market shares. As such, the dependent variable is the market share of each EV model from total auto sales in a given market plus a constant that is smaller than the smallest share(i.e., 0.000001 in this regression). I estimate EV shares on both measures of incentive: dollar values (in $1000, shown in cloumn 1) and relative to an EV's MSRP (shown in column 2), as well as on log fuel cost savings (i.e., the cost of fuel saved due to driving 1 km in an EV comapred to driving a gasoline car). Linear regression with EV-model-province, EV-model-time, and province-time fixed effects are applied, and standard errors are clustered by province∗class, in both specifications.

Table 1.12: Monthly Aggregated Specifications on EV Shares with Provincial Controls

	1	2
Mean Incentive (in $1000)	0.08**	0.09**
	[0.03]	[0.03]
Log real gasoline price	0.49	0.42
	[0.31]	[0.27]
Log real electricity price	-0.06	-0.06
	[0.41]	[0.4]
Log real labor income	-3.21	-3.81*
	[1.86]	[1.86]
Log percent female population	42.23	49.57
	[55.29]	[54.61]
Log percent adults with college diploma	-1.13	-1.19
	[1.71]	[1.7]
Log median age	-7.87	-6.56
	[14.35]	[14.24]
Log unemployment rate	-0.23	-0.17
	[0.45]	[0.45]
Province FE	Yes	Yes
Year-Month FE	Yes	Yes
N	520	208
R^2	0.80	0.80

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the results of aggregate EV shares by province and month after accounting for other provincial controls. Columns 1 and 2, respectively, present the GLM results of aggregate EV shares across all provinces, and in each of the rebating provinces versus the “Rest of Canada”, after controlling for province and month fixed effects. Other controls include log real gasoline price, log real electricity price, log real labor income, log percent female population, log percent adults with a college diploma, log median age, and log unemployment rate, and bootstrap standard errors using wild cluster bootstrapped t-statistics (WCBSTs).

Chapter 2

The Effect of Gasoline Price on New Vehicle Fuel Efficiency: Canadian Evidence

2.1 Introduction

The transportation sector generates a significant portion of greenhouse gas (GHG) emissions in most countries. In Canada, the transportation sector accounted for 23% of the total national emissions in 2014, with light vehicles (including cars, light trucks and motorcycles) being responsible for 37% of these emissions.[1] The emissions from light vehicles (such as carbon dioxide emissions) are mainly generated through gasoline consumption; motor gasoline emissions accounted for 93% of total greenhouse gas emissions (GHGs) associated with light vehicles. Therefore, the ongoing policy debates concerning the environment and pollution have drawn particular attention to the determinants of gasoline consumption from on-road

[1] Emissions from light vehicles constitute 75% of total passenger transport emissions. Passenger transport includes bus, rail and domestic aviation in addition to cars, trucks and motorcycles. Between 1990 and 2014, total passenger transportation emissions increased by 15%, emissions from cars declined by 30%, while emissions from light trucks (including trucks, vans and sport utility vehicles (SUVs)) increased by 123% (Environment Canada (2014)).

vehicles.[2]

Among all determinants of gasoline consumption from on-road vehicles, the effect of gasoline price on new vehicle demand has important implications over reducing gasoline consumption. Several studies in the US, including Klier and Linn (2010b), Li et al. (2009), Small and Van Dender (2007), identify the relationship between gasoline price and demand for fuel-efficient vehicles, and all suggest that rising gasoline prices would improve the fuel economy of the new vehicle fleet. On the other hand, there exists only a few studies in Canada (e.g., Rivers and Schaufele (2017a), Barla et al. (2009), and Barla et al. (2016)) investigate the effect of gasoline price on new vehicle purchases.

In light of the rapid increase in Canadian gasoline prices from 2000 to 2010[3], my study focuses on the connection between gasoline prices and demand for vehicle fuel efficiency. In particular, I evaluate consumer response to changes in gasoline price with respect to the fuel efficiency of their new vehicle purchase across the Canadian forward sortation areas (FSAs)[4] over this decade. Variations in gasoline price have differential effects on gasoline cost of driving various vehicle models (per 100 km) depending on their fuel consumption rating (in L/100 km).I estimate changes in the fuel economy of new vehicle sales in a given market (FSA-year) by exploiting variations in gasoline cost of driving various models (in $/100 km) within a forward sortation areas (FSA) over years.

I employ two empirical approaches to perform estimations. First, by exploiting a rich data-set, including all new vehicle registrations by detailed vehicle models (make, fuel consumption, engine size, and etc), I estimate changes in gasoline cost on market share of individual models over years (following the methodology in Klier and Linn (2010b)). Sec-

[2]Some examples of the Canadian federal and provincial programs to reduce gasoline consumption in road transportation in recent decades are: purchase incentives to encourage sales of plug-in electric vehicles (PEVs) across some Canadian provinces (Canadian Electric Vehicle Policy Report Card (2016)), British Columbia and Quebec impose carbon pricing policies on the use and purchase of fossil fuels (Antweiler and Gulati (2016); Rivers and Schaufele (2015)), the federal government and the province of Ontario implement feebate/rebate programs on new vehicle purchases to promote sales of more fuel-efficient vehicles (Rivers and Schaufele (2017b)).

[3]In Canada, real average gasoline prices experienced sudden and continuous rises of about 31 cents per liter from the average rates of 0.68 (¢/L) in 2002 to 0.99 (¢/L) in 2008.

[4]FSA refers to the first digits of the Canadian postal codes.

ond, I estimate a reduced-form model on sales-weighted fuel efficiency of the average vehicle sales in a given market (FSA-year) and find the elasticity of fleet-wide fuel economy with respect to gasoline price.

I find that consumers are responsive to changes in gasoline price when selecting the fuel efficiency of their new vehicle. My results indicate that the gasoline price increases from 2000 to 2010 caused shifts in preferences to more fuel-efficient vehicles, thus improving the average fleet fuel efficiency. According to the counter-factual results of my preferred specification, an increase in gasoline price, all else equal, causes a larger increase in the gasoline cost of fuel-inefficient vehicles relative to fuel-efficient vehicles. This price increase would result in an increase in the market share of fuel-efficient vehicles relative to fuel-inefficient vehicles, thus causing an increase in the average fuel efficiency of the entire fleet. These counter-factual results indicate that a one percent increase in gasoline price causes a 0.06-0.14 percent improvement in average fleet fuel efficiency. I obtain similar elasticity estimates from the aggregate regressions on fleet-wide fuel economy, suggesting a 0.1-0.16 percent improvement in fleet fuel economy due to a one percent increase in gasoline price. These estimates are in the range of those reported in the literature using Canadian vehicle data: Rivers and Schaufele (2017a) find elasticity estimates ranging from -0.08 to -0.13 (2000-2010); and Barla et al. (2009) report an elasticity of -0.1 (1990 to 2004).

This study makes several advances beyond the existing literature. First, I exploit two sources of variation to identify gasoline cost effects on vehicle market shares: 1) variations in gasoline price within a forward sortation areas (FSA) over years; 2) variations in fuel consumption rating (measured in L/100 km) within a particular vehicle over time. I employ different combination of fixed effects for each identification and show that results are robust to a number of specifications.

Second, the richness of the vehicle data by detailed model allow me to control for the unobserved vehicle attributes as well as the potential heterogeneity between vehicles observed and unobserved attributes. As Berry et al. (1995) argue, it is crucial to account for the potential heterogeneity that exists between vehicle prices and unobserved vehicle and consumer characteristics.

Finally, the panel structure of the data allows me to perform straightforward linear estimation techniques without worrying about the strong assumptions in time series or cross sectional studies. In cross sectional studies, such as Bento et al. (2009) and West (2004), it is assumed that unobserved consumer preferences are uncorrelated with gasoline price. Cross-sectional studies do not control for the unobserved region-specific preferences that are correlated with gasoline price and therefore may obtain biased estimates. Also, since unobserved consumer characteristics may have positive or negative correlations with gasoline price, we can not define the direction of the bias from economic theory (Klier and Linn (2010b)). Time series studies, such as Small and Van Dender (2007), estimate the overall changes in the fleet fuel economy and therefore do not account for unobserved vehicle attributes such as model-specific fuel efficiency.

Lastly, results of my additional analyses indicate that consumers tend to be more sensitive to gasoline price increases than decreases, and that residents of suburban regions are more responsive to gasoline price rises compared to the residents who live closer to city center points. Moreover, I find the sensitivity of different vehicle classes to increases in gasoline price; sales of compact and sport utility vehicles (SUVs) increase, whereas sales of minivans, intermediate cars, and sport cars decrease, due to gasoline price increases over this period.

The rest of the paper has five sections. Section 2.2 reviews the literature. Section 2.3 provides an overview of the data and the trends for the key variables. Next, I discuss identification strategy and econometric specifications in Section 2.4. I present results of multiple models in Section 2.5 and conclude in Section 2.6.

2.2 Literature Review

Several studies in the recent literature investigate the effects of gasoline prices on the gasoline consumption from vehicles. Consumers may respond to increases in gasoline price (due to taxes or other market-induced factors) by reducing gasoline consumption through different margins: 1) reducing the number of liters consumed by driving less along the intensive margin, 2) shifting their new vehicle purchases to more fuel-efficient vehicles along the extensive margin. Some studies, such as Gillingham (2014) and Gillingham et al. (2016), investigate changes in gasoline consumption along the vehicle-utilization margin (i.e., the intensive margin) and find the elasticity of driving distance with respect to gasoline price. Other studies, including Barla et al. (2009) and Small and Van Dender (2007), measure changes in gasoline consumption through changes in both vehicle utilization (i.e., the intensive margin) and vehicle fuel efficiency (i.e., the extensive margin).[5] As my study focuses on the impacts of gasoline price on vehicle fuel efficiency, I will discuss the methodology and findings of similar research in the literature.

Barla et al. (2009) and Small and Van Dender (2007) rely on aggregated data to identify gasoline price effects on fleet fuel economy, and therefore find less precise estimates for the elasticity of fleet fuel economy with respect to gasoline price. Barla et al. (2009) use provincial-level data for light-duty vehicles across the Canadian provinces from 1990 to 2004; Small and Van Dender (2007) use US state-level passenger vehicle data from 1966 to 2001. Results of both studies suggest a similar short-term elasticity estimate (i.e., -0.03), while the long-term estimate in Small and Van Dender (2007) is higher (equal to -0.19) than the estimates found in Barla et al. (2009) (ranging between -0.09 and -0.12).

Some other studies, including Klier and Linn (2010b) and Li et al. (2009), use more detailed data by vehicle model, state, and year to estimate changes in individual vehicle market shares in response to changes in gasoline price, and therefore provide more precisely-

[5] In addition to the vehicle fuel efficiency and utilization margins, these studies also estimate the responsiveness of vehicle stock to changes in gasoline prices.

estimated elasticities. In addition, unlike the above mentioned studies, their disaggregated data allow them to control for the unobserved vehicle characteristics that might be correlated with vehicle fuel efficiency. Klier and Linn (2010b) observe monthly changes in gasoline price and vehicle sales data in US from 1970 to 2007, enabling them to exploit within model-year variations in individual vehicle market shares to changes in gasoline price. Their findings indicate that the elasticity of vehicle fuel economy with respect to gasoline prices is -0.12 (in the short run). Li et al. (2009) exploit vehicle sales data across 20 US Metropolitan Statistical Areas (MSAs) from 1997 to 2005 and find that a 10% increase in gasoline price (from price levels in 2005) causes the fleet fuel economy to increase by 2.04% in the long run (and a 0.22% increase in the short run).

Finally, using similar data as mine, Rivers and Schaufele (2017a) identify changes in new vehicle fuel economy to gasoline price variations across Canadian forward sortation areas (FSAs) from 2000 to 2010. They perform a reduced-form approach to estimate the elasticity of fleet fuel economy with respect to gasoline price, and they find that a 1% increase in gasoline price results in a 0.09% to 0.13% improvement in vehicle fuel economy.

The current study makes several contributions to these studies. As mentioned above, I use similar data as in Rivers and Schaufele (2017a), but unlike their study, I take two alternative approaches to identify changes in fleet fuel economy. In addition to a reduced-form approach, as was done in their study, I employ a differentiated-products demand approach to estimate changes in individual vehicle market shares due to changes in gasoline cost. My empirical approach is similar to those in Klier and Linn (2010b) and Li et al. (2009); I use a micro-level vehicle sales data (by detailed vehicle model, FSA, and year) to precisely estimate gasoline cost effects on the demand for fuel-efficient vehicles. Also, similar to their analysis, I am able to account for the unobserved vehicle and consumer attributes. I, however, exploit two sources of variation over time to identify the gasoline cost effects: within-FSA variations in gasoline price and within-vehicle variations in model-specific fuel efficiency (in liters per 100 km of driving). Exploiting two different sources of variation has a few advantages. First, it allows me to compare the sensitivity of new-vehicle purchase decisions to changes in vehicle fuel efficiency as opposed to changes in gasoline price. Second, it provides more robustness to my main results. Another contribution of my study over these existing studies is that I explore heterogeneity in consumer response to changes in gasoline price in the following dimensions (which are different than those used in Rivers and Schaufele (2017a)): rising versus falling gasoline price and imported versus domestic vehicles. Finally, using estimates from both aggregated and dis-aggregated empirical models, I perform simulations to calculate how the fuel economy of the entire fleet responds to gasoline price variations in the long run (over the entire sample period). Overall, my empirical results suggest long-term elasticity estimates ranging between -0.08% to 0.15% (depending on model specifications), which are in the range of the estimates of Rivers and Schaufele (2017a), Klier and Linn (2010b), and Li et al. (2009), as reported above.

I provide a summary of the elasticity estimates obtained in the studies listed above in Table 2.1.

2.3 Data and Background

This section starts with a description of the data and summary statistics of the Canadian vehicle market from 2000 to 2010, and continues with an overview of the trends in gasoline prices, average fuel economy, and market share of new vehicles in Canada over this period.

2.3.1 Data and Summary Statistics

I combine data from four different sources: vehicle registration data, gasoline price data, demographics and income data, and FSA-city-distance data, to create the final data-set used in this study. Desrosiers Automotive Consultants provides new vehicle registration data in each FSA and each year from 2000 to 2010. As the goal of this study is to investigate changes in new vehicle purchases across the Canadian FSAs, I treat every registration whose model-year is the same as the year it is sold in as a sale.[6]

The new vehicle registrations are classified by make, model, model-year, series, engine size, and the number of cylinders. I define the combination of these five characteristics as a "vehicle" throughout my analysis. The Desrosiers data-set also classifies vehicles by 15 segments according to the Automobile Industry standards in Canada. According to this classification, Passenger Cars are grouped into subcompact, compact, sports, intermediate, luxury, luxury high end, luxury sports, and Light Trucks are classified into compact sport utility, intermediate sport utility, large sport utility, luxury sport utility, small pickup, large pickup, small van, and large van. The data on the highway and city fuel efficiency ratings are provided by Natural Resources Canada, with the exception of a very small number of low-volume vehicles for which the data are gathered from the US Environmental Protection Agency (EPA).

The average retail gasoline prices are retrieved from online surveys collected by MJ Ervin/Kent Marketing Services.[7]. Kent Group conducts weekly surveys to collect the retail price of gasoline, diesel, propane, and furnace fuel from 57 major cities in Canada. Every week, the gasoline price data are collected from more than 700 gasoline stations throughout each city. Figure 2.1 presents these 57 cities across Canada according to their geographical location. The survey also provides monthly and annual gasoline price data using sales-weighted averages over weeks and months in each city. Throughout my analysis, I use the annual average retail gasoline prices inclusive of all taxes to match with the annual vehicle registration data. As the focus of this paper is to capture gasoline price variations at the FSA level, I map the city-level gasoline prices to FSAs according to the following approach. I create a distance file including the geographical center points of all the FSAs in

[6]This means that only vehicle registrations with a model year t that are also sold in year t are treated as new sales. This is because some vehicle models are sold one year prior to their actual model year; a 2005 Toyota may have been sold in 2004 and therefore is recorded in both 2004 and 2005 registration data. These records cause double counting in the true number of sales in each year. As such, I treat these registrations according to their first appearance in the data, i.e., the first time a model-year appears in the data, I record it as a new sale.

[7]http://charting.kentgroupltd.com/

Canada, and calculate the distance from each FSA center point to the center points of the cities reported in the Kent Group survey. Then, I keep the FSAs that are located within a certain predetermined distance to the given city center points in the data. Three distance measurements: 10, 15, and 20 km, are defined to test the precision of this algorithm. As a result, only the FSAs that are within the 10, 15, or 20 km radius of the city center points remain in the data. I estimate all regression models using each of these three measures separately. The map of the city of Ottawa along with its FSAs is presented as an example in Figure 2.2. Out of a total of 1621 FSAs in Canada, there are respectively 758, 650, and 453 FSAs located within a 20, 15, and 10 km radius of the given cities from the Kent Group survey.

Next, I merge the gasoline price data with median income and other demographics data (i.e., median age, percent females and percent married individuals in population, and percentage of residents living in apartments) from Statistics Canada.[8] Finally, the demographics and gasoline price data are combined with the vehicle registration data, constructing a data-set that includes over 1,300,000 observations across 758 FSAs. The average number of new vehicle registrations in this data-set is 849, by FSA-year, with a minimum of one and a maximum of 21,411. Table 2.2 presents summary statistics for the FSA level data.

2.3.2 Overview of Gasoline Price Trends, New Vehicle Fuel Economy, and Market Shares

Figure 2.3 presents the trend of real and nominal average retail price of gasoline inclusive of all taxes in Canada from 2000 to 2010.[9] Gasoline prices follow an increasing trend from 2002 to 2008, changing from the lowest rate of \$0.68/L in 2002 to their peak at \$0.99/L in 2008. This means that the real price of gasoline increased by 31 cents per liter between 2002

[8] There are inconsistencies across the gasoline price and demographics data-sets which result in missing a few FSAs in the final data. First, the demographics data cover a larger number of cities throughout the country than the gasoline price data, and second, some of the FSAs from the gasoline price data do not exist in the demographics data.

[9] All nominal dollar values are converted to real terms based on the 1999 prices to account for inflation.

to 2008. It is important to study whether gasoline price increases have an impact on fleet fuel economy over this period.

To understand how consumers respond to variations in gasoline price, we require information about their expectations of future fuel prices when estimating their willingness to pay for fuel efficiency. It is commonly assumed in the literature that consumers use current fuel prices as expected future prices Anderson et al. (2013)).[10] Anderson et al. (2013) find that consumers expect the real future gasoline prices to be equal to the current price levels under normal economic conditions. As such, following the literature, I also assume a no-change forecast in gasoline prices throughout my study.

In Figure 2.4, the left panel shows changes in real tax-inclusive gasoline prices (in \$/L), and the right panel shows changes in average sales-weighted fuel economy of new vehicles (in L/100 km) over the period of 2000 to 2010. The sales-weighted average fuel efficiency of all new vehicles in FSA f and year t is calculated using: $F_{ft} = \frac{\sum_{j=1}^{J}(sales_{jft} * fe_{jt})}{\sum_{j=1}^{J} Sales_{jft}}$, where the sales of model j is multiplied by its combined fuel consumption rating (fe_{jt} in L/100 km) and then aggregated across all vehicle models (J) in the given market (in the numerator). Finally, this product is divided by aggregate sales in that market (the denominator).[11] As such, the fleet fuel economy is the sum of sales-weighted fuel efficiency (in L/100 km) of all new vehicles in the fleet. According to the right panel, the overall trend of fuel consumption from new vehicles declines over this period, starting from above 10 L/100 km and falling to below 9.5 L/100 km towards the end of the period. This means that new vehicle fuel economy has improved (fewer liters per 100 km) as average gasoline prices increase over time. However, other unobserved temporal and regional factors may have caused the fuel economy improvements observed in this figure. As a result, in my estimations, I will control

[10] This assumption is commonly used in studies that model demand for fuel consuming durable goods such as automobiles, e.g., studies such as Klier and Linn (2010b), Langer and Miller (2011), Li et al. (2009), and Busse et al.(2013).

[11] I use combined fuel consumption rating, i.e., 0.55 (highway fuel efficiency) + 0.45 (city fuel efficiency), in all my analyses in this paper. As is evident, the fuel economy ratings may not perfectly reflect the actual performance of vehicles on the road. Therefore, the gasoline price effects on vehicle on-road performance may not perfectly be captured in my empirical analyses.

for the unobserved factors that vary by region and time and may influence vehicle fuel consumption.

It is also interesting to note that vehicle fuel consumption exhibit higher and more consistent improvements when gasoline price is increasing continuously (i.e., between 2002 and 2008). As such, I will also estimate whether consumers have differential responses to gasoline price increases versus gasoline price decreases when selecting the fuel efficiency of their vehicle purchases.

Figure 2.5 shows a decomposition of the trend in fuel consumption according to vehicle category. I classify vehicles into four categories: cars, SUVs, trucks, and vans, and plot changes in market share (shown in the left panel), as well as changes in the aggregate fuel economy (shown in the right panel), by category. I perform this decomposition based on the following formula: $F_c = \sum_{j=1}^{n}(share_j * fe_j)_c$, where the fuel efficiency of all vehicles in category c (F_c in L/100 km) is the product of individual vehicle market shares from aggregate sales in category c, $share_j$, and their fuel consumption ratings, fe_j in L/100 km, aggregated over all vehicles (denoted by n) within the given category. It is evident from the figure that cars are the most fuel-efficient, and trucks are the least fuel-efficient categories. The average fuel efficiency of SUVs change more noticeably compared to other categories, decreasing from above 12 (L/100 km) in 2000 to below 11 (L/100 km) in 2010. This means that more fuel-efficient SUVs have been purchased during this period. Left panel shows that cars (as the most fuel-efficient category) have the highest market share, and trucks (as the least fuel-efficient category) have the lowest market share over this period (except for the last four years, where market share trend for vans drops below that of for trucks). Also, market share for cars and trucks experience smooth trends whereas SUVs, and vans show more noticeable changes over time. It appears that there is a shift from vans to SUVs that might be related to the improved fuel efficiency of SUVs compared to vans over this period.

2.4 Identification Strategy and Econometric Specification

2.4.1 Identification Strategy

This section presents the with identification strategies and model specifications to capture variations in gasoline costs on new vehicle market shares. Gasoline cost of driving vehicle model j in FSA f and year t (i.e., GC_{jft} in dollars per 100 kilometers) is the product of gasoline price (denoted by GP_{ft} in dollars per liter) and fuel efficiency of the given vehicle model (denoted by fe_j in liter per 100 kilometers) in: $GC_{jft} = GP_{ft} \times fe_{jt}$. Therefore, changes in the gasoline cost of driving a particular model can be the result of changes in gasoline price, model-specific fuel efficiency ratings, or a combination of these two factors. According to this decomposition, I exploit two sources of variation to identify gasoline cost effects on vehicle market shares: variations in gasoline price within a given FSA over time, and variations in model-specific fuel consumption ratings (in L/100 km) over time. I try different identification techniques to capture the effect of each source of variation in gasoline costs separately, as well as to test the robustness of the results according to each identification. I employ different arrangements of fixed effects to explain each source of variation and its underlying identification.

The first source of identification is based on variations in real tax-inclusive gasoline prices within a given city over time. As mentioned in Section 2.3, I observe gasoline prices for 57 cities in Canada. The city-level gasoline price data are assigned to the FSAs located closest to city center points. As such, this within-city variation in gasoline price over time is used to identify the effect of gasoline prices on new vehicle market shares. This identification is based on the assumption that the price of gasoline is exogenous to other determinants of new vehicle demand. As a common assumption in the automobile literature (e.g., Klier and Linn (2010b) and Leard et al. (2017)), I believe that this is a valid assumption in my analysis as well. I include various fixed effects to account for the unobserved preferences that vary by vehicle, FSA, and year and are correlated with gasoline costs. Regarding the effect of supply shocks, I believe that it is less likely that the supply-based determinants of sales have correlations with gasoline prices at the dis-aggregated FSA (or city) level.[12] However, it is still likely that the price of gasoline has correlations with factors such as vehicle transaction prices. As documented by Langer and Miller (2013), automobile manufacturers respond to gasoline price fluctuations by offering cash incentives to new vehicle buyers to offset the vehicle expected fuel costs. As such, the failure to account for vehicle transaction prices when estimating the gasoline cost effects on vehicle purchases may underestimate consumer demand for fuel efficiency.[13] As such, if manufacturers offer cash incentives to new vehicle buyers in Canadian vehicle market, the gasoline cost estimates in my study may underestimate consumer demand for fuel efficiency.[14]

As the first source of identification only relies on variations in gasoline price, I control for variations in the fuel efficiency of individual vehicles over time (i.e., the second component in gasoline costs). It is important to note that fuel efficiency (in L/100 km) does not vary within a model-year, but it may vary across model years. As such, the first identification is achieved by comparing the market share of individual vehicles, whose fuel efficiency ratings do not vary from one year to the next, within the same FSA while varying gasoline price over time.

The second identification strategy, following Rivers and Schaufele (2017b), relies on within-vehicle changes in fuel efficiency over time. As mentioned previously, the second source of variation in gasoline cost is related to changes in fuel consumption rating (in L/100 km) of a "vehicle" over time. Fuel efficiency variations over time can be the result of changes

[12] As Klier and Linn (2010b) argue, supply shocks (such as seasonal trends in vehicle sales within the model-year) are attributed to complex inventory and vehicle optimization problems, and therefore are assumed to be uncorrelated with fuel costs.

[13] I do not observe vehicle transaction prices in my data and therefore can not account for manufacturers incentives in my analysis.

[14] Having mentioned this, it is important to note that the econometric models in my study capture the equilibrium impacts of gasoline costs on vehicle market shares. As such, changes in vehicle market shares depend on the relationship between gasoline prices and equilibrium sales (which take into account both consumer and manufacturer response).

in major vehicle attributes, such as make, model, series, engine size, etc, and usually take place over longer periods of time in the supply process. This model does not aim to capture the fuel efficiency variations caused by these major overhauls, as it is highly likely that consumers also change their preferences in accordance with these redesigns over time. Therefore, I control for vehicle major attributes at the level of a "vehicle", i.e., make, model, series, engine size, and number of cylinders, in this specification. Moreover, manufacturers sometimes apply minor modifications to some vehicles over shorter periods of time. These minor modifications that happen through vehicles' year-to-year revisions (such as refresh and face-lift) may slightly change the fuel efficiency of a vehicle without affecting its major attributes. According to Rivers and Schaufele (2017b), minor characteristics like the design or weight, which are more likely to change over shorter periods of time, can also cause changes in the energy efficiency of a vehicle. These changes usually occur through some updates to a vehicle such as a revised front or rear bumper, option packages or new wheel designs.[15] However, a vehicle that undergoes a refresh or a face-lift will still use the same engines and platform as its predecessor. For example, rated fuel efficiency of a new Acura CL, 3.2 series with 3.2 liter engine size and 6 cylinders improves from 10.04 L/100 to 9.98 L/100 km between 2001 and 2002 due to some minor updates, even though its major attributes stay unchanged. The identification strategy in the second model relies on these small modifications in a vehicle's fuel efficiency as a result of year-to-year updates.

