Electric Vehicle Subsidies: Cost-Effectiveness and Emission Reductions

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Abstract

This paper studies the impact of the Roulez Vert program, which subsidized new purchases of electric vehicles in the province of Quebec, Canada. I study the impact of the program on sales, firms' pricing behavior, and charging station deployment, and estimate the marginal cost of avoiding carbon emissions using subsidies. To evaluate the impact of subsidies, I rely on a structural model in which demand follows a nested logit specification and supply is determined by multi-product firms competing on prices. I augment the model to incorporate charging station deployment. Specifically, I allow for county-level governments to choose where and how many stations to install in their region to provide charging capacity to electric vehicle owners. I find that the program explains 45% of electric vehicle sales and 26% of charging stations installed between 2012 and 2018. Taking into account gains to consumer surplus, I estimate the marginal abatement cost to be \$340 per ton of CO_2, well above conventional estimates of the social cost of carbon emissions. Part of the reason behind this high estimated cost is that more than half of the subsidies went to infra-marginal consumers and would have purchased an electric vehicle whether or not subsidies are available. Additionally, my results suggest that only 43% of the additional hybrid and electric vehicles sales generated by the program are replacing fuel vehicle sales which limits carbon emission savings. JEL Codes: L, L1, L91, Q50, Q58.

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1 Introduction

Electric vehicles (EV) constitute one of the most promising innovations for lowering carbon emissions from the transportation sector wherever clean energy production is available. Several barriers exist that prevent the widespread adoption of this technology. The high initial purchasing cost or the low availability of charging outlets may lead potential buyers to select internal combustion engines over electric ones even if they place a high value on reducing their carbon footprint, factor in future fuel cost savings, or the lower maintenance costs associated with driving an EV. In turn, if demand for these vehicles is low, there is little incentive for charging station operators to expand local networks or for car manufacturers to develop better and cheaper products, slowing down the transition to electric.

This paper focuses on the introduction of the electric car in the province of Quebec, Canada, and on the role of financial incentives in speeding up the adoption of this new technology. Specifically, I investigate if Quebec's Roulez Vert program, which subsidizes electric vehicle purchases by up to \$8,000, is a cost-effective way of achieving lower total carbon emissions from new car sales. I explore the effect the program had on the deployment of charging stations, firms' pricing decisions, consumer surplus, profits, and welfare. Whether or not subsidizing EV is cost-effective depends crucially on several factors: how fuel-efficient are the vehicles that are being replaced by EV, to what extent car manufacturers can manipulate prices to capture part of the subsidy as profits, and on the magnitude of the network effects, since the deployment of charging stations depends on EV adoption and vice versa.

As a preliminary step, I correlate sales of EV to charging station deployment and vice versa to confirm the presence and the magnitude of network effects in this market. I rely on an instrumental variable approach to break the simultaneity and to control for shocks that could affect both sides of the market. My results indicate that expanding the network by 10% leads to 5.5% additional sales of EV and that increasing the total fleet of EV by 10% leads to 6.3% more charging station installations. This provides evidence of a positive feedback effect that amplifies the impact of policies that promote EV adoption. These findings have repercussions for estimating the cost-effectiveness of rebate programs as ignoring these network effects would result in biased estimates of core parameters of the model (for example, elasticities), an underestimation of the environmental gains, and an overestimation of the cost of reducing emissions. As a robustness check, I perform the same analysis using fuel and hybrid vehicles sold instead of electric and find no evidence of a link with stations deployment.

Building on these results, I propose a structural model to evaluate the efficiency of subsidies targeted at buyers of an EV. My approach allows consumers, firms, and station providers to interact with the policy under different counterfactual environments. I model demand for cars following the nested logit specification as in Berry (1994). Specifically, the demand model allows for preferences for electric vehicles to depend not only on car characteristics and pricing, but also on the number of charging stations available locally (Springel, 2017; S. Li et al., 2017; Pavan et al., 2015), and the driving range of each EV (J. Li, 2016). On the supply side, I assume prices to be the outcome of a Bertrand-Nash equilibrium between multi-product firms (Berry, Levinsohn, and Pakes, 1995; Petrin, 2002). I derive a new model for station entry in the spirit of Springel (2017) and Berry and Reiss (2007) to match the specific setup in Quebec, where regional-level governments choose both the quantity and the location of new stations to maximize social benefit in their region. My specification of the entry model improves on currently available methods in that it allows for very flexible patterns for the elasticity of supply of stations. To fix ideas, the model allows for the elasticity of supply to vary freely with the state of the each market, producing more realistic and varied supply curves across regions.[1]

I rely on a structural approach for several reasons. First, a direct estimation of the effect of the policy on prices or quantities cannot separately identify demand and supply responses from each other or from network effects. Varying the policy environment entails a re-optimization from all agents, which includes a reallocation of charging station resources. It is unlikely that estimates from a reduced form analysis be still valid once we move to a new equilibrium unless one is ready to make strong assumptions about the causal effect of the policy concerning the outcomes of interest.

[1] A fixed elasticity of supply imposes strict restrictions on the underlying supply curve. Under my specification, more flexible supply curves can be estimated. In particular, the elasticity of supply could be increasing or decreasing, and converge or not towards a fixed elasticity.

Second, several outcomes relevant for this analysis, for example avoided carbon emissions, can be expressed readily as structural parameters of the model. Finally, a structural approach is necessary to disentangle demand, supply, and network responses to the policy environment and from each other.

I use the structural model to study what would have happened if the Roulez Vert program was never implemented. I estimate that reducing carbon emissions using the current rebate structure to have an average cost of $95 and a marginal cost of $340 per metric ton of CO_2, taking into account changes to both total spending on the program and consumer surplus.[2] Furthermore, I find that the program explains 45% of the 41,025 electric and plug-in hybrids sales, 1.8% of the 49,800 hybrids sales, and 26.2% of the 1,920 charging stations installations between 2012 and 2018. In assessing the successfulness of the program, it is critical to consider the composition and fuel efficiency of the vehicles that are being replaced by EVs. Avoided emissions should be larger if more SUVs are being replaced than compacts or subcompacts which are more fuel-efficient. My results suggest that 19.2% of the additional electric, plug-in hybrid and hybrid registrations are replacing relatively fuel-efficient vehicles, and 23.7% are replacing vehicles with poor fuel efficiency. Part of this result follows from the fact that several large/luxury car buyers are willing to substitute towards buying a Tesla when financial incentives are available. The remaining 57.1% can be explained by substitution away from the outside option: consumers who had no car and bought one, purchased a second car, or advanced their purchasing decision to take advantage of the rebate. This sizeable market expansion contributes to reducing the impact of the policy as these additional EV do not replace internal combustion engine sales and do not generate a reduction in the stock of carbon emission. These findings contribute to explaining the large estimated marginal abatement cost. On one hand, 47% of of battery electric, 60.8% of plug-in hybrid and 98.2% of hybrid buyers are infra-marginal consumers and would have picked the same alternative without incentives. Of the marginal consumers that are influenced by the program, 57.1% are substituting away from the outside option, generating no emission reduction, and 19.2% are substituting away from relatively fuel efficient vehicles, raising questions about how accurately the program targets high emission

[2]The marginal cost is computed as the cost of reducing emissions by one metric ton following a marginal increase in the subsidy amount, evaluated at the current level of subsidy.

vehicle purchases, affecting it's ability to reduce emissions at a low cost.

The counterfactual analysis I conduct suggests that the policy had an asymmetric effect on firms' profits creating winners and losers. However, overall industry profits increased by $149.6 million due to the expansion in total sales between 2012 and 2018. Generally, firms that offered several electric or plug-in hybrid alternatives benefitted while firms that focussed on internal combustion engines experienced a decrease in profits. I estimate that firms did not significantly change their pricing decision in response to the program such that 98.1% of the value of the subsidy benefitted consumers. This result is in line with both Muehlegger and D. S. Rapson (2018) and Sallee (2011) who provide evidence from the United States car market. In particular, Sallee (2011) finds that local incentives benefitted consumers entirely in the case of the introduction of the Toyota Prius in the United States. He explains this surprising result with the fact that manipulating prices at precise times when the tax exemptions were either changed or phased out would be observed by consumers and could be damaging to Toyota's reputation, harming future sales of Prius.

I propose an alternative explanation to the observed passthrough. Similar to Springel (2017), my finding suggests EV are complements to each other rather than substitutes when taking network effects into account. In this context, the rebate program has a multiplicative effect on EV sales and lead to a sizeable market expansion. Firms do not find it optimal to increase their profit per unit by capturing the subsidy since they benefit more from the increased sales. Other works from Beresteanu and S. Li (2011) on the United States hybrid car market and Fershtman, Gandal, and Markovich (1999) on the Israeli car market find contrasting evidence of an incomplete passthrough. Analyzing the welfare implications of the program indicates that the gains in consumer and producer surpluses more than offset the cost of implementing this rebate scheme, leading to a net gain in welfare of $123.5 million.

This paper contributes to the literature on several fronts. First, I contribute to the growing literature that explores the effect of rebates on green car adoption. In their study of the French *Bonus/Malus* program, d'Haultfoeuille, Givord, and Boutin (2014) find that taxing fuel-inefficient vehicles and subsidizing fuel-efficient ones led to a decrease in average emissions, but an increase in total emissions. DeShazo, Sheldon, and Carson (2017) assess the relative performance of alternative rebate schemes to the California plug-in hybrid rebate program. Their findings suggest this policy led to 7% more sales of EVs and cost roughly 36,000$ (30,000 USD) for each additional sale. My paper is not the first to study the Quebec car market. Barla, Couture, and Samano (2016) study the short-run impact of a gasoline price increase on fleet composition and fuel efficiency and compare it to the effect of a feebate program that subsidized vehicles with high fuel economy. Closer to this project is the work of Springel (2017). She proposes a structural model of demand for cars and supply of charging stations to study the non-neutrality of subsidizing each side of the market, taking network effects into account. In her study of the Norway electric car market, she finds that every dollar spent towards subsidizing stations led to 2.16 times more sales than subsidizing car purchases directly. She demonstrates that charging station subsidies exhibit decreasing returns, such that subsidizing cars becomes more cost-effective once the network is large enough. Pavan et al. (2015) find a similar result in their study of the Italian car market: subsidizing the installation of new alternative fuel pumps generates more sales per dollar spent than subsidizing new car purchases.

I contribute to estimating the cost of reducing emissions from passenger cars through government policy. In a study of the United States EV market, Xing, Leard, and S. Li (2021) estimate that reducing emissions using subsidies costs between $581 and $662 (484–552 USD) per metric ton of CO_2. Their analysis differs from my current work in two regards: their structural model does not allow for a dependency between charging station deployment and sales of EV or for substitution away from the outside option. I find both factors to be important in evaluating the cost-effectiveness of subsidies. While network effects work towards making subsidies more effective, having a large share of buyers coming from the outside option can have a multiplicative effect on the cost of reducing emissions as these buyers would not have generated emissions in the first place. Other estimates range from $131–158 (109–132 USD) per ton of CO_2 (Huse and Lucinda, 2014 on the Swedish green car rebate), $212 (177 USD) per ton (Beresteanu and S. Li, 2011 on tax incentives for hybrids in the U.S.), and as high as $540 (450 USD) per ton (Knittel, 2009 on a hypothetical 'cash for clunker' program).

This paper fits in the wider literature that studies the effect of regulating the car market on environmental outcomes. Several works have focussed on other policy tools such as gas taxes (Grigolon, Reynaert, and Verboven, 2018; Allcott and Wozny, 2014), emission standards (Durrmeyer and Samano, 2016; Klier, Linn, et al., 2013; Reynaert, 2014), attribute-based regulation and taxation (Knittel, 2011; Ito and Sallee, 2018; Chaves, 2019), or comparing financial and non-monetary incentives (Jenn, Katalin Springel, and Gopal, 2018). Advances on estimating the environmental impacts of these policies include Durrmeyer et al. (2018) which studies the distributional impacts of the French rebate program, Holland et al. (2016) on air pollution patterns that occur upstream in the production process, Archsmith, Kendall, and D. Rapson (2015) and Muehlegger and D. S. Rapson (2020) on air pollution abatement.

Lastly, I contribute to the literature on estimating network effects and their role in the adoption of breakthrough innovations. Advances in this field touch a wide range of new products: green cars (Springel, 2017; Pavan et al., 2015; J. Li, 2016; S. Li et al., 2017), compact discs (Gandal, Kende, and Rob, 2000), video games (Corts and Lederman, 2009; Clements and Ohashi, 2005), software (Gandal, 1995), microcomputer chips (Gandal, Greenstein, and Salant, 1999), and personal digital assistants (Nair, Chintagunta, and Dubé, 2004). Similar to the works cited above, I find network effects to be important in explaining the adoption rate of this new technology.

The choice of Quebec as a relevant jurisdiction for studying these questions is justified for several reasons. First, the offered rebates are substantial, \$8,000 for new battery electric vehicles and \$4,000 for plug-in hybrids, and broadly known to be available since their introduction in March 2012, meaning that their effect on sales should be considerable. Second, applying for the rebate is made through the retailer and is applied directly to the transaction price.[3] Thus, everyone eligible for a rebate receives it, eliminating the possibility that self-selection or non-awareness of the program could corrupt my results. Finally and most importantly, Quebec's electricity production comes from over 99% renewable sources,[4] and the substantial electricity surpluses recorded every year would

[3] The only exception is Tesla, which does not operate any point of sale in the province. Tesla buyers instead need to mail in the paperwork to receive the subsidy.

[4] In 2018, hydroelectricity accounted for 95% of Quebec's electricity generation, with wind energy coming second at 4%. Other sources of electricity generation included natural gas for peak winter demand, diesel for power in remote communities, and biomass (Source: Hydro-Quebec, *Annual Report 2018*).

allow for a large-scale expansion of the fleet of EV without relying on non-renewable sources.[5] This is a fundamental consideration as air pollution upstream in the production process can mitigate, negate, or even reverse any gains from replacing fuel vehicles with electric alternatives (Holland et al., 2016). In this regard, my estimates of the marginal abatement cost of emissions can be seen as a lower bound when comparing to jurisdictions where clean energy is not readily available.

The rest of the paper is organized as follows. Section 2 provides background information on the Quebec electric vehicle market, the *Roulez Vert* program, and the data. Section 3 presents reduced form evidence that network effects are an important consideration in this setup. I describe a structural model of demand and supply for cars and the evolution of the charging stations network in section 4. Estimation and counterfactual results are relayed to section 5 and 6 respectively. Section 8 provides concluding remarks.