This identification, however, requires an assumption; consumers do not value the redesigned vehicles differently than the original models except for the potential changes in fuel efficiency. I believe that this is a valid assumption, since the indicator for model controls for the vehicle major characteristics that normally form the consumers' preferences for a particular vehicle. These vehicle updates are normally minor and are unlikely to affect the desirability of the original model compared to its updated version (Rivers and Schaufele

[15]For example, a refresh applies some minor revisions to a car's exterior styling and possibly small changes to its interior. And a face-lift is one level above a refresh and therefore may update a vehicle model with a heavily revised interior and more new features than is expected from a simple refresh.

(2017b)). Having mentioned this, it is likely that consumers shift their preferences towards or away from the original version of a model due to a change in its fuel efficiency. For example, if a minor change in the exterior styling of a vehicle causes an improvement in its fuel efficiency, it is likely that consumers would switch from the original to the updated model. As such, this identification requires an additional assumption; the minor changes that improve or worsen fuel consumption are uncorrelated with changes in gasoline price over time. In other words, small year-to-year updates on vehicle models do not systematically occur in correlation with gasoline price changes. I believe that this assumption is also reasonable because: (1) it is unlikely that vehicle manufacturers apply vehicle redesigns to respond to gasoline price changes at the disaggregated FSA level, (2) fuel efficiency can decrease or increase, meaning that the vehicle updates can improve or worsen energy efficiency as the gasoline price changes.[16] It is also important to add that, since the second model aims to capture the gasoline cost variations caused exclusively by vehicle redesigns on their market share, variations in gasoline price over time must be held constant. As such, in this specification, I apply FSA-year fixed effects to control for within-FSA changes in gasoline price (as well as other time-varying and FSA-specific factors) over time.

Finally, I estimate an additional specification, as the most comprehensive specification, to capture the effect of changes in gasoline costs as a result of variations in both gasoline price and vehicle fuel efficiency on new vehicle purchases. This specification allows for the year-to-year changes in fuel efficiency within a "vehicle" to interact with gasoline price variations within a given FSA over time.[17] As a result, in this specification, as opposed to the first specification, I allow for the fuel efficiency of each "vehicle" to vary over time. I will further explain the fixed effect combinations used in each of the specifications explained above in the next section.

[16] An example of a vehicle whose fuel efficiency worsened due to a vehicle redesign, in contrast to the Acura example, is a new 5.3 liter 8 cylinder Chevrolet C1500 EXT Silverado, with a fuel efficiency changing from 14 to 14.07 L/100 from 2001 to 2002.

[17] This means that vehicle fuel efficiency plays a role in changing the slope of the demand curve in addition to gasoline price.

2.4.2 Econometric Specification

In this section, I discuss the conceptual framework and econometric specifications to estimate the effects of gasoline cost on new vehicle market shares across the Canadian FSAs from 2000 to 2010. For all the identification strategies explained in Section 2.4.1, I employ a conventional differentiated products demand approach. Markets are defined as FSA-years.

Assuming that there are J vehicle models in FSA f and year t, the utility to individual i for purchasing a new vehicle j (from J models) can be characterized as follows:

$$U_{ijft} = \alpha_i(Y_{ift} - q_{jft}) + \beta_i x_j + \lambda_i GC_{jft} + \delta_{jft} + \varepsilon_{ijft} \tag{2.1}$$

where Y indicates the individual i's income, q is the price of vehicle j, x_j and δ_{jft} represent vehicle j's observed and unobserved characteristics, GC_{jft} is the gasoline costs of driving model j (in \$/100 km), and finally ε is the mean zero stochastic term that captures individual i's preferences for vehicle j. Parameters α_i and β_i capture individual i's preferences over vehicle prices and other observable characteristics.[18] λ captures the differential effects of gasoline price on the utility obtained from each vehicle model depending on their fuel efficiency.

A representative consumer decides to purchase a particular vehicle among all other alternative vehicle choices including the outside option of not purchasing a vehicle. This means that consumers may choose to not buy a new vehicle and spend their entire income on products other than vehicles. I define $U_{i0pt} = \alpha_i Y_{ipt}$ as the utility obtained from the outside good and assume that consumers will choose one unit of the good (a new vehicle or an outside good) that provides the highest utility. As such, consumer i will choose to purchase vehicle

[18] Equation 3.2 assumes a quasilinear utility function and therefore doesn't include wealth effects on the purchase of product j. The assumption of a quasilinear utility function imposes a constant marginal utility of income (α_i). This might be a reasonable assumption for products such as ready-to-eat cereals as they constitute a small part of an individual's income (Nevo (2000)). However, the marginal utility of income may not be constant over the mix of vehicle prices as they constitute a large proportion of income. As a result, other more flexible functional forms are suggested in the literature; Nevo (2000) suggest using $f(y_i - q_{jt})$; and Berry et al. (1995) propose a Cobb-Douglas utility function as in $\log(y_i - q_j)$. I am unable to use a specific functional form for utility in Equation (1) as I don't have access to vehicle prices in my data-set.

j, among all other alternatives including the outside option, if:

$$P_{ijft} = Pr(U_{ijft} > U_{ikft}) \quad \text{for} \quad j = 0, 1, 2, 3, \ldots, J \quad \text{and} \quad j \neq k \tag{2.2}$$

I decompose preferences into deterministic and random components, as in $U_{ijft} = V_{ijft} + \varepsilon_{ijft}$.[19] This allows for the choice probabilities to be derived from the differences between the utilities from available alternatives (rather than the absolute values of individuals' utility), i.e., $P_{ijft} = Pr(V_{ijft} - V_{ikft} > \varepsilon_{ikft} - \varepsilon_{ijft}) \quad \text{for} \quad j \neq k$.

The aggregate market shares for vehicle j (s_{jft}) can then be obtained by integrating over preferences of all the individuals that choose vehicle j in each market:

$$s_{jft} = \int_{\varepsilon} I(V_{ijft} - V_{ikft} > \varepsilon_{ikft} - \varepsilon_{ijft} \quad \text{for} \quad j \neq k) f(\varepsilon) d\varepsilon \tag{2.3}$$

I assume that there is no systematic heterogeneity across individuals' preferences in my analysis, such that $\alpha_i = \alpha$, $\beta_i = \beta$, and $\lambda_i = \lambda$, and the only source of heterogeneity is in the mean zero stochastic term (ε_{ijft}). Assuming that the stochastic term for all individuals is distributed independently and identically multivariate type-I extreme value, there is a closed-form solution for the integral in Equation 3.3 which yields the standard logit model:

$$s_{jft} = \frac{e^{V_{jft}}}{\sum_k e^{V_{kft}}} \tag{2.4}$$

s_{jft} is the market share of vehicle j among all vehicle alternatives (including the outside good) in a given market. I divide the market share of individual vehicles by the share of the outside good (as I define by s_{0pt}) and estimate the log-odds ratio of purchasing a new vehicle relative to the outside good ($\log(\frac{s_{jft}}{s_{0ft}})$) as a function of product characteristics using the following standard logit specification[20]:

[19] The deterministic component V_{ijft} captures observed consumer attributes as well as observed and unobserved vehicle attributes, and the random term ε_{ijft}, captures unobserved consumer preferences over their vehicle choice.

[20] Note that dividing individual model shares s_{0pt} and taking logs will cancel out Y_{ipt} and ε_{jpt} from the equation.

$$\log(\frac{s_{jft}}{s_{0ft}}) = \beta x_j + \lambda GC_{jft} + \delta_{jft} \tag{2.5}$$

As mentioned previously, λ captures the effects of changes in gasoline cost of driving a particular vehicle on its market share relative to the share of the outside good. λ is expected to be negative, which, according to Equation 3.5, means that as the gasoline cost of driving a vehicle increases, the odds ratio of purchasing that vehicle relative to the outside good would decrease. In other words, a significantly negative estimate for λ would imply that by any increase in gasoline costs, consumers would shift their preferences from buying to not buying a new vehicle (i.e., the outside good). This seems to be unrealistic, as we expect gasoline costs to affect vehicle market shares by causing substitutions across vehicles within the vehicle market (rather than relative to the outside choice). As such, as stated in the literature (e.g., Nevo (2000)), it is highly likely that the effects are driven due to the Independence of Irrelevant Alternatives (IIA) assumption implicit in the standard logit specification.

The IIA assumption of the standard logit model implies unrealistic own and cross price elasticities.[21] This means that the odds ratio, and consequently the cross price elasticities, between two available alternatives with respect to vehicle attributes (for example gasoline cost in my analysis) depend only on vehicle market shares. As such, the model would predict substitutions across the available alternatives to happen in proportion to their market shares. This would, in particular, mean that the alternatives with highest market shares would see the biggest change in share due to an increase in the vehicle attribute (like gasoline cost, in this case). And since the outside good represents the option of not purchasing a new vehicle in a FSA and year in my analysis, share of the outside good would be the highest. This, as pointed out by Chandra et al. (2010), indicates that the logit model would predict that a

[21]The standard logit specification assumes that unobserved vehicle characteristics (included in the error component) are distributed identically and independently Type I extreme value. Although this assumption allows for a convenient closed-form solution for the choice probabilities (P_{ijft}), it assumes the Independence of Irrelevant Alternatives (IIA) among products and therefore imposes restrictions on substitution patterns across available alternatives.

large portion of the new vehicle buyers would not have bought a new vehicle if gasoline costs had increased. As a result, for all regressions in this study, I will directly estimate vehicle market shares (from aggregate vehicle sales in each market, i.e.,s_{jft}) without accounting for the outside good. The model in Equation (5) is technically a variant of the model that doesn't consider the outside good; the share of the outside good has moved from left to right hand side of the equation and is included in the error term. While both models yield similar results, the second model allows for a more straightforward interpretation of the coefficients.

Another reason to model market shares without considering the outside good is that I do not find any empirical evidence that gasoline price affects aggregate new vehicle sales over the period of analysis. In other words, if gasoline costs cause shifts in preferences from buying to not buying a new vehicle, aggregate new vehicle sales must have changed in response to changes in gasoline price. I perform an additional estimation on aggregate new vehicle sales[22] and find that the total number of new cars sold are unaffected by the variations in gasoline price. Results of this specification are presented in the appendix.

The estimating equation captures the observed and unobserved vehicle attributes (i.e., x_j and δ_{jft}) by including vehicle fixed effects. The vehicle fixed effects control for all the observed and unobserved preferences for individual vehicles (including vehicle list prices) that are constant across FSAs and over years. As argued by Berry et al. (1995), failure to account for vehicle-specific effects will result in biased estimates due to the potential endogeneity that likely exists between vehicle unobserved attributes and vehicle list prices and potentially other observed attributes.[23]

I employ different configurations of vehicle-FSA (denoted by δ_{jf}) and vehicle-year (de-

[22]I perform the following estimation:

$$\log S_{ft} = \gamma \log GP_{ft} + X_{ft} + +\varphi_f + \xi_t + \epsilon_{ft} \tag{2.6}$$

where S_{ft} is total new vehicle sales per capita in FSA f and year t, GP_{ft} is real gasoline price, and X are other factors including log median income, log median age, log percent female, and log percent married individuals in the population, φ_f and ξ_t are FSA and year fixed effects, and finally ϵ_{ft} is the error term.

[23]Examples of the observed and unobserved vehicle attributes are make, mode, engine size, horsepower, number of cylinders, fuel efficiency, interior and exterior design, optional features, performance, reliability, and model reputation.

noted by θ_{jt}) fixed effects to capture average preferences for each "vehicle" in each FSA and each year, respectively. As mentioned previously, a "vehicle" is defined as a combination of make, model, series, engine size, and number of cylinders. I change the source of identification by changing the structure of these fixed effects. Vehicle-FSA fixed effects, δ_{jf}, capture preferences that vary by FSA but are constant over time, i.e., preferences that are usually related to the geography, density, and make-up of a population and other characteristics that are specific to a region. θ_{jt} capture national preferences that vary over years and can affect the vehicle market.[24] Having mentioned this, it is important to add that the 2008 financial crisis is an exceptional setting in which consumers' expectations of future gasoline prices may differ from the current price. Anderson et al. (2013) find that consumers predicted that gasoline prices would rebound after the sharp decline in 2008. As such, since I assume a no-change forecast in gasoline price throughout my study, consumers' demand for fuel efficiency during the financial crisis may have been over-estimated in my specifications.

Including these fixed effects will leave the error component in Equation 3.5 with other unobserved vehicle-FSA-year effects (i.e., μ_{jft}) that are not captured by the fixed effects:

$$\log s_{jft} = \lambda GC_{jft} + \delta_{jf} + \theta_{jt} + \mu_{jft} \tag{2.7}$$

Similar to the previous model, λ is expected to be negative and can be interpreted as the percent change in vehicle market share due to \$1 increase in gasoline cost (per 100 km of driving). For example, assuming that λ is -0.03, a \$1 increase in the gasoline cost of driving 100 km (due to a \$1 increase in gasoline price) in a Toyota Corolla, with an average market share of 0.04 in a given market (FSA-year), would cause its market share to decline by 3 percent (i.e., from 0.04 to 0.038).

According to Equation 3.7, an increase in the gasoline price, all else constant, increases the gasoline cost of driving (per 100 km) for all vehicles. The vehicle-year fixed effects control

[24]Factors such as the federal regulations on the vehicle market, year-specific demand shocks, the financial crisis in 2008 and so on.

for the effect of gasoline price increases on the average cost of driving (per 100 km). However, an increase in the gasoline price has differential effects on the fuel cost of various vehicles depending on their fuel efficiency. The gasoline price increase imposes lower fuel costs on vehicles with high fuel efficiency relative to vehicles with low fuel efficiency. Therefore, the changes in relative gasoline costs cause an outward shift of the demand curves of fuel-efficient vehicles and an inward shift of the demand curves of fuel-inefficient vehicles. We expect that an increase in the gasoline price raises the market share of vehicles with higher fuel economy, thus improving the sales-weighted average fuel economy of the entire fleet.

I will employ two approaches to estimate the effect of changes in gasoline price on the fuel economy of new vehicle sales. First, I estimate changes in the fuel efficiency of new vehicles sold across FSAs and years as a result of changes in gasoline price using aggregate regressions on average fuel efficiency in each market (i.e., FSA-year). Second, I calculate the fleet fuel economy over the period of study using the predicted market shares from the most comprehensive logit specification in response to a one percent increase in gasoline price. Following these two approaches, I will quantify the elasticity of fleet fuel economy with respect to gasoline price and compare the elasticity estimates obtained from each estimating approach (discussed in Section 2.5.6).

I apply linear regression to estimate all the logit specifications using two high dimensional fixed effects.[25] Finally, standard errors across all specifications are clustered by city.[26] This allows for the unobserved vehicle attributes (included in the error component) to have serial correlations with one another within a given city over time. It is more likely for the unobserved factors affecting vehicle sales to be serially correlated within the same city (as opposed to across cities).[27]

[25]There are hundreds of thousands of fixed effects in each of the estimations imposing computational complexity over estimations. Therefore, as suggested by Rivers and Schaufele (2017b), I use estimations with high dimensional fixed effects. This technique employs repeated demeaning algorithm to estimate models with two or three dimensional fixed effects (Guimaraes and Portugal (2009)).

[26]I also try clustering by FSA and find that the reported standard errors do not substantially change across the two clustering approaches.

[27]Vehicles within the same city are more likely to undergo similar city-specific changes over time than vehicles across cities. For example, the economy is more agricultural-based in Calgary than in Vancouver,

2.5 Results

2.5.1 Effect of gasoline costs on new vehicle demand

Table 2.3 reports results for the logit models exploiting each source of variation in gasoline cost. All models estimate the effect of variations in gasoline costs (in $/100 km) at the vehicle-by-FSA level over years on the log of market share of a "vehicle". Across all specifications, the dependent variable is the market share of a "vehicle" from total new vehicle sales in a given market (i.e., FSA-year), and the independent variable is gasoline cost of driving the given model. As mentioned previously, a "vehicle" is a combination of make, model, series, engine size, and number of cylinder. Therefore, in all models, changes in the market share of a "vehicle" is compared with the counter-factual market share of this particular vehicle while varying the vehicle gasoline cost. Reported coefficients measure the percent change in the market share of a particular vehicle in response to a one dollar increase in gasoline cost of driving that vehicle (per 100 km). They capture the sensitivity of consumers to changes in gasoline cost and evaluate whether consumers substitute toward more fuel-efficient vehicles in response to an increase in gasoline cost.

Results across all columns indicate negative effects of gasoline costs on new vehicle market shares, although are not significant in column (1). Each column includes a distinct array of vehicle-FSA and vehicle-year fixed effects. I change the source of identification by changing the configuration of these fixed effects. In column (1), the identification comes from within-city variations in gasoline price, as the first source of variation in gasoline cost, over years. The identification in column (2) is based on within-vehicle variations in fuel efficiency, as the second source of variation in gasoline cost, due to vehicle redesigns. Column (3), as the most comprehensive specification, relies on variations in gasoline price and vehicle fuel efficiency together.

Column (1) identifies the effect of gasoline cost on market share of each "vehicle" through

therefore demand for SUVs and trucks in a city in Alberta in 2000 is more likely to be correlated with the demand in the same city in 2001, than in a city in Vancouver in 2001.

variations in gasoline price in each FSA over years. Consistent with other specifications in this table, I include vehicle-FSA and vehicle-year fixed effects to capture average preferences for each "vehicle" that vary across FSAs and years, respectively, and are correlated with the gasoline cost. However, to isolate the effect of variations in gasoline price (as the first source of variation in gasoline cost), I must control for variations in the fuel consumption rating of each "vehicle" across years. Therefore, in this specification, vehicle fixed effects (interacted with each FSA and year) control for changes in the fuel efficiency rating of each "vehicle". In other words, in this model, the resolution of vehicle fixed effects is at the level of make, model, series, engine size, number of cylinder, and fuel efficiency.[28] The results of this specification suggest a negative relationship between gasoline cost and vehicle market share, implying that an increase in the gasoline cost of driving a particular vehicle, as a result of increases in gasoline price, causes a decline in its market share. While the effect is economically meaningful in sign and magnitude, the reported coefficient is not statistically significant.

Column (2) includes FSA-year fixed effects in addition to vehicle-year and vehicle-FSA fixed effects, identifying the effect of gasoline cost from within-vehicle variation in fuel consumption rating and market share. The identification comes from the minor modifications that manufacturers apply on some vehicles, causing changes in the fuel efficiency of the given vehicles (i.e., improved or worsened fuel efficiency) from one year to the next. In the same fashion as in other columns in the table, the level of analysis is a "vehicle". Therefore, changes in the market share of a particular vehicle over time are estimated in response to changes in the gasoline cost of this particular vehicle due to the vehicle redesign.[29] To isolate the effect of within-vehicle variation in fuel efficiency (as the second source of variation

[28]This implies that changes in the market share of a Honda (as a make), Acura (as a model), CL 9 (as a series), 3.2 (as an engine size) with 6 cylinders and a combined fuel consumption rating of 10.04 (L/100 km), whose fuel efficiency does not change from one year to the next, is compared with the counter-factual market share of this particular vehicle while varying gasoline price within a FSA over years.

[29]As mentioned previously, since I control for the major characteristics of each vehicle, i.e., make, model, series, engine size, and number of cylinders, other year-to-year modifications are relatively minor, thus causing small changes in the vehicle fuel efficiency (rather than major overhauls).

in gasoline cost), I include FSA-year fixed effects to control for variations in gasoline price across FSAs and years. These fixed effects also control for other unobserved factors (such as median income, median age, population, percent female in the population and so forth) that vary by FSA and year and can influence new vehicle purchases. As is observable in the results, the number of observations in this specification is less than the observations in the other columns. This is because only changes in the market share of the vehicles whose fuel efficiencies change from one year to the next (due to vehicle redesigns) are estimated in response to changes in their gasoline cost. The results in this column are statistically significant (at the 1% level), implying that a one dollar increase in the gasoline cost of driving a particular vehicle (per 100 km) as a result of changes in the vehicle fuel efficiency (due to vehicle minor updates) causes its market share to decline by 7 percent.

Column (3) presents the results of the most comprehensive specification, identifying the effect of gasoline cost through changes in the market share of a particular vehicle within a FSA over time in response to changes in both gasoline price and the fuel efficiency of this particular vehicle. More precisely, the model exploits within-FSA variations in gasoline price interacted with within-vehicle variations in fuel efficiency over time. Consistent with the other specifications, I include vehicle-FSA and vehicle-year fixed effects to control for the average preferences for each "vehicle" that vary by FSA and year, respectively.[30] Results suggest a negative significant (at the 1% level) relationship between gasoline cost and vehicle market share, implying that a one dollar increase in the gasoline cost of a "vehicle" (per 100 km of driving) is associated with a 3 percent decline in the market share of this particular vehicle, all else constant.

Overall, the results are robust across all models regardless of the identification and fixed effect configurations. A one-dollar increase in gasoline cost of driving a vehicle, all else equal, is associated with a 2 to 7 percent decline in its market share. Having mentioned this, the sensitivity of vehicle market shares with respect to gasoline cost is larger when we only

[30]It is important to note that, in this specification, as opposed to the specification in column (1), a "vehicle" is defined as a combination of make, model, series, engine size, and number of cylinders.

account for fuel efficiency variations (due to vehicle redesigns) in gasoline cost. This implies that, between the two components of gasoline cost, consumers are more sensitive to changes in the fuel efficiency of a vehicle than to changes in gasoline price when selecting their new vehicle choice.

Finally, as explained previously, an increase in the price of gasoline increases the cost of driving for all vehicles, all else constant. However, this price increase has differential effects on the cost of driving various vehicles depending on their fuel efficiency. An increase in gasoline price imposes lower fuel costs on fuel-efficient vehicles relative to fuel-inefficient vehicles. Therefore, the change in relative gasoline costs causes the demand curve for fuel-efficient vehicles to shift out and the demand curve for fuel-inefficient vehicles to shift in. A negative coefficient for gasoline cost, therefore, implies that an increase in gasoline price raises the market share of vehicles with low fuel costs, relative to vehicles with high fuel costs. My interpretation is that increases in gasoline price cause shifts in preferences for vehicles with higher fuel efficiency, thus causing an increase in sales-weighted average fuel economy of the fleet.

2.5.2 Nested Logit Specification

As discussed previously, the IIA assumption implicit in the logit specification imposes unrealistic substitution patterns across available vehicle alternatives. Under this assumption, substitutions across vehicles depend only on their market shares and not on product characteristics. For example, the logit model implies that if two vehicles like the BMW X5 and Chrysler Sebring have the same market shares, then substitution away from a third vehicle like Mercedes-Benz, due to an increase in its price (or gasoline cost in my analysis), to either of these products would be the same. This is intuitively unrealistic, since we expect that Mercedes buyers would substitute more to the BMW than to Chrysler as the BMW offers them more comparable vehicle characteristics. Therefore, the model does not account for substitutions across vehicles that are considered to be closer substitutes.

To overcome this problem, I estimate a nested logit model to partially relax the IIA assumption implicit in the standard logit specification.[31] The nested logit specification allows for consumer preferences to be correlated (in a restricted fashion) across products with similar attributes (Berry (1994)). According to this model, vehicles need to be grouped into exhaustive and mutually exclusive nests in a way that vehicles with more similar attributes fall into one nest. This nesting structure permits the vehicles within each nest to be considered as closer substitutes for one another than vehicles in other nests.[32] The nested logit estimation is written as:

$$\log s_{jft} = \lambda GC_{jft} + \delta_{jf} + \theta_{jt} + \phi(S_{j/n})_{ft} + \mu_{jft} \tag{2.8}$$

where all the variables and subscripts are the same as in Equation 2.7 with an additional variable ($S_{j/n}$) as the within-nest market share. $S_{j/n}$ is the market share of vehicle j within nest n and ϕ is a parameter that defines the degree of substitutability of vehicles within a given nest. This parameter ranges between zero and one; as it approaches one, substitution between vehicles within the same nest becomes higher, and as it approaches zero, the within-nest substitution between vehicles becomes lower.

As the nesting structure allows for a more flexible substitutions across vehicles with more similar attributes within a nest, it is important how we determine the grouping of products prior to estimation. I classify vehicles by category, segment, and make, in order to compare the results depending on the nesting approach. Based on the classification by category, vehicles are grouped into four categories of cars, SUVs, pickup trucks, and vans. The classification by segment, which is based on the RL Polk classification, groups vehicles into 15 segments.[33] Finally, I classify vehicles based on their make; for example, Civic for a

[31] It is widely common in the literature (for example, Berry et al. (1995)) to use a nested logit model to relax the distributional assumptions of the standard logit model while still allowing for the application of linear estimation techniques.

[32] It is important to note that, in the nested logit model, the within-nest substitution patterns still depend on market shares because the IIA assumption is still preserved between vehicles within each nest.

[33] The segments are: subcompact car, compact car, sport car, intermediate car, luxury car, luxury high car, luxury sport car, compact SUV, intermediate SUV, large SUV, luxury SUV, small pickup, large pickup,

Honda, as some consumers are more sensitive to the make of a vehicle than the category or segment.[34]

A challenge with the nested logit model is that the within-nest share variable is endogenous, since an increase in the market share of a vehicle in the vehicle market clearly increases its share relative to all other vehicles within its nest. As such, I control for the potential endogeneity that exists between within-nest shares and unobserved vehicle-year-FSA factors in the error term by using a two-stage linear regression with instrumental variables (IVs) (Following Berry (1994)).[35] I use the sum of the characteristics of other vehicles in the same nest as vehicle j as instruments, because these characteristics are correlated with within-nest shares, but are unlikely to be correlated with the vehicle's share from total sales, as well as the consumers' valuation of vehicle j. The consumers' valuation of vehicle j is only a function of vehicle j's own characteristics. Three characteristics of other vehicles in the same segment as vehicle j, i.e., number of cylinders, engine size, and combined fuel efficiency, are considered as potential IVs for vehicle model j.