2 The Market for Electric Vehicles in Quebec

2.1 The *Roulez Vert* program

The transportation sector is the greatest contributor to greenhouse gas emissions in Quebec, accounting for 43% of all emissions.[6] As such, it has become a key target of environmental policy. The Roulez Vert program was enacted at the beginning of 2012 as part of a broader initiative to electrify all types of transportation in the province, including personal vehicles, public transports, and the transportation of goods. The program targets specifically personal vehicle sales, setting the ambitious goal of reaching 100,000 new EV registrations by the end of 2020. To achieve this, the government offers direct financial incentives targeting buyers of new or used battery electric, plug-in hybrid and hybrid vehicles, subsidizes the installation of home chargers (up to $600), and of charging capacity in multi-unit housing or at work locations (up to 50% of installation costs). This

[5] Energy production and purchases from Hydro-Quebec, the state-owned power utility, has surpassed consumption and exports by on average 15.89TWh per year between 2012 and 2018 (Source: Hydro-Quebec, *Annual Report 2012-2018*). Ignoring the effect on winter peak load, back of the envelope calculations suggests that replacing every electric vehicle sold in that period with battery electric vehicles would have increased the total demand for electricity by 10.93TWh per year by the end of 2018.

[6] Source: Quebec Ministry of Environment and Climate Change, *Inventory of Greenhouse Gas Emissions in Quebec 1990-2017*.

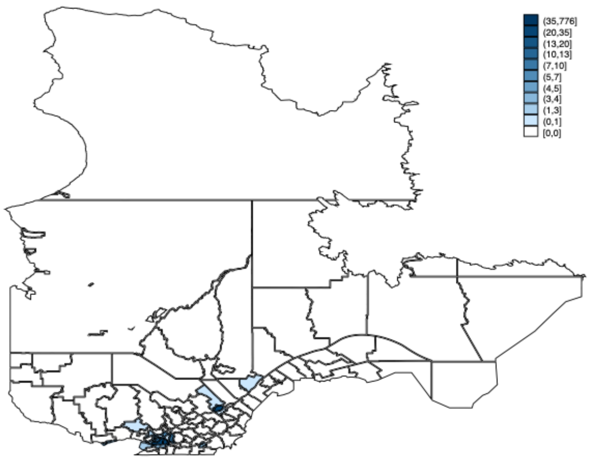
research focuses on one aspect of this policy, subsidies targeted at new car sales, described in Table 1. Although subsidizing used cars could be an important feature of the program, the data does not allow for tracking car ownership through time, such that transactions on the secondary market are not observable. In any case, the secondary market for such a new product is expected to represent a small fraction of transaction and spendings on the program. For example, 78% of EV in my sample are less than three years old by the end of the sample period and buyers would typically keep a new vehicle for longer than that as payments usually extend over four or five years. I also ignore the effect of subsidies toward installing home charging capacity due to data limitations. I do not observe home charger purchases nor do I observe which buyers applied and received a home charger subsidy. Also, there is no requirement that buyers purchase and install a home charger in the same year as they purchase an EV. Acquiring a home charger can cost between a few hundred to a few thousand dollars depending on charging capacity, the type of outlet, and the amount of electrician work required for the installation, but is not absolutely necessary to charge at home.

Table 1: Subsidy structure

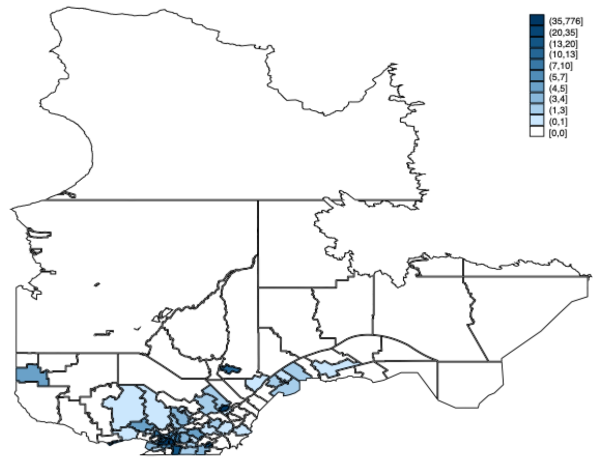
Engine type	less than $75,000	$75,000 to $125,000	more that $125,000
Battery electric	$8,000	$3,000	$0
Plug-in hybrid	$500, $4,000 or $8,000[a]	$0	$0
Hybrid	$500[b]	$500[b]	$500[b]

[a] Rebate on plug-in hybrids depend on battery capacity and power.
[b] Rebate on hybrids was $1,000 until 2013. Not all hybrids are eligible to the subsidy.

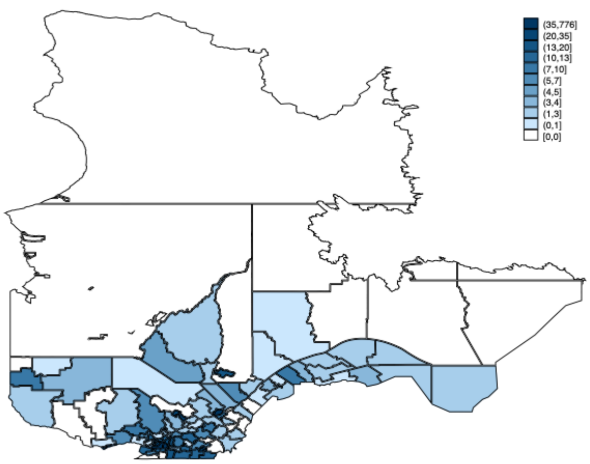
Aside from financial incentives to buyers, the government of Quebec participates in the development of a public charging station infrastructure in partnership with county-level governments. In March 2012, it launched the Circuit Électrique, a province-wide network of public charging stations to be operated by Hydro-Quebec, the state-owned grid operator. While the provincial government is responsible for installing fast-charging stations on highways (such that all regions are interconnected) and providing the software infrastructure necessary for operating the network (website, smartphone app, billing, interoperability with other networks), it relies on partnerships with county-level governments and sometimes shopping malls, restaurant chains or other businesses for the development of local networks within each region. Typically, the cost of installing a Level 2 charger (i.e. 240V)



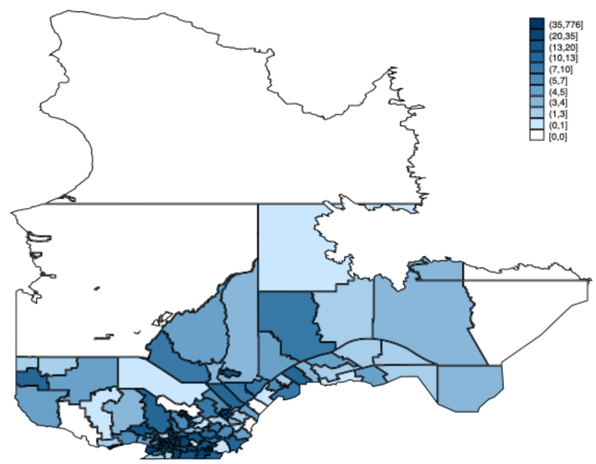
(a) Network in 2012



(b) Network in 2014



(c) Network in 2016



(d) Network in 2018

Figure 1: Evolution of charging station network over time

is around \$7,000 and is paid entirely by the partner.[7] Revenues from operating each local network also belong entirely to partners. Since the provincial government does not have property rights over potential charging station sites within each county, this means that partners control the final installation decision and reap all benefits from operating local networks which is crucial to my analysis. Figure 1 presents a map of the evolution of these local networks over time.

[7]For FastDC chargers (i.e. 400V), the provincial government is responsible for 50% of all costs up to the cost of the charger itself, while the partner is responsible for the remaining costs. A single charger cost over \$35,000 excluding installation and infrastructure costs. Revenues are shared based on investment ratios.

2.2 Data

To estimate the impact of subsidies on sales of electric vehicles, prices, and the development of a charging station infrastructure, I assemble a novel and rich dataset of all car registrations and public charging stations available in Quebec between 2012 and 2018. The data is aggregated at the regional county municipality level (RCM), Quebec's equivalent of metropolitan statistical areas (MSA) in the United States. Markets are defined as county-year combinations. I select this level of aggregation for two reasons. First, counties capture relatively well commuting areas for car owners: 68.3% of households' have their work location within the county of residence (74.7% if we exclude residents of Montreal and surrounding counties). Second, county-level governments are responsible both for the decision to install and the location of new stations for most of the public stations in my sample. The remaining stations are usually installed by workplaces, shopping malls, restaurant chains, or other venues that wish to attract customers that own an EV. In those cases, the installation and location decisions are taken at a more disaggregated level than counties. Even though county authorities do not decide on the exact location of all stations within the local network, I claim that they hold the final decision for how many stations are available. The reasoning behind this assumption is simple: county-level governments could forgo installing some stations if for example more private installations occur, meaning that they have the final say on the size of their local network. In total, my dataset contains 3.35 million individual cars registered in 89 counties over seven years. I observe a total of 34 car manufacturers producing 297 different models.

The data on car registrations is summarized in Table 2. I use publicly available data from the Société d'Assurance Automobile du Québec, Quebec's vehicle registration agency, to reconstruct all new vehicle registrations that occurred between 2012 and 2018. I supplement the car registration data with car characteristics taken from The Car Guide, which publish on their website comprehensive information on all makes and models available in the province. EV and traditional vehicles differ along three main axes. First, EV are on average more expansive than fuel vehicles even when taking into account government subsidies. Second, driving range is significantly shorter for EV. Consumers care about driving range because it decreases their dependence to the network for some

Table 2: Average characteristics, by engine type

VARIABLE	Fuel	Battery electric	Plug-in hybrid	Hybrid
Characteristics				
Retail price, in CAD	31,982	51,078	48,024	33,987
Rebate, in CAD	0	7,764	5,831	293
Power, in kW	152.4	132.6	123.0	99.4
Power-to-weight ratio, in W/kg	93.4	77.8	67.3	62.1
Length, in m	4.68	4.44	4.65	4.65
Width, in m	1.59	1.56	1.58	1.56
Height, in m	1.60	1.53	1.53	1.53
Weight, in 100kg	16.0	16.4	17.8	15.7
Autonomy, in km	727	272	752	1002
Fuel consumption, in L/100km	8.85	0	6.25	5.33
Electricity consumption, in kWh/100km	0	16.4	26.0	0
Cost of driving 100km	11.44	1.83	7.40	6.89
CO_2 emissions, in g/km	204.6	0	71.4	123.3
Transmission				
Manual	0.29	0	0	0
Automatic	0.71	0	0.84	1
Singlespeed	0	1	0.16	0
Fuel type				
Regular	0.87	0	0.68	0.93
Premium	0.12	0	0.32	0.07
Diesel	0.01	0	0	0
Market segment				
Subcompact	0.10	0.19	0	0
Compact	0.30	0.49	0.18	0.46
Midsize	0.04	0	0.07	0.21
Luxury	0.05	0.20	0.48	0.12
Sport	0.01	0	0	0
SUV	0.37	0.12	0.25	0.21
Minivan	0.04	0	0.02	0
Pick-up	0.09	0	0	0
Observations	3150880	17435	23597	49800

NOTE: All characteristics are weighted by sales. All dollars values are in 2018 CAD. 1 Kilowatt = 1.341 Horsepower.

Table 3: Driving range of battery electric vehicles, by model-year

Model	Driving range, in km						
	2012	2013	2014	2015	2016	2017	2018
BMW i3	-	-	160	160	160	200	200
Chevrolet Bolt EV	-	-	-	-	-	383	383
Chevrolet Spark	-	-	131	131	131	-	-
Ford Focus Electric	120	120	120	120	122	185	185
Hyundai IONIQ	-	-	-	-	-	175	200
Kia Soul EV	-	-	-	160	150	150	179
Mitsubishi iMiev	135	135	135	135	135	96	-
Nissan Leaf	160	160	160	160	133-172	133-172	133-172
Smart Fortwo	-	145	145	138	138	160	160
Tesla Model 3	-	-	-	-	-	-	499
Tesla Model S	260	250	370	345-460	370-435	466-572	417-539
Tesla Model X	-	-	-	-	354-410	381-475	383-475
Volkswagen e-Golf	-	-	-	-	-	201	201

types of travels. Table 3 presents a breakdown of driving ranges by model-year. While there is some improvement to autonomy over time, firms typically increase driving range by introducing new models rather than improving on existing ones. Most models have a driving range between 120km and 200km which implies that charging on the go is usually required even for medium-distance trips. Lastly, EV exhibit a lower carbon footprint and a lower operation cost (i.e. cost of driving 100km).

Table 4 summarize the evolution of battery-electric and plug-in hybrid sales between 2012 and 2018, as well as the entry of new models over the same period. Three models were available near the end of 2011, the Mitsubishi iMiev, the Nissan Leaf, and the Chevrolet Volt, totalizing 173 sales (not show in the table). Sales have increased exponentially over the period reaching 3.4% of yearly sales by 2018. At the same time, several new models were released in every marketing segment, including SUVs (Kia Soul EV, Mitsubishi Outlander) and minivans (Chrysler Pacifica). Around 35 new EV were introduced between 2012 and 2018 (three discontinued), totalizing 17,435 battery-electric and 23,597 plug-in hybrid registrations.

The data on charging station infrastructure is provided by Hydro-Quebec. It contains the exact geographic location and address of each station, pricing, power, type of station, and entry date. This data covers all public and semi-public stations accessible through the online platform. Information

Table 4: Electric vehicle sales, by year

Model	Sales						
	2012	2013	2014	2015	2016	2017	2018
Battery electric							
BMW i3[a]	-	-	16	68	90	78	103
Chevrolet Bolt EV	-	-	-	-	-	1,154	1,490
Chevrolet Spark	-	2	18	42	37	6	-
Ford Focus Electric	24	46	21	27	61	184	445
Hyundai IONIQ	-	-	-	-	-	284	770
Kia Soul EV	-	-	16	125	412	316	478
Mitsubishi iMiev	113	99	66	82	59	43	8
Nissan Leaf	111	205	623	755	950	548	2,559
Smart Fortwo	-	-	-	-	-	10	111
Tesla Model 3	-	-	-	-	-	-	1,560
Tesla Model S	21	126	172	589	441	328	233
Tesla Model X	-	-	-	-	203	274	211
Volkswagen e-Golf	-	-	-	-	-	263	633
Plug-in hybrid							
Chevrolet Volt	649	621	1,204	1,156	2,351	2,533	2,063
Chrysler Pacifica	-	-	-	-	1	215	344
Ford C-Max	-	100	284	160	214	187	9
Ford Fusion	1	98	206	123	183	305	732
Hyundai IONIQ	-	-	-	-	-	5	676
Mitsubishi Outlander	-	-	-	-	-	2	2,279
Porsche Cayenne	-	-	36	312	343	338	312
Toyota Prius	6	79	55	15	6	683	1,731
Volvo XC-90	-	-	-	178	488	539	662
Others	0	17	57	45	117	246	350
Total	925	1,393	2,774	3,677	5,956	8,541	17,759

[a]. Sales of BMW i3 includes both the fully electric and the plug-in hybrid specifications.

on private stations is not available. I observe that 127 of the 1,920 charging stations are fast-charging stations (FastDC) and that the remaining stations are standard Level 2 chargers. I use the power output of each type of station and pricing per hour to recover the cost per kWh of charging at either type of facility. I estimate the cost of recharging to be \$0.14 per kWh at a Level 2 charger and \$0.23 at a FastDC charger.[8] Alternatively, charging at home costs \$0.09 per kWh. I combine these into a single price index that I use to compute the cost of driving an EV for an average owner.[9]

[8]Level 2 chargers have a maximum power output of 7.2kW and a median per hour price of \$1 while FastDC chargers have a maximum power output of 50kW and a median per hour price of \$11.50. The per kWh price estimates assume that all vehicles can recharge at the maximal output for each type of station.

[9]I assume that 80% of charging occurs at home, 10% on Level 2 chargers and 10% on FastDC chargers during

Table 5: Stations network

Year	Number of stations	Share of counties with			
		0 stations	1-5 stations	6-10 stations	>10 stations
2012	136	0.78	0.13	0.04	0.03
2013	238	0.61	0.26	0.06	0.07
2014	384	0.44	0.39	0.06	0.10
2015	665	0.24	0.46	0.10	0.19
2016	919	0.12	0.47	0.15	0.25
2017	1440	0.06	0.47	0.17	0.29
2018	1920	0.02	0.38	0.19	0.39

Table 5 presents the evolution of the network at the provincial level both in terms of the raw number of stations and its density at the county level. Because driving range is limited on several EV models throughout the period, charging station availability at the local level is crucial for consumers considering purchasing an EV. While the network has grown over time, reaching 1,920 stations in 2018, it has done so unevenly, such that coverage remains low in several non-urban counties.

I complete my dataset with gas prices and gas station density, obtained from Régie de l'Énergie, and various demographics at the county-level, obtained from the Canadian Census Survey.

3 Evidence of Network Effects

Consider the following simple structural equation model that characterize the equilibrium outcome in the car market:

$$\mathbf{q} = \alpha_0 + \alpha_1 \mathbf{p} + \alpha_2 \mathbf{n} + \alpha_3 \mathbf{x} + \alpha_4 \mathbf{y}_1 + \mathbf{u}^D \tag{1}$$

$$\mathbf{p} = \beta_0 + \beta_1 \mathbf{q} + \beta_2 \mathbf{x} + \beta_3 \mathbf{w} + \mathbf{u}^S \tag{2}$$

$$\mathbf{n} = \gamma_0 + \gamma_1 \mathbf{q} + \gamma_2 \mathbf{y}_2 + \mathbf{v} \tag{3}$$

long distance trips. The resulting cost of charging is \$0.107 per kWh.

where $(\mathbf{q}, \mathbf{p}, \mathbf{n})$ are (the log of) the equilibrium vectors of the quantities, prices and number of stations (i.e. endogenous), $\mathbf{x}$ is a matrix of car characteristics, $\mathbf{w}$ are cost shifters that affect supply only, $(\mathbf{y}_1, \mathbf{y}_2)$ are demographics that affect demand for cars and supply of charging stations respectively and $(\mathbf{u}^D, \mathbf{u}^S, \mathbf{v}) \sim N(\mathbf{0}, \Sigma)$ are residuals. The parameters of interest are α_2 and γ_1 which together measure the importance of network effects in this market. I impose two standard assumption on the equilibrium described above: first, that demand is a decreasing function of prices $(\alpha_1 < 0)$, and second, that supply is an increasing function of quantities $(\beta_1 > 0)$.

Since I am not interested in the supply equation, I replace (2) in equation (1) which yields the following reduced form:

$$\mathbf{q} = \frac{\alpha_0 + \alpha_1\beta_0}{1 - \alpha_1\beta_1} + \frac{\alpha_2}{1 - \alpha_1\beta_1}\mathbf{n} + \frac{\alpha_3 + \alpha_1\beta_2}{1 - \alpha_1\beta_1}\mathbf{x} + \frac{\alpha_1\beta_3}{1 - \alpha_1\beta_1}\mathbf{w} + \frac{\alpha_4}{1 - \alpha_1\beta_1}\mathbf{y}_1 + \frac{\mathbf{u}^D + \alpha_1\mathbf{u}^S}{1 - \alpha_1\beta_1}. \quad (4)$$

A few clarifications are necessary at this point. By assumption, the term $\alpha_1\beta_1$ is negative, hence the denominators in equation (4) have to be positive. This means that we can recover the sign of α_2 but not its magnitude. The same will not be true for the coefficients in front of car characteristics. Consider for example horsepower, and assume that consumers value horsepower positively but that it is costly for firms to produce powerful cars (i.e. $\alpha_3 > 0, \beta_2 > 0$). Since α_1 is negative, the term $\alpha_3 + \alpha_1\beta_2$ can take any sign, depending on the magnitudes of α_1, α_3 and β_2. With this in mind, rewrite the system of equations as:

$$\mathbf{q} = \lambda_0 + \lambda_1\mathbf{n} + \lambda_2\mathbf{x} + \lambda_3\mathbf{w} + \lambda_4\mathbf{y}_1 + \mathbf{u} \quad (5)$$

$$\mathbf{n} = \gamma_0 + \gamma_1\mathbf{q} + \gamma_2\mathbf{y}_2 + \mathbf{v} \quad (6)$$

with $(\mathbf{u}, \mathbf{v}) \sim N(\mathbf{0}, \Omega)$. To estimate λ_1 and γ_1, I rely on instrumental variable techniques to break the simultaneity between charging station deployment and sales and to control for potential shock that could affect both sides of the market at the same time. I use charging stations in distant regions to instrument for the local charging station network. The intuition is that charging station installations are correlated across all regions through common installation and maintenance costs, but that they correlate through cross-regional usage only for neighbouring regions.[10] To instrument for quantities, I use gas station density (i.e. number of gas stations per 5,000 inhabitants), gas prices and the interaction between the two. I claim that these satisfy the exclusion restriction. Gas prices and gas station density measure the level of competition in the fuel market and are likely to affect charging station deployment through substitution between fuel and electric vehicles. However, it is unlikely that they affect charging station decisions directly: once sales are realized, charging stations do not compete directly with refuelling stations as these serve two different segments of the market.

One concern is that shocks that affect fuel prices may also affect energy prices, which would render this instrumental variable strategy invalid. I claim that this is unlikely in this setup: energy production and distribution in Quebec are controlled entirely by Hydro-Québec, and prices are further regulated by the Régie de l'Énergie, an independent government agency charged with monitoring energy prices.[11] Another threat to this instrumental variable strategy is that gas prices, and especially gas station density may reflect the market potential for charging and thus could be correlated to station installations directly. I suggest that this is not an issue in this particular setup since revenues from charging are usually not an important consideration in local governments' installation decision.

Results from estimating equation (5) are presented in Table 6. I estimate a set of results with horsepower, power consumption, length as car characteristics and weight as a cost shifter. I also include the share of graduates as a proxy for the taste for green technologies since more educated people are more likely to be aware of the environmental consequences of driving an internal combustion vehicle. The parameter on the log of stations (i.e. λ_1) has a direct elasticity interpretation: an increase in the size of networks of 10% leads to an increase in EV sales of 5.2–5.6%. In the second set of results, I add the rebate as an extra cost shifter. In this case, firms set the final price paid

[10] This is the same instrument I use in the demand estimation. The instrument is constructed using a linear combination of all stations that are located more than 300km away from each county's centroid. Details are provided in Section 4.4.

[11] Electricity prices are typically determined on April 1st and remain stable for a full year. I observe in practice very little variation over the sample period once we account for inflation. Gas prices on the other hand are very volatile and can vary on a daily basis to adjust for potential shocks to the fuel market.

Table 6: Reduced form evidence: Electric vehicles

VARIABLES	(1) OLS	(2) OLS	(3) IV	(4) IV
Log of stations	0.013	0.011	0.522**	0.562**
	(0.028)	(0.028)	(0.265)	(0.269)
Rebate		0.058***		0.057***
		(0.007)		(0.008)
Power-to-weight	0.007***	0.003**	0.007***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Length	0.417**	0.368**	0.457***	0.412**
	(0.164)	(0.158)	(0.169)	(0.164)
Power consumption	0.006*	0.012***	0.008**	0.013***
	(0.004)	(0.003)	(0.004)	(0.004)
Weight	-0.047***	-0.025	-0.054***	-0.033*
	(0.016)	(0.016)	(0.017)	(0.017)
Log of income	-1.348	-1.369	-1.687*	-1.735*
	(0.908)	(0.899)	(0.982)	(0.980)
Share of graduates	9.094**	8.301**	7.297*	6.371
	(3.767)	(3.669)	(3.990)	(3.936)
Observations	4,469	4,469	4,469	4,469
Brand FE	YES	YES	YES	YES
Market segment FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

NOTE: Includes both battery electric and plug-in hybrid vehicles. *Rebate* is the value of the subsidy, in 1,000 CAD, *Power-to-weight* is the power-to-weight ratio, in W/kg; *Length* is in m; *Power consumption* is in kW/100km; and *Weight* is in 100kg. Robust standard errors are in parenthesis. Significance level: * = 0.1, ** = 0.05, *** = 0.01.

by consumers and internalize any effect of the rebate through a reduction in costs. This allows for two things: to estimate how the rebate correlates with sales of EV and to test hypotheses about passthrough. If for example the estimated coefficient on the rebate is zero, firms set the same final price whether or not a rebate is offered for a given vehicle, implying a passthrough of zero. This hypothesis is strongly rejected. Since I cannot recover separately β_3, it is not possible to test the hypothesis that passthrough is complete (i.e. $\beta_3 = 1$), however we can interpret the coefficient on rebate as a semi-elasticity: an increase in the rebate of $1,000 leads to a 5.7% increase in sales of EV. I also recover a positive correlation between charging stations and sales of EV. To rule out the fact that this result is driven by a population effect, I run the same regression using sales of fuel vehicles or hybrids as the dependent variable. Results are reported in Table 7. I do not find any significant relationship between fuel or hybrid vehicle sales and charging station deployment.

Table 7: Reduced form evidence: Fuel and hybrid engines

	Fuel		Hybrid	
VARIABLES	OLS	IV	OLS	IV
Log of stations	-0.011	-0.038	0.000	0.229
	(0.007)	(0.095)	(0.022)	(0.246)
Power-to-weight	0.005***	0.005***	-0.012***	-0.012***
	(0.000)	(0.000)	(0.002)	(0.002)
Length	0.411***	0.411***	0.992***	0.991***
	(0.022)	(0.022)	(0.106)	(0.107)
Fuel consumption	-0.163***	-0.163***	0.027	0.027
	(0.004)	(0.004)	(0.017)	(0.017)
Weight	-0.093***	-0.093***	-0.132***	-0.132***
	(0.003)	(0.003)	(0.017)	(0.017)
Log of income	0.822***	0.765**	0.218	0.447
	(0.264)	(0.333)	(0.754)	(0.792)
Share of graduates	0.404	0.606	3.493	2.479
	(0.883)	(1.128)	(2.879)	(3.108)
Observations	94,307	94,307	5,719	5,719
Brand FE	YES	YES	YES	YES
Market segment FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

NOTE: *Power-to-weight* is the power-to-weight ratio, in W/kg; *Length* is in m; *Fuel consumption* is in L/100km, and *Weight* is in 100kg. Robust standard errors are in parenthesis. Significance level: * = 0.1, ** = 0.05, *** = 0.01.

Finally, I estimate equation (6) and present the results in Table 8. I include a full set of county and year fixed effects and again the share of graduates as a measure of 'greenness'. I estimate three specifications, using in turn the cumulative sales of fuel vehicles, the cumulative sales of EVs and the cumulative sales of hybrids. Again we see that a correlation exists only between charging stations and the total fleet of EVs. The coefficient has a direct elasticity interpretation: an increase in size of the fleet of EV by 10% leads to an increase in the size of the network of 6.6%. Combining the results from both equations provides evidence that network effects are important in this market and exist only between electric vehicles and charging stations, and not between fuel or hybrid vehicles and charging stations.

Table 8: Reduced form evidence: Station entry

	Fuel		Electric		Hybrid	
VARIABLES	OLS	IV	OLS	IV	OLS	IV
Log of cummulative sales	-1.898**	0.181	0.240***	0.658*	-0.063	0.843
	(0.825)	(6.150)	(0.091)	(0.369)	(0.187)	(1.380)
Share of graduates	11.071**	11.598**	10.094**	7.552	11.545**	11.646**
	(4.581)	(4.837)	(4.489)	(5.063)	(4.580)	(4.660)
Observations	616	616	616	616	616	616
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

NOTE: *Electric* includes both battery electric and plug-in hybrid vehicles. Robust standard errors are in parenthesis. Significance level: * = 0.1, ** = 0.05, *** = 0.01.

4 The Model

To analyse the effect of subsidizing the purchase of a new electric vehicles on prices, sales and charging station deployment, I rely on a structural model with three main components: the demand for cars, the supply for cars and the supply for a charging station infrastructure. Demand for cars is determined using the nested logit specification as in Berry (1994). On the supply side, we consider the case of multi-product firms competing on prices over differentiated products (Berry, Levinsohn, and Pakes, 1995; Petrin, 2002). Finally, I propose a model for charging station deployment inspired by Springel (2017), Pavan et al. (2015) and Berry and Reiss (2007). I develop the model to fit the specific economic and political context in Quebec, where local county-level government are responsible for installing stations.