Table 2.4 reports the results of the nested logit models. Column (1) presents the results of the specification where vehicles are grouped into four categories (super segments) of cars, SUVs, trucks, and vans). Column (2) shows the model in which vehicles are grouped by segment. Finally column (3) presents the nested logit results based on the classification by make. The within-nest market share variables included in these models allow for the vehicles within each nest (category, segment, and make) to have a greater degree of substitutions with one another than with vehicles from other nests. This partially relaxes the Independence of Irrelevant Alternatives (IIA) assumption implicit in the logit model. It is evident that the

small van, and finally large van. These segments are also subgroups of the bigger categories in the first classification.

[34]The idea behind the nested logit model in my analysis is that consumers first decide the category, segment, or make of the new vehicle they are willing to purchase. Next, they choose the vehicle model among all other available alternatives within the nest selected in the first stage.

[35]To test the endogeneity of within-nest shares, I estimate the reduced-from model in Equation (9) but use the endogenous variable as the dependent variable: $(S_{j/n})_{ft} = \lambda GC_{jft} + \delta_{jf} + \theta_{jt} + \mu_{jft}$. I obtain the residuals of this estimation (i.e., $\hat{\mu_{jft}}$) and then estimate Equation (9) $\log s_{jft} = \lambda GC_{jft} + \delta_{jf} + \theta_{jt} + \psi \hat{\mu_{jft}}$. A significant ψ implies that $(S_{j/n})_{ft}$ are endogenous. results of the endogeneity tests are reported in Table 2.3.

sign and significance of the coefficient of interest does not change as I change the nesting structure. However, the classification by vehicle category implies a larger ϕ, implying that the substitutability of vehicles within a category (0.60) is higher than within a segment or a make. Overall, results indicate that a $1 increase in gasoline cost of driving a particular model (per 100 km) causes its market share to decline by 1% to 3% percent. It is also interesting to note that the results of the nested logit specifications are consistent with the logit results, thus providing more robustness to the significant effects of gasoline cost on vehicle market shares.

Finally, I perform a number of post estimation techniques to test the quality of the instruments. Two conditions must be satified. First, the instruments (i.e., the sum of the characteristics of other vehicles in the same nest as vehicle j) are relevant, meaning they are correlated with the endogenous variable (i.e., within-nest shares). Second, they must not be correlated with the unobserved preferences contained in the error component. To check the first condition, F-statistics for the joint significance of the coefficients on additional instruments are checked and reported in Table 2.4. F-statistics are significant at the one percent level, implying that the instruments are relevant. To check the second condition, the Wooldridge's robust score test of overidentifying restrictions (Wooldridge, 1995), or the Sargan-Hansen test, is used. The null hypothesis holds that the instruments are valid, meaning they are uncorrelated with the error term. Results of the Sargan-Hansen test suggest that the instruments are valid as the null hypothesis is not rejected (Wooldridge's robust score is not significant). Finally, I reject the weak instruments test since the F-statistic is larger than Stock Yogo (2005) weak ID test critical values.

2.5.3 Effect of gasoline prices on fuel economy of new vehicle

In this section, I perform an alternative specification to capture the impact of gasoline price on the fuel efficiency of new vehicles sold across the Canadian FSAs over the period of analysis. The model estimates changes in sales-weighted fuel economy of the average new vehicle sold in each FSA and year in response to changes in gasoline price.[36] The estimating equation is expressed as:

$$\log F_{ft} = \gamma GP_{ft} + X_{ft} + \varphi_f + \xi_t + \epsilon_{ft} \tag{2.9}$$

F_{ft} is the sales-weighted average fuel consumption of new vehicle sales of new vehicle sales (in L/100 km) in FSA f and year t, GP_{ft} is real average gasoline price (inclusive of all taxes) (in \$/L), X is a matrix containing additional FSA-specific factors, including log median income, log median age, and log percent females, and log percent-married individuals in the population, φ_f and ξ_t are FSA and year fixed effects, respectively, and finally ϵ_{ft} is idiosyncratic error. FSA and year fixed effects are included to control for all the unobserved factors that vary by FSA and by year which can influence vehicle fuel consumption. The identification, therefore, is based on the within-FSA variations in gasoline price and the fuel economy of new vehicle sales over years.[37]

γ captures the percent change in new fleet fuel economy due to a 1 \$/L change in gasoline price. I also estimate the log-log version of Equation 2.9 to allow for the interpretation of γ as the elasticity of fuel economy with respect to gasoline price. I apply least square estimation to estimate Equation 2.9 and cluster standard errors by FSA to account for serial correlations that likely exist between the residuals within a given FSA.

The advantage of this model over the logit specifications on vehicle market shares is that it allows for a straightforward estimation of changes in vehicle fuel economy as a result of changes in gasoline price without making assumptions regarding consumer preferences and the distribution of unobserved parameters. Also, it provides a simple interpretation of the effect of gasoline price on average fuel economy (Klier and Linn (2010b)). However, the

[36] As mentioned in the earlier sections, the sales-weighted average fuel economy (i.e., F_{ft} in L/100 km)) is calculated using: $F = \frac{\sum_{j=1}^{J}(sales_j * fe_j)}{\sum_{j}^{J} Sales_j}$, where the sum of sales-weighted fuel consumption of all vehicles in a given market is divided by the sum of vehicle sales in the given market.

[37] Note that, as mentioned in Section 2.3, the FSA-level gasoline price data report the city-level gasoline price values from the 57 cities obtained from Kent Marketing Group. I do not observe the exact gasoline price values for individual FSAs in my data.

estimates from the aggregated models are not as precise as the estimates from the logit and nested logit models as they do not account for consumer preferences at a disaggregated vehicle model level. In any case, both models have similar implications for the effect of an increase in gasoline price on vehicle fuel efficiency.

Table 2.5 reports the results of semi-log and log-log specifications. In both models, the dependent variable is the log of sales-weighted new vehicle fuel consumption (in L/100 km). In column (1), gasoline prices (inclusive of all taxes) enter as levels ($/L), while in column (2), they enter as logs. Both models demonstrate significant negative effects of gasoline price on new vehicle fuel economy. In column (1), λ implies that the vehicle fuel consumption (in L/100 km) improves by 0.19% due to a $0.01/L increase in gasoline price (inclusive of all taxes). Column (2) demonstrates an elasticity estimate of -0.16, which indicates that a 1% increase in gasoline price causes a 0.16% improvement in new vehicle fuel economy, all else equal.

Elasticity estimates capturing gasoline price effects in the results above are consistent with those in several recent studies: Rivers and Schaufele (2017a) find an elasticity of -0.08 to -0.12 (depending on the fixed effects and identification) using Canadian new vehicle data (2000-2010); Barla et al. (2009) report an elasticity of -0.1 using Canadian vehicle data from 1990 to 2004, and Klier and Linn (2010b) estimate a 0.12 elasticity using the US vehicle sales data from 1970 to 2007.

Finally, none of the coefficient estimates for other covariates included in the model are statistically significant, implying that the additional FSA-level factors do not affect fleet fuel economy.

2.5.4 Heterogeneity in gasoline price response

This section demonstrates heterogeneity in consumer response to variations in gasoline price using logit estimations, as explained in Section 2.4.2. I present three specifications to explore heterogeneity and present the results in Table 2.6. All specifications have the same dependent and independent variables and control for vehicle-FSA and vehicle-year fixed effects. Therefore, the identification is again based on the within-FSA variations in gasoline cost (in $/100 km) on new vehicle shares across all models.

In column (1), the sample is split into two groups: the first group includes the FSAs that experience an increase or no change in gasoline price from the prior year, and the second group contains the FSAs experiencing a decrease in gasoline price from the prior year. Each group is indicated by a dummy variable interacted with gasoline costs to allow for heterogeneity in response to changes in gasoline cost across the groups.The coefficient for the reference group captures the effect of gasoline cost when gasoline prices are increasing or constant, and the interaction effect reflects the effect of gas cost when gasoline prices are declining. Results suggest that consumers have larger response to increasing or constant gasoline prices than to decreasing gasoline prices. A $1/L increase in gasoline cost results in 4.7 percent decrease in market shares when gasoline prices are increasing or constant whereas it causes a 3.2 percent (- 0.047 + 0.015 = - 0.032) decrease in shares when gasoline prices are falling (both estimates are significant at the 1% level). Leard et al. (2017) also find larger changes in new vehicle market shares in response to rising than falling or stable gasoline prices in the US automobile market.

In a separate model, I change the sample size and compare consumer response to variations in gasoline price by changing the number of FSAs included in the analysis. I assign city-level gasoline price data to FSAs depending on their distance to the city center points. FSAs are grouped based on three distance measures: FSAs within 10 km, FSAs within 15 km, and FSAs within 20 km, from city center points. The reference group includes the FSAs located within the 10 km of city center points (mainly urban residents). Results in column (2) indicate a slightly larger response by the reference group, implying that consumers in urban regions (i.e., closer to the city core) are slightly more responsive to variations in gasoline price. I find a 3, 2.9, and 2.8 percent decrease in new vehicle shares in response to a $1 increase in gasoline costs (per 100 km) as we move farther from city center points, respectively. This implies that residents of urban regions have a higher tendency to shift to more fuel-efficient vehicles in response to gasoline price increases. This can be due to the size of more fuel-efficient vehicles that are generally smaller than fuel-inefficient vehicles (such as large SUVs), and therefore would not cause limitations, such as parking and congestion, for urban residents in city center points. Also, the transportation facilities and easier and faster commuting devices are more accessible in regions located closer to city centroids than suburbs.

Finally, I investigate whether consumers respond similarly to gasoline price variations when buying an imported vehicle versus a domestic vehicle. I group vehicles into two groups: imported and domestic. Imported vehicles account for 52% of total observations (i.e., 729,962 number of observations in the sample). The results of the last column in Table 2.6 suggest that both groups of consumers are sensitive to gasoline price variations (both coefficients are significant at the 1% level), but there is a slightly higher sensitivity in demand for domestic vehicles. A \$1/L increase in gasoline costs (in \$/100 km) is associated with a 3 and 2.8 percent decrease in the market share of domestic and imported vehicles, respectively, all else equal.

2.5.5 Effects of gasoline costs on vehicle type

In Section 2.5.4, I analyzed how increases in gasoline cost result in improvements in the fuel efficiency of new vehicle sales. Equation 2.7, however, assumes that fuel costs affect market shares proportionately for all vehicles. In this section, I investigate an alternative model in which I allow gasoline costs to differentially affect vehicle shares based on their type or fuel efficiency. The model demonstrates how the observed improvements in fleet fuel economy (obtained in the previous results) occurred through changes in fleet composition.

I group vehicles based on classifications by segment (i.e., subcompact-cars, compact-cars, and etc.) and estimate changes in vehicle market shares in each segment in response to changes in gasoline cost. Table 2.7 presets the summary statistics for classification by segment. According to Table 2.7, compact and subcompact cars are the most fuel-efficient segments (with 7.1 L/100 km and 7.6 L/100 km fuel efficiency, respectively), whereas large vans vans, large pickup trucks, and large SUVs (with 14.5 L/100, 14.6 L/100, and 15.1 L/100, respectively) are the least fuel-efficient segments.

The estimating equation is expressed as:

$$\log s_{jft} = \lambda_i GC_{jft} + \delta_{jf} + \theta_{jt} + \mu_{jft} \tag{2.10}$$

The dependent and independent variables are the same as the previous models for individual shares. The model, however, allows λ to vary by vehicle segment i. As in the previous models, identification is based on variations in gasoline cost within a FSA over years while capturing the differential effects of gasoline cost across segments. Least square estimation technique is applied, vehicle-FSA and vehicle-year fixed effects are included, and standard errors are clustered by FSA.

Table 2.8 reports results for estimation on market shares by segment. I define the segment for compact cars as the reference group in the table. Results indicate that, the coefficient estimates across vehicle segments are relatively consistent in value, implying a negative relationship between gasoline costs and vehicle market shares by segment. The only segment with a significant positive coefficient for gasoline cost is the compact cars segment. The coefficient indicates that sales of compact cars, as the second most fuel-efficient segment, increase by 10 percent (0.03 + 0.07 = 0.10) in response to a \$1/100 km increase in gasoline costs (significant at the 5% level).

On the other hand, increases in gasoline cost have largest impacts on sales of sports and intermediate cars and minivans, causing their market share to decline by 5 , 8, and 7 percent, respectively, due to a \$1/100 km increase in gasoline costs.

2.5.6 Counter-factual Simulations

In this section, I perform counter-factual simulations to calculate changes in the fleet fuel economy associated with a one percent increase in gasoline price over the period covered by my data. To conduct the simulations, I use the results of two different specifications to allow for comparison between models with a different estimating approach. First, I calculate the predicted sales-weighted fuel efficiency (in L/100 km) using the results of the most comprehensive logit specification (presented in column (3) in Table 2.3)[38], and second by using the results of the aggregate regression on average fuel efficiency (presented in column 2 in Table 2.5).

Using the estimated coefficient from the most comprehensive logit model, I first obtain predicted market shares in response to changes in the observed gasoline price levels, $\hat{s_{jft}}$. Similarly, I obtain predicted market shares setting the gasoline price level 1% higher than the observed price, s^{*}_{jft}. The predicted number of cars sold for each model in each market (FSA-year) can then be calculated using predicted market shares under each scenario multiplied by by total vehicle sales in the given market, i.e., $(\hat{s_{jft}} \times S_{ft})$ and $(s^{*}_{jft} \times S_{ft})$.[39] Note that I conduct the simulation under the assumption that the total new vehicle sales in each market are unchanged during this period, which implies that the sum of predicted shares in each market should sum to one. Next, I calculate sales-weighted fuel efficiency for each vehicle model using predicted sales multiplied by model-specific fuel efficiency in each case. I then sum fuel efficiency over all vehicles in a given market and divide them by total predicted sales ($\hat{S}_{ft}$ and S^{*}_{ft}) in that market to obtain aggregate predicted fuel economy under each scenario: $(\hat{F_{ft}} = \frac{\sum_{j=1}^{J}(\hat{fe_{jft}} \times \hat{s_{jft}})}{\hat{S_{ft}}})$ and $(F^{*}_{ft} = \frac{\sum_{j=1}^{J}(fe^{*}_{ft} \times s^{*}_{ft})}{S^{*}_{ft}})$.

Using the estimated coefficient from the aggregate regression on average fuel efficiency, I calculate the predicted sales-weighted fuel efficiency (in L/100 km) in each market in response

[38]Note that the counter-factual results of the nested logit specification yield similar results to those obtained from the preferred logit model.

[39]Note that since I use log market shares in my estimations, I take the exponential of the predicted market shares under each scenario.

to the observed gasoline price levels versus the increased gasoline price levels by one percent.

The elasticity of vehicle fuel efficiency with respect to gasoline price can then be calculated based on the predicted results of each estimating approach. I calculate this elasticity by dividing the percent changes in fuel efficiency under each scenario by the percent changes in gasoline price (which is equal to unity based on the 1% increase in gasoline price adopted in the simulation).

Figure 2.6 illustrates the elasticity of fleet fuel economy with respect to gasoline price for each year from 2000 to 2010. The left panel presents the elasticity estimates based on the the counter-factual results of the aggregated model, whereas the right panel corresponds to the counter-factual results of the aggregate regression.

Both panels suggest relatively similar elasticity estimates for new vehicle fuel economy over this decade, with slightly larger fuel efficiency improvements based on the counter-factual results of the aggregate regression (in column 2 in Table 2.5). According to the results of the left panel, the elasticity estimates range from -0.06 in 2000 to -0.14 in 2010, with an average of - 0.09, whereas the estimates in the right panel vary from -0.12 in 2000 to -0.16 in 2010.

Overall, the counter-factual results based on each estimating approach suggest relatively similar elasticity estimates, both implying similar improvements in new vehicle fuel efficiency in response to an increase in gasoline price. However, it is important to state that the counter-factual results of the logit specification are more precisely estimated as they take into account changes in model-specific fuel efficiency as a result of changes in gasoline price.

In line with the previous results, the counter-factual results indicate that a one percent increase in gasoline price improves (fewer liters per 100 kilometers) new vehicle fuel efficiency by about 0.06-0.16 percent over this decade. The elasticity estimates are also consistent with the estimates obtained by Rivers and Schaufele (2017a), implying 0.08% to 0.13% improvement in fleet fuel economy over the same period in Canada.

2.6 Conclusion

This study intends to estimate the effect of changes in gasoline price on demand for fuel efficiency in the Canadian vehicle market at the dis-aggregated FSA level from 2000 to 2010. I estimate changes in the gasoline cost of driving a vehicle (per 100 km) on the market share of the given vehicle following the methodology in Klier and Linn (2010). Identification relies on the within-FSA variations in gasoline costs for new vehicle shares over time. Results indicate that increases in gasoline price cause shifts in preferences toward more fuel-efficient vehicles, thus improving the average fleet fuel economy. Consistent with the results of other relevant studies in the literature, the counter-factual results in my study indicate that the elasticity of fuel economy for new vehicles sold across the Canadian provinces with respect to gasoline price is between -0.06 to -0.16 from 2000 to 2010. Finally, I find that consumers are more responsive to rising and constant gasoline prices than falling prices. The findings also show that consumers in urban regions, and those who live closer to city center points, are slightly more responsive to variations in gasoline price compared than suburban consumers.

2.7 Figures

Figure 2.1: Cities with gasoline price data in Canada from 2000 to 2010

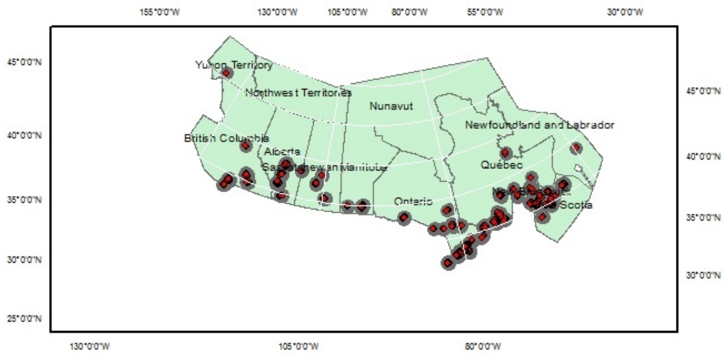
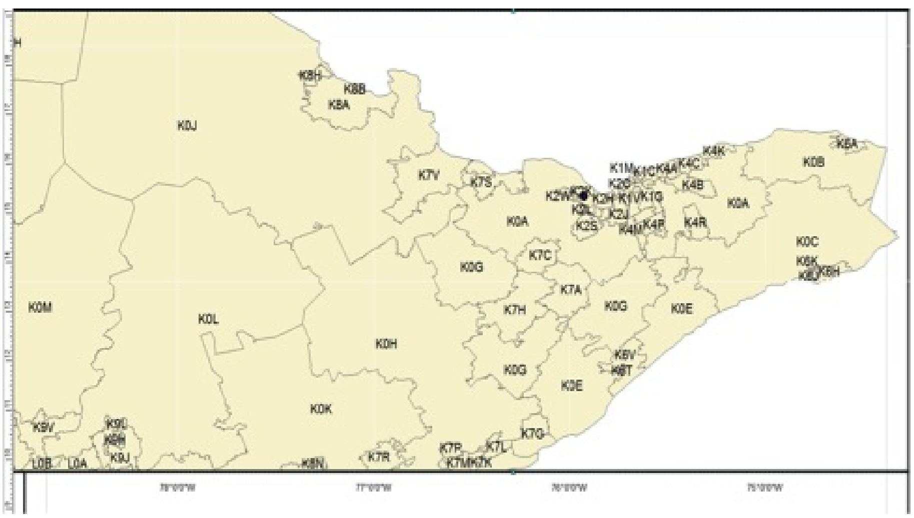


Figure 2.2: Map of the city of Ottawa including forward sortation areas



In the top figure (Figure 1), the buffered circles in the figure show the cities that are included in the analysis. The cities that have the annual sales-weighted gasoline price data retrieved from the Kent Group Services. The bottom figure (Figure 2) shows the FSA-city matching method used in the analysis. The forward sortation areas (FSAs) in Ottawa (yellow polygons) are matched to the city point (black circle) that has the gasoline price data.

Figure 2.3: Real vs nominal annual average retail gasoline prices in Canada from 2000 to 2010

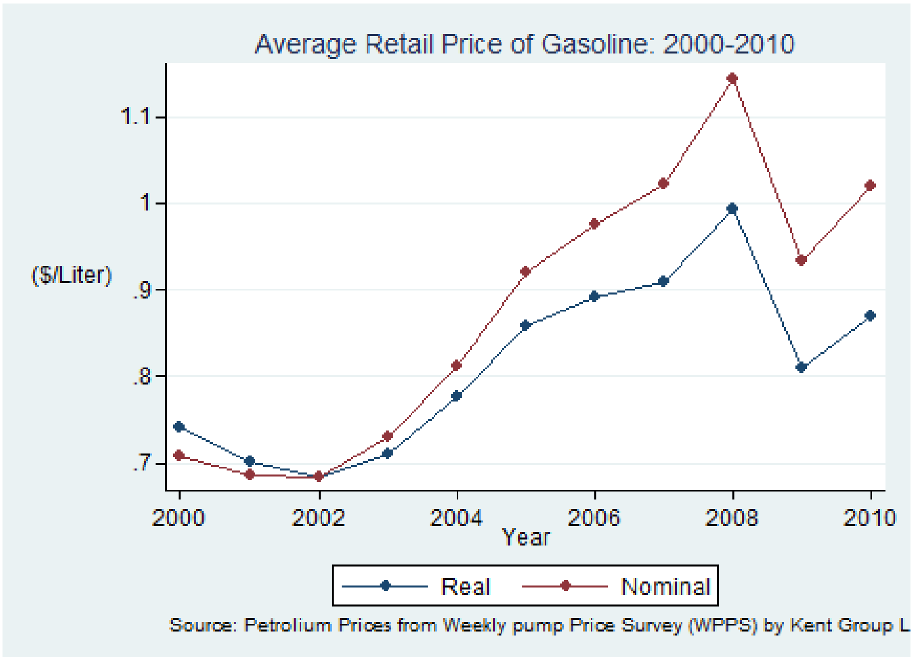


Figure 2.4: Real annual average gasoline prices (left panel) versus aggregate sales-weighted fuel economy of vehicle fleet (right panel) in Canada from 2000 to 2010

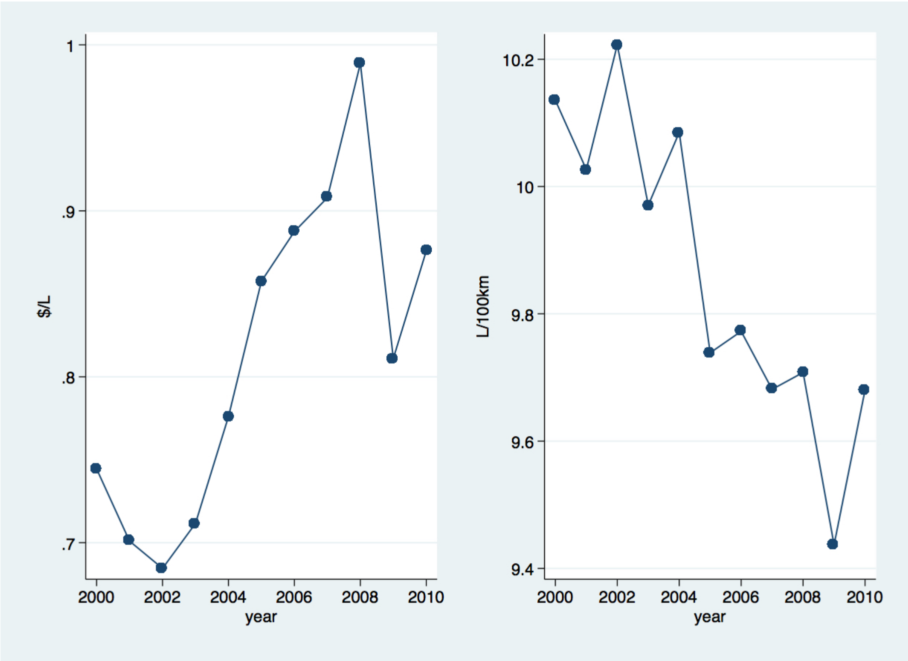
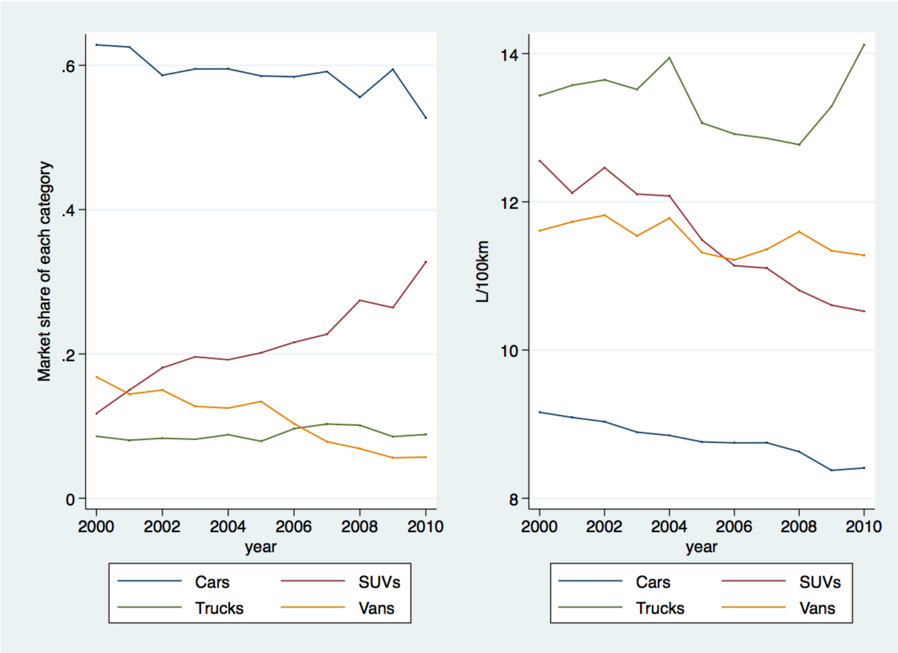


Figure 2.5: Changes in market share (Left Panel) versus changes in aggregate fuel economy (Right Panel) by vehicle category in Canada from 2000 to 2010



This graph shows the trends in aggregate fuel consumption (in L/100 km) versus market shares by vehicle category. Four categories (i.e., super segments): Cars, SUVs, Trucks, and Vans are defined

.

Figure 2.6: Counter-factual average elasticity of fleet fuel economy, 2000 to 2010

The left panel corresponds to the elasticity of fleet fuel economy with respect to gasoline price for each year based on the counter-factual results of the most preferred logit specification whereas the right panel shows these elasticity estimates based on the counter-factual results of the aggregate model on average fuel efficiency.

Table 2.1: Literature Review Summary

Study	**Country & Time Period**	**Fleet Fuel Economy Improvement (Long-term)**
Barla et al. (2009)	1990-2004, Canada	0.19% due to a 1% increase in gasoline price
Small and Van Dender (2007)	1966-2001, US	0.09% to 0.12% due to a 1% increase in gasoline price
Li et al.(2009)	1997-2005, US	0.2% due to a 1% increase in gasoline price
Klier and Linn (2010)	1970-2007, US	0.12% due to a 1% increase in gasoline price
Rivers and Schaufele (2017)	2000-2010, Canada	0.08% to 0.13% due to a 1% increase in gasoline price

Source: Author

2.8 Tables

Table 2.2: Summary statistics for FSA-year and unique vehicle-FSA-year

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
FSA-Year Level				
Number of New Vehicle Sales	849.03	1106.58	1	21411
Car Share	0.55	0.49	0	1
SUV Share	0.25	0.43	0	1
Truck Share	0.19	0.31	0	1
Tax-inclusive Gasoline Price	87.92	15.96	62.1	132.1
Gasoline Cost (dollars/100 km)	8.49	9.23	5.59	12.32
Sales-weighted Fuel Economy	9.70	0.69	7.60	13.94
"Vehicle"-FSA-Year Level				
Gasoline cost (dollars/100 km)	8.27	2.11	21.71	20.06
Highway Fuel Efficiency	8.14	1.90	3.10	16.6
City Fuel Efficiency	11.84	2.79	3.7	27.7
N		1,394,250		

Table 2.3: Effect of Price of Gasoline on New Vehicle Market Share

	(1)	(2)	(3)
Gasoline cost ($/100 km)	-0.02	-0.07***	-0.03***
	[0.03]	[0.01]	[0.009]
Make-model-series-engine size-cylinders-fuel efficiency-year FE	Yes		
Make-model-series-engine size-cylinders-fuel efficiency-FSA FE	Yes		
Make-model-series-engine size-cylinders-year FE		Yes	Yes
Make-model-series-engine size-cylinders-FSA FE		Yes	Yes
FSA-year FE		Yes	
N	1,394,250	535,155	1,394,250
R^2	0.88	0.90	0.95

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table reports the logit results of the effect of gasoline cost (in $/100 km) on new vehicle market shares. The dependent variable is the log of individual model shares. The first specification is based on the first identification (i.e., within-FSA variation in gasoline price over time) and therefore controls for variations in model-specific fuel consumption rating (in L/100 km) in addition to the five major characteristics of the given model: make, model, series, engine size, and number of cylinders. The second specification corresponds to the second identification (i.e., vehicle redesign) and therefore controls for gasoline price variations over time through FSA-year fixed effects. The third specification, as the most preferred model, allows for both fuel efficiency and gasoline price to vary over time. Standard errors are clustered by FSA. Finally, the last model reports results for the average effect of gasoline price on the entire vehicle market. Standard errors are clustered by city in all models.

Table 2.4: Nested Logit Results of Gasoline Cost Effects on Vehicle Market Share

	(1)	(2)	(3)
Gasoline cost ($/100 km)	-0.01***	-0.03***	-0.03***
	[0.004]	[0.007]	[0.007]
Log share-in-category	0.60***		
	[0.01]		
Log share-in-segment		0.29***	
		[0.01]	
Log share-in-make			0.14***
			[0.01]
Make-model-series-engine size-cylinders-year FE	Yes	Yes	Yes
Make-model-series-engine size-cylinders-year FE-FSA FE	Yes	Yes	Yes
N	1,394,250	1,394,250	1,394,250
R^2	0.95	0.84	0.79
Weak identification test			
First stage robust- F statistic	496***	486***	482***
Overidentifying restrictions test			
Wooldridge's robust score	77.6	26.8	27.5
Tests of endogeneity			
Robust score chi2	0.36***	0.36***	0.36***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the nested logit results of the effect of gasoline cost (in $/100 km) on new vehicle market shares. All specifications account for within-nest market shares. Across columns, from left to right, vehicles are classified by category, segment, and make, respectively. I use the sum of the characteristics of other vehicles in the same nest as vehicle j as instruments to control for the endogeneity of the within-nest shares. Three instruments: number of cylinders, engine size, and combined fuel efficiency, are used across all models. Standard errors are clustered by FSA in both models.

Table 2.5: Effect of Gasoline Price on the Average Rated Fuel Economy of the New Vehicle Market in Canada, 2000-2010

	(1)	(2)
Gasoline Price ($/L)	-0.19***	
	[0.02]	
Log Gasoline Price		-0.16***
		[0.02]
Log Median Income	-0.009	-0.008
	[0.01]	[0.01]
Log Median Age	-0.000	-0.000
	[0.000]	[0.001]
Log Percent Female	0.01	0.01
	[0.02]	[0.02]
Log Percent Married Individuals	-0.000	-0.000
	[0.003]	[0.003]
FSA FE	Yes	Yes
Year FE	Yes	Yes
N	7089	7089
R^2	0.91	0.91

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows the results of changes in overall fleet-wide fuel economy with respect to changes in gasoline price as logs and as levels (in $/L). In column (1), the results of the effect of gasoline price variations on log sales-weighted fuel economy in a given market (FSA-year) are presented. In column (2), the elasticity of fleet fuel economy with respect to gasoline price is presented. Standard errors are clustered by FSA.

Table 2.6: Heterogeneity in Response to Gasoline Costs

	(1)	(2)	(3)
Gasoline cost ($/100 km)	-0.047***	-0.03***	-0.03***
	[0.005]	[0.005]	[0.008]
Gasoline cost ($/100 km × FSAs with decreasing/constant gasoline price	0.015***		
	[0.0003]		
Gasoline cost ($/100 km), FSAs within 15k		0.001***	
		[0.000]	
Gasoline cost ($/100 km), FSAs within 20k		0.002***	
		[0.000]	
Gasoline cost ($/100 km), Imported Vehicles			0.002***
			[0.005]
Vehicle-year FE	Yes	Yes	Yes
Vehicle-FSA FE	Yes	Yes	Yes
N	1394250	1394250	1394250
R^2	0.81	0.81	0.81

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results show the heterogenous effects of gasoline costs on vehicle shares. In all specifications, the independent variable is dollars per 100 kilometers of driving a vehicle and the dependent variable is the log of individual market shares. Standard errors are clustered by FSA.

Table 2.7: Summary Statistics for Vehicle Segments from 2000 to 2010

Segment	Number of Observations	Fuel Efficiency	SD	Min	Max
Subcompact Cars	72890	7.11	0.97	3.5	8.99
Compact Cars	250980	7.69	1.08	3.83	11.46
Sports Cars	234963	9.40	0.99	7.38	15.78
Intermediate Cars	55673	9.17	1.45	6.29	14.01
Luxury Cars	87697	9.76	0.92	5.73	13.98
Luxury High Cars	58076	10.97	1.24	7.55	19.31
Luxury Sport Cars	15008	10.94	1.58	7.78	22.70
Compact SUV	164269	10.13	1.39	7.78	14.32
Intermediate SUV	109633	11.97	1.56	7.80	19.34
Large SUV	18039	15.11	1.29	12.49	19.77
Luxury SUV	59014	12.63	1.91	7.77	19.14
Small Pickup Truck	43169	11.51	1.06	8.51	16.07
Large Pickup Truck	110737	14.06	1.34	10.11	20.41
Small Van	106649	11.33	1.11	8.78	15.8
Large Van	7453	14.58	0.96	12.25	19.10

Source: Author

Table 2.8: Effect of Gasoline Costs on Vehicle Segments

	(1)
Gasoline cost ($/100 km)	0.03
	[0.0004]
Gasoline cost ($/100 km), Compact-Cars	0.07**
	[0.02]
Gasoline cost ($/100 km), Sport-Cars	-0.08***
	[0.01]
Gasoline cost ($/100 km), Intermediate-Cars	-0.11***
	[0.02]
Gasoline cost ($/100 km), Luxury-Cars	-0.08
	[0.03]
Gasoline cost ($/100 km), Luxury High-Cars	0.008
	[0.03]
Gasoline cost ($/100 km), Luxury Sport-Cars	-0.1
	[0.05]
Gasoline cost ($/100 km), Compact-SUVs	-0.02*
	[0.01]
Gasoline cost ($/100 km), Intermediate-SUVs	-0.03*
	[0.01]
Gasoline cost ($/100 km), Large-SUVs	-0.008
	[0.02]
Gasoline cost ($/100 km), Luxury-SUVs	-0.01
	[0.01]
Gasoline cost ($/100 km), Small-Pickup Trucks	0.02
	[0.02]
Gasoline cost ($/100 km), Large-Pickup Trucks	-0.02*
	[0.009]
Gasoline cost ($/100 km), Small-Vans	-0.10***
	[0.01]
Gasoline cost ($/100 km), Large-Vans	-0.02
	[0.1]
Vehicle-year FE	Yes
Vehicle-FSA FE	Yes
N	1,394,250
R^2	0.72

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results show the heterogeneous effects of gasoline costs on each vehicle segment separately. The independent variable is the gasoline cost (in $/100 km). The dependent variable is the log market share of a particular vehicle in a given market. Vehicle-FSA and vehicle-year fixed effects are applied at the "vehicle" level. Standard errors are clustered by FSA.

Chapter 3

The Effect of Carbon Taxes on New Vehicle Purchase Decisions

3.1 Introduction

The transportation sector is recognized as one of the largest contributors to greenhouse gas (GHG) emissions in most countries. In Canada, this sector was responsible for 24% of overall greenhouse gas (GHG) emissions in 2011.[1] Due to the significance of the transportation sector in generating carbon emissions, the federal and provincial governments began to implement more stringent regulations on the on-road vehicles.[2] The province of British Columbia (BC) introduced a unique carbon tax policy on the use or purchase of all fossil fuels in 2008, with the main objectives of reducing fuel consumption and generating incentives for consumers and producers to shift to cleaner products and technologies.

Consumers respond to increases in gasoline price (due to taxes or other market-induced

[1]Passenger and freight transport, which rely primarily on the combustion of fossil fuels, together accounted for 89% of overall transportation emissions in 2011. The emissions from these two sectors comprised 82% of overall emissions in 2008 in Canada, with gasoline and diesel generating 19% of total transportation emissions (Canada (2012)).

[2]Some examples of such regulations are: carbon pricing mechanisms, transportation infrastructure investments, and the further evolution of low-carbon and smart transportation technologies (Transportation in Canada (2015)).

factors) by reducing gasoline consumption from vehicles along two margins: 1) reducing the number of liters consumed by driving less along the intensive margin, 2) shifting their new vehicle purchases to more fuel-efficient vehicles along the extensive margin.[3] The intensive margin effect of an increase in gasoline price on gasoline consumption has been well studied in the recent literature.[4] But only a few studies in Canada investigate the extensive margin effects of gasoline price and taxes on vehicle fuel efficiency (e.g., Rivers and Schaufele (2017a), Antweiler and Gulati (2016)). This study adds to this growing literature by evaluating the extensive margin effects of carbon tax and gasoline price (net of carbon tax) through changes in the fuel efficiency of new vehicle sales in Canada. By exploiting a rich data-set including all new vehicle model registrations across the Canadian provinces, as well as all forward sortation areas (FSAs)[5], for 11 years from 2000 to 2010, I find empirical evidence on the effect of British Columbia's carbon tax policy on consumers' new vehicle purchase decisions.

While adding to the literature on vehicle fuel economy, my study takes the analysis further and investigates whether consumers respond to the carbon tax component of gasoline price differently from other components. Based on the standard assumption in economics, consumers are expected to respond similarly to commodity tax changes than to price changes induced by market fluctuations. Under this assumption, the previous literature (e.g., Klier and Linn (2010a), Small and Van Dender (2007), Bento et al. (2009), and Li et al. (2009)) estimates the effect of gasoline price on gasoline consumption and therefore suggest using the consumer response to gasoline prices as a proxy for the response to equivalent changes in gasoline taxes (Li et al. (2014)). However, in line with behavioral economics theories, an emerging literature has focused on the saliency of taxes as a factor that influences consumer choice (Tiezzi and Verde (2016)). Salience is the phenomenon when consumers respond to the

[3]In addition to fuel efficiency and utilization adjustments, which usually take place in the short run, consumers also make other decisions in the long term. For example, they may replace their vehicles with alternative modes of transportation, reduce the number of vehicles they own, change their residential locations to reduce travel distance to work, and etc. These long-term adjustments in fuel consumption are not analyzed in this study.

[4]Some examples are: Li et al. (2014), Barla et al. (2009), and Gillingham et al. (2015).

[5]A forward sortation area refers to the first three digits of the Canadian postal codes.

tax component of gasoline price differently than the components driven by market-induced fluctuations (Rivers and Schaufele (2015)).

With reference to vehicle fuel economy, recent studies including Li et al. (2014), Rivers and Schaufele (2017a), and Antweiler and Gulati (2016), find that consumers respond more strongly to gasoline taxes than to equivalent changes in tax-exclusive gasoline price.[6] Each of these studies provide different explanations for such behavioral responses. Li et al. (2014) attribute the saliency of gasoline taxes to the persistence of taxes compared with market-based price movements. They indicate that consumers perceive taxes as longer-lasting than other price movements, therefore they are more likely to change their long-run expectations with respect to gasoline consumption.

British Columbia's carbon tax policy provides a fruitful ground to contribute to this growing literature. I provide the following reasons to explain why we may observe a different response to a carbon tax than to other components of gasoline price. As addressed in the literature (for example, Chetty et al. (2009) and Finkelstein (2009)), consumers are more sensitive to the price changes that are more visible. Even though, in Canada, gasoline taxes (including the carbon tax) are included in gasoline price, the public announcement and large media attention about the BC's carbon tax increased the public awareness and made it more visible to consumers. Also, a carbon tax, as an environmental tax, may influence consumers differently than other consumption taxes, such as an excise tax (as studied by Rivers and Schaufele (2017a) and Li et al. (2014)). Rivers and Schaufele (2015) state that carbon taxes, as opposed to excise taxes, are explicitly enacted to eliminate negative externalities associated with fossil fuel consumption (in addition to reducing consumption in the short run).[7] In addition, consumers in Canada, especially in British Columbia, may respond differently to

[6]With respect to gasoline consumption, Davis and Kilian (2011), Li et al. (2014), and Rivers and Schaufele (2015) find larger reductions in gasoline consumption in response to changes in gasoline taxes than to changes in market price of gasoline.

[7]Rivers and Schaufele (2015) state that "Even though excise and sales taxes reduce gasoline demand in the short-run, they are not overtly designed to correct environmental externalities. Revenues from gasoline taxes, for example, are frequently earmarked for road infrastructure projects, which lower the long-run costs of driving".

gasoline taxes than consumers in the US (as studied by Li et al. (2014)). British Columbians tend to be more environmental friendly than consumers in other provinces, and therefore may have already made fuel-efficient vehicle choices prior to the implementation of the carbon tax. Due to all of the above reasons, it is important to analyze the implications of an actual carbon tax policy on consumer vehicle purchase behavior.

I find that both carbon tax and gasoline price play as disincentives to shift preferences to more fuel-efficient vehicle choices and consequently improve the overall fleet fuel economy. Results of my preferred FSA-level estimation indicate that a 1% increase in the carbon tax causes a 0.22% to 0.26% improvement in new vehicle fuel consumption, whereas the same change in the carbon tax-exclusive gasoline price is associated with a 0.1% to 0.15% improvement in fleet fuel economy. The counter-factual results of my preferred estimation (on model-level market shares) suggest that a $0.01 increase in the carbon tax is associated with an eight-times-larger reductions in overall fuel economy (i.e., 0.02 versus 0.0026 (L/100 km) reductions). Moreover, I find that the carbon tax has relatively similar impacts on overall fuel economy as other provincial taxes in British Columbia; my results imply that the elasticity of fleet fuel economy with respect to the excise and transit taxes is -0.23.

Another contribution of this study is the demonstration of carbon tax and gasoline price effects on the composition of the fleet. This additional analysis allows me to address the observed changes in fleet fuel economy (associated with the carbon tax) conditional on fleet composition. I find that intermediate cars and minivans experience the largest improvements in fuel efficiency in response to the carbon tax. Gasoline price, net of the carbon tax, also causes improvements in the fuel efficiency of these two segments, but with much smaller effects than the carbon tax.

Finally, I find empirical evidence that the carbon tax policy also causes substitutions across vehicle segments. Among cars, subcompact and compact cars are the most sensitive segments to carbon tax; sales of subcompact cars increase, whereas sales of compact cars decrease due to the carbon tax. All sport utility vehicles (SUVs), except for luxury sport utility vehicles (SUVs), experience a decline in market share due to an increase in both the carbon tax and the carbon tax-exclusive gasoline price. Also, there appears to be substitutions from large pickups to other relatively less fuel-inefficient segments, such as small pickups and large vans, as a result of an increase in the carbon tax. Overall, all segments respond more strongly to changes in the carbon tax than to equivalent changes in the carbon tax-exclusive gasoline price, providing more robustness to the main results.

The remainder of the paper contains five sections. Section 3.2 summarizes the existing literature. Next, I explain the decomposition of gasoline price from the carbon tax and provide an overview of BC's carbon tax policy in Section 3.3. In Section 3.4, data and the empirical methodology are presented. Section 3.5 presents the results and finally Section 3.6 concludes the paper.

3.2 Literature Review

A large body of the literature investigates changes in the fuel economy of the vehicle fleet in response to changes in gasoline prices. Li et al. (2009) and Klier and Linn (2010a) estimate the elasticity of fleet fuel economy with respect to gasoline price using vehicle data in the US automobile market, and Barla et al. (2009) conduct a similar analysis for the Canadian vehicle market.

Li et al. (2009) use data on the stock of all vehicle models in 20 US Metropolitan Statistical Areas (MSAs) from 1997 to 2005 to directly estimate changes in fleet fuel economy in response to changes in gasoline price in the short and long run. They find that an increase in the price of gasoline leads to a higher demand for more fuel-efficient vehicles such that the fleet fuel efficiency would increase by 0.22% in the short run (and 2.04% in the long run) due to a 10% increase in gasoline prices (from price levels in 2005).

Klier and Linn (2010a)estimate the effect of gasoline price on demand for new vehicles with respect to their fuel consumption using monthly new vehicle sales from 1978 to 2007.

They control for consumer and vehicle unobserved heterogeneity by exploiting within model-year variations in gasoline price and vehicle sales. They find that a 1% change in gasoline price leads to a 0.12% improvement in vehicle fuel economy.

Barla et al. (2009) conduct a panel data analysis using provincial-level data on light-duty vehicles across the Canadian provinces from 1990 to 2004 to estimate the elasticity of the vehicle fleet with respect to gasoline price. The results of their analysis suggest that a 10% increase in gasoline price would improve average fuel economy by 1%.

All the above studies find a relatively small consumer response to gasoline price when selecting the fuel efficiency of vehicles. This means that only large increases in gasoline price will significantly reduce gasoline consumption. Moreover, these studies assume a similar consumer response to changes in different components of gasoline price (i.e., taxes versus market-based price movements). Therefore, the policy proposals that use these estimates for the response to equivalent changes in gasoline tax may underestimate the effectiveness of higher gasoline taxes at reducing gasoline consumption and improving fleet fuel economy. Several recent studies, including Li et al. (2014), Rivers and Schaufele (2017a), and Antweiler and Gulati (2016), examine the impacts of gasoline taxes as distinct from equivalent market-induced gasoline price increases on vehicle fuel efficiency. They all find that consumers respond more strongly to gasoline taxes versus equivalent changes in tax-exclusive gasoline price. I provide a summary of the elasticity estimates obtained in these studies in Table 3.1.

Li et al. (2014) estimate changes in gasoline consumption in response to gasoline taxes versus tax-exclusive gasoline price using data from two different sources: US state-level data from 1966 to 2008 to measure changes in gasoline consumption; and household-level data to estimate changes in vehicle miles traveled (VMT) and vehicle fuel economy. They find that the elasticity of new vehicle fuel economy with respect to gasoline price ranges between 0.09 to 0.13, whereas this elasticity with respect to the tax ratio varies from 0.20% to 0.40% (depending on the model specifications).

Rivers and Schaufele (2017a) use Canadian new vehicle registration data from 2000 to

2010 to measure the elasticity of new vehicle fuel economy with respect to gasoline price, while also adding to the existing literature on consumer differential response to taxes versus tax-exclusive gasoline price. They compare the effect of provincial excise and municipal transit taxes with gasoline base prices on new vehicle fuel economy and find that fuel consumption improves by 3.6% due to a \$0.10/L increase in provincial gasoline excise taxes, whereas the same change in other components of gasoline price only causes a 0.03% improvement in fuel consumption.

Antweiler and Gulati (2016) examine the effects of British Columbia's carbon tax along with other fuel taxes on new vehicle fuel economy and compare their impacts with tax-exclusive gasoline price using Canadian vehicle data from 2000 to 2014. Their empirical results suggest that a 1% increase in gasoline taxes (including the carbon tax) would improve the fleet fuel economy by 0.79%, while the same change in the tax-exclusive gasoline price leads to a 0.28% improvement.

Similar to the studies focusing on the elasticity of fleet fuel economy with respect to gasoline price as stated above (i.e.,Li et al. (2009) and Klier and Linn (2010a), and Barla et al. (2016)), one of the contributions of this study is to find the elasticity estimate for gasoline price using the Canadian vehicle data. However, unlike these studies, my study adds to the growing literature on the salience of gasoline taxes to improve vehicle fuel economy. By decomposing gasoline price into two components of carbon tax and gasoline price excluding the carbon tax, I examine whether consumers respond differently to the carbon tax than to other components of gasoline price.

The gasoline price elasticity estimates in my study are similar to those reported by Klier and Linn (2010a) and Li et al. (2009), indicating relatively similar consumer behavior patterns in Canada and the US over this period. In contrast to Barla et al. (2009), which is based on provincial-level data, I obtain a more precisely estimated elasticity for gasoline price using dis-aggregated FSA-level data. I find that a 10% increase in the carbon tax-exclusive gasoline price improves fleet fuel economy by 0.9% to 1.5% (depending on level of data aggregation and fixed effects).

I adopt a similar empirical analysis to all the above listed studies that estimate the differential effects of taxes verses tax-exclusive gasoline price. My research is most closely related to Antweiler and Gulati (2016), but it makes several contributions beyond the existing literature. First, similar to Antweiler and Gulati (2016), I estimate the elasticity of fuel taxes in BC, but use the carbon tax as the main regressor (rather than all fuel taxes as in their study). Second, I investigate the impacts of carbon tax (alone) and carbon tax-exclusive gasoline price on the fuel efficiency of all new vehicles using model-level sales data by detailed model, FSA, and year. Data at a more dis-aggregated FSA level allow me to obtain more precisely estimated effects of the carbon tax than the effects estimated in the provincial-level regressions in Antweiler and Gulati (2016). Third, I perform an additional analysis to address the fuel economy improvements associated with the carbon tax through changes in fleet composition. This analysis explains the mechanisms through which the fleet fuel efficiency improvements associated with the carbon tax occur. Fourth, I investigate the asymmetric responses to the tax-exclusive gasoline price by considering whether the relationship between gasoline prices and fleet fuel economy has changed over time. This also allows me to compare the response to changes in the carbon tax with the asymmetric responses to equivalent changes in gasoline price. Fifth, I estimate the differential responses to various provincial taxes in BC; I compare the elasticity of fleet fuel economy with respect to the carbon tax with the elasticity with respect to the provincial excise and transit taxes. Finally, I demonstrate the long-term effects of the carbon tax and tax-exclusive gasoline price on new vehicle fuel economy and compare their impacts in the long-term as well.

Consistent with the results of the indicated studies, I find differential responses to taxes versus equivalent increases in tax-exclusive gasoline price. I find that the elasticity estimate for BC carbon tax (-0.26%) is smaller than the fuel tax estimate in the preferred specification in Antweiler and Gulati (2016) (i.e., -0.79%). It is, however, closer to the fuel tax estimates suggested by Li et al. (2014) (between 0.20% to 0.40%).