4.1 Demand

I consider individual i living in county m at time t. Each year, this consumer chooses to purchase one of the $j = 1, ..., J$ car makes available or purchase nothing at all, which is denoted as $j = 0$. In making this choice, consumers considers the net price of a given make, but also its characteristics such as horsepower, fuel efficiency or engine type. For all models with an electric engine, the number of charging stations that are available locally also enters the demand specification as an extra characteristic in the model. Since driving range impacts if and how often an electric vehicle user charges on the go, preferences for charging stations are allowed to vary with driving range, defined as the total mileage traveled on a single charge. Finally, I classify car makes into $g = 1, ..., G$ market segments (i.e. subcompact, SUV, etc.) with the outside good being in a separate segment, $g = 0$. Consumers first choose a market segment, then select a make within this market segment, giving rise to the nested logit specification.[12]

Under this specification, preference of consumer i for make j in segment g are given by the following linear equation,[13]

$$u_{ijmt} = \delta_{jmt} + \mu_{jmt} + \zeta_{igmt} + (1 - \sigma)\epsilon_{ijmt},$$

$$\delta_{jmt} = \mathbf{x}'_{jt}\beta + \alpha(p_{jt} - \tau_{jt}) + \xi_{jmt},$$

$$\mu_{jmt} = \gamma_{jt} \ln(1 + N_{jmt})$$

where $\mathbf{x}_{jt}$ is the set of observed characteristics of the product, p_{jt} is the price, τ_{jt} is the rebate associated with purchasing an electric vehicle, N_{jmt} is the number of charging stations in the county interacted with an electric engine dummy variable, and ξ_{jmt} represents unobserved characteristics of make j. The δ_{jmt} represent the mean utilities of each product and μ_{jmt} are network effects. Preference for charging stations, denoted γ_{jt} is allowed to depend on driving range, that is

$$\gamma_{jt} = \gamma_1 + \gamma_2 \cdot DrivingRange_{jt}.$$

Following Berry (1994), the preference shock ϵ_{ijmt} is assumed to be distributed as extreme-value type I and the segment specific shock ζ_{igmt}, which can be viewed as a random coefficient on a market segment dummy variable, has the unique distribution such that $\zeta_{igmt} + (1 - \sigma)\epsilon_{ijmt}$ is also distributed as extreme-value. The parameter $\sigma \in (0, 1)$ governs the substitution within and across market segments. Whenever σ approaches zero, the model collapses to the standard logit model, and market segments are not a relevant dimension to explain substitution patterns. If on the

[12] While this approach does not solve completely the IIA problem associated with the logit assumption, whether or not it produces rich enough substitution patterns is application specific. In the case of this study, I believe that this approach is appropriate for two reasons: first, market segments are a strong driver of substitution in the car market; and second, our results depend on the substitution towards or away from electric vehicles, which is driven strongly by network effects that arise naturally in the model.

[13] The county m and year t subscripts have been omitted for simplicity.

other hand σ approaches 1, then consumers view the products within a segment as being perfect substitutes, and the choice of a model within the segment becomes deterministic.

Under these distributional assumptions, the market share of product j is given by

$$s_{jmt}(\delta,\mu,\sigma) = s_{jmt|g}(\delta,\mu,\sigma)\cdot s_{gmt}(\delta,\mu,\sigma) = \frac{e^{(\delta_{jmt}+\mu_{jmt})/(1-\sigma)}}{D_{gmt}^{\sigma}\cdot\sum_{g'} D_{g'mt}^{(1-\sigma)}},$$

$$D_{gmt} = \sum_{k\in\mathcal{J}_g} e^{(\delta_{kmt}+\mu_{kmt})/(1-\sigma)},$$

where $\mathcal{J}_g$ is the set of all products belonging to segment g. Normalizing $\delta_{0mt} = \mu_{0mt} = 0$ and solving yields the following linear model to be estimated,

$$\ln(s_{jmt}) - \ln(s_{0mt}) = \mathbf{x}'_{jt}\beta - \alpha(p_{jt}-\tau_{jt}) + \gamma_{jt}\ln(1+N_{jmt}) + \sigma\ln(s_{jmt|g}) + \xi_{jmt},$$

where price, charging stations and the within-segment market shares all suffer from an endogeneity issue and have to be instrumented for.

4.2 Supply

Whether or not firms are able to manipulate prices to capture part of the subsidy as profits is crucial in determining the cost-effectiveness of reducing CO_2 emissions using financial incentives. That depends on firms' technology (fixed or increasing marginal costs), market structure (single-product vs multi-product firms), and the level of competition in this industry. I consider the market for personal vehicles to be an oligopoly of $f = 1, ..., F$ multi-product firms selling differentiated products and competing on prices. Furthermore, I restrict this study to the case where marginal costs are constant as is common in the literature related to the car market (see for example Berry, Levinsohn, and Pakes, 1995 or Petrin, 2002). More importantly, this assumption provides a useful benchmark for studying pricing decision under oligopolistic competition: under perfect competition, consumers benefit from the full amount of the subsidy when marginal costs are constant. Under these assumptions, each firm maximizes its profits in each period, given by the following expression,

$$\Pi_{ft} = \sum_{j \in \mathcal{J}_f} \sum_m (p_{jt} - c_{jt}) \cdot q_{jmt}\big(\mathbf{p}_t - \tau_t, N_{mt}(\mathbf{p}_t - \tau_t)\big)$$

where $\mathcal{J}_f$ is the set of products offered by firm f. Note that the demand for a particular product depends on the full price vector, the full vector of rebates and on the installed base of charging stations in county m.

The optimal price vector satisfies the firms first-order condition,

$$\mathbf{p}_t^* - \mathbf{c}_t = \left(\sum_m \Omega(\mathbf{p}_t^* - \tau_t) \right)^{-1} \cdot \sum_m \mathbf{q}_{mt}(\mathbf{p}_t^* - \tau_t, N_{mt}(\mathbf{p}_t^* - \tau_t))$$

where $\Omega_{jk} = -\partial q_{jmt}/\partial p_{kt}$, if j and k are sold by the same firm, and zero otherwise.

4.3 Station entry

We consider the case of a local social planner or local government responsible for supplying charging stations in county m. Define the benefits associated with station n to be

$$B(n) = Q^{ev} \cdot b(n, \mathbf{y})$$

where Q^{ev} is the total stock of electric vehicles in the county, $b(n, \mathbf{y})$ is the average per driver benefit derived from station n, and $\mathbf{y}$ is a vector of county-level controls and demographics. $B(n)$ may represent profits generated from operating the network, a measure of social welfare, political support from electric vehicle drivers, or even some measure of favorable public opinion towards the governing political party. I impose two simple assumption on these benefits: (1) that they are strictly decreasing in n, such that each additional station is less valuable than the previous one for given Q^{ev} and $\mathbf{y}$, and (2) that there exists a saturation point S, such that $B(n) = 0, \forall n > S$, irrespective of Q^{ev} and $\mathbf{y}$.[14]

[14]This saturation point can take different values for different markets, in particular it can be a function of the number of households in a given region, i.e. $S = S(L)$. The intuition for this restriction is simple: the total stock of EV in each region has to be bounded above because population is finite and no individual cannot own an infinite number of vehicles. It follows that demand for charging has to be bounded above and thus can always be satisfied by a finite number of stations. The current saturation point is set to $S = L/200$ in each region.

The stream of benefits associated with installing station n in period t can be written as

$$V_t(n) = -F_t + \sum_{s=t}^{\infty} \left(\frac{1}{1+r}\right)^{s-t} B_s(n)$$

where F_t is the unobserved fixed cost of installing a new station in period t. The social planner chooses to install station n today if it is more beneficial than waiting, that is, station n enters if

$$V_t(n) \geq \left(\frac{1}{1+r}\right) V_{t+1}(n)$$

or

$$B_t(n) \geq F_t - \left(\frac{1}{1+r}\right) F_{t+1}$$

Consider the last station installed, N. It must be true that the local planner found it profitable to install station N, but unprofitable to install station $N+1$. Hence the equilibrium number of charging stations available has to satisfy the following two conditions:

$$V_t(N) \geq \left(\frac{1}{1+r}\right) V_{t+1}(N) \tag{7}$$

and

$$V_t(N+1) < \left(\frac{1}{1+r}\right) V_{t+1}(N+1). \tag{8}$$

In what follows, I impose the following functional form assumption on the average benefit function,

$$b(n, \mathbf{y}) = a_0 n^{-a_1} \cdot e^{\mathbf{y} a_2}.$$

Substituting into equation (7) and (8) and taking logs leads to the following inequality condition which must be satisfied in equilibrium,

$$\frac{\ln(N_{mt}) - \lambda_1 \ln(Q_{mt}^{ev}) - \mathbf{y}_{mt}' \lambda_2}{\omega} \leq \eta_{mt} < \frac{\ln(N_{mt}+1) - \lambda_1 \ln(Q_{mt}^{ev}) - \mathbf{y}_{mt}' \lambda_2}{\omega}$$

where η_{mt} is unobserved to the econometrician and assumed to follow the standard normal distribution (the full derivation is in the appendix). Given this distributional assumption, I construct the following conditional log-likelihood

$$\ell(\lambda \mid \cdot) = \sum_m \sum_t ln \left[\Phi \left(\frac{\ln(N_{mt}+1) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2}{\omega} \right) - \Phi \left(\frac{\ln(N_{mt}) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2}{\omega} \right) \right] \quad (9)$$

and I recover the paramters λ and ω using maximum likelihood estimation. A control function approach is used to address the endogeneity of Q^{ev} in estimating the conditional log-likelihood in (9), as sales of EV and station deployment occur simultaneously.

4.4 Identification

Demand: Identification of the effect of the rebate on green vehicles requires that I observe both cross-sectional variation and variation over time in the policy. While there is some variation in the subsidy across models, I do not observe geographic or time variation in the policy within model, which means that I cannot identify separately the effect of the rebate from prices. This implies that what matters to consumers is the net price of the vehicles they are considering, and not whether price changes originate from car manufacturers or the policy maker. It is still possible to conduct counterfactual analysis in this setup, but the elasticity to price and the elasticity to the rebate are restricted to be the same in the model.

I also have to deal with several sources of endogeneity. First, prices depend not only on observed product characteristics but also on unobserved characteristics (to the econometrician), leading to the price endogeneity issue described in Berry, Levinsohn, and Pakes (1995). The nesting structure of the demand equation implies that market shares, and in particular within-segment market shares are also endogenous since they are determined jointly with unobserved car attributes (Gandhi and Houde, 2019). Concretely, this means that an instrumental variable is needed both for prices and for the within-segment market share in the demand model. Second, sales of electric vehicles and the entry of charging stations occur simultaneously in the model, hence identifying the causal effect of sales on the network or of the network on sales is impossible without instrumental variables. Changing the structure of the model to break this simultaneity (for example, changing the timing of the station entry decision) is not enough to solve this endogeneity issue completely: taste for green technologies is captured by the residuals in both the demand and the entry models, hence they are correlated. This implies that both stations and sales of electric vehicles are endogenous in both equations.

I solve the various endogeneity issues described above using instrumental variable techniques. In order to solve for the endogeneity of prices and market shares, I follow Gandhi and Houde (2019) to construct instruments based on characteristic differences between each product j and their competitors within the same marketing segment.[15] The validity of using characteristics differences instruments can be justified as follows: exogenous characteristics of competitors measure the degree of isolation of product j along each characteristic (or the degree of competition product j is facing), and thus are valid markup shifters. Berry, Levinsohn, and Pakes (1995) suggest taking the sum of exogenous characteristics of competing products to construct instrument for both prices and market shares in the demand equation, however Gandhi and Houde (2019) show that this can lead to weak instruments and poor identification of the price coefficient and elasticities. To solve this issue, they suggest using the symmetry of the demand model to construct basis functions based on characteristic differences as instruments. Assuming product j belongs to segment g, I construct four such differentiation instruments using this approach: the number of products available in segment g, the sum of differences in power-to-weight ratio, size, and driving cost between product j and its competitors within segment g.

To solve the endogeneity of the charging station network in the demand equation, I use the approach proposed by Hausman (1996) and Nevo (2001), which uses the panel structure of the data to construct instruments for local charging stations using stations in other regions. The idea is that the installation of new stations depends on local consumption (i.e. the installed base of electric vehicles in a given region) and a common cost component across regions that does not depend on

[15] To fix ideas, let $d_{jk} = x_j - x_k$ be the difference between product j and k along some exogenous characteristic x. Assuming product j belongs to group g, the Gandhi-Houde differentiation instrument then takes the following form:

$$z_j = \sum_{k \in \mathcal{J}_g} d_{jk},$$

that is, the sum of characteristic differences between model j and competitors within the same group.

consumption once we account for region fixed effects. Stations in other regions are valid instruments for local stations, as long as the correlation between stations in different regions comes only from sharing a common cost and not from users charging over region lines, or from common shocks that affect all markets together. This assumption cannot hold for markets that are geographically close to each other: people travel between neighboring regions for work and other daily activities and these commuting patterns could lead to a significant portion of charging within a region to come from EV owners outside the region and vice-versa. To solve this issue, I impose a distance threshold to select regions that I use as instruments using this method, such that it is unlikely that a significant portion of the charging comes from car owners that live beyond that distance. I then construct a first-order basis functions using combinations of stations in regions beyond the distance threshold, specifically,

$$g_{jmt}(N_{mt}) = \theta_{jt} \cdot \frac{\sum_{l \neq m} \mathbb{1}(dist_{l,m} > K) \cdot \ln(1 + N_{lt})}{\sum_{l \neq m} \mathbb{1}(dist_{l,m} > K)},$$

where

$$\theta_{jt} = \theta_1 + \theta_2 \cdot DrivingRange_{jt}$$

which gives me the required additional instruments to include in the demand estimation. Several factors could break this instrumental variable strategy: large scale environmental advertisement campaigns that raise awareness about environmental issues or large investment into charging stations from the provincial or federal governments that affects all regions together are examples. To the best of my knowledge, there was no change in the policy environment over the period of interest that would threaten identification.

Station entry: I address the issue of the endogeneity of the stock of electric vehicles in the structural entry model. Since the entry model is highly non-linear, traditional two-stage least-square estimation is not possible. I rely instead on a control function approach to deal with the endogeneity issue.

Rewrite the structural equation for station entry as

$$N_{mt} = \sum_{k=1}^{S-1} k \cdot \mathbb{1}\left(\frac{\ln(k) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2}{\omega} \leq \eta_{mt} < \frac{\ln(k+1) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2}{\omega}\right) \tag{10}$$

$$+ S \cdot \mathbb{1}\left(\frac{\ln(S) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2}{\omega} \leq \eta_{mt}\right) \tag{11}$$

Consider a set of valid instruments for Q^{ev}, denoted $\mathbf{w} = (\mathbf{w}_1, \mathbf{y})$, and define the control function to be the linear projection of Q^{ev} on $\mathbf{w}$,

$$Q^{ev}_{mt} = \mathbf{w}'_{mt}\Gamma + \nu_{mt}, \tag{12}$$

where $(\eta, \nu) \perp \mathbf{w}$. Estimation of the parameters of (10) is done in two stages: first, obtain a consistent estimate of $\widehat{\nu}_{mt}$ by estimating equation (12), then add $\widehat{\nu}_{mt}$ as an extra regressor in the structural equation

$$N_{mt} = \sum_{k=1}^{S-1} k \cdot \mathbb{1}\left(\frac{\ln(k) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2 - \rho\widehat{\nu}_{mt}}{\omega} \leq \eta_{mt} < \frac{\ln(k+1) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2 - \rho\widehat{\nu}_{mt}}{\omega}\right)$$

$$+ S \cdot \mathbb{1}\left(\frac{\ln(S) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2 + \rho\widehat{\nu}_{mt}}{\omega} \leq \eta_{mt}\right).$$

The parameters of the model can then be estimated by maximizing the conditional log-likelihood[16]

$$\ell(\lambda \mid \cdot) = \sum_m \sum_t \ln\left[\Phi\left(\frac{\ln(N_{mt}+1) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2 - \rho\widehat{\nu}_{mt}}{\omega}\right) - \Phi\left(\frac{\ln(N_{mt}) - \lambda_1 \ln(Q^{ev}_{mt}) - \mathbf{y}'_{mt}\lambda_2 - \rho\widehat{\nu}_{mt}}{\omega}\right)\right].$$

I use gas station density,[17] gas prices and the interaction between the two to instrument for the total fleet of electric vehicles in a given region. Gas prices and gas station density measure the level of competition in the fuel industry and influence the number of electric vehicle sales through the substitution between fuel and electric. These instruments satisfy the exclusion restriction, since charging stations and fuel stations do not compete directly with one another once sales of electric

[16] In the estimation stage, the saturation point is set to be $S = L/200$ in each county, well above network sizes at any give point in time.