3.3 Decomposition of Fleet Fuel Efficiency

Gasoline consumption from vehicles can be decomposed into two parts. The first part (referred to as the extensive margin) is the fuel efficiency of the current stock of vehicles (measured in liters per 100 kilometers traveled). I classify vehicle models in the fleet into i segments (such as subcompact cars, compact cars, sports cars, and etc.) and define F_i as the vehicle fuel efficiency by segment. The second part (referred to as the intensive margin) is the mileage driven by vehicles conditional on their fuel consumption rating. I denote M_i as the mileage driven by vehicles in each segment. Consumers respond to changes in gasoline price (denoted by q) when deciding their vehicle fuel efficiency and the distance traveled conditional on the vehicle fuel efficiency. This means that the first part (i.e., vehicle fuel efficiency, F_i) is a function of gasoline price and the second part (i.e., vehicle mileage, M_i) is a function of both gasoline price and fuel efficiency. As such, G denotes gasoline consumption from all vehicles in the fleet, which consists of new and old vehicles, conditional on fleet composition and is decomposed as follows:

$$G = F_i^{old}(p)M_i^{old}(F_i^{old}(p), p) + F_i^{new}(p)M_i^{new}(F_i^{new}(p), p) \tag{3.1}$$

In this study, changes in gasoline consumption from new vehicles is evaluated, as I only have data on new vehicle registrations across Canadian provinces. Moreover, the evaluation of gasoline consumption along the intensive margin (i.e., $M_i^{new}(F_i^{new}(p), p)$) is outside the scope of this study, as I do not have data on vehicle kilometers traveled (VKT).[8] Therefore, this study focuses on changes in new vehicle fuel efficiency conditional on fleet composition (i.e., $F_i^{new}(p)$) in response to changes in gasoline price. More precisely, I estimate changes in sales-weighted fuel consumption of different vehicle segments (i.e., i segments) in response to gasoline price using:

[8]Several studies in the literature estimate the effect of gasoline price and tax on vehicle use along the intensive margin. For example, Barla et al. (2009), and Gillingham et al. (2015) find the elasticity of vehicle distance traveled with respect to gasoline price for Canada and the US, respectively, and Li et al. (2009) estimate the elasticity of gasoline tax on vehicle miles traveled (VMT) in the US.

$$F_i^{new}(p) = \Sigma_{i=1}^{n} fe_i(p)s_i(p) \tag{3.2}$$

fe_i is the total fuel efficiency of vehicle segment i, and s_i is the market share of segment i from total vehicle sales in a given market (province-year or FSA-year); and both are a function of gasoline price. Taking the total derivative of Equation 3.2 with respect to gasoline price yields:

$$\frac{dF_i}{dp} = \Sigma_{i=1}^{n} \frac{dfe_i}{dp} s_i + \Sigma_{i=1}^{n} fe_i \frac{ds_i}{dp} \tag{3.3}$$

Equation 3.3 provides the decomposition of the observed changes in fleet fuel efficiency: the first term ($\frac{dfe_i}{dt} s_i$) captures changes in overall fuel efficiency (in L/100 km) of a given segment, and the second term ($fe_i \frac{ds_i}{dt}$) shows changes in market share of each vehicle segment in the fleet.

3.3.1 Background on BC's Carbon Tax Policy

British Columbia was the first province in North America to implement a carbon tax policy. In February 2008, Premier Gordon Campbell, the leader of BC's liberal government, introduced a new climate change agenda including the carbon tax and a suite of stringent policies focusing on pollution emissions. Despite the growing public interest in environmentally related policies in BC at the time, the carbon tax policy was a complete shock for the majority of the residents and the government's business community alliances.[9] The carbon tax policy was supported by the majority of voters and finally took effect in July 2008. The main objectives of the policy were to reduce greenhouse gas emissions by deductions in the consumption of all types of fossil fuels and shift to more environmentally friendly products and cleaner technologies.

[9]More specifically, the carbon tax policy received its substantial unprecedented support from representatives of 16 environmental groups, who would previously expect larger cuts in the environment budget in favor of the new oil and gas exploration and electricity generating projects (Harrison (2012)).

According to BC's Ministry of Finance (2014), the carbon tax policy applies to the purchase or use of all types of fuels, such as gasoline, diesel, natural gas, heating fuel, propane and coal, and to peat and tires to produce energy or heat.[10] The rate varies over fuel types depending on their anticipated carbon emissions and is calculated based on per tonne of carbon dioxide equivalent emissions of each fuel. The carbon tax was initially set at $10 per-tonne of carbon dioxide in 2008 and gradually increased by $5 per-tonne every year, until it reached to $30 per tonne in January 2012. BC maintained the 2012 rates until April 2018, in which they were increased again to $35 per-tonne. The $10, $30, and $35 per-tonne tax rates were equivalent to increasing the price of gasoline by 2.34 ¢/L, 6.67 ¢/L, and 7.78 ¢/L, respectively.

A distinct characteristic of the carbon tax policy when it was introduced was its revenue neutrality, which contributed to higher levels of public support for the policy. Revenue neutrality means that all the government revenue generated by the carbon tax is returned to all individuals and businesses through deductions in corporate and personal taxes and other lump-sum payments. The carbon tax continued to be revenue neutral until 2012/13 but stopped being so in 2013/14.[11] The personal and corporate tax cuts were applied broadly across individuals, families, and industries, creating incentives to reduce greenhouse gas emissions while minimizing the negative economic impacts of the carbon tax. In addition to the tax shifts, low-income and rural residents received tax credits in the form of lump-sum transfers to minimize the carbon tax burden.[12] It is believed that the appealing properties of the carbon tax policy drew consumers' attention to the environmental aspect of the policy and encouraged them to shift to more environmentally friendly products.

[10] It is a separate tax on the purchase or use of fuels in addition to the motor fuel tax, which alone includes Dedicated Motor Fuel and Provincial Motor Fuel taxes. These two sets of taxes constitute the total provincial tax on fuel in BC.

[11] In 2008/09, BC enacted four offsetting tax measures: a reduction in the bottom two personal income tax (PIT) rates, a reduction in the general corporate income tax (CIT) rate, a reduction in the small business CIT rate, and the introduction of the low income climate action refundable tax credit. However, in 2013/14, the government began using pre-existing tax reductions in its revenue neutrality calculation instead of relying on new tax measures to offset the carbon tax revenue (CLIFTON et al. (2017)).

[12] The government also distributed a one-time payment of 100$ to all BC residents, as the Climate Action Dividend, in 2008).

In addition to the taxes commonly imposed on gasoline prices across all Canadian provinces (i.e., federal excise tax and sales taxes including goods and services tax (GST) and harmonized sales tax (HST)), the three provinces of British Columbia, Quebec, and Alberta impose a carbon tax on gasoline. Quebec introduced a carbon tax policy on gasoline price in October 2007, but at a much lower rate of $3 per tonne of carbon dioxide (equal to 0.7 cents per liter) compared to the BC carbon tax. In 2007, Alberta imposed a carbon pricing policy only on industrial emitters (companies with annual emissions greater than 100,000 tonnes) to reduce emissions intensity by 12%, or pay a tax of $15 per tonne if they pass their limit. In January 2017, in addition to the carbon pricing policy on large industrial emitters, Alberta imposed a carbon levy on the purchase of all fossil fuels, which started at a rate of $20 per tonne of carbon dioxide-equivalent emissions (equal to 4.49 ¢/L on gasoline), and reached to $30 per tonne (equal to 6.73 ¢/L on gasoline) in January 2018.[13] Unlike the case of BC, the Quebec carbon tax is not revenue neutral and is essentially designed to generate revenue to implement environmental projects.

BC also changed the rates of other provincial gasoline taxes, in addition to the carbon tax, during the decade of 2000 to 2010. Figure 3.1 plots the breakdown of all provincial taxes in BC over this period. As shown in the figure, the provincial excise taxes increased from $0.11/L to $0.14/L outside of Vancouver in 2003. Excise taxes in Vancouver changed every year, from a minimum of $0.03/L in 2000 to a maximum of $0.10/L in 2003. The rates stayed unchanged at $0.10/L from 2003 to 2007 and then decreased to $0.08/L in 2008. In addition to provincial excise taxes, there are also local transit taxes in Vancouver and Victoria. In Victoria, transit taxes remained at $0.03/L from 2000 to 2006 and increased to $0.04/L in 2007. Meanwhile Vancouver experienced various rates throughout the decade; transit taxes started from the lowest rates of $0.08/L in 2000 to $0.12/L in 2003 and stayed at this rate up to 2010, in which they were again increased to $0.15/L. In Section 3.5.6, I will discuss the differential effects of various provincial taxes on BC's fleet fuel economy over the period

[13] Alberta Fiscal Plan (2016).

covered by my data.

3.4 Data and Empirical Approach

This section consists of two parts: an overview of the dataset and empirical specifications. The econometric models are estimated using two levels of data aggregation: provincial-level and FSA-level. Therefore, throughout the study, markets are defined either as province-years or FSA-years.

3.4.1 Data

The dataset used in this study combines information from several sources. Desrosiers Automotive Consultants (provider of RL Polk in Canada) provides new vehicle registration data for all Canadian provinces from 2000 to 2010. As the focus of this study is to investigate changes in fuel consumption from new vehicle sales, I treat each new vehicle registration whose model-year is the same as the year it is sold in as a sale.[14]

Vehicle data are observed by characteristics, such as make, model, model-year, series, engine size, the number of engine cylinders, and fuel type. RL Polk dataset also classifies vehicles into 15 segments[15] according to the Automobile Industry standards in Canada. Moreover, vehicle models are assigned with both a city and highway fuel consumption rating obtained from Natural Resources Canada (NRCan) and measured in liters per 100 kilometers of driving a given vehicle (Rivers and Schaufele (2017b)).The fuel consumption rating of a very small number of low-volume vehicles are retrieved from the US Environmental

[14]This means that only vehicle registrations with a model year t that are also sold in year t are treated as new sales. This is because some vehicle models are sold one year prior to their actual model year; a 2005 Toyota may have been sold in 2004 and therefore is recorded in both 2004 and 2005 registration data. These records cause double counting in the true number of sales in each year. As such, I treat these registrations according to their first appearance in the data, i.e., the first time a model-year appears in the data, I record it as a new sale.

[15]According to this classification, passenger cars are grouped into subcompact, compact, sports, intermediate, luxury, luxury high end, luxury sports, and light trucks are classified into compact sport utility, intermediate sport utility, large sport utility, luxury sport utility, small pickup, large pickup, small van, and large van.

Protection Agency (EPA).[16] Table 3.2 presents a summary of the 15 segments including the segment average fuel efficiency and the percentage of observations associated with each segment. According to Table 3.2, the most fuel-efficient vehicle segment is subcompact cars (with a fuel efficiency rating of 5.93 (L/100 km)), and the least fuel-efficient segment is large vans (with a 12.21 fuel efficiency (L/100 km)).

Vehicle registration data are available at two levels of aggregation: provincial and forward sortation area (FSA). The provincial-level data consist of over 600 distinct types of vehicles in each province in each year, constructing a total of above 76,000 observations. The FSA-level data include the number of registrations of each distinct vehicle model according to the residential postal code (the first three digits of the postal code) of the vehicle registrant. The dis-aggregated FSA-level data provides a more detailed analysis on new vehicle purchase decisions across Canada. According to this level of aggregation, markets are defined as FSA-years based on 1621 FSAs and an average of 849 new vehicle registrations in a given FSA and year.

The dataset also includes retail gasoline prices, median income, unemployment rate, and other demographic variables for each province (and FSA) and year supplied by Statistics Canada. The provincial and FSA-level income and demographic data are from Canada Revenue Agency's T1 tax filer data, which are also provided by Statistics Canada.

Data on gasoline price for each FSA in Canada are compiled according to the following approach. I obtain average retail gasoline price data for 57 major cities across Canada from the online surveys by MJ Ervin/Kent Marketing Services. Kent Marketing group conducts weekly surveys to collect the retail prices of gasoline, diesel, propane, and furnace fuel from 700 gasoline stations throughout each city. I take the sales-weighted average annual gasoline price series for each city and map the city-level gasoline price data to FSAs using the concordance between cities and FSAs. By creating a distance file including the geographical

[16] It is important to note that all fuel economy analyses in this paper are based on combined fuel consumption of vehicles (i.e., 0.55 (highway fuel efficiency) + 0.45 (city fuel efficiency). And, as is evident, the fuel economy ratings may not perfectly reflect the actual performance of vehicles on the road. Therefore, the gasoline price effects on vehicle on-road performance may not perfectly be captured in my empirical analysis.

center points of all the FSAs in Canada, I calculate the distance between the center point of each FSA and each city. I assign gasoline prices of each city to the FSAs that are located the closest, and within the 20 kilometers distance, to the given city. I test the sensitivity of this algorithm using three distance measures: 10, 15, and 20 kilometers radius, and find that results are virtually unchanged. As such, only the FSAs that are within the 20 km radius of the city center points are retained in the data and therefore create an unbalanced panel dataset consisting of 758 FSAs.

Figure 3.2 shows changes in average real tax-inclusive gasoline prices (in cents per liter) in Canada during the period of study. The left panel presents changes in real gasoline price in British Columbia versus the rest of Canada, and right panel shows the trends across the four major provinces of British Columbia, Alberta, Ontario, and Quebec. The overall trend shows that real gasoline prices are on average increasing across all provinces over this period. They, however, experience a sharp decline in 2008 due to the financial crisis, but begin to rise again in 2009. It is evident that gasoline prices follow a similar trend across all major provinces, with British Columbia having the highest real annual average gasoline prices (inclusive of all taxes including the carbon tax) among the selected provinces (as of early 2003).

Table 3.3 presents summary statistics for province-year, FSA-year, and vehicle-FSA-year data, respectively.

3.4.2 Empirical Approach

In this section, I estimate the effect of the carbon tax on the fuel efficiency of new vehicle purchases. If consumers have responded to the disincentive associated with the carbon tax policy along the fuel efficiency margin channel, they may have shifted their preferences to more fuel efficiency vehicles when purchasing a new vehicle. Identification is based on the presence and rates of the carbon tax policy in BC after 2008 versus before, and versus the rest of Canada.

I take two approaches to perform the estimations. First, I estimate an aggregated regression that quantifies the effect of the carbon tax and gasoline price (net of carbon tax) on average fuel efficiency. More precisely, I estimate changes in the sales-weighted fuel efficiency of the average vehicles sold in a given market (province-years or FSA-years) in response to changes in the carbon tax and carbon tax-exclusive gasoline prices. The estimates obtained from the aggregate regressions are simple to interpret; they imply the elasticity of new vehicle fuel economy with respect to the carbon tax and gasoline price (net of the carbon tax). However, since these estimates are derived from aggregated data, they do not account for consumer preferences for fuel efficiency at a dis-aggregated vehicle level. As such, as an alternative specification, I take advantage of my detailed model-level data across FSAs and years to estimate the effects of changes in carbon tax and gasoline price using the methodology in Klier and Linn (2010a).[17] By exploiting variations in market share of individual models, this estimation allows me to analyze consumer new vehicle purchase behavior and find how the market shares of different vehicle models respond to changes in the carbon tax and gasoline price. Regardless of the differences between the two estimating approaches, they both have similar implications for the effect of carbon tax and gasoline price on vehicle fuel efficiency, thus providing more robustness to the results.

Figure 3.3 plots changes in sales-weighted fuel consumption rating (in L/100 km) for all new vehicles sold across Canadian provinces from 2000 to 2010. The left panel of Figure 3.3 shows the trends in sales-weighted fuel efficiency of all new vehicles across four selected provinces: Alberta, British Columbia, Ontario, and Quebec, and the right panel shows the same trends in British Columbia versus “Rest of Canada”. As is visually observable in the right panel, there is a common trend in BC and the rest of Canada showing an overall improvement in new vehicle fuel consumption (i.e., fewer liters per 100 km) in Canada over this decade. It is also evident that vehicle fuel consumption in BC is below that of for “Rest of Canada” almost entirely during this period. The left panel shows that among the four

[17]For the second approach, I only use the more dis-aggregated FSA-level data.

selected provinces, Alberta has the highest average fuel consumption, followed by Ontario and British Columbia. All four major provinces, however, follow a similar downward trend over this period.

I also plot changes in aggregate vehicle sales in BC versus the "Rest of Canada" over the same period in Figure 3.4 to see whether we observe a common trend in total vehicle sales. As shown in the figure, the number of vehicles per person is increasing in BC as well as in the rest of Canada, but with fewer vehicles in BC than the rest of Canada. However, a sudden decline in BC in 2008 is observable, and the trend becomes flatter after that year. In Section 3.5.7, I will demonstrate the extensive margin effects of the carbon tax policy operating through changes in aggregate vehicle sales and test the common trend assumption observable in Figure 3.4.

Following the first estimating approach, I use a semi-log model to estimate the average sales-weighted fuel efficiency of the new vehicles sold in each market (province-year or FSA-year)[18] (i.e., FE_{pt}) according to:

$$\log \mathrm{F}_{pt} = \alpha + \beta GP_{pt} + \gamma CT_{pt} + \sigma \log X_{pt} + \Omega_p + \vartheta_t + \epsilon_{pt} \tag{3.4}$$

F_{pt} is the sales-weighted fuel consumption (L/100 km) of all new vehicles in a given market. It is calculated using: $\frac{\sum_{j=1}^{J}(sales_{jpt} * fe_j)}{Sales_{pt}}$, where the sales of model j is multiplied by its fuel consumption rating (fe_j in L/100 km) and then aggregated across all vehicle models in the fleet (in the numerator), and finally divided by aggregate sales (the denominator). GP_{pt} is gasoline price inclusive of all taxes except the carbon tax, and CT_{pt} is the carbon tax (both in dollars per liter). Coefficients β and γ, therefore, capture the percent change in new fleet fuel economy due to a \$1/L change in carbon tax and gasoline price (net of carbon tax). X_{pt} includes additional provincial (or FSA) controls including log median income, log unemployment rate, log median age, log percent females, log percent married individuals,

[18]For estimations at the FSA level, index p refers to a given FSA.

log percent college graduates, and log percent individuals living in apartments.[19] Ω_p and ϑ_t are province (or FSA) and year fixed effects, respectively, and ϵ_{pt} is the idiosyncratic error term. The application of province (or FSA) fixed effects allows for the identification to be based on within-province (or within-FSA) variations in carbon tax and gasoline price. In FSA-level estimations, I cluster standard errors by FSA to account for serial correlations that likely exist between the residuals within a given FSA over time.[20] However, in provincial-level estimations, clustering by province leads to downwards biased standard errors as the number of clusters by province is small. As a result, I bootstrap standard errors using wild cluster bootstrapped t-statistics (WCBSTs).[21]

I also estimate the log-log version of Equation 3.4 to allow for the interpretation of β and γ coefficients as the elasticity of fuel economy with respect to carbon tax and gasoline price. For this alternative specification, I follow the Li et al. (2014)'s approach:

$$\log \mathrm{FE}_{pt} = \alpha + \beta \log GP_{pt} + \gamma \log(1 + \frac{CT_{pt}}{GP_{pt}}) + \sigma \log X_{pt} + \Omega_p + \vartheta_t + \epsilon_{pt} \tag{3.5}$$

In both specifications, β and γ are expected to be negative, indicating that the new fleet fuel consumption declines in response to an increase in carbon tax and gasoline price, respectively. As only a very small number of observations use carbon tax in the data (especially at the province-level), a log transformation of carbon tax would result in the loss of lots of observations. As such, I follow an approach by Li et al. (2014) to include the log of the carbon tax variable as follows: $\log(GP_{pt} + CT_{pt}) = \log(1 + \frac{CT_{pt}}{GP_{pt}})$. The first component is gasoline price net of carbon tax, and the second component is the carbon tax ratio. The

[19]For FSA-level regressions, I only include log median income, log median age, log percent females, and log percent married individuals as I do not have data for the rest of the variables at the FSA level. The exclusion of these variables, however, do not virtually affect the results when the same models are estimated on provincial-level data.

[20]Note that clustering by city does not affect the results in any of the specifications in my study.

[21]I also attempt to estimate the regressions by bootstrapping standard errors using pairs cluster bootstrapped t-statistics (PCBSTs) and cluster-adjusted t-statistics (CATs), but find that WCBSTs performs better in my panel data analysis. PCBSTs are more effective in controlling the size of hypothesis tests with serially correlated panel data for a moderate number of clusters (not very few clusters, like in my data), and CATs cannot be estimated when a key independent variable doesn't vary within the cluster (Esarey and Menger (2017)).

following assumption would allow me to directly use γ as an elasticity of fuel economy with respect to carbon tax in Equation 3.5. I assume that all the tax burden is entirely passed on to consumers, and therefore changes in carbon tax ratio does not affect the tax-exclusive price of gasoline (i.e., $\frac{dGP}{dCT} = 0$). Li et al. (2014) and Marion and Muehlegger (2011) find strong empirical evidence for the validity of this assumption and demonstrate that the entire tax burden is on consumers. Using this assumption and taking the derivative of Equation 3.5 with respect to the carbon tax yields: $(\lambda \frac{1}{GP+CT})$. On the other hand, the derivative of Equation 3.5 with respect to gasoline price is: $\frac{1}{GP}(\gamma - \lambda \frac{CT}{GP+CT})$. If I find equal estimates for β and γ, these two terms will be equal, implying that consumers have equivalent responses to a carbon tax change and to a change in gasoline price net of carbon tax. According to this specification, γ can be interpreted as the percent change in overall fuel economy as a result of a 1% increase in the price of gasoline due to the carbon tax.

Finally, I apply the second approach and use the model-level data by FSA and year to estimate the effect of carbon tax on market share of individual models sold in BC in each year following the methodology used in Klier and Linn (2010a). This model provides information on consumers' vehicle purchase behavior and evaluates whether consumers respond to changes in the carbon tax (and gasoline price) by changing their new vehicle purchases to more fuel-efficient vehicles. I perform a reduced-form estimation on the share of sales of model j in FSA f and year t (denoted by s_{jpt}) in response to changes in the carbon-tax-only cost, as well as net-of-carbon tax gasoline cost, of driving the given model following equation:

$$\log s_{jft} = \mu(GP_{ft} * FE_{jft}) + \lambda(CT_{ft} * FE_{jft}) + \theta_{jt} + \delta_{jf} + \varepsilon_{jft} \tag{3.6}$$

The net-of-carbon tax gasoline cost of driving model j per 100 kilometers (i.e., $GP_{ft} * FE_{jft}$) is the product of gasoline prices in each FSA and year and the combined fuel consumption rating of model j (FE_{jft}, measured in L/100 km).[22] Analogously, the carbon-tax

[22]For this estimation, I assume a no-change forecast in gasoline prices which implies that consumers use current fuel prices as assumed future prices when selecting the fuel efficiency of their new vehicle choice. This is a common assumption in the automobile literature; Anderson et al. (2013) state that consumers expect

only cost of driving model j per 100 kilometers (i.e., $CT_{ft} * FE_{jft}$) is the product of carbon tax and model-level combined fuel consumption ratings. Finally, θ_{jt} and δ_{jf} are model-FSA and model-year fixed effects and ε_{jft} is the idiosyncratic error.

The advantage of this approach over the first approach is that it accounts for consumer preferences at the individual vehicle level (rather than an aggregate response), and therefore provides more precise estimates of demand for fuel efficiency. However, the unbiased estimation of consumer demand for fuel efficiency requires that we control for the unobserved vehicle and consumer characteristics. As such, I include model-specific fixed effects (interacted with each FSA and year) to capture all the observed and unobserved vehicle-specific attributes (such as make, model, engine size, interior and exterior design, performance, reliability, etc.), as well as the potential endogeneity between the average retail price and vehicle characteristics (Nevo (2000)).[23]

Model-FSA fixed effects capture the time-invariant FSA-level preferences over each particular model. These fixed effects control for the unobserved factors that vary across FSA and can affect share of particular vehicles; factors such as geography, density, climate, make-up of the population, road networks, region-specific regulations and taxation on the vehicle market, and etc. Model-year fixed effects capture national time-varying preferences for a particular model in each year. They include national unobserved factors, such as demand shocks, the federal taxes and regulations, the effect of recession on the vehicle market and so forth.[24]

the real future gasoline prices to be equal to the current price levels under normal economic conditions.

[23]It is important to note that I can not account for the manufacturer or dealer incentives at the time of purchase in my analysis, as I do not observe the vehicle transaction price data. As documented by Langer and Miller (2013), manufacturers or dealers may respond to changes in gasoline price by changing vehicle transaction prices to offset the expected fuel costs. As such, the failure to account for manufacturer incentives may result in imprecise estimates of demand for fuel efficiency. However, this is not problematic in my study as my estimation captures the reduced-form impacts of fuel costs on vehicle market shares. Therefore, changes in vehicle market shares depend on the relationship between gasoline prices and equilibrium sales (which take into account both consumer and manufacturer response).

[24]Note that during the financial crisis in 2008, consumers' expectations of future gasoline prices may differ from the current price. As noted by Anderson et al. (2013), consumers predicted that gasoline prices would rebound after the sharp decline in 2008. To the extent that this has occurred, the gasoline price effects in this model may have been over-estimated.

The main coefficient of interest, λ, captures the effect of changes in the carbon tax cost of driving a particular model (in \$/100 km) on its market share, all else equal. It can be interpreted as the percent change in the vehicle market share due to a \$1 increase in carbon tax costs (per 100 km). λ is expected to be negative, meanings that an increase in the fuel cost of driving a particular model due to the carbon tax would cause its market share to decline, all else equal. Similarly, μ captures the effect of changes in the carbon tax-exclusive gasoline cost of driving a particular model (in \$/100 km) on its market share, which is also expected to be negative.

Equation 3.6 assumes that an increase in fuel costs (due to the carbon tax or to other components of gasoline price), all else constant, affect market shares proportionately for all vehicles. This is in light of the fact that we expect that an increases in fuel costs differentially affect the expected driving costs across different vehicle models depending on their fuel efficiency. For example, an increase in carbon tax (or gasoline price) imposes higher additional fuel costs on fuel-inefficient vehicles relative to fuel-efficient vehicles. Therefore, the changes in the relative carbon tax (or gasoline) costs cause the demand curves for fuel-efficient vehicles to shift outward and the demand curves for fuel-inefficient vehicles to shift inward. This results in an increase in the market share of fuel-efficient vehicles, thus improving the average fuel efficiency of the entire fleet. To address this issue, I estimate an additional model that is more flexible than Equation 3.6 and shows whether the carbon tax has differential effects on the market shares of different vehicles based on their fuel efficiency ratings. I classify vehicles into five quantiles based on their fuel consumption ratings: Quantile-1=[3.5-8.5 L/100 km], Quantile-2=[8.5-9.5 L/100 km], Quantile-3=[9.5-10.5 L/100 km], Quantile-4=[10.5-12 L/100 km], and Quantile-4=[12-22.7 L/100 km], and allow the effect of fuel costs on market shares to vary by fuel efficiency quantile. Vehicles are grouped into quantiles such that total sales of each quantile is approximately equal. The equation to be estimated is expressed as:

$$\log s_{jft} = \mu_q(GP_{ft} * FE_{jft}) + \lambda_q(CT_{ft} * FE_{jft}) + \theta_{jt} + \delta_{jf} + \varepsilon_{jft} \tag{3.7}$$

All the variables and fixed effects are the same between Equations 3.6 and 3.7, but Equation 3.7 allows for a separate λ and μ parameter for each fuel efficiency quantile (denoted by q).

I apply linear regressions with fixed effects across all of the above models and cluster standard errors by FSA-class[25] to allow for the unobserved factors affecting the sales of each vehicle class to have serial correlations with one another within a given FSA over time.[26]

3.5 Results

Results of the provincial-level estimations do not show statistically significant impacts of the carbon tax on new vehicle fuel economy. However, the FSA-level regression results suggest that BC's carbon tax policy has statistically significant impacts on the fuel efficiency (in L/100 km) of new vehicle sales, causing an improvement of about 0.25% in fleet fuel economy due to a 1% increase in carbon tax. While the results also indicate negative significant impacts of gasoline price (net of carbon tax) on new vehicle fuel economy, the variable of fleet fuel economy responds more strongly to changes in the carbon tax than to equivalent changes in other components of gasoline price. This section presents the results of provincial-level estimations on aggregate fuel economy followed by FSA-level results based on both aggregate and model-level estimations.

3.5.1 Provincial Results

Table 3.4 reports province-level results. Across all models, the dependent variable is the log aggregate sales-weighted fuel efficiency of new vehicles sold in each province and year. The independent variables of interest, i.e., carbon tax and gasoline price (inclusive of all taxes net of the carbon tax) (both in $/L), enter as levels in the first two columns and as logs in

[25]Vehicle classes are defined based on the RL Polk classification: Subcompact-Car, Compact-Car, Sports-Car, Intermediate-Car, Luxury-Car, Luxury high end-Car, Luxury sports-Car, Compact-SUV, Intermediate-SUV, Large SUV, Luxury-SUV, Small-Pickup, Large-Pickup, Small-Van, and Large-Van.

[26]Note that clustering by city-class does not substantially change the results.

the last two columns. Therefore, the last two columns report the elasticities of new vehicle fuel economy with respect to carbon tax and gasoline price. All columns include province and year fixed effects. Columns (2) and (4) include other provincial controls in addition to the province and year fixed effects.

The estimates are almost identical across columns with provincial controls and columns without them, meaning that additional provincial controls (denoted by X_{pt} in Equation (1)) do not add much explanatory power to the estimation. Across all columns, the carbon tax effect is consistent in sign and magnitude but is not statistically significant while gasoline price demonstrates negative significant impacts on fleet fuel economy. I raise the size of my sample by using dis-aggregated FSA-level data and find that the carbon tax effects gain statistical significance when a larger sample size is used. The results of these specifications are discussed in Section 3.5.2. The negative significant effects of gasoline price, net of carbon tax, is also consistent across all specifications, indicating an improvement of about 0.12% in average fleet fuel economy due to a \$0.01/L increase in gasoline price.

Elasticity estimates capturing gasoline price effects in the results above are consistent with those in several recent studies: Rivers and Schaufele (2017a) find an elasticity of 0.08 to 0.12 (depending on fixed effects) using Canadian new vehicle data (2000-2010); Li et al. (2014) estimate an elasticity with respect to tax-exclusive gasoline price ranging between 0.09 to 0.13 using household level data on new vehicle purchases in the US.

3.5.2 FSA-level Results

Carbon Tax Effects on Average Fleet Fuel Economy

Table 3.5 replicates all the models in Table 3.4 using the dis-aggregated FSA-level data. Across all columns, the dependent variable is the log of sales-weighted fuel consumption (in L/100 km). FSA and year fixed effects are used in all specifications. Columns (1) and (2) use carbon tax and gasoline price as levels, while columns (3), (4), and (5) use the log variants of these variables. Columns (2), (4), and (5) control for other explanatory variables including log median income, log median age, log percent females, and log percent married individuals in the population, in addition to the FSA and year fixed effects. Across all models (except in column (5)), the identification comes from within-FSA variations in carbon tax and gasoline price over time. In column (5), identifications relies on within-province variations in carbon tax and gasoline price over time; I include province-by-year fixed effects in this regression to capture the unobserved factors that vary by province, year, and by both, and it may be correlated with the carbon tax. These factors include provincial regulations that change over time (including the vehicle scrap program and changes in other provincial taxes), the effect of the recession in 2008 and onward, and so forth.[27]

Results suggest that including additional FSA-level controls does not add much explanatory power to the estimations. Moreover, adding province-by-year fixed effects does not considerably affect the magnitude of the carbon tax coefficient, meaning that the effect of unobserved provincial factors that vary over time are minimal. The negative relationship between the carbon tax and fleet fuel economy is apparent across all specifications, which is significant at the 5% level in almost all models. FSA-level results indicate that the fuel economy of new vehicles sold in BC improved by 0.18% due to a \$0.01/L increase in the carbon tax. The log-log estimation results in columns (3), (4), and (5) imply that the elasticity of new vehicle fuel economy with respect to the carbon tax ranges between -0.22 and -0.25, depending on the controls. This implies that a 1% increase in gasoline price due to the carbon tax causes a 0.22% to 0.25% reductions in overall fleet fuel economy.

The coefficients for the carbon tax-exclusive gasoline price demonstrate similar effects on fleet fuel consumption, indicating a 0.18% decrease in fuel consumption (in L/100 km) due to a \$0.01/L increase in gasoline price (net of carbon tax). However, results of the log-log variant of the same estimations show smaller elasticity estimates with respect to gasoline

[27] It is important to note that I am unable to include FSA-by-year (or city-by-year) fixed effects as there are no variations in the carbon tax and gasoline price within a given FSA, and therefore FSA-year fixed effects will drop these variables from the estimation. However, since there are variations in the carbon tax ratio across FSAs within the province, I can include province-by-year fixed effects while maintaining the carbon tax variable in the regression.

price relative to the elasticity with respect to the carbon tax ratio. This difference becomes even larger when I account for the province-by-year fixed effects. This implies that as I raise the resolution of fixed effects, the effect of gasoline price becomes smaller. The Wald test for the hypothesis of equality of the tax and tax-exclusive coefficients is rejected at the 5 percent level in each of the specifications, implying that the new vehicle fuel efficiency responds differently to the carbon tax than the tax-exclusive gasoline price.

In line with the literature, the FSA-level results suggest that consumers have a larger response to changes in fuel taxes than to equivalent changes in the tax-exclusive price of gasoline. Li et al. (2014), Rivers and Schaufele (2017a), and Antweiler and Gulati (2016) find that, in the short run, the tax component of gasoline price is more salient than equivalent market price movements. These studies argue that consumers may respond more to the components of gasoline price that are perceived as more permanent than the market-driven component of gasoline price. For example, Rivers and Schaufele (2017a) find that the elasticity of Canadian new vehicle fuel efficiency with respect to excise taxes is ten times greater than is the case with respect to changes in other components of gasoline price (i.e., -0.36 relative to -0.03). I find elasticity estimates which are more similar to those obtained by Li et al. (2014); their reported estimates change between -0.2 to -0.4 depending on the model specification and controls.

Carbon Tax Effects on Vehicle Market Shares

Table 3.6 presents the results of the regressions on model-level market shares in response to changes in carbon tax costs and tax-exclusive gasoline costs. The dependent variable is the log market share of each vehicle model in each FSA and year and the independent variables are gasoline costs and carbon tax costs of driving each model (in \$/100 km).

Column (1) lists the results of the estimation on individual market shares based on Equation 3.6 whereas column (2) reports the differential effects of carbon tax costs and gasoline costs on market share of different fuel efficiency quantiles (based on Equation 3.7).

According to Column (1), I find that any increase in both the carbon tax cost and gasoline cost of driving a particular model (per 100 km) causes a reduction in the market share of the given model, all else constant. These price increases affect the market share of various models differently depending on their fuel consumption rating. The same increase in fuel prices (due to taxes or other components of gasoline price) results in a larger increase in the fuel cost of fuel-inefficient vehicles relative to fuel-efficient vehicles, thus causing the market share of fuel-inefficient vehicles to decline more than the market share of fuel-efficient vehicles. As such, an increase in gasoline prices is associated with substitutions towards more fuel-efficient vehicles, which results in an improvement in overall fleet fuel economy. However, as is evident, carbon tax costs have much larger impacts on model shares than gasoline costs. Results indicate that a \$0.01/L increase in the carbon tax cost of driving a particular model (per 100 km) leads to a 0.34% decline in its market share whereas an equivalent increase in gasoline costs causes a 0.04% decline in the vehicle market share (both effects are significant at the 1% level). This suggests that an increase in the carbon tax is associated with effects that are eight times larger on a vehicle share than an equivalent increase in the carbon tax-exclusive component of gasoline price.

As Equation 3.6 assumes that fuel costs (i.e., carbon tax costs and gasoline costs) affect market shares proportionately for all vehicles, I allow these effects to vary by fuel efficiency quantile and report the results in column (2). I find that both the carbon tax and gasoline price coefficients vary across fuel efficiency quantiles, implying that the effect of carbon tax and gasoline price (net of the carbon tax) becomes smaller as we move from the most fuel-efficient to the least fuel-efficient quantiles. In other words, the reduction in market share from a \$1/L increase in the carbon tax (or gasoline price) is larger for more fuel-efficient quantiles (i.e., Quantiles 1 and 2) than less fuel-efficient quantiles (i.e., Quantiles 3 and 4). All coefficients are statistically significant (mostly at the 1% level) providing more robustness to the effect of carbon tax and gasoline price in shifting preferences to more fuel-efficient vehicles.

Overall, results imply that there are substitutions to higher-fuel-efficiency vehicles within each fuel efficiency quantile as a result of an increase in the carbon tax, with larger substitutions for the most fuel-efficient quantiles than for the least fuel-efficient quantiles. Moreover, a \$1/L increase in the price of gasoline (net of carbon tax) causes an increase in the market share of the most fuel-efficient quantile and a decrease in the share of the remaining three quantiles. Finally, consistent with the results in column (1), changes in the carbon tax have much larger impacts on the market share of each quantile than changes in the tax-exclusive component of gasoline price do.

Counter-factual Simulations

I perform a counter-factual simulation to find the fuel efficiency improvements associated with the carbon tax policy using both aggregate and model-level market share estimates to allow for comparison between the two estimating approaches. I calculate the predicted sales-weighted fuel consumption rating (in L/100 km) in the presence and absence of the carbon tax policy using the coefficient estimates from column (2) in Table 3.5 (for the aggregate regression) and column (1) in Table 3.6 (for the model-level market share regression).[28]

Using the coefficient estimates in column (1) in Table 3.6, I calculate the predicted market shares in the presence and absence of the carbon tax policy, i.e., $\hat{s_{jft}}$ and s^*_{jft}, respectively. I then calculate the predicted number of vehicles sold for model j in FSA f and year t under each scenario by multiplying predicted shares by total vehicle sales in the given market following: $(\hat{s_{jft}} \times S_{ft})$ and $(s^*_{jft} \times S_{ft})$.[29] The sales-weighted fuel efficiency for each vehicle is the product of predicted sales and the vehicle fuel efficiency rating (in L/100 km) of the given vehicle. I then sum fuel efficiency over all vehicles in a given market and divide it by total predicted sales (i.e., $\hat{S}_{ft}$ and S^*_{ft}) in that market to obtain aggregate predicted fuel

[28]Note that using the coefficients in other regressions in Tables 3.5 and 3.6 do not considerably change the counter-factual results.

[29]Note that since I use log market shares in my estimations, I take the exponential of the predicted market shares under each scenario.

economy under each scenario: ($\hat{F_{ft}} = \frac{\sum_{j=1}^{J}(\hat{fe_{jft}} \times \hat{s_{jft}})}{\hat{S_{ft}}}$) and ($F^*_{ft} = \frac{\sum_{j=1}^{J}(fe^*_{ft} \times s^*_{ft})}{S^*_{ft}}$).[30]

Using the coefficient estimate from the aggregate regression (from column (2) in Table 3.5), I obtain the predicted sales-weighted fuel efficiency (in L/100 km) in each market in the presence and absence of the carbon tax policy.[31] The fuel efficiency improvements associated with the carbon tax policy can then be calculated based on the predicted results of each estimating approach.

The counter-factual results of each regression are calculated separately for 2008, 2009, and 2010. Figure 3.5 plots changes in the predicted market shares by fuel efficiency quantiles in the presence versus the absence of the carbon tax policy. The blue bars are the predicted market shares in the presence of the carbon tax. Results are according to our expectations; in the absence of the carbon tax policy, market share of models in the most fuel-efficient quantiles (i.e., Q1=[3.5-8] L/100 km and Q2=[8-9.5] L/100 km) would decrease, whereas market share of the remaining quantiles, which include vehicles with fuel efficiency rating above 9.5 (L/100 km), would increase. Figure 3.6 plots the predicted average fuel efficiency in the presence and absence of the carbon tax in BC after 2008 based on the results of the model-level regressions (illustrated in the left panel), as well as the results of the aggregate regression (illustrated in the right panel). According to Figure 3.6, the counter-factual results of the model-level regression indicate that the predicted reductions in fleet fuel efficiency (in L/100 km) due to the carbon tax are 0.03, 0.06, and 0.09 in 2008, 2009, and 2010, respectively. For example, with the carbon tax, the predicted fleet-weighted-fuel-efficiency rating of new cars sold in BC in 2010 was 9.43 (L/100 km). If the carbon tax had not been implemented, the fleet fuel economy would have been 9.52 (L/100 km) in that year. The counter-factual results of the aggregate FSA-level regression suggest similar reductions in fleet-wide fuel efficiency due to the carbon tax policy as shown in the right panel of Figure 3.6.

[30]Note that I conduct the simulation under the assumption that the total new vehicle sales in each market are unchanged during this period, which implies that the sum of predicted shares in each market should add to one.

[31]Note that I take the exponential of the predicted sales-weighted fuel efficiency under each scenario as I use the logarithm of this variable in my estimation.

I also investigate whether BC's fleet fuel economy would respond similarly to changes in the carbon tax than to equivalent changes in the carbon tax-exclusive gasoline price using the counter-factual results of both estimations (same as above). I calculate the predicted fleet fuel economy under two scenarios. First, I calculate changes in predicted fleet fuel consumption rating in response to a \$0.01/L increase in the carbon tax. Second, I calculate this rating in response to a \$0.01/L increase in gasoline prices (net of the carbon tax). Figure 3.7 plots changes in the predicted market shares of each fuel efficiency quantile due to a \$0.01/L increase in the carbon tax (illustrated in the left panel) and to the carbon tax-exclusive gasoline prices (illustrated in the right panel). It is evident that an increase in the carbon tax and gasoline price has a positive impact on the share of more fuel-efficient quantiles (i.e., Q1=[3.5-8] L/100 km and Q2=[8-9.5] L/100 km) and a negative impact on the share of less fuel-efficient quantiles. However, consistent with my previous results, a greater response from each fuel efficiency quantile to increases in the carbon tax than to equivalent increases in the carbon tax-exclusive gasoline price is discerned.

Finally, Figure 3.8 plots the reductions in BC's fleet fuel economy associated with the carbon tax increase versus the tax-exclusive gasoline price increase. The left panel uses the counter-factual results of the model-level regression, and the right panel uses the counter-factual results of the aggregate regression. Results in both panels indicate improvements in fleet fuel economy due to an increase in both the carbon tax and gasoline price (excluding the carbon tax), but with larger reductions in fuel consumption rating (in L/100 km) as a result of an increase in the carbon than of an equal-sized increase in other components of gasoline price. However, the counter-factual results of the model-level regression suggest larger effects of the carbon tax than the results of the aggregate regression. This is consistent with the magnitude of the estimated coefficients for carbon tax and gasoline price as reported in Table 3.6. Results in left panel indicate that a \$0.01/L increase in the carbon tax leads to a 0.017, 0.018, and 0.022 (L/100 km) reductions in fleet fuel economy (i.e., fewer liters per 100 km) in BC in 2008, 2009, and 2010, respectively. However, the same gasoline price increase (net of the carbon tax) causes an average reduction of 0.0026 (L/100 km) during these three years. This suggests eight-times-larger effects of the carbon tax on average fleet fuel economy compared to the tax-exclusive gasoline price, which is consistent with the reported coefficients in Table 3.6 column (1). In line with the magnitude of the reported coefficients form the aggregate regressions in Table 3.5, the results of the right panel does not show substantial differences between the effect of the carbon tax and gasoline price, although the fuel efficiency improvements are still larger when the carbon tax is increased.

Overall, as the model-level regressions use data at the dis-aggregated vehicle-level data, the predicted change in fleet fuel economy based on these models are more precisely estimated. As such, these results, along with the results of the estimation on quantile market shares, lead me to conclude that the carbon tax has larger impacts on fleet fuel economy than other components of gasoline price. In the next section (Section 3.5.3), the results of aggregate regressions on the fuel economy of different vehicle segments will provide more robustness to the above results.

3.5.3 Carbon Tax Effects on Fleet Fuel Consumption Conditional on Composition

The previous section provided empirical evidence on the negative effects of BC's carbon tax and gasoline price on fleet fuel consumption. In this section, I address the observed changes in fleet fuel economy conditional on fleet composition. For the remaining specifications in my study, I will use linear regressions to perform the estimations, as they provide straightforward estimations and easy-to-interpret results.

I group vehicles in the FSA-level data into 15 segments according to the RL Polk classification.[32] As shown in Table 3.2, the fuel efficiency of vehicle models vary within each segment, as well as across segments. Therefore, the effects of carbon tax and gasoline price

[32]RL Polk classifies vehicles into: Subcompact-Car, Compact-Car, Sports-Car, Intermediate-Car, Luxury-Car, Luxury high end-Car, Luxury sports-Car, Compact-SUV, Intermediate-SUV, Large SUV, Luxury-SUV, Small-Pickup, Large-Pickup, Small-Van, and Large-Van.

can be identified by exploiting changes in sales-weighted fuel consumption of each vehicle segment within a given FSA over time, as well as across segments in a given FSA and year.[33] The estimating equation takes the form of:

$$\log F^i_{ft} = \gamma^i CT_{ft} + \beta^i GP_{ft} + \sigma^i \log X_{ft} + \rho_f + \vartheta_t + \epsilon_{ft} \tag{3.8}$$

where F_{ipt} is the sales-weighted fuel consumption of segment i in FSA f and year t (used as logs), carbon tax and gasoline prices (net of carbon tax) are specified as levels rather than as logs (in \$/L), but the rest of the explanatory variables (i.e., median income, median age, percent females, and percent married individuals, and percent individuals living in an apartment) are used as logs. ρ_f and ϑ_t are FSA and year fixed effects, respectively, to eliminate the unobserved factors that vary by FSA and year. γ^i and β^i can be interpreted as the percent change in fuel efficiency segment (in L/100 km) due to a \$0.01/L change in the carbon tax and carbon tax-exclusive gasoline price, respectively.

I present Figure 3.9 to report the coefficient estimates for fuel consumption by segments.[34] Results show that among cars, the carbon tax has significant negative impacts on fuel consumption (in L/100 km) of sports and intermediate cars. This means that fuel consumption of these two segments was improved due to the carbon tax policy. A \$0.01/L increase in the carbon tax causes a 0.42% and 0.43% fuel efficiency improvements for sports and intermediate cars, respectively. However, the fuel consumption of luxury high-end cars worsened due to the carbon tax, experiencing a 0.58% higher fuel consumption (L/100 km) due to a \$0.01/L increase in carbon tax. With respect to SUVs, all SUVs (except compact SUVs) experience fuel efficiency improvements in response to the carbon tax, however their estimates are not statistically significant. For compact SUVs, fuel consumption increases (i.e., fuel efficiency is lower) due to the carbon tax; a \$0.01/L increase in the carbon tax leads to a 0.5% increase in fuel consumption of compact SUVs. Among the least fuel-efficient segments

[33] Carbon tax, similar to gasoline price, may cause differential effects on fuel consumption of various vehicle segments because of the differences in sales-weighted fuel consumption across segments.

[34] Results of this specification are also presented in Table 3.10 in appendix.

(i.e., pick-up trucks and vans), carbon tax only has significant negative effects on minivans, meaning that the fuel consumption of minivans was improved. Among all segments, the carbon tax has largest impacts on fuel consumption of minivans, resulting in 1.5% fewer liters of gasoline consumption due to a \$0.01/L increase in the carbon tax. This is perhaps because there are more fuel-efficient minivans available in the market that offer the minivan buyers comparable characteristics in comparison with other vehicle segments.

The carbon tax-exclusive gasoline price has significant negative effects on fuel consumption of compact, sports, intermediate, and luxury cars. Gasoline prices have larger impacts on fuel consumption of sports cars, compared with the carbon tax, whereas their effects on fuel consumption of intermediate cars are smaller than the carbon tax effects. It is interesting to note that among all segments, the segment for intermediate cars is the most sensitive to gasoline price increases, experiencing the highest improvement in fuel consumption over this period. In contrast to the carbon tax, increases in the gasoline price leads to higher demand for more fuel-efficient compact SUVs and less fuel-efficient luxury SUVs. Finally, the estimates of the least fuel-efficient segments show that gasoline price has negative impacts on fuel consumption of all of these segments, but only the effects on minivans are statistically significant. Results indicate that the fuel consumption of the minivans purchased over this period improved by 0.11% due to a \$0.01/L increase in gasoline price (net of carbon tax).

Overall, carbon tax has larger impacts on fuel consumption of almost all segments in the fleet, providing more robustness to the previous results indicating a larger consumer response to carbon tax versus the pre-carbon tax gasoline price.

3.5.4 Carbon Tax Effects on Fleet Composition

In this section, I estimate changes in market share of different vehicle segments in response to the carbon tax and gasoline price (net of carbon tax). Similar to the previous specification, I use linear regressions to perform the estimations of the following equation:

$$s_{ft}^{i} = \tau^{i} CT_{ft} + \pi^{i} GP_{ft} + \sigma^{i} \log X_{ft} + \rho_{f} + \theta_{t} + \epsilon_{ft} \quad (3.9)$$

where s_{ft}^{i} is the market share of segment i in FSA f and year t, carbon tax and gasoline price are used as levels rather than as logs in dollars per liter, but the rest of the explanatory variables (i.e., median income, median age, percent females, and percent married individuals) are used as logs.[35] ρ_f and ϑ_t are FSA and year fixed effects, respectively, to eliminate the unobserved factors that vary by FSA and year. τ^i and π^i are the predicted change in segment market shares, in percentage points, due to a \$1/L change in carbon tax and gasoline price (net of carbon tax), respectively. Linear regressions are used to estimate this specification for each vehicle segment separately, and standard errors are clustered by FSA in all models.

I provide Figure 3.10 to report the coefficient estimates for market shares by segment.[36] Results show that, among cars, the carbon tax has statistically significant positive impacts on sales of subcompact and luxury sports cars (at the 1% and 10% levels). Compact cars are the most responsive vehicle segment to the carbon tax after luxury SUVs. Among cars, the carbon tax has significant negative effects on sales of compact cars, causing a 0.63 percentage points decline in their market share due to a \$1/L increase in carbon tax. After compact cars, subcompact cars have the largest response to the carbon tax, gaining 0.56 percentage points of market share due to a \$1/L increase in carbon tax. As expected, almost all classes of SUVs (except for luxury SUVs) lost market share due to changes in the carbon tax. Sales of intermediate SUVs decrease the most; by 0.58 percentage points due to a \$1/L increase in carbon tax. Among the least fuel-efficient segments (i.e., vans and pickup trucks), I find declines in market share of minivans and large pickup trucks, although neither of the coefficients are statistically significant. Small pickup trucks, on the other hand, experience the largest change in market share among the least fuel-efficient segments; a 0.16 percentage

[35]Note that the market share variable in Equation (9) is a share by nature and therefore is not included as logs. I use the log transformation of the other variables in this estimation as they offer a more precise estimates.

[36]Results of this specification are also presented in Table 3.11 in Appendix.

point increase in shares due to a $1/L increase in carbon tax. This shows that there are likely shifts from large pickups to other relatively less fuel-inefficient segments like small pickups and large vans.

Gasoline price (net of carbon tax) has similar effects as carbon tax in decreasing sales of intermediate cars, and in increasing sales of luxury high-end cars. However, unlike carbon tax, it causes an increase in sales of compact cars. Moreover, I find that compact cars respond the most to gasoline price among cars, experiencing a 0.23 percentage point increase in share due to a $1/L increase in gasoline price (significant at the 1% level). I also find that an increase in the gasoline price, as in the case with the carbon tax, causes a decline in the market share of all SUVs (except Luxury SUVs). Among SUVs, compact SUVs experience the largest decline in market shares; by 0.09 percentage points due to a $1/L increase in gasoline price. This is not surprising as SUVs are usually replaceable by some car segments that offer comparable vehicle characteristics. Gasoline price effects on pickup trucks and vans are similar in sign to carbon tax effects, both causing an increase in sales of small pickups and large vans, and a decrease in sales of minivans and large pickups. Minivans and large pickups experience a 0.07 and 0.02 percentage points decline in market share due to a $1/L increase in gasoline price (net of the carbon tax).

Overall, I find that almost all segments have larger response to changes in the carbon tax than to changes in the gasoline price. Consistent with my previous results, as well as with findings of other relevant studies (as mentioned previously), the new results (on segment market shares) also imply that consumers are more responsive to changes in the carbon tax than to changes in carbon tax-exclusive gasoline price.

3.5.5 Asymmetric and Lagged Responses to Carbon Tax and Gasoline Price

The estimations in the preceding sections assume that the effect of fuel prices on fleet fuel economy is constant over the period of my data (i.e., 2000 to 2010). In this section, I investigate whether consumer response to changes in gasoline prices when selecting the fuel efficiency of their new vehicle is dependent on gasoline price levels. This also allows me to compare the carbon tax effects with the effects of other components of gasoline price based on the price levels. I also estimate additional regressions to determine the long-term responses to the carbon tax and tax-exclusive gasoline price and test whether the differential effects of the two variables also exist in the long-run. As stated previously, I estimate linear regressions on aggregate FSA-level data using the same fixed-effect strategy and clustering technique as the regressions presented in Table 3.5. Table 3.7 reports the results of these specifications.

There is some empirical evidence in the literature (e.g., Klier and Linn (2010a) and Leard et al. (2017)) that suggests a stronger consumer response to gasoline price increases than decreases. Since the carbon tax only increases over my sample period, I am unable to assess statistically whether an asymmetric tax response exists. It is, however, possible to address asymmetric responses to the carbon-tax exclusive gasoline price. I perform two different specifications to test this possibility. First, following Klier and Linn (2010a), I group my sample into three periods based on the overall gasoline price trends across Canadian FSAs: 1) 2000-2002, when gasoline prices are low and relatively stable; 2) 2003-2007, when gasoline prices are high and increasing ; and 2008-2010, when gasoline prices are relatively high and volatile. I interact the carbon tax-exclusive gasoline price variable (in logs rather than in levels) with an indicator for each time period and estimate changes in log sales-weighted fuel consumption rating of the vehicles sold across FSAs and years. Column (1) in Table 3.7 reports the results of this regression. All the coefficients are statistically significant at the 1 percent level. In line with the findings of the aforementioned studies, my results demonstrate a stronger response to gasoline prices after 2003 (when gasoline prices are rising and high) than before (when gasoline prices are low and stable). The hypothesis is rejected at the 1 percent level that the gasoline cost coefficients for each time period are equal, meaning that gasoline price variations in each time period have differential effects on fleet fuel efficiency.