[17] Gas station density is calculated as the number of gas station in a given region divided by population, in 5,000.

vehicles are realized. Also, common shocks are unlikely to affect both markets together: electricity prices are regulated by the provincial government and do not fluctuate with the price of gas such that it is unlikely that shocks that affect the fuel market are also affecting charging station entry decisions through higher electricity prices.

4.5 Elasticities and Network Effects

One important implication for introducing network effects is that they enrich substitution patterns compared to the baseline logit or nested logit specifications. The intuition behind this is that substitution towards electric vehicles depends on the elasticities that arise in the traditional demand model, but also on changes in the network configuration that can occur when the total fleet of electric vehicles increases in a given market. Vehicles that do not require charging are also affected by network effects. While increases in the size of the network do not impact fuel vehicle utility directly, they affect mean utilities of competing alternatives, therefore affecting the market shares of all vehicles, including fuel vehicles.

Springel (2017) shows how to derive elasticities for discrete choice models with network effects when demand has the more general random-coefficient specification. I follow the same methodology to derive elasticities when demand has the nested logit formulation and station entry follows the structural model defined above. Using chain rule, the derivative of the market share of car make j with respect to the price of make k has the form

$$\frac{\partial s_j(p, N(p))}{\partial p_k} = \underbrace{\frac{\partial s_j}{\partial p_k}}_{\text{Nested logit}} + \underbrace{\frac{\partial s_j}{\partial N} \cdot \frac{\partial N}{\partial Q^{\text{ev}}} \cdot \frac{\partial Q^{\text{ev}}}{\partial p_k}}_{\text{Network effects}},$$

where the first term is the derivative that arises naturally in nested logit demand models and the second term accounts for network effects. Assuming that product j belongs to segment g, we can write each component as

$$\frac{\partial s_j}{\partial p_k} = \begin{cases} \frac{\alpha}{1-\sigma}\big(1-\sigma s_{j|g}-(1-\sigma)s_j\big)s_j, & \text{if } k=j \\ -\frac{\alpha}{1-\sigma}\big(\sigma s_{k|g}+(1-\sigma)s_k\big)s_j, & \text{if } k\neq j \text{ and } k\in\mathcal{J}_g \\ -\alpha s_k s_j, & \text{if } k\neq j \text{ and } k\notin\mathcal{J}_g \end{cases}, \tag{13}$$

$$\frac{\partial s_j}{\partial N} = \begin{cases} \frac{\gamma_j}{1-\sigma}\cdot\frac{1}{1+N}\big(1-\sigma\sum_{\ell\in\mathcal{J}_g}s^{\text{ev}}_{\ell|g}-(1-\sigma)\sum_\ell s^{\text{ev}}_\ell\big)s_j, & \text{if } j\in EV \\ -\frac{\gamma_j}{1-\sigma}\cdot\frac{1}{1+N}\big(\sigma\sum_{\ell\in\mathcal{J}_g}s^{\text{ev}}_{\ell|g}+(1-\sigma)\sum_\ell s^{\text{ev}}_\ell\big)s_j, & \text{if } j\notin EV \end{cases}, \tag{14}$$

$$\frac{\partial N}{\partial Q^{\text{ev}}} = \sum_{k=1}^{S} k\cdot\int\frac{\partial Pr(N=k\mid Q^{ev},\mathbf{y},\nu)}{\partial Q^{ev}}dF_\nu(\nu), \tag{15}$$

and

$$\frac{\partial Q^{\text{ev}}}{\partial p_k} = \frac{L\cdot\sum_\ell\frac{\partial s^{\text{ev}}_\ell}{\partial p_k}}{1-L\cdot\frac{\partial N}{\partial Q^{\text{ev}}}\sum_\ell\frac{\partial s^{\text{ev}}_\ell}{\partial N}}, \tag{16}$$

with $s^{\text{ev}}_\ell = s_\ell$ if product ℓ has an electric engine and zero otherwise. The expressions $\partial s_j/\partial p_k$ and $\partial s_j/\partial N$ are straightforward and follow directly from the nested logit specification of the demand side. The expression $\partial N/\partial Q^{ev}$ is achieved following Blundell and Powell (2004) by computing the partial effect of a change in Q^{ev} on N. Finally, derivation of $\partial Q^{ev}/\partial p_k$ requires a straightforward application of the chain rule, and replacing the expressions in (13), (14) and (15). The full derivation is in the appendix.

5 Estimation

I estimate both the demand for cars and entry of stations at the market-level, where each product is a make-model-engine combination and each market is a county-year combination. Before I proceed with the estimation, I manually remove counties with fewer than 15,000 inhabitants. These counties include northern Quebec which is largely uninhabited, remote areas not easily accessible by road, and rural areas with very low population density. Most importantly, these regions exhibit very few sales of vehicles, let alone electric ones, and usually do not have stations installed over the period of study. In total, the analysis is conducted on 89 of the 99 regional county municipalities, and covers around 98% of the population of Quebec.

Results from the estimation of the demand side are presented in Table 9. I include power-to-weight ratio (a measure of acceleration), size (a proxy for security), driving cost[18] (dollars per kilometer) and a dummy variable for automatic/singlespeed transmission as observed characteristics. I also include a large number of fixed effects: car make (34 different makes), market segment (subcompact, compact, midsize, large/luxury, SUV, minivan, pickup, sport), engine-by-county (4 engine types $\times$ 89 counties) and year fixed effects. The engine-by-county fixed effects are particularly important to account for potential differences in taste for green technologies which could vary on average across regions. Instruments for prices and market shares are constructed following Gandhi and Houde (2019) using power-to-weight, size and driving cost as dimensions of differentiation. I also include the number of competing products within segment as an additional mark-up shifter to instrument for the within-group market share. Finally, charging station instruments include the average of (the log of) stations located more than 300 km from the centroid of the county of interest. The choice of a threshold is somewhat arbitrary, I produce a robustness analysis to the choice of threshold in the appendix.

All of the estimated coefficients have the expected sign and are highly significant. The estimated nesting parameter is 0.366, meaning that the nesting structure explains part of the substitution patterns observed in the data (i.e. standard logit is rejected). This is expected in the car market, where marketing segments are well defined and are a clear source of differentiation along which consumers make choices (Verboven, 1996; Verboven, 2002). The parameter on price is -0.491 and leads to an average own-price elasticities of -2.989. The average own-price elasticity is -3.638 for electric vehicles. Two factors contribute to this difference. First, EVs are on average more expansive

[18] For fuel and hybrid vehicles, driving cost is computed by multiplying fuel consumed for traveling 100km by gas price in that county and year. For battery electric vehicles, driving cost is measured as power required for traveling 100km, times an average charging cost of 0.15CAD per kWh. For plug-in hybrid, I compute a weighted average of both measures based on the share of the total driving range that is achievable driving only on electric.

Table 9: Demand estimation

VARIABLES	Demand estimation
Price - Rebate	-0.491***
	(0.097)
Log of stations	0.357***
	(0.055)
Log of stations $\times$ Driving range	-0.029***
	(0.006)
Power-to-weight	0.015***
	(0.002)
Size	0.367***
	(0.045)
Cost of driving	-0.045***
	(0.004)
Automatic	0.119***
	(0.021)
σ	0.366***
	(0.050)
Own-price elasticity	
Mean	-2.989
Std. dev.	1.432
Own-price elasticity (EV)	
Mean	-3.638
Std. dev.	2.291
# of inelastic demands	560
Observations	104,495
R-squared	0.506
Manufacturer FE	YES
Market segment FE	YES
Engine $\times$ County FE	YES
Year FE	YES

NOTE: *Power-to-weight* is the power-to-weight ratio, in W/kg; *Length* is in m; *Driving range* is the maximum distance traveled on a single charge, in 100km; and *Driving cost* is in CAD/100km. The model includes manufacturer, market segment, year and engine type $\times$ county fixed effects. Standard errors are clustered at the model $\times$ county level. Significance level: * = 0.1, ** = 0.05, *** = 0.01.

than fuel vehicles, and elasticity is still proportional to price in the nested logit model. Second, network effects accentuate the difference since increasing the price of a particular EV will reduce sales directly but also indirectly through a reduction in network size. Interestingly, our estimate of -3.698 is close to the estimates in Muehlegger and D. S. Rapson (2018), which estimate an implied elasticity for EV between -3.2 and -3.4 using a quasi-experimental setup in California. Finally, the coefficients on the log of charging station (0.357) and the interaction with driving range (-0.029) are consistent with the range anxiety assumption: consumers value charging stations positively when considering an EV with a limited driving range, but that dependence diminishes as driving range is increased.[19]

Results from the station entry model are presented in Table 10. I include several demographics in the model that try to capture consumers' taste for green technologies and home charging availability. To proxy for taste for green technologies, I use the share of residents that have an undergraduate degree and the share of conservative voters in the county. The idea behind these choice is that more educated individuals are on average more aware of environmental issues which should correlate positively with taste for green technology. Meanwhile, conservative voters tend to be less sensitive to environmental outcomes compared say to purely economic concerns. I measure the potential for home charging by the share of renters in each county, which should correlate directly since it may be hard or impossible to install a charger at home if you are not a home-owner. Finally, I add the share of resident that have their work location within the county of residence as an additional measure of the aggregate preference for large networks. Because of the highly non-linear nature of the model being estimated, I cannot include county fixed effects as these would not be identified with only seven years of data and corrupt the estimation of other parameters in the model. To account for regional differences, I instead include average income, average age and average household size for each county, and dummies for large commuting areas that include several counties (i.e. Montreal, Quebec city, Sherbrooke, Trois-Rivières and Gatineau commuting areas). The instruments I use in the control function estimation include the number of gas stations per 5,000 inhabitants, gas prices,

[19] The overall effect of stations is positive, as driving range does not exceed 539km with currently available models. As an example the overall effect of stations would be 0.595 for a vehicle with a 100km driving range and 0.323 for a vehicle with a 500km driving range.

Table 10: Station entry estimation

VARIABLES	(1) Entry estimation	(2) Control function
Log of Q^{ev}	0.425***	–
	(0.143)	
Gas station density	–	-0.317**
		(0.155)
Price of gas	–	-2.621**
		(1.117)
Gas station density × Price of gas	–	0.047
		(0 .121)
Avg. income	-0.128	0.232***
	(0.148)	(0.074)
Avg. age	2.576***	-0.022
	(0.538)	(0.015)
Share of graduates	8.959***	7.509***
	(0.513)	(0.773)
Share of renters	3.753***	4.758***
	(0.561)	(0.546)
Share commuters	0.561	-0.999
	(0.498)	(0.255)
Share conservatives	-0.634	-0.001
	(0.568)	(0.225)
ρ	-0.193*	–
	(0.103)	
ω	0.799***	–
	(0.065)	
Marginal effect ($\partial N/\partial Q^{ev}$)		
Mean	0.054	–
Std. dev.	0.047	–
F-statistic	–	19.84
Prob. > F	–	0.000
Observations	616	616
Log-likelihood	-2.186	–
Commuting Areas FE	YES	YES
Year FE	YES	YES

NOTE: Log of Q^{ev} is the log of the cumulative installed base of electric vehicles. Standard errors in the entry model are based on 200 bootstrap replications and are clustered at the county level. Significance level: * = 0.1, ** = 0.05, *** = 0.01.

and the interaction between the two, which reflect competition in the fuel market and should affect sales of EV only through the substitution between fuel and electric. The null hypothesis that these are jointly irrelevant is strongly rejected.

The coefficient on (the log of) the stock of EV is 0.425 and is significant at the 1% level. The implied average partial effect of 0.054 which means that on average one extra station should be installed for every 18.5 new EV sales. This result is driven by the large number of counties which have very low station and EV stocks. The coefficient on the control function term is -0.193 and is significant at 10%. The coefficients on average age, the share of graduates, and the share of renters are all highly significants, however the parameter on average income is insignificant.

6 Counterfactual Analysis

6.1 Effect on sales, emissions, and station deployment

I use the structural model estimated above to reconstruct what would have happened if the program Roulez Vert had never been adopted. To achieve this, I remove the subsidy, then solve the firms' optimality condition and the station providers' problem to determine the counterfactual prices, market shares and station deployment.[20] The main results are presented in Table 11. The program led to 9,238 more sales of battery electric vehicles, 9,251 more sales of plug-in hybrids, and 896 sales of hybrids. Together, the additional sales of battery electric and plug-in hybrids account for 45% of all EV sales that occurred between 2012 and 2018. While the subsidies did a good job in inducing additional battery electric, plug-in hybrids and to some extend hybrid vehicle sales, it fell short in reducing the number of fuel vehicle sold in the period: only 43% of the additional battery electric, plug-in hybrids and hybrids sold are replacing fuel vehicles. The remaining 57% results from an expansion of total sales. Having such a large portion of sales coming from the outside option seriously reduces the efficiency of subsidizing EVs. Consumers choosing not to purchase a

[20]The firms' problem is solved for every market using Matlab's built in non-linear solver. To solve for the optimal number of stations, first notice that any structural model can be rewriten in the form $N = E(N \mid Q^{ev}, \mathbf{y}, \lambda) + v$. We recover an estimate for v as the solution to $\widehat{v} = N - E(N \mid Q^{ev}, \mathbf{y}.\widehat{\lambda})$, then use it to recover the counterfactual value $\widetilde{N} = E(N \mid \widetilde{Q}^{ev}, \mathbf{y}, \widehat{\lambda}) + \widehat{v}$ in each market. Estimation of the expectation requires a straightforward application of the law of iterated expectations, i.e. $E(N \mid Q^{ev}, \mathbf{y}, \lambda) = \sum_k \int Pr(N = k \mid Q^{ev}, \mathbf{y}, \nu, \lambda) dF(\nu)$.

Table 11: Effect of the subsidy

Outcome	Subsidy	No Subsidy	Difference
Sales			
Fuel	3,150,880	3,172,404	-8,327
Battery electric	17,435	8,197	9,238
Plug-in hybrid	23,597	14,346	9,251
Hybrid	49,800	48,903	896
TOTAL	3,241,712	3,230,654	11,058
CO_2 emissions, in million tons			
Fuel	166.07	166.51	-0.444
Battery Electric	0	0	0
Plug-in hybrid	0.43	0.29	0.146
Hybrid	1.58	1.56	0.024
TOTAL	168.08	167.36	-0.274
Charging stations network			
2012	136	106	30
2013	238	177	61
2014	384	283	101
2015	665	452	213
2016	919	599	320
2017	1,450	1,062	388
2018	1,920	1,417	503

NOTE: CO_2 emissions are calculated for a total lifetime mileage of 257,600 km.

vehicle do not add to the total stock of carbon from new cars, hence no gains can be realized by inducing them to purchase an EV using subsidies.

I measure the total lifetime emissions of the current fleet of vehicles and contrast it with the counterfactual fleet that would have occurred without the subsidy. Assuming that all vehicles can drive a total of 257,000 km over their lifetime (20,000 km per year, for 12.88 years), I measure total avoided carbon emissions to be in the order of 0.274 million metric tons. In calculating avoided emissions, I consider the difference in lifetime emissions between the vehicles that were bought under the policy and the vehicles that would have been bought without it. I ignore consumers' previous vehicle since they are resold on the secondary market and continue producing emissions until they reach the end of their useful life. It is also important to note that while mileage decisions could matter in determining yearly levels of CO_2 emissions, they do not affect litefime emissions so long as they do not affect the total lifetime mileage achievable on a given vehicle. Finally, I estimate

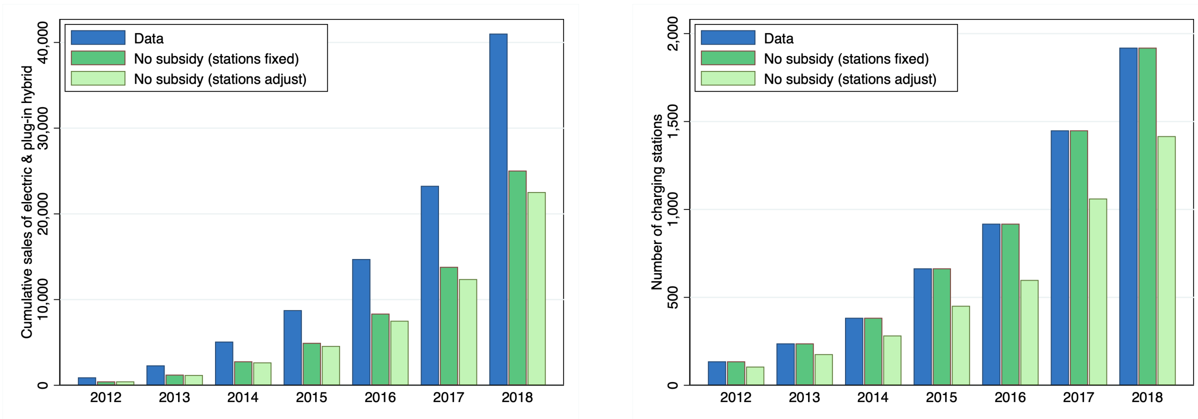
Table 12: Fuel efficiency and CO_2 emissions of vehicles replaced

Market segment	ΔSales	Avg. fuel consumption (in L/100km)	Avg. CO_2 emissions (in g/km)
Subcompact	-705	6.7	153.4
Compact	-2,721	7.9	182.5
Midsize	-305	8.4	194.0
Large/Luxury	-2,460	9.7	224.7
Sport	-15	10.1	233.8
SUV	-1,727	10.2	234.9
Minivan	-180	10.4	240.8
Pickup	-214	12.2	283.7
TOTAL	-8,327	9.5	218.5

that the subsidy was responsible for 503 of the 1920 charging stations available in Quebec.

I look next at the composition of the fuel vehicles that are being replaced by the policy and present results in Table 12. I find that 3,731 of the 8,327 fuel vehicles replaced came from the subcompact, compact and midsize segments, which have better fuel efficiency and produce fewer emissions than the average vehicle, while the remaining 4,596 come the other marketing segments which are less fuel efficient. Perhaps unsurprisingly, substitution occurs disproportionately from the large/luxury car segment which represents only 6% of all car sales, but account for over 29.5% of all fuel cars replaced. One explanation for this fact is that Tesla cars, which are among the most popular EV, are close substitutes both in price and other characteristics to several models in the luxury segment. Therefore, a lot of consumers are willing to substitute towards buying a Tesla when financial incentives are offered. At the other end of the spectrum, sales of minivans and pickup trucks are largely unaffected by the policy, as there exists no close substitutes for these vehicle types among the electric vehicle offering.

Finally, I assess the importance of network effects. Figure 2 offers a decomposition of both the direct and indirect effect of the subsidy on cumulative sales. Removing the subsidy leads to a direct decrease in sales of EV by 15,980 keeping stations constant and a further decrease of 2,509 if we allow for station operators to adjust supply. This implies that indirect network effects account for 13.6% of the decrease in sales that would have occured if we removed the policy. In order to provide a complete picture, I also compute several other counterfactuals in which I remove stations



(a) Electric vehicle market

(b) Charging station network

Figure 2: Impact of subsidy over time

altogether to disentangle further the effect of the network from the effect of the subsidy. Results are presented in Table 13. These results highlight the importance of the network in increasing the efficiency of the rebate program. Absent a charging station infrastructure, subsidies leads to 6,503 more sales of EV. With the current network configuration, the same rebate program increases sales by 18,489, almost tripling the effect of the program on sales. This suggests that policymakers should both provide financial support to buyers and incentivize new station installations to take advantage the high level of synergy between the two markets.

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Table 13: Counterfactuals

Counterfactuals	ΔSales	ΔSales EV	ΔCO_2 emissions (in million tons)
With subsidy, with stations (data)	17,230	29,909	-0.444
No subsidy, stations fixed	7,906	13,929	-0.183
No subsidy, stations adjust†	6,172	11,420	-0.170
With subsidy, no stations	4,242	6,503	-0.098
No subsidy, no stations (baseline)	0	0	0

† Same as Table 11.

Table 14: Incidence of the rebate for selected electric and plug-in hybrid

Make/Model	Retail Price	Marginal Cost	Mark-up (%)	Δp ($)	$\Delta p/\Delta\tau$ (%)	Passthrough (%)
Chevrolet Bolt EV	43952	30419	30.8	249	3.1	96.9
Chevrolet Volt	42062	28031	33.5	240	2.9	97.1
Chrysler Pacifica	54725	38650	29.5	44	0.5	99.5
Ford C-Max	36740	23551	36.5	30	0.6	99.4
Ford Fusion	36878	23152	37.6	75	1.8	98.2
Kia Soul	36414	22597	38	3	0.0	100.0
Mitsubishi Outlander	42999	29349	31.7	220	5.5	94.5
Nissan Leaf	40245	27136	32.6	119	1.5	98.5
Tesla Model 3	45600	32393	29	271	3.4	96.6
Tesla Model S	106227	93416	12.4	118	2.1	97.9
Volkswagen e-Golf	36489	22789	37.6	-59	-0.7	100.7

NOTE: Marginal costs are implied by the market structure. All values are in 2018 CAD.

6.2 Incidence

I analyze car manufacturers' response to the program and the effect it had on profits. An important consideration in assessing the efficiency of rebate schemes is whether or not firms have sufficient market power to increase prices and capture some of the rebate as profits. Results for a selection of battery electric and plug-in hybrids are presented in Table 14. I find that that manufacturers increase prices of EV by $126 on average when subsidies are available. These price increases are relatively small in magnitude compared to the offered rebates. Interestingly, some manufacturers find it optimal to decrease some prices slightly such that passthrough is more than 100% for a small number of EVs. The Tesla 3, Chevrolet Bolt EV and Chevrolet Volt, three of the most popular models of EV, exhibit the largest increases in price ranging from $240 to $271, which implies a passthrough between 96.6% to 97.1%. Across all models, regions and years, I estimate passthrough to be on average 98.1%. This is encouraging from the policymaker's perspective: almost all of the rebate lands in the pockets of consumers which helps generating more sales and reaching governmental targets. I reestimate passthrough under different market structure to evaluate how results are affected by the assumption I impose on the supply side. I evaluate three scenarios: each product is produced by a single-product firm (i.e. each product competes against all other products), multi-product firms (the baseline), and the case where a single firm produces all cars (i.e. equivalent to full collusion or a multi-product monopolist). Results are presented in Table 15. I find the average price increase to be of $124 for single-product and $126 for multi-product firms, implying a passthrough of 98.2% and 98.1% respectively. The price response is more pronounced in the perfect collusion scenario ($155 on average) but remains reasonably small compared to the size of the offered rebate (passthrough is 97.3%). The high passthroughs are a direct consequence of the large market expansion that can be linked directly to the rebate program. To see why, notice that firms can capture surplus from the rebate program in two ways. First, they can raise prices to increasing their profit per unit sold. Second, they can forgo raising prices and benefit from increased sales. In this instance, the latter effect dominates the former. This happens because all EV are all subsidized at the same time and are market complements (i.e. negative cross-price elasticities). Raising prices in this setup harms sales both directly and indirectly since station providers install fewer stations when fewer EV are being sold.

Table 15: Incidence of the rebate under alternative market structure

Market structure	Implied # of firms	Δp ($)	$\Delta p/\Delta\tau$ (%)	Passthrough (%)
Single-product firms	297	124	1.8	98.2
Multi-product firms	16	126	1.9	98.1
Monopolist	1	155	2.7	97.3

NOTE: All statistics are sales weighted.

Next, I explore the effect of the program on firms profits and present results in Table 16. I find that total industry profits increased by $149.6 million between 2012 and 2018. However, the program had an asymmetric effect on car manufacturers profits, creating winners and losers. In general, firms that offered several battery electric, plug-in hybrid and hybrid alternatives saw their profits increase, while firms that focussed on fuel alternatives experienced a small decrease in profits. General Motors (the producer of Chevrolet), Nissan-Renault and Tesla which sell the most popular models ripped most of the benefits from the program, totalizing an increase in total profits of $154.2 million. Surprisingly, BMW, Daimler (the producer of Mercedes-Benz) and Volkswagen figure amongst the losers even though they offer several EV alternatives. The high level of substitutability between BMW, Daimler and Tesla explains in large parts the decrease in profits experienced by BMW and Daimler. In the case of Volkswagen, all of their battery electric and plug-in hybrid alternatives were introduced after 2016. The decrease in profits incurred in the initial years of the sample was

Table 16: Effect on firms profits

Firm	# of Alternatives			ΔProfits	
	Electric	Plug-in	Hybrid	million $	%
Winners					
Ford	1	2	4	12.29	0.27
General Motors	2	1	3	84.17	1.92
Hyundai-Kia	2	3	4	6.07	0.08
Nissan-Renault	2	1	3	44.13	1.02
Tesla	3	0	0	25.89	48.06
Toyota	0	1	9	8.08	0.16
Volvo	0	1	0	4.92	3.42
Losers					
BMW	1	4	0	-2.70	-0.28
Daimler	1	1	0	-7.18	-0.25
FCA	0	1	0	-0.82	-0.03
Honda	0	0	4	-13.78	-0.29
Mazda	0	0	0	-5.92	-0.22
Subaru	0	0	1	-3.46	-0.22
SUZUKI	0	0	0	-0.03	-0.05
Tata Motors	0	0	0	-0.17	-0.18
Volkswagen	1	3	3	-1.89	-0.06

not compensated by the gains from 2017 and 2018.

6.3 Welfare

Results from a welfare analysis is presented in Table 17. Compensating variation is computed using the difference in inclusive value between the data and the counterfactual. Using the same notation as Durrmeyer and Samano (2016), the inclusive value from segment g can be written as

$$v_g = (1-\sigma) \cdot \ln \left(\sum_{j \in \mathcal{J}_g} e^{(\delta_j + \mu_j)/(1-\sigma)} \right).$$

Compensating variation then takes the following form

$$CV_i = -\frac{1}{\alpha} \cdot \ln \left(1 + \sum_g e^{v_g} \right) + \frac{1}{\alpha} \cdot \ln \left(1 + \sum_g e^{v_g^{CF}} \right)$$

Consumer surplus increases by $261.4 million over the period. Since firms do not modify prices too much when rebates are available, the program increases the utility of EVs and only affect marginally

Table 17: Impact on profits, compensative variation and costs, 2012-2018

Year	ΔProfits	Compensating Variation	ΔWelfare	Cost of Program
2012	5.38	9.75	15.13	11.70
2013	4.63	8.47	13.10	10.15
2014	11.17	19.84	31.01	23.57
2015	14.53	25.70	40.23	28.49
2016	24.28	42.02	66.30	46.36
2017	30.35	52.30	86.65	56.30
2018	59.27	103.3	162.60	111.00
TOTAL	149.61	261.43	411.04	287.58

NOTE: All values are in million 2018 CAD.

the utility of non-subsidized vehicles. It is easy to see that no consumer can be worse off in an expected utility sense, leading to an automatic increase in consumer surplus. Total industry profits also increase from the large expansion in sales. Interestingly, the combined gains in consumer and producer surpluses more than offset the large cost associated with implementing this program.

Whether or not implementing this policy is worth it from the point of view of the policymaker depends on several factors. First, it depends on whether or not the policymaker internalizes the gains in consumer or producer surpluses which affects the total economic cost of the program. For example, governments may internalize profits only for firms that have operations, pay taxes, and generate employment locally. Second, it depends on how much emissions are avoided with the program, and how much could have been avoided by spending the same funds on an alternative policies. Finally, dynamic considerations which I cannot capture in this analysis are important. In particular, charging station installations are more or less permanent, and a government could be willing to spend a lot of public funds upfront to kick-start the market and reach station saturation faster. I explore these issues in the next section.