Results indicate that the elasticity of fleet fuel economy with respect to the carbon tax-exclusive gasoline price changes from 0.11 before 2003 to 0.16 after. It is important to note that the effect of changes in the carbon tax is larger than the effect of changes in the tax-exclusive gasoline price for each period; the hypothesis that the carbon tax and gasoline price coefficients are equal is also rejected at the 1 percent level.

In order to better identify the non-linear relationship between gasoline price and fleet fuel efficiency, I estimate an alternative specification in which I interact gasoline prices with an indicator variable equal to one if prices increased (or stayed constant) between the previous and current years. Column (2) reports the results of this regression. The results listed in column (2) is comparable to those listed in column (1), as gasoline prices were more likely to increase during 2003-2008 than before and after. Results imply that gasoline prices have slightly larger impacts on average fuel efficiency when fuel prices are rising rather than falling, although with small differences in magnitude; the hypothesis of the equality of the two gasoline price coefficients is rejected at the 1 percent level. Moreover, consistent with the above results, the elasticity of fleet fuel efficiency with respect to the carbon tax is larger than the elasticity with respect to the carbon tax-exclusive gasoline prices regardless of whether fuel prices are rising or falling; the equality hypothesis is rejected at the 5 percent level.

The specifications listed in columns (3) and (4) investigate the long-run effects of the carbon tax and the tax-exclusive gasoline price on fleet fuel efficiency. Consumers may respond differently to increases in gasoline price in the short-run versus the long-run when selecting the fuel efficiency of their new vehicle purchase. As documented by Klier and Linn (2010a), due to the durable nature of automobiles, the potential impacts of an increase in gasoline prices on fleet fuel economy are associated with longer-term effects of gasoline prices on vehicle sales. I investigate lagged responses by adding lags of the carbon tax and tax-exclusive gasoline price to the regression. As the carbon tax policy was implemented in 2008, I can only add two lags to capture the long-run response to the carbon tax. The specification in column (3) includes 1-year lags for the carbon tax and gasoline price (net of carbon tax), while column (4) includes both 1-year and 2-year lagged variables. The results in both columns show that adding 1-year and 2-year lags reduces the point estimates on the lagged tax and tax-exclusive variables. The coefficients on the current carbon tax and tax-exclusive variables are larger than their lagged coefficients, and are statistically significant as opposed to their lagged counterparts. This implies that we can not make conclusions on the long-term effects of the carbon tax and tax-exclusive gasoline price on overall fuel economy. This may in part be due to the insufficient number of time periods for analysis after the carbon tax policy was implemented (i.e., only three years from 2008 to 2010). The hypothesis is rejected at the 5 percent level that the 1-year lagged carbon tax and tax-exclusive gasoline price are equal. The hypothesis that the sum of the current and 1-year lagged carbon tax coefficients are equal to those for the tax-exclusive gasoline price variable is also rejected; the larger effects of the carbon tax and gasoline price (net of the carbon tax) are still discernible. This suggests that the differential effect between the long-run responses to the carbon tax and other components of gasoline price could exist.

3.5.6 Comparison of British Columbia's Provincial Gasoline Taxes

As illustrated in Figure 3.1, there are other provincial taxes, in addition to the carbon tax in BC, which experienced changes over the decade of 2000 to 2010. These variations allow me to perform a comparative analysis between the effects of different provincial taxes in BC and investigate whether consumers respond differently to various gasoline taxes.

Similar to the previous sections, I estimate a linear regression on log sales-weighted fuel consumption rating (in L/100 km) to find the effect of various provincial taxes in BC and report the results in Table 3.8. Across all columns, I estimate the elasticity of fleet fuel economy with respect to various taxes using my preferred FSA-level specification, as reported in Table 3.5 column (4). All specifications control for FSA and province-year fixed effects as well as other FSA-level controls.

Column (1) lists the estimates of the elasticity of fleet fuel economy with respect to gasoline price excluding all provincial taxes (i.e., carbon, transit, and excise taxes). Column (2) reports the estimates of this elasticity with respect to the carbon tax ratio and the carbon tax-exclusive gasoline price (similar to the results in Table 3.5 column (4)). In column (3), I include the log of the excise tax ratio and report the elasticity estimates with respect to the excise tax; this specification allows for a comparison between the effect of an excise tax and of a carbon tax. In column (4), I add the log of excise and transit tax ratio and report the elasticity estimates with respect to the transit and excise taxes.

Results are consistent across all columns, validating the larger impacts of the carbon tax on overall fuel economy relative to the tax-exclusive gasoline price as well as to the excise and transit taxes. The hypothesis of equal coefficients for the carbon tax and other provincial taxes in each specification is rejected at the 5 percent level. Moreover, the hypothesis of the equality of each of the gasoline taxes and the tax-exclusive gasoline price is also rejected at the 5 percent level. Results imply that the elasticity of fleet fuel economy with respect to the carbon tax is -0.26, whereas this elasticity is -0.20 with respect to the excise tax and -0.23 with respect to excise and transit taxes in British Columbia. Although the test results reject the equality of the coefficients, the effect of the carbon tax is relatively equal to the effect of the excise and transit taxes. Finally, all specifications demonstrate stronger impacts of provincial taxes versus the tax-exclusive gasoline price.

3.5.7 Extensive Margin Effects of Carbon Tax

In this section, I investigate whether the total number of vehicles sold in BC changed as a result of the carbon tax policy. Consumers may respond to the carbon tax policy by replacing their vehicles with alternative means of transportation, or by delaying the time of their new vehicle purchase (in addition to adjustments through the channels indicated in the previous sections). This may affect the aggregate number of vehicles sold in BC after 2008. As previously shown in Figure 3.3, the sudden decline in aggregate sales in BC in 2008 can be attributed to the carbon tax policy. As such, in this section, I investigate whether these changes are due to the carbon tax or to other provincial and temporal factors affecting sales after 2008. I estimate changes in sales per capita in each market (province-year and FSA-year) to changes in the carbon tax and gasoline price after controlling for other time and province (or FSA) specific factors that may affect sales. The estimating equation is specified as:

$$\log(\frac{sales}{pop})_{pt} = \Gamma CT_{pt} + \Theta GP_{pt} + \sigma X_{pt} + \Omega_p + \vartheta_t + \epsilon_{pt} \tag{3.10}$$

where the dependent variable is the log of total new vehicle sales per capita in province p[37] and year t and the independent variables are carbon tax (i.e., CT_{pt} in \$/L), average gasoline price (including all taxes except the carbon tax) (GP_{pt} in \$/L), X_{pt} which includes other provincial factors of log real GDP, log real per capita income, log unemployment rate, log median age, log percent female and married individuals in the population, log percent individuals living in apartments, and log percent college graduates. Finally, Ω_p and ϑ_t are province and year fixed effects and ϵ_{pt} is the idiosyncratic error.

Tables 3.9 summarizes the results of the estimations on log aggregate sales per capita at the provincial-level and FSA-level. Columns (1) to (5) report the results of provincial-level regressions, and columns (6) and (7) report the results of the FSA-level regressions. I use linear regressions with different combinations of fixed effects and raise the precision of the estimation by increasing the sample size and increasing the resolution of fixed effects across the specifications. In the provincial-level regressions (columns (1) to (5)), the standard errors are bootstrapped using wild cluster bootstrapped t-statistics (WCBSTs) (as explained in the previous provincial regressions), and in the FSA-level estimations (columns (6) and (7)), they are clustered by FSA to account for serial correlations that likely exist between the residuals within a given FSA.

Column (1) reports the results of the most parsimonious specification with no fixed effects or provincial controls. Both carbon tax and gasoline price have statistically significant effects

[37] In FSA-level regressions, index f is used to refer to a FSA.

on aggregate sales per capita. Carbon tax has negative impacts on total vehicles per capita, while gasoline price (net of the carbon tax) has positive impacts (with smaller effects in magnitude). The specification in column (2) adds provincial controls to the estimation. Unlike the case of gasoline price, the carbon tax still has negative significant (at the 1% level) effects on total vehicles per capita with slightly higher magnitude than the first column. The specification in column (3) includes province and year fixed effects and excludes the additional provincial controls. The effect of the carbon tax, unlike tax-exclusive gasoline prices, is still negative and statistically significant but much smaller in magnitude than the estimates contained in column (2). Finally, in the preferred provincial-level specifications in columns (4) and (5), I include province and year fixed effects as well as additional provincial controls. The specification in column (4) includes the carbon tax and gasoline price (net of the carbon tax) in levels (in \$/L), while the specification in column (5) includes them in logs. The sign, magnitude, and statistical significance of the carbon tax coefficient is similar to the coefficient in column (3), meaning that the additional provincial controls do not add much explanatory power to the estimation. Results listed in column (4) indicate that a \$0.01/L increase in the carbon tax leads to a 0.97% decline in total vehicle sales per capita. Interpreting in elasticity terms in reference to column (5), a 1% increase in gasoline price due to the carbon tax is associated with a 1% decrease in new vehicle sales per capita. Although the results based on these specifications suggest that the carbon tax has negative significant impacts on aggregate new vehicle sales, there may be some unobserved factors (such as the vehicle scrap policy in BC, changes in other provincial taxes, and the effect of recession on the vehicle market in 2008) that change by province and year and can affect aggregate sales. The unobserved factors that change by province and year are perfectly correlated with the carbon tax policy but can not be controlled for in the provincial regressions by using province-by-year fixed effects. As such, the specifications in columns (6) and (7), I extend the analysis to the dis-aggregated FSA level to allow for the application of province-by-year fixed effects. The specification in column (6) includes FSA and year fixed effects as well as additional

FSA-level controls. Results still suggest the existence of significant negative impacts of the carbon tax on total vehicle sales, but with larger magnitudes than the provincial-level results. However, the specification in column (7), as the most comprehensive specification in this table, includes province-by-year fixed effects in addition to FSA fixed effects. Note that I use the log-log estimation on the FSA-level data, as this is the only specification that includes the carbon tax ratio (i.e., $1 + \frac{CT}{GP}$) and therefore allows for the application of province-by-year fixed effects without dropping the carbon tax variable. As expected, the carbon tax no longer has statistically significant impacts on aggregate sales once the province-by-year unobserved factors are controlled for. This implies that failure to account for these unobserved factors in the left-most columns in the table may have resulted in an omitted variable bias, thus invalidating the statistically significant effects of the carbon tax on overall sales.

Overall, the inconsistency of the results in the preferred model with the rest of the results leads me to conclude that the carbon tax has minimal implications along the extensive margin channel of changing the size of the vehicle fleet.

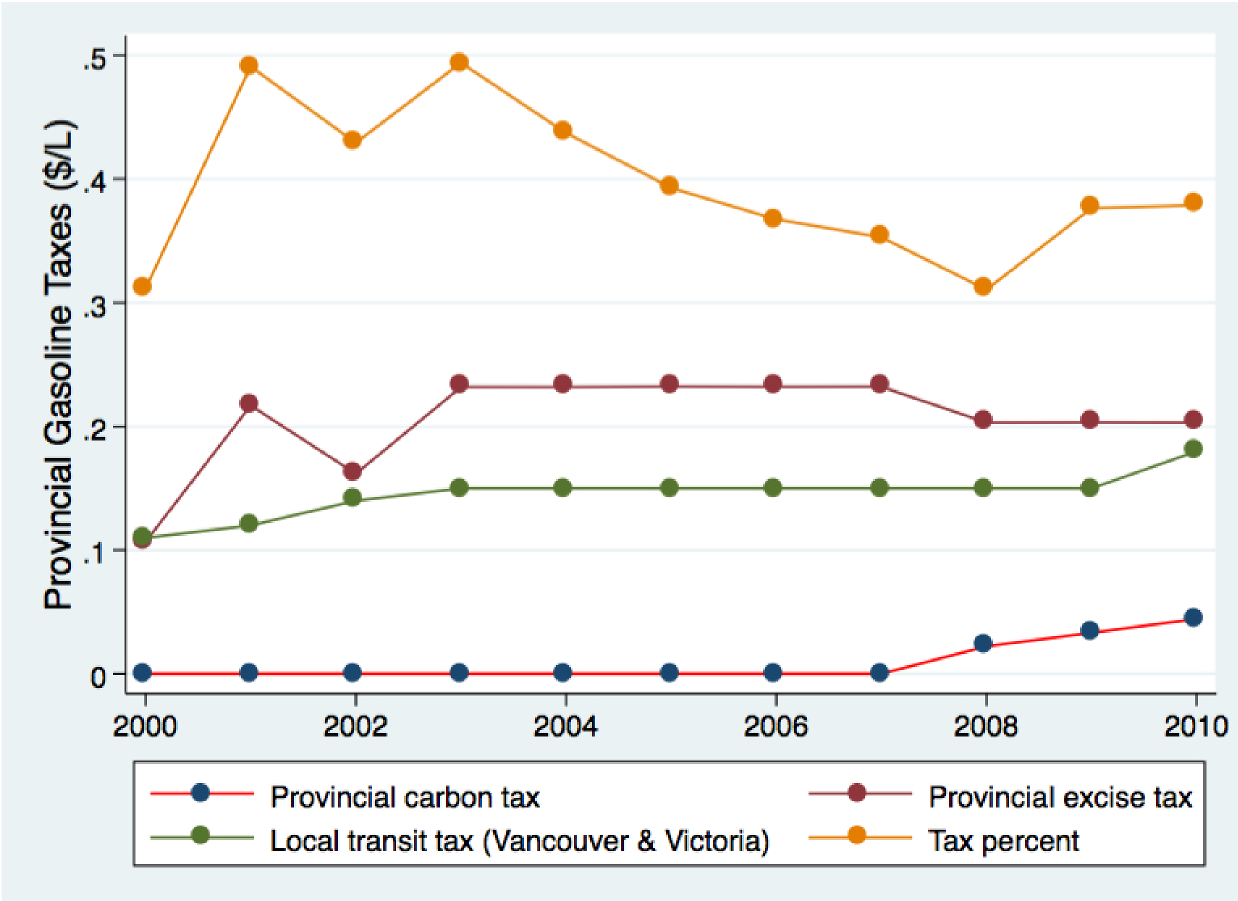
3.6 Conclusion

This paper investigates the introduction of the carbon tax policy implemented by the Canadian Province of British Columbia on households' new vehicle purchase decisions. I use a rich dataset including all new vehicle model registrations, combined with model-specific fuel consumption ratings (in L/100 km), to estimate the effect of changes in the carbon tax on the fuel efficiency of new vehicle purchases in BC. Vehicle data are available at province-level and FSA-level, allowing for a detailed analysis at a more disaggregated FSA-level in addition to an aggregate provincial-level analysis. Changes in fleet fuel economy are also estimated in response to changes in the carbon-tax exclusive gasoline price to compare with the carbon tax effects. As such, identification is derived from variations in the carbon tax and gasoline price within a province (and FSA) over time.

I find that consumers respond to the disincentives associated with the carbon tax policy by shifting towards more fuel-efficient vehicles when purchasing a new vehicle. Results also indicate that consumers respond more strongly to changes in the carbon tax than to equivalent changes in carbon tax-exclusive gasoline price when selecting the fuel efficiency of their new vehicles. Results indicate that a 1% increase in BC's carbon tax improves the average fuel efficiency of the new vehicle fleet by 0.26%, while a 1% increase in pre-carbon tax gasoline price improves vehicle fuel economy by up to 0.15% (between 0.09% to 0.15% depending on the level of data aggregation and fixed effect combination).

My finding also suggests that the fuel consumption levels of intermediate cars and minivans improve in response to changes in both BC's carbon tax and gasoline price (net of carbon tax). Also, among all segments, the fuel consumption of minivans and sports and intermediate cars improve the most, whereas fuel consumption of luxury high-end cars and compact SUVs increase the most, due the carbon tax. Finally, carbon tax causes substitutions across vehicle segments; sales of almost all SUV segments (except luxury SUVs) decrease; and there appears to be shifts from large pick-up trucks to small pick-up trucks and large vans, in response to the carbon tax.

Figure 3.1: Breakdown of Provincial Gasoline Taxes in British Columbia, 2000-2010



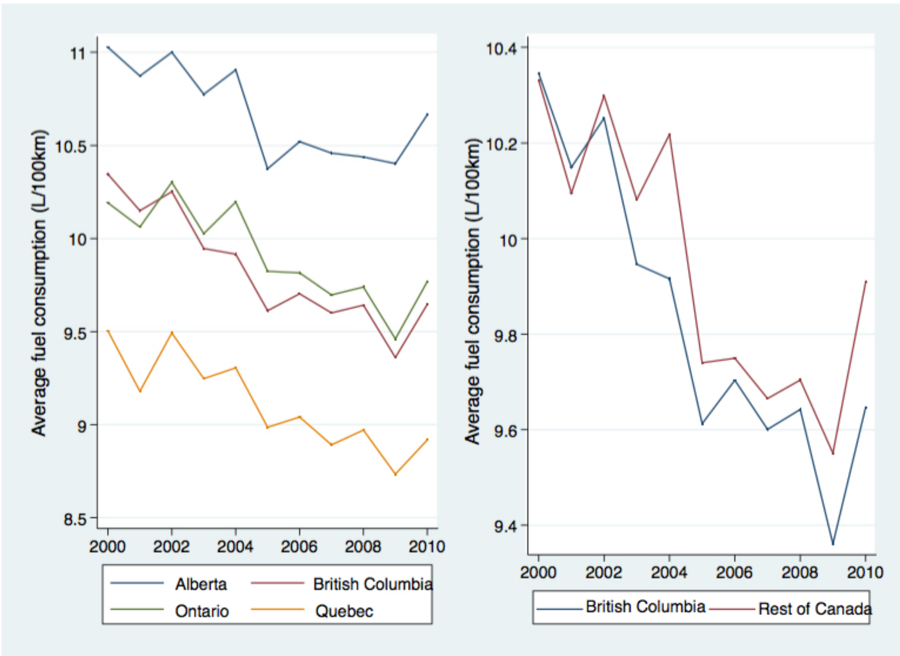
This figure is the breakdown of all provincial taxes: carbon, excise, and local transit taxes on gasoline as well as the percent of these taxes from average provincial gasoline prices in British Columbia from 2000 to 2010.

3.7 Figures

Figure 3.2: Average Retail Gasoline Price (cents per liter), 2000-2010

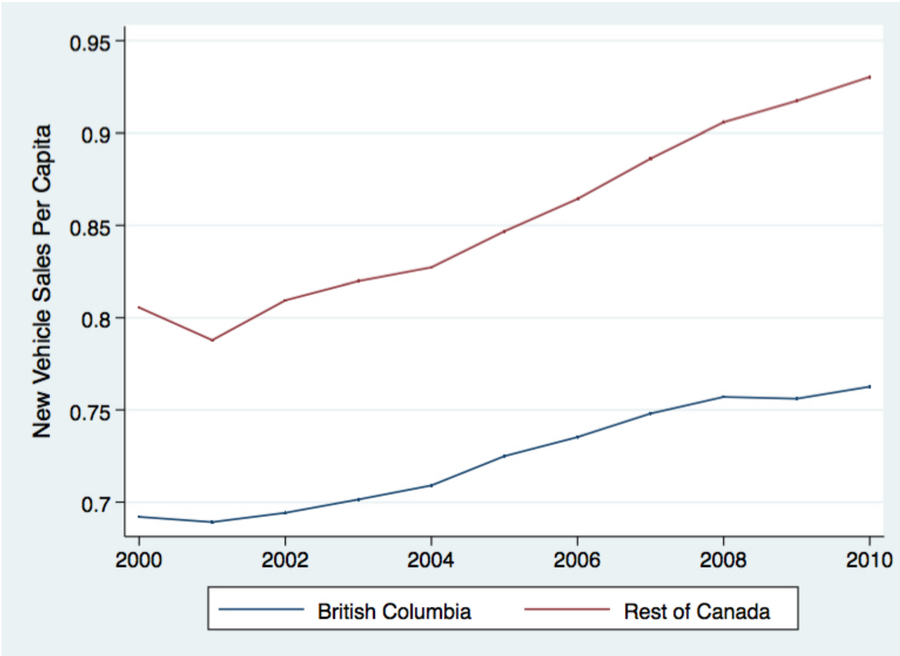
Left panel shows real average retail gasoline price in British Columbia versus Rest of Canada from 2000 to 2010. Right panel shows real average retail gasoline price across four selected provinces from 2000 to 2010.

Figure 3.3: Sales-weighted Fuel Consumption for all Vehicles across Canadian Provinces, 2000-2010



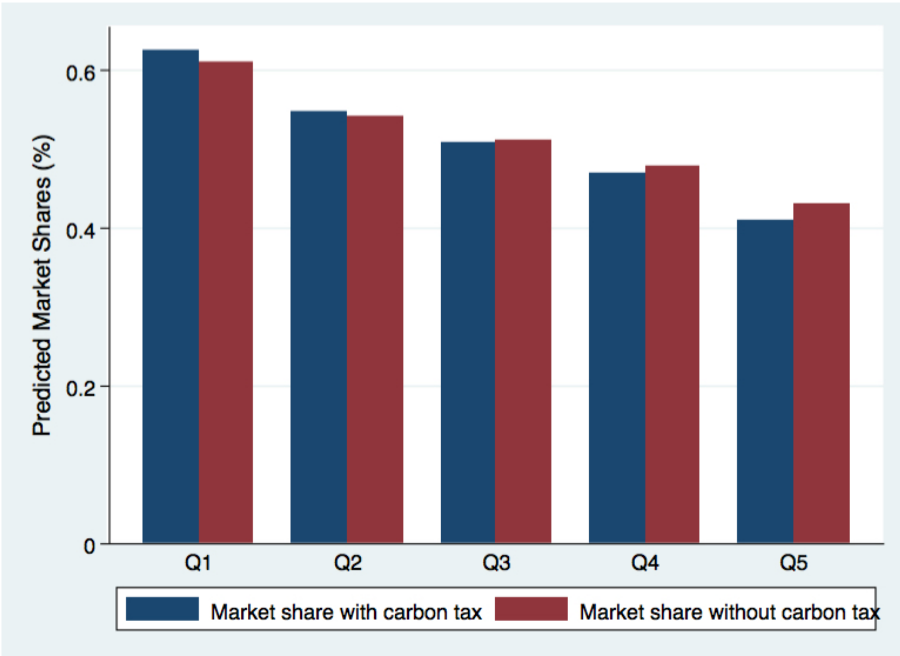
Left panel shows the trends in sales-weighted fuel consumption rating (in L/100 km) of all vehicles sold in British Columbia versus "Rest of Canada" from 2000 to 2010. Right panel shows the same trends across four selected provinces: Alberta, British Columbia, Ontario, and Quebec, during the same period.

Figure 3.4: Vehicles Per Capita, 2000-2010



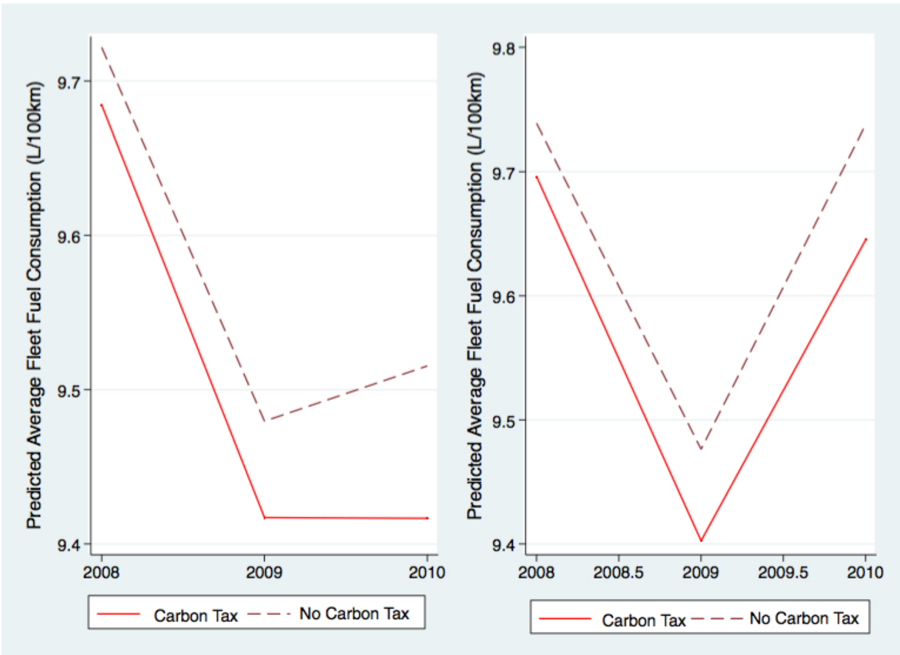
This figure illustrates the number of new vehicle sales per capita in British Columbia versus "Rest of Canada". "Rest of Canada" corresponds to all provinces and territories in Canada excluding British Columbia.