7 Cost-efficiency

7.1 Setup

To study cost-efficiency and optimal policy design from the social planer's point of view requires that we precise several concepts. First, we must define the policy variable to be considered and its support. Then we need a precise formulation of the planner's objective function to be optimized. I begin by choosing an appropriate policy variable. Since the policy targets several vehicles over several regions and time periods, optimizing over all possible (asymmetric) policies is unreasonable from a computational point of view. Let τ_0 be the current rebate scheme described in Section 2 and consider the following policy

$$\tau = \kappa \cdot \tau_0,$$

where $\kappa \geq 0$ is a scalar policy shifter. In what follows, I consider the set of policies available to the social planner to be the set

$$T = \{\tau \in \mathbb{R}^J : \tau = \kappa \cdot \tau_0,\ \kappa \in \mathbb{R}^+\}.$$

In other words, I restrict the set of policies available to the social planner to be proportional to the current rebate scheme. This serves two goals. First, it lowers the computational burden associated with studying the universe of possible rebate schemes. This includes for example different EVs receiving different rebates, but also a given EV receiving different rebates over time or across regions. This restriction also insure that the policy is fair and easy to understand from the point of view of buyers. Governments typically would have strong incentives to preserve some sort of regional or temporal fairness for electoral purposes when designing these sort of policies. Additionally, varying the rebate at the model level can make it complicated for buyers to figure out the final price of all EVs to be considered when choosing a vehicle.

Next, I define the government objective function. Let SCC be the social cost of carbon, or social damage in dollars associated with producing one ton of carbon. Define $E(\tau)$ as the avoided carbon emissions from policy τ and $C(\tau)$ be the total cost of implementing τ. I define the central planner's problem as

$$
\begin{aligned}
\kappa^* = \underset{\kappa}{\operatorname{argmax}} \quad & E(\kappa) \cdot SCC - C(\kappa) \\
\text{s.t.} \quad & \kappa \geq 0,
\end{aligned}
\tag{17}
$$

that is, I define the choice of policies in terms of κ instead of τ. Both are equivalent since by definition

$$
\tau^* = \kappa^* \cdot \tau_0,
$$

however using κ simplifies both the interpretation and the computational parts of the problem. The first-order condition associated with this problem is[21]

$$
\underbrace{\frac{\partial C(\kappa^*)}{\partial E(\kappa^*)}}_{\substack{\text{Marginal}\\ \text{Abatement}\\ \text{Cost}}} \quad = \quad \underbrace{SSC}_{\substack{\text{Social}\\ \text{Cost of}\\ \text{Carbon}}}. \tag{18}
$$

I propose three different functional forms for the function $C(\tau)$. First, I consider the case where the central planner cares only about the total spendings on the program, that is,

$$
C_1(\tau) = \sum_j \sum_m \sum_t q_{jmt}(\tau) \cdot \tau_j. \tag{19}
$$

To introduce flexibility in the planner's problem, I also consider the case where the social planner internalizes gains to consumer surplus, and the case where it internalizes gains to both consumer and producer surplus. As an example, a social planner could consider consumers' welfare when designing the policy, but also profits if for example several large car manufacturers are active locally, providing employment and paying taxes. In these two cases, the cost functions take the

[21] I consider only the set of interior solutions.

following forms respectively[22]

$$C_2(\tau) = C_1(\tau) - \sum_i \sum_m \sum_t CS_{imt}(\tau), \tag{20}$$

$$C_3(\tau) = C_1(\tau) - \sum_i \sum_m \sum_t CS_{imt}(\tau) - \sum_f \sum_m \sum_t \Pi_{fmt}(\tau). \tag{21}$$

7.2 Results

I present the estimated average emission abatement costs and marginal emission abatement costs in Table 18. Average abatement costs are computed as the average ray cost per ton of carbon, obtained by comparing current avoided emissions with the no subsidy counterfactual, that is

$$AAC_i(\kappa) = \frac{C_i(\kappa) - C_i(0)}{E(\kappa) - E(0)}.$$

Results are displayed for each of the cost measures. Additionally, I report the results per avoided fuel vehicle sale. In this case, $E(\cdot)$ represents avoided sales of fuel vehicles rather than avoided emissions.

The estimated average abatement cost is estimated to be \$1,045 per metric ton of CO_2, \$95 taking into account changes to consumer surplus, and -\$450 if we consider the global impact on the economy. Additionally, I compute the average cost of decreasing sales of fuel vehicles by one unit to be \$34,535, 3,140, and -\$14,826 respectively for our three cost measures. These results can be compared to recent studies. (Xing, Leard, and S. Li, 2021) estimates that reducing emissions using a similar program in the United States to have and average cost between \$581 and \$662 (484-552 USD) per ton of CO_2, less than half of my most conservative estimate. My methodology differs in that I allow for both network effects and substitution from the outside option to enter the model. Network effects improve carbon emission reductions per dollar spent, however substitution from

[22] Consumer surplus is defined as the inclusive value from the nested logit model times the number of consumers in market mt, that is

$$CS_{imt}(\tau) = -\frac{1}{\alpha} \cdot \ln\left(1 + \sum_g e^{v_g(\tau)}\right)$$

Table 18: Emission abatement cost, evaluated at the current rebate

Cost Measure	Total cost (million $)	Cost per ton CO_2 ($)	Cost per fuel vehicle ($)
Average abatement cost			
C_1: Cost of program only	287.6	1,049	34,535
C_2: Cost of program and compensating variation	26.2	95	3,140
C_3: Cost of program, compensating variation and profits	-123.5	-450	-14,826
Marginal abatement cost			
C_1: Cost of program only	–	1,257	43,908
C_2: Cost of program and compensating variation	–	340	11,865
C_3: Cost of program, compensating variation and profits	–	-195	-6,797
Social cost of carbon			
Mean	–	45	–
95% Confidence Interval	–	183	–

NOTES: *Cost per fuel vehicle* is the cost of reducing sales of fuel vehicles by 1 unit. *Average abatement cost* are calculated by taking the total costs and dividing by either the total abated emissions or the total reduction in fuel fleet sales. *Marginal abatement cost* are computed as the cost per ton of CO_2 and per fuel vehicle of an incremental change in the rebate program, evaluated at the current policy.

the outside option contributes to decreasing cost-efficiency. In this case, the latter effect dominates the former which explains the higher cost estimates. Other works also estimate the cost of reducing emission from the car sector. For example Huse and Lucinda (2014) study the effect of the Swedish green car rebate and estimate the emission abatement cost to be between $131 and $158 (109-132 USD). Beresteanu and S. Li (2011) find that tax incentives on hybrids in the United States to have reduced emission at a cost of $212 (177 USD) per ton. Finally, Knittel (2009) evaluate the cost of reducing emissions from a hypothetical 'cash for clunker' program, and finds that abating emissions in this way could cost up to $540 (450 USD) per ton.

Addressing the cost-efficiency of this program requires however that we consider instead the optimality condition in equation (18). I compute counterfactual scenarios for several levels of κ, and

Table 19: Optimal policy

Cost Measure	Social Cost of Carbon	
	\$45	\$183
C_1: Cost of program only	\$0 ($\kappa^* = 0$)	\$0 ($\kappa^* = 0$)
C_2: Cost of program and compensating variation	\$3,234 ($\kappa^* = 0.40$)	\$5,404 ($\kappa^* = 0.68$)
C_3: Cost of program, compensating variation and profits	\$11,628 ($\kappa^* = 1.45$)	\$13,831 ($\kappa^* = 1.73$)

NOTES: The current policy is $\tau = \tau_0$, i.e. occurs at $\kappa = 1$.

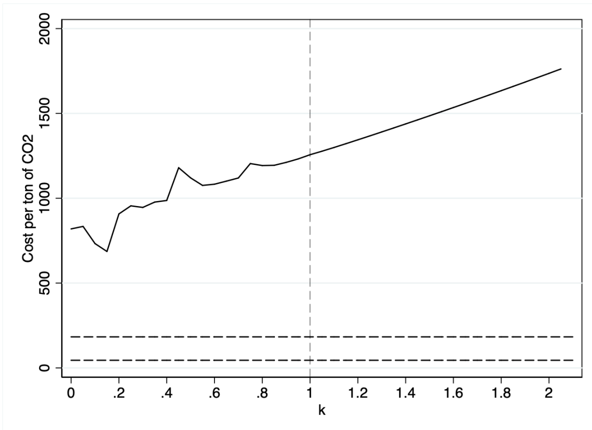
define marginal abatement cost as

$$MAC_i(\kappa) = \frac{\Delta C_i(\kappa)}{\Delta E(\kappa)} = \frac{C_i(\kappa + h) - C_i(\kappa)}{E(\kappa + h) - E(\kappa)}.$$

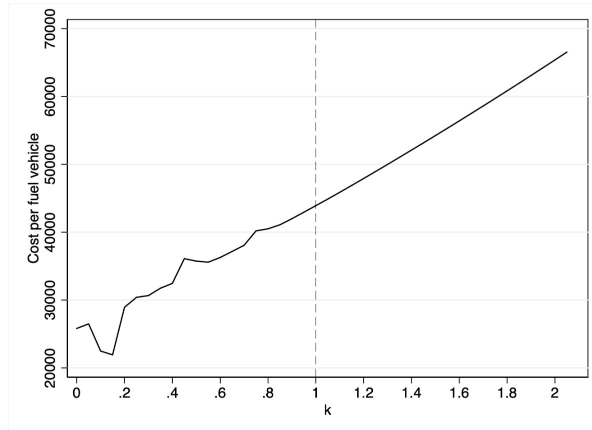
I then compare the marginal abatement cost estimates to the social cost of carbon estimates from Environment and Climate Change Canada.[23] Both set of results are available in Table 18. My results suggest that the central planner is over-investing on rebates when using the first two cost measures, but underinvesting when taking the full impact on the economy into account.

In order to better understand what would constitute the optimal level of investment in the rebate program, I reconstruct the marginal abatement costs curve for each of the cost measures. Results are presented in Figure 3. I report two sets of marginal abatement cost curves, first in terms of avoided CO_2 emissions, then in terms of avoided fuel vehicle sales. I highlight several facts from these figures. First, considering only the costs associated with the program, it is immediately obvious from Figure 3a that no level of rebate is optimal, that is $MAC_1 > SCC$, for $\kappa > 0$. In this case, the optimal policy is $\kappa^* = 0$, a corner solution. In contrast, when taking either consumer surplus or both consumer and producer surpluses into account, Figure 3c and 3e suggests that an optimal policy with $\kappa^* > 0$ exists. I use a basic interpolation to recover the optimal levels of κ and present the results in Table 19.

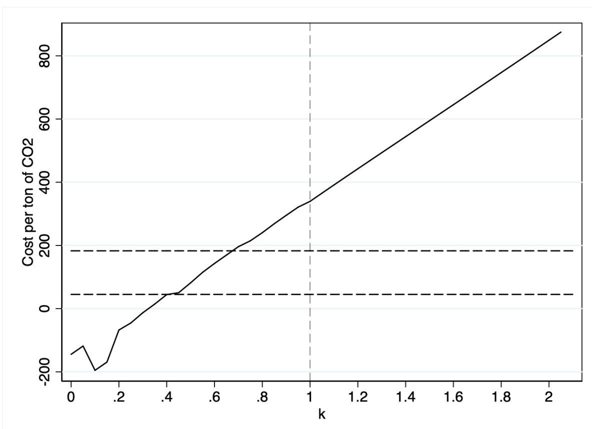
[23] Source: Environment and Climate Change Canada, *Technical Update to Environment and Climate Change Canada's Social Cost of Greenhouse Gas Estimates 2016.*



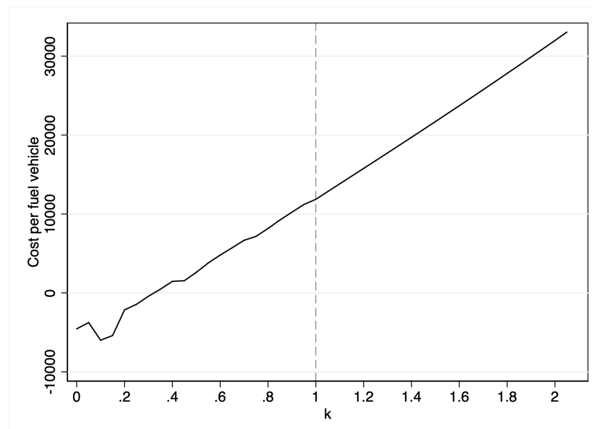
(a) C_1: Cost of program only



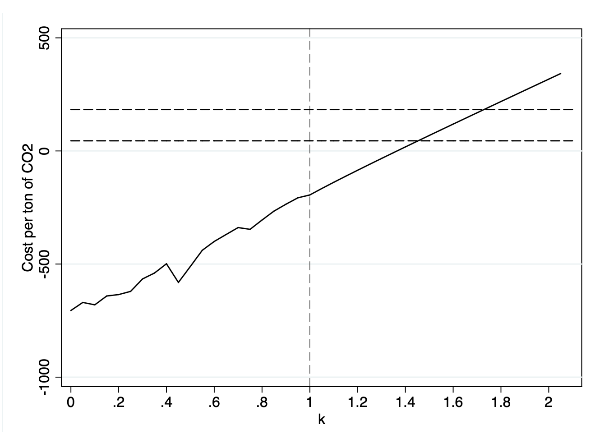
(b) C_1: Cost of program only



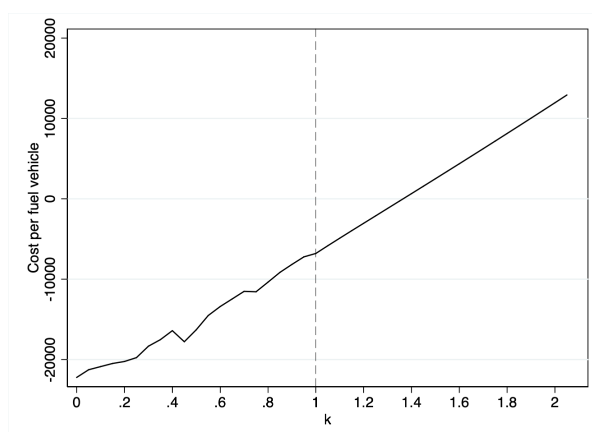
(c) C_2: Cost of program and CS



(d) C_2: Cost of program and CS



(e) C_3: Cost of program, CS and PS



(f) C_3: Cost of program, CS and PS

Figure 3: Marginal abatement cost curve

7.3 Discussion

To provide more perspective on what these results mean, I consider the specific case of Quebec. Since no car manufacturers are active in the province, we can hypothesize that the government of Quebec would internalize costs associated with the program as well as consumer surplus, but not profits. In this case, the optimal policy for the provincial government would lie between $\kappa^* = 0.40$ and $\kappa^* = 0.68$, which is equivalent to subsidizing EVs by up to \$3,234–5,404. On the other hand, several car manufacturers have active plants in Canada. It is credible to think that the Canadian government would internalize the impact of the program on firms along consumer surplus and costs in his assessment of the optimal policy. My results suggest in that case that subsidies should be higher than the current policy, with maximal subsidies ranging from \$11,628 to \$13,831. These misaligned incentives across different levels of government could explain why the government of Quebec is over-investing in the program compared to the optimum.