Figure 3.5: Counter-factual Market Shares by Fuel Efficiency Quantile in the Presence and Absence of BC Carbon Tax, 2008-2010



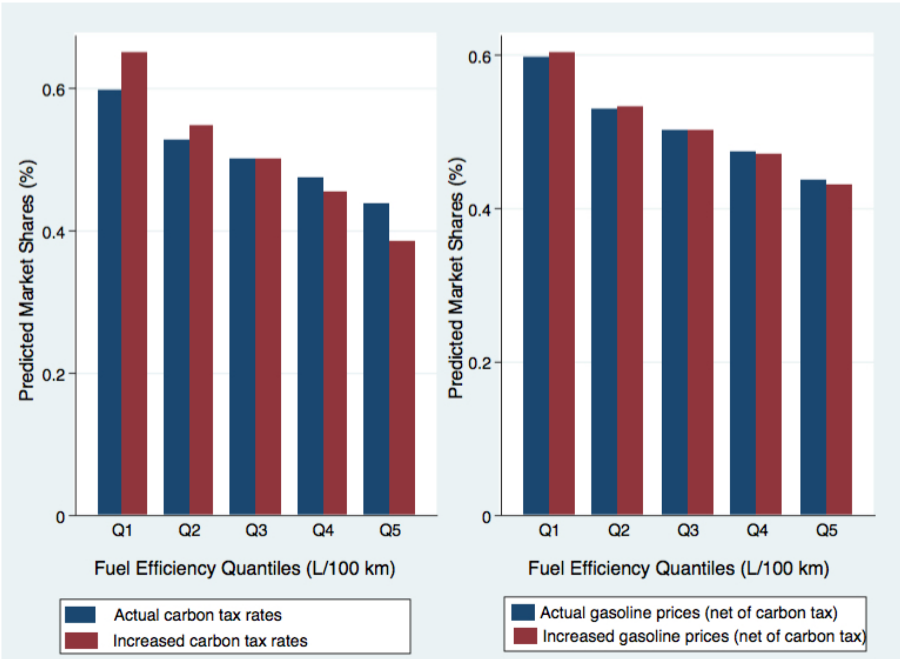
The figure illustrates the counter-factual market shares by fuel efficiency quantile in the presence versus the absence of the carbon tax policy in British Columbia from 2008 to 2010. Fuel efficiency quantiles are: Q1=[3.5-8.5 L/100 km], Q2=[8.5-9.5 L/100 km], Q3=[9.5-10.5 L/100 km], Q4=[10.5-12 L/100 km], and Q5=[12-22.7 L/100 km]. The counter-factual simulations in the figure correspond the regression results reported in column (1) in Table 3.6.

Figure 3.6: Predicted Average Fleet Fuel Efficiency in the Presence and Absence of BC Carbon Tax, 2008-2010



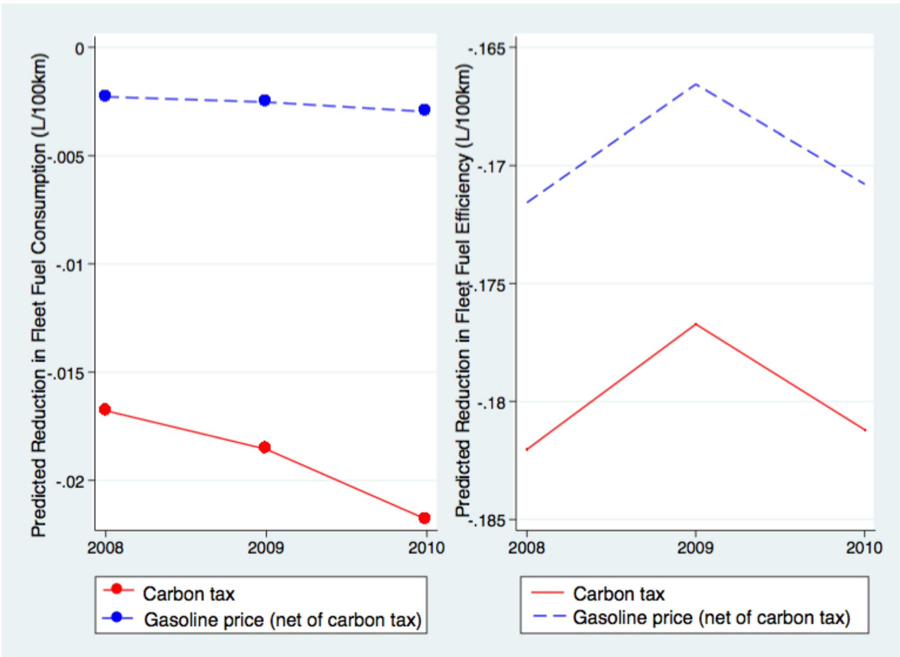
The figure plots the average fuel consumption rating (in L/100 km) in the presence and absence of the carbon tax policy for each year in British Columbia after 2008. The left figure is based on the counter-factual results of the model-level market shares reported in Table 3.6 column (1) and the right figure is based on the counter-factual results of the aggregate FSA-level regression reported in Table 3.4 column (4).

Figure 3.7: Counter-factural Market Shares by Fuel Efficiency Quantile Due to Actual versus Increased Rates of Carbon Tax and Gasoline Price in BC, 2008-2010



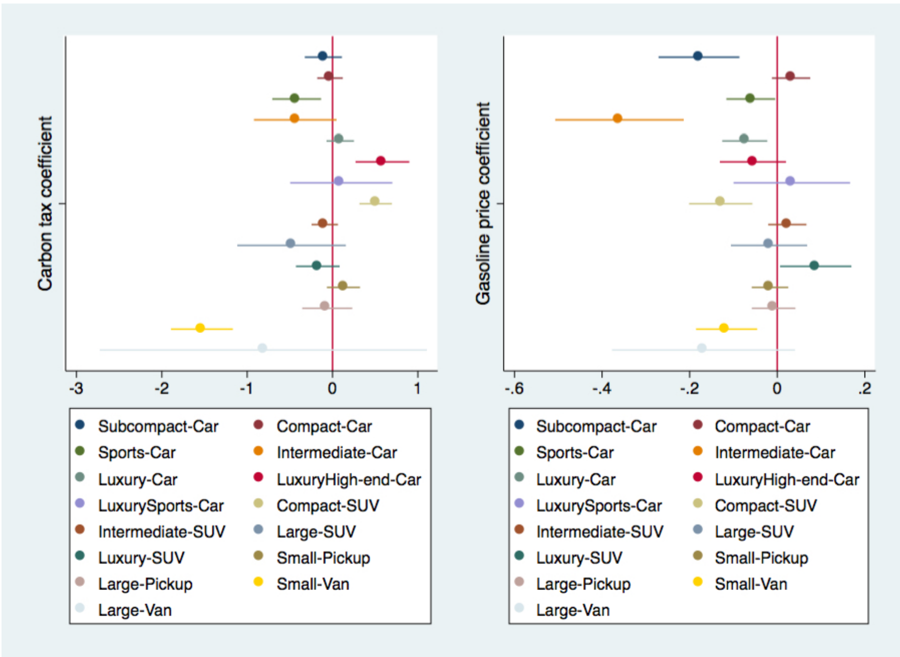
Left figure plots the predicted market shares due to the actual rates of the carbon tax versus the increased rates by a \$0.01/L in British Columbia from 2008 to 2010. Right figure plots the predicted market shares due to the current levels of gasoline price versus the increased rates by a \$0.01/L in British Columbia from 2008 to 2010. Fuel efficiency quantiles are: Q1=[3.5-8.5 L/100 km], Q2=[8.5-9.5 L/100 km], Q3=[9.5-10.5 L/100 km], Q4=[10.5-12 L/100 km], and Q5=[12-22.7 L/100 km]. The counter-factual simulations in the figure correspond to the regression results reported in Table 3.6 column (1).

Figure 3.8: Predicted Reductions in Fleet Fuel Efficiency Due to Increases in BC Carbon Tax versus Gasoline Price, 2008-2010



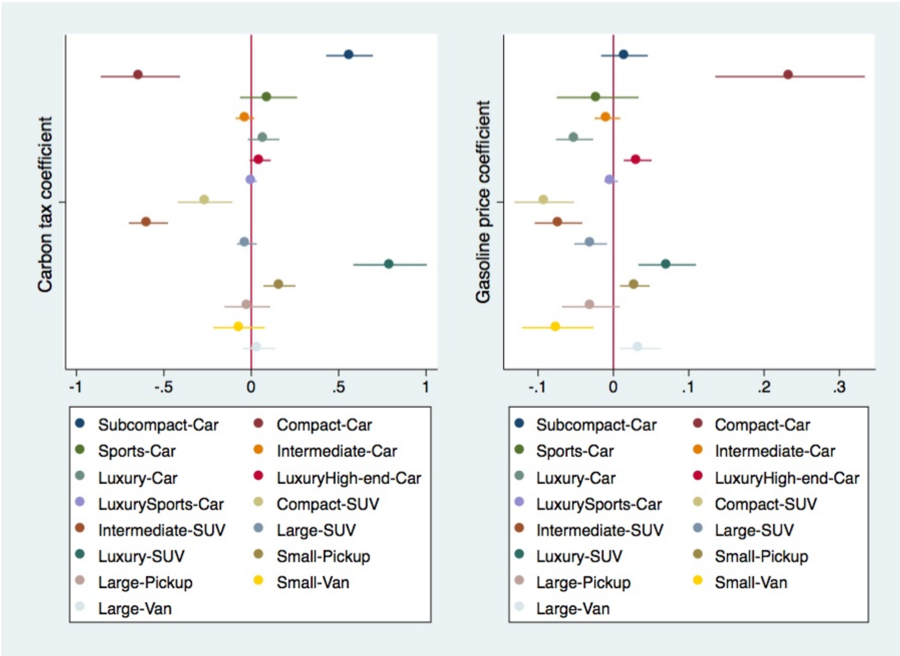
This figure corresponds to the predicted average reductions (or improvements) in the fleet fuel consumption rating (in L/100 km) due to a \$0.01/L increase in the carbon tax versus a \$0.01/L increase in the carbon tax-exclusive gasoline price. The figure on the left plots these changes using the counter-factual results of the regression on individual market shares reported in Table 3.6 column (1) and the figure on the right uses the counter-factual results of the aggregate regression reported in Table 3.4 column (4).

Figure 3.9: Results of Aggregate Estimations on Sales-weighted Fuel Consumption by Segment



Left panel shows the coefficient estimates for carbon tax from the results of aggregate regressions on sales-weighted fuel consumption by segment. Right panel shows the coefficient estimates for gasoline price from the aggregate regressions on sales-weighted fuel consumption by segment.

Figure 3.10: Results of Aggregate Estimations on Market Shares by Segment



Left panel shows the coefficient estimates for carbon tax from the results of aggregate regressions on market shares by segment. Right panel shows the coefficient estimates for gasoline price from the aggregate regressions on market shares by segment.

Table 3.1: Literature Review Summary

Study	**Country & Period**	**Elasticity wrt. gasoline taxes**	**Elasticity wrt. tax excl. gasoline price**
Li et al.(2014)	1966-2008, US	-0.2 to -0.4	-0.08 to -0.13
Antweiler and Gulati (2016)	2000-2014, Canada	-0.13 to -0.79	-0.09 to -0.26
Rivers and Schaufele (2017a)	2000-2010, Canada	-0.33 (excise and transit taxes)	-0.027

Source: Author

3.8 Tables

Table 3.2: Average Fuel Economy with the observations percentage share for each segment 2000-2010

Segment	Average Fuel Economy	Observations percentage share for each group
Subcompact	5.9	3.41
Compact	6.4	9.79
Sports	7.3	4.25
Intermediate	7.5	14.80
Luxury	7.6	7.93
Luxury High	8.4	7.51
Luxury Sport	9.0	11.15
Compact SUV	9.0	4.92
Intermediate SUV	9.1	4.42
Large SUV	9.2	3.98
Luxury SUV	9.8	7.37
Small Pickup	10.8	5.70
Large Pickup	11.3	9.43
Small Van	12.0	2.81
Large Van	12.2	2.54

Source: Author

Table 3.3: Summary Statistics for Province-Years and FSA-Years

Variable	**N**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Province-Year					
Number of Vehicle Registrations	110	98,844.2	124,849.2	1,869	435,507
Carbon Tax-exclusive Gasoline Price (¢/L)	110	91.5	16	63.3	123.6
Carbon Tax ($/L)	3	0.033	0.001	0.022	0.044
Sales-weighted Fuel Consumption (L/100 km)	110	9.9	0.54	8.7	11.02
Median Income ($1000)	110	24.7	3.9	15.8	35.7
Unemployment Rate	110	8.14	3.27	3.5	16.7
Median Age	110	38.2	1.52	35	41
Percent Female	110	51.6	0 .49	50	52
Percent Married Individuals	110	40.49	3.38	30	45
Percent College Graduates	110	0.002	0.0009	0.0004	0.005
FSA-Year					
Number of Vehicle Registrations	7,071	849.03	1,106.5	1	21,411
Carbon Tax-exclusive Gasoline Price	7,071	87.92	15.96	62.1	132.1
Carbon Tax	267	0.032	0.009	0.022	0.044
Sales-weighted Fuel Consumption (L/100 km)	7,071	9.70	0.69	7.60	13.94
Median Income ($1000)	7,071	28.2	7.8	5.8	67.2
Median Age	7,071	37.9	3.6	24.0	64.0
Percent Female	7,071	52.2	2.1	27	68.8
Percent Married Individuals	7,071	38.9	8	0	67
Vehicle-FSA-Year					
Gasoline cost ($/100 km)	1,394,250	8.27	2.11	21.71	20.06
Carbon tax cost ($/100 km)	50,928	0.31	0.12	0.09	0.87
Combined Fuel Efficiency (L/100 km)	1,394,250	10.17	2.36	3.5	22.7

Table 3.4: Provincial-level Estimations on Aggregate Fuel Economy of New Vehicle Sales

	(1)	(2)	(3)	(4)
Carbon tax ($/L)	-0.12	-0.11		
	[0.21]	[0.21]		
Gasoline price ($/L)	-0.13**	-0.12***		
	[0.05]	[0.01]		
Log(1 + carbon tax ratio)			-0.08	-0.03
			[0.24]	[0.26]
Log(gasoline price)			-0.12**	-0.09+
			[0.04]	[0.05]
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Other controls		Yes		Yes
N	110	110	110	110
R^2	0.95	0.97	0.95	0.96

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In all models, the dependent variable is the log sales-weighted fuel consumption (in L/100 km) in each province and year. All models control for province and year fixed effects. Columns (2) and (4) include other provincial controls, including log per capita income, log unemployment rate, log average age, log percent females, as well as married individuals, in the population, log proportion of individuals living in apartments, in addition to the fixed effects. Across columns, linear regressions with fixed effects are used and standard errors are clustered by FSA. Across columns, I use linear regressions with fixed effects and bootstrap standard errors using wild cluster bootstrapped t-statistics (WCBSTs).

Table 3.5: FSA-level Estimations on Aggregate Fuel Economy of New Vehicle Sales

	(1)	(2)	(3)	(4)	(5)
Carbon tax ($/L)	-0.19*	-0.18+			
	[0.09]	[0.1]			
Gasoline price ($/L)	-0.18*	-0.19+			
	[0.03]	[0.002]			
Log(1 + carbon tax ratio)			-0.25**	-0.26**	-0.22**
			[0.09]	[0.09]	[0.07]
Log(gasoline price)			-0.15***	-0.15***	-0.1***
			[0.03]	[0.03]	[0.02]
Year FE	Yes	Yes	Yes	Yes	
FSA FE	Yes	Yes	Yes	Yes	Yes
Province-year FE					Yes
Other controls		Yes		Yes	Yes
N	7093	7093	7093	7093	7093
R^2	0.90	0.90	0.90	0.90	0.9

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In all models, the dependent variable is the log sales-weighted fuel consumption (in L/100 km) in each FSA and year. In columns (1) and (2), carbon tax and gasoline price (net of carbon tax) are used as levels, while in columns (3), (4), and (5), they are used as logs. As such, columns (3), (4), and (5) report the elasticity estimates with respect to the carbon tax and gasoline price. I include FSA and year fixed effects across all columns. Columns (1) and (3) do not include additional FSA-level controls as opposed to the other columns. Finally, in column (5), I raise the resolution of fixed effects by including province-by-year fixed effects (in addition to the FSA fixed effects). Across all models, linear regressions are used and standard errors are clustered by FSA.

Table 3.6: Regressions on Model-level Market Shares

	(1)	(2)
Carbon tax cost ($/100 km)	-0.34***	
	[0.0387]	
Gasoline tax cost ($/100 km)	-0.04***	
	[0.00285]	
Carbon tax cost ($/100 km), Quantile-1		-0.57***
		[0.08]
Carbon tax cost ($/100 km), Quantile-2		-0.74***
		[0.05]
Carbon tax cost ($/100 km), Quantile-3		-0.13*
		[0.05]
Carbon tax cost ($/100 km), Quantile-4		-0.25***
		[0.05]
Carbon tax cost ($/100 km), Quantile-5		-0.24***
		[0.05]
Gasoline cost ($/100 km), Quantile-1		0.01*
		[0.006]
Gasoline cost ($/100 km), Quantile-2		-0.06***
		[0.005]
Gasoline cost ($/100 km), Quantile-3		-0.01***
		[0.005]
Gasoline cost ($/100 km), Quantile-4		-0.03***
		[0.005]
Gasoline cost ($/100 km), Quantile-5		-0.000*
		[0.006]
Model-Year FE	Yes	Yes
Model-FSA FE	Yes	Yes
N	1,394,250	1,394,250
R^2	0.58	0.58

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of estimations on vehicle market shares by individual model and fuel efficiency quantile. In both models, the dependent variable is market share of each vehicle model in a given market (FSA-year) and the independent variables are carbon tax cost ($/100 km) and tax-exclusive gasoline cost ($/100 km) of driving each vehicle model. Column (1) is the regression on individual market shares in the vehicle market, while column (2) allows the effect of tax and gasoline costs on market shares to vary by 5 fuel efficiency quantiles. Fuel efficiency quantiles are: Quantile-1=[3.5-8], Quantile-2=[8-9.5], Quantile-3=[9.5-10.5], Quantile-4=[10.5-11.5], and Quantile-5=[11.5-22.7]. Across all models, model-FSA and model-year fixed effects are included and standard errors are clustered by FSA-class.

Table 3.7: Aggregate Regressions on Asymmetric and Lagged Responses to Carbon Tax

	(1)	(2)	(3)	(4)
Log(1 + carbon tax ratio)	-0.23*	-0.24*	-0.37*	-0.47**
	[0.11]	[0.09]	[0.14]	[0.14]
Log(gasoline price)			-0.13***	-0.13***
			[0.03]	[0.03]
Log(gasoline price), 2000-2002	-0.11***			
	[0.03]			
Log(gasoline price), 2003-2008	-0.167***			
	[0.03]			
Log(gasoline price), 2008-2010	-0.169***			
	[0.03]			
Log(gasoline price), price increase		-0.157***		
		[0.03]		
Log(gasoline price), price decrease		-0.145***		
		[0.03]		
1-year lag Log(1 + carbon tax ratio)			0.26	0.53
			[0.17]	[0.34]
2-year lag Log(1 + carbon tax ratio)				-0.30
				[0.27]
1-year lag Log(gasoline price)			-0.01	
			[0.01]	
2-year lag Log(gasoline price)				0.01
				[0.02]
FSA FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Other FSA-level controls	Yes	Yes	Yes	Yes
N	7093	7093	6413	5755
R^2	0.90	0.90	0.90	0.90

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of the asymmetric and lagged responses to the carbon tax and gasoline price (net of the carbon tax) on overall fuel economy in each FSA and year are presented. The dependent variable is log sales-weighted fuel consumption rating in each FSA and year. Column (1) compares the effects of the tax-exclusive gasoline price interacted with the indicated time periods with the carbon tax effects. Column (2) includes interactions of gasoline price with indicators for rising versus falling gasoline prices. Columns (3) includes 1-year lagged responses to the carbon tax and tax-exclusive gasoline price, while column (4) includes 1-year and 2-year lagged responses. Across all models, FSA and year fixed effects are included and standard errors are clustered by FSA.

Table 3.8: Elasticity Estimates with Respect to Various Provincial Taxes

	(1)	(2)	(3)	(4)
Log(gasoline price incl. all taxes)	-0.15***			
	[0.03]			
Log(gasoline price no carbon tax)		-0.14***		
		[0.03]		
Log(gasoline price no excise tax)			-0.15***	
			[0.02]	
Log(gasoline price no excise & transit taxes)				-0.15***
				[0.02]
Log(1 + carbon tax ratio)		-0.26**	-0.26**	-0.26**
		[0.09]	[0.09]	[0.09]
Log(1 + excise tax ratio)			-0.20**	
			[0.06]	
Log(1 + (excise+transit) ratio)				-0.23***
				[0.06]
FSA FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Other FSA-level controls	Yes	Yes	Yes	Yes
N	7093	7093	7093	7093
R^2	0.90	0.90	0.90	0.90

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In all models, the dependent variable is the log sales-weighted fuel consumption (in L/100 km) in each FSA and year. Column (1) includes log of gasoline price including all taxes and therefore estimates the elasticity of fleet fuel economy with respect to gasoline price. Column (2) reports the elasticity estimates for the carbon tax versus the carbon tax-exclusive gasoline price. Column (3) estimates this elasticity with respect to the excise tax and the carbon tax.Finally, in column (4), I report the elasticity with respect to the excise plus transit taxes versus the elasticity to the carbon tax.

3.9 Appendix

Table 3.9: Provincial-level Regressions on Aggregate New Vehicle Sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Carbon tax ($/L)	-4.58***	-2.15**	-1.01***	-0.97***			
	[0.31]	[0.66]	[0.05]	[0.06]			
Gasoline price ($/L)	0.29***	0.07	-0.03	-0.027			
	[0.01]	[0.06]	[0.03]	[0.02]			
Log(1 + carbon tax ratio)					-1.09***	-5.3**	14.9
					[0.06]	[1.82]	[43.7]
Log(gasoline price)					-0.027	-0.52	-0.47
					[0.01]	[0.48]	[0.59]
Year FE			Yes	Yes	Yes	Yes	
Province FE			Yes	Yes	Yes		
Provincial controls		Yes		Yes	Yes		
Province-year FE							Yes
FSA FE						Yes	Yes
FSA-level controls							Yes
N	110	110	110	110	110	7093	7093
R^2	0.99	0.99	0.80	0.46	0.99	0.61	0.64

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the provincial and FSA-level results of estimations on aggregate new vehicle sales. Across all models, the dependent variable is the log of the aggregate sales per capita and the independent variables are carbon tax, average retail gasoline price including all taxes except the carbon tax, and other provincial controls. Additional controls include log real GDP, log real per capita income, log unemployment rate, log median age, log percent female and married individuals in the population, log percent college graduates. Across columns, I include different combinations of fixed effects and controls. Column (1) does not include any fixed effects or additional controls. Column (2) only adds additional provincial controls but does not include province and year fixed effects. Column (3) includes province and year fixed effects but does not include additional controls. Columns (4) and (5) report the preferred provincial-level results including additional provincial controls as well as province and year fixed effects. Column (4) uses the carbon tax and gasoline price (net of the carbon tax) in levels (in $/L), while column (5) uses them in logs. Columns (6) and (7) report the results of the preferred FSA-level estimations. Column (6) includes FSA and year fixed effects and FSA-level controls. Column (5), as the most comprehensive specification in this table, includes FSA and province-year fixed effects as well as additional FSA-level controls. I apply linear regressions across all columns. Standard errors are bootstrapped (using wild cluster bootstrapped t-statistics (WCBSTs)) in the provincial-level specification, and clustered by FSA in the FSA-level specifications.

Table 3.10: Regressions on Fuel Consumption of Vehicle Segments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Carbon tax ($/L)	-0.10	-0.02	-0.42^{**}	-0.43^{+}	0.09	0.58^{***}	0.1	0.5^{***}	-0.09	-0.48	-0.17	0.12	-0.06	-1.53^{***}	-0.81
	[0.11]	[0.07]	[0.14]	[0.24]	[0.08]	[0.16]	[0.3]	[0.09]	[0.07]	[0.32]	[0.13]	[0.09]	[0.14]	[0.18]	[0.97]
Gasoline price ($/L)	-0.17^{***}	0.03	-0.06^{*}	-0.36^{***}	-0.07^{**}	-0.05	0.03	-0.12^{***}	0.02	-0.01	0.08^{*}	-0.01	-0.008	-0.11^{**}	-0.16
	[0.04]	[0.02]	[0.02]	[0.07]	[0.02]	[0.03]	[0.06]	[0.03]	[0.02]	[0.04]	[0.04]	[0.02]	[0.02]	[0.03]	[0.1]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6957	7066	7065	6853	6767	6410	4902	7034	7012	5367	6515	6702	6983	7049	3096
R^2	0.31	0.60	0.63	0.40	0.6	0.35	0.24	0.73	0.85	0.6	0.55	0.36	0.52	0.72	0.53

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of estimations on fuel consumption of vehicle segments in each FSA and year are presented. Across all models, log of sales-weighted fuel efficiency of each segment (in L/100 km) is estimated separately in response to the carbon tax and gasoline price (both in $/L) and other controls. Additional controls include log median income, log median age, log percent female, and log percent married individuals in the population. 15 segments are included: Subcompact-Car, Compact-Car, Sports-Car, Intermediate-Car, Luxury-Car, Luxury high end-Car, Luxury sports-Car, Compact-SUV, Intermediate-SUV, Large SUV, Luxury-SUV, Small-Pickup, Large-Pickup, Small-Van, and Large-Van. Across all models, FSA and year fixed effects are included and standard errors are clustered by FSA.

Table 3.11: Regressions on Market Share of Vehicle Segments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Carbon tax ($/L)	0.56***	-0.63***	0.09	-0.03	0.07	0.05+	0.003	-0.26**	-0.58***	-0.02	0.79***	0.16***	-0.02	-0.06	0.04
	[0.06]	[0.11]	[0.08]	[0.02]	[0.04]	[0.03]	[0.01]	[0.07]	[0.05]	[0.02]	[0.1]	[0.04]	[0.06]	[0.07]	[0.04]
Gasoline price ($/L)	0.01	0.23***	-0.02	-0.007	-0.05***	0.03***	-0.002	-0.09***	-0.07***	-0.03**	0.07***	0.02**	-0.02	-0.07**	0.03*
	[0.01]	[0.05]	[0.02]	[0.008]	[0.01]	[0.009]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6953	7063	7061	6853	6767	6409 4902	7032	7010	5367	6513	6702	6982	7049	3095	
R^2	0.80	0.83	0.75	0.46	0.84	0.87	0.68	0.75	0.64	0.72	0.81	0.68	0.89	0.77	0.49

Standard errors in brackets

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of estimations on market share of vehicle segments in each FSA and year are presented. Across all models, market share of each segment is estimated separately in response to the carbon tax and gasoline price and other controls. Additional controls include log median income, log median age, log percent female, and log percent married individuals in the population. 15 segments are included: Subcompact-Car, Compact-Car, Sports-Car, Intermediate-Car, Luxury-Car, Luxury high end-Car, Luxury sports-Car, Compact-SUV, Intermediate-SUV, Large SUV, Luxury-SUV, Small-Pickup, Large-Pickup, Small-Van, and Large-Van. Across all models, FSA and year fixed effects are included and standard errors are clustered by FSA.

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