Another possible explanation to over-investing is that subsidizing EV not only increases sales directly, but also future sales through a faster expansion of the charging station network. This means that once the program expires and subsidies are phased out, network effects persist and generate additional EV registrations at no additional cost to the policymaker. Large subsidies also sends a clear signal to car manufacturers about the current and future demand for EV, and could lead them to increasing investment into electric vehicle technology which contributes to developing cheaper and better products. Because some of these investment are sunk and capacity is not easily adjusted in the short run, the effect of the rebate on firms should also persist in time to some degree even once the program is phased out.

Finally, addressing the important question of the cost efficiency of this program requires that we compare the estimates above with alternative policies aimed at lowering emissions. Gillingham and Stock (2018) compile an up-to-date summary of marginal abatement costs obtained from various economic studies. They document that policies targeted at the agricultural sector (i.e. reforestation, soil and livestock management, agricultural emissions policies) tend to be very inexpensive ways of reducing emissions, with a cost between \$13 and \$85 (11–71 USD) per ton of CO_2. On the other hand, policies aimed a replacing coal energy production cost between $29 (for onshore wind power or natural gas combined cycle) and $158 per ton (for solar thermal power). Their review also covers policies aimed at the car market, such as gas taxes ($22–56 per ton of CO_2) and emission standards ($58–372 per ton of CO_2).

8 Conclusion

The Quebec electric car market presents a unique opportunity to study the impact of subsidizing electric vehicle sales on key economic outcomes. Putting a price on carbon is crucial for policymakers who are trying to achieve better environmental outcomes at the lowest cost possible. My findings suggest that while subsidizing EV does a good job at diffusing the technology, both in terms of increased sales and inciting charging stations operators to expand local networks, the cost of reducing emissions in this way remains prohibitive compared to the social cost of air pollution. Several avenues are possible which could increase cost-effectiveness: tying rebate eligibility to income, or imposing a 'cash for clunker' condition could contribute to improve targeting consumers that would not have purchased an EV without subsidies while avoiding subsidizing consumers substituting away from the outside option. Increasing the gas tax could also be considered as a complementary policy to help targeting both drivers of fuel-inefficient vehicles and owners who use their vehicle intensively (i.e. high mileage users).

While the model used in this analysis is static, several dynamic considerations may justify a policymaker to pay such a high price for emission abatement. First, this sends a clear signal to car manufacturers about the future importance of this technology and could generate additional research and development towards achieving better and cheaper EV. Second, because station installation is nearly permanent, kick-starting this technology may generate future carbon emission savings at no cost if the network reaches saturation faster and rebates are eventually phased out.

Future research could also explore several other avenues. For example, forecasting sales of EV and station deployment could help predicting the optimal time for phasing out the policy, and evaluating the long-run emissions abatement cost from subsidizing EV after subsidies have been phased out.

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Appendix

A. Details on the data

Car registration: The car registration data is constructed from 8 yearly datasets that are released publicly by the Société d'Assurance Automobile du Québec (SAAQ), Quebec's car registration agency. Each dataset contains of the universe of all registered vehicle in Quebec in a given year, starting in 2011 and up to 2018. I reconstruct new vehicle registrations in year t recursively, by comparing the full fleet of vehicles in year t and $t-1$, and keeping only new entries. Because I intend to use charging stations in a given year as an extra characteristic in the demand estimation, I cannot simply use the model's year as a proxy for registration year since they do not overlap perfectly: model year $t-1$, t and $t+1$ can all be sold in year t. Table 20 depicts a breakdown of sales in each registration year by model year to document this phenomenon. I remove vehicles that are not owned by individuals (i.e. company vehicles, taxis, etc), exotic brands (Ferrari, Aston Martin, etc) and also vehicles with a price tag above $150,000. These vehicles do not form a significant share of the total car market, and they have zero market shares in the vast majority of markets. The registration dataset includes the make, model and year of each individual car registration, along with some car characteristics (including curb weight, original color, number of cylinders and cylinder capacity) and some demographics of the owner (age, gender, county of residence).

Car characteristics: The car characteristics are scrapped from The Car Guide's which publishes on their website comprehensive information on all makes and models available in Quebec. This

Table 20: Registrations per year

Registration	Model Year								
Year	2011	2012	2013	2014	2015	2016	2017	2018	2019
2012	62,304	294,419	94,264	-	-	-	-	-	-
2013	-	80,960	323,645	77,542	-	-	-	-	-
2014	-	-	81,836	313,247	85,830	-	-	-	-
2015	-	-	-	64,266	331,247	85,483	-	-	-
2016	-	-	-	-	69,680	335,160	80,785	-	-
2017	-	-	-	-	-	77,662	341,229	70,988	-
2018	-	-	-	-	-	-	79,666	342,792	54,911

website has been the go-to reference for information about the different car makes since the mid-90s and has wide public recognition in the province. The car characteristics dataset includes pricing and various characteristics such as the engine type, horsepower, size, fuel consumption and carbon emissions, all recorded at the brand-model-year-specification level (i.e. Ford Focus 2017 S-Sedan). Car registrations on the other hand are recorded at the brand-model-year level only (i.e. Ford Focus 2017).

I define each product to be a brand-model-year-engine combination. To avoid any potential endogeneity issues arising from aggregating over specifications, I match each car registration to the base specification within each model. Unfortunately, engine type is not recorded in the car registration data, which poses a problem whenever a particular model is offered with several engine options. To recover the engine type in these few cases, I first merge the registration dataset with the characteristics dataset using the make, model, and model year, and pick the specification with the closest weight which is observed in both dataset. Once the engine type is recovered, I assign characteristics of the base model by engine type. In practice, engine types are well identified by curb weight differences since battery components are typically heavy and increase the total weight considerably (up to a few hundred kilograms) compared to the baseline internal combustion engines.

Charging station network: The data on charging stations was obtained from Le Circuit Éectrique, the online platform operated by Hydro-Quebec. The dataset contains the exact geographic location and address of all stations available on December 31st of 2018, as well as pricing, power, and the type of installation. The data includes both stations that are connected directly to Le Circuit Électrique as well as those connected to competing platforms. Entry dates which allow to reconstruct the network over time are provided by Hydro-Quebec directly but include only stations that are connected directly to their platform (about 75% of all stations) and not competing platforms. In order to recover the installation year for the remaining stations, I use Wayback Machine, an online archive of all past web contents, to access previous versions of the charging station dataset and construct the closest possible installation date by comparing versions of the same dataset over time.

B. Robustness check

Next I want to address the issue of charging station instruments which are based on distance thresholds. The idea behind this instrumental variable strategy is similar to Hausman (1996) and Nevo (2001), in that we use charging station networks in other markets to construct instruments. In Nevo (2001) for example, prices in other regions are combined to construct indices which are used as instruments for price in ta given region. The idea behind this identificaiton strategy is that prices are correlated across region lines through a common marginal cost component once we account for fixed effects, but uncorrelated to local price shocks. The basic idea for this identification strategy is used here to instrument for the size of local networks, but with a caveat. The identifying assumption is that local networks are correlated across regions through a common installation and operation cost when taking into account fixed effects, but uncorrelated to shock in other markets. Since local authorities are responsible for developing their own local network independently of others, shocks in one region is unlikely to affect station deployment in other regions, unless they are coordinated together. One example could arise if for example the provincial government engaged in a widespread advertising campaign that promoted green technologies everywhere at the same time. I did not find evidence of such occurrences in the period of interest.

The biggest threat to this instrumental variable strategy lies in the fact that consumers travel across region lines and charge in neighbouring regions while shopping, visiting friends, or working. If a large share of the total demand for charging is due to these types of travel, then a shock to consumer preferences for EV in one region could cause an increase in network sizes in neighbouring regions, invalidating the instrumental variable strategy. In order to circumvent this issue, I impose a distance threshold of 300 km on stations that I use as instruments in the basis function. The claim I support is that while charging across region lines may be frequent for neighbouring regions, it is a rare event for regions that are far away such that the fraction of charging in a given county that comes from distant regions is trivial. Whenever this assumption is satisfied, then shocks to preferences for EV in region that are sufficiently far away have no impact on a given local network since only a negligible share of total charging comes from these users.

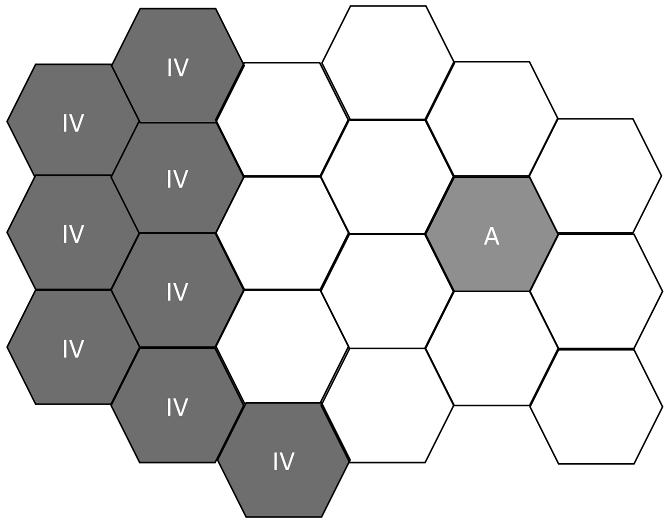

Figure 4: Instruments for local network A

The choice of a threshold seems somewhat arbitrary. To document what happens when we increase or decrease this threshold, I estimate the demand model without instruments, and then using instruments constructed from using various thresholds, in 50 km increments. The results are presented in Table 21. There are a few interesting findings. First, looking at column (2) which includes all regions without any threshold, we see that the on the network both increase in magnitude, from 0.195 to 0.340 and from -0.005 to -0.025, hinting that the parameters are both biased towards zero. As we increase the distance thresholds, the parameters increase slightly in absolute value (although the change is not significant). The parameter values seem to stabilize beyond 200 km, which I take as evidence that using any distance threshold beyond that point is somewhat equivalent. Interestingly, most EV have a driving ranges below 200 km, meaning that this distance wouldn't be achievable on a single charge say on the way to work or for other daily activities which strengthens the idea that these types of travels are somewhat uncommon. To be on the safe side, I select 300 km as my preferred threshold.

Table 21: Robustness to distance threshold

VARIABLES	(1) No instr.	(2) Dist. 0	(3) Dist. 50	(4) Dist. 100	(5) Dist. 150	(6) Dist. 200	(7) Dist. 250	(8) Dist. 300	(9) Dist. 350	(10) Dist. 400	(11) Dist. 450	(12) Dist. 500
Price - Rebate	-0.513***	-0.491***	-0.491***	-0.491***	-0.491***	-0.491***	-0.491***	-0.491***	-0.491***	-0.490***	-0.490***	-0.490***
	(0.062)	(0.060)	(0.060)	(0.060)	(0.060)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Log of stations	0.195***	0.340***	0.345***	0.347***	0.349***	0.353***	0.359***	0.357***	0.353***	0.354***	0.353***	0.354***
	(0.048)	(0.054)	(0.054)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Log of stations × Driving range	-0.005	-0.025***	-0.026***	-0.027***	-0.028***	-0.028***	-0.030***	-0.029***	-0.028***	-0.028***	-0.028***	-0.029***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Power-to-weight	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Size	0.382***	0.368***	0.368***	0.368***	0.368***	0.368***	0.368***	0.367***	0.368***	0.367***	0.367***	0.367***
	(0.047)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Cost of driving	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Automatic	0.124***	0.119***	0.119***	0.119***	0.119***	0.119***	0.119***	0.119***	0.119***	0.119***	0.119***	0.119***
	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
σ	0.345***	0.365***	0.365***	0.365***	0.365***	0.365***	0.366***	0.366***	0.366***	0.366***	0.366***	0.367***
	(0.052)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.049)
Observations	104,495	104,495	104,495	104,495	104,495	104,495	104,495	104,495	104,495	104,495	104,495	104,495
R-squared	0.474	0.505	0.505	0.505	0.504	0.504	0.505	0.506	0.505	0.507	0.507	0.507
Brand FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Market segment FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Engine type × County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

NOTE: This table highlights how the coefficients on *Log of stations* and *Log of stations × Driving range* change as we increase the distance threshold which was used to construct the basis function which serves as instruments. Distance thresholds are in km from centroid to centroid for each region pair. Column (1) instruments for price and within-group share but not charging stations. Column (2) uses all stations that are located outside of any given county without filtering for distance. Column (8) is the chosen specification.

C. Derivation of the entry model

The stream benefits from installing station n in period t is given by

$$V_t(n) = -F_t + \sum_{s=t}^{\infty} \left(\frac{1}{1+r}\right)^{s-t} B_s(n) \tag{22}$$

where $B_t(n)$ is the total benefit derived from station n in period t and F_t is a fixed (and unobserved) installation cost.[24] The social planner chooses to install station n today if it is more profitable than waiting one period, that is if

$$V_t(n) \geq \left(\frac{1}{1+r}\right) V_{t+1}(n), \tag{23}$$

$$-F_t + \sum_{s=t}^{\infty} \left(\frac{1}{1+r}\right)^{s-t} B_s(n) > -\left(\frac{1}{1+r}\right) F_{t+1} + \sum_{s=t+1}^{\infty} \left(\frac{1}{1+r}\right)^{s-t+1} B_s(n)$$

$$B_t(n) \geq F_t - \left(\frac{1}{1+r}\right) F_{t+1}. \tag{24}$$

We impose the following functional form on the benefits function

$$B_t(n) = Q_t^{ev} \cdot n_t^{-a_1} e^{\mathbf{y}_t' a_2}. \tag{25}$$

Replacing in (24) and taking logs yields

$$\ln(n_t) - \frac{1}{a_1}\ln(Q_t^{ev}) - \mathbf{y}_t' \frac{a_2}{a_1} \leq \frac{1}{a_1} \ln\left(\frac{1}{F_t - \left(\frac{1}{1+r}\right) F_{t+1}}\right)$$

[24]The county subscript m is omitted for simplicity

or

$$\ln(n_t) - \lambda_1 \ln(Q_t^{ev}) - \mathbf{y}_t'\lambda_2 \leq \omega\eta_t, \tag{26}$$

where η_t is assumed to be distributed as independent standard normal.

Consider the case where N is the chosen size of the network in equilibrium. It has to be that it was profitable to install station N, but unprofitable to install station $N+1$ which means that the inequality in equation (26) must hold for N, but not for $N+1$ Using the distributional assumption on η_t, the probability that N_t is chosen in period t is

$$Pr\left(\frac{\ln(N_t) - \lambda_1 \ln(Q_t^{ev}) - \mathbf{y}_t'\lambda_2}{\omega} \leq \eta_t < \frac{\ln(N_t+1) - \lambda_1 \ln(Q_t^{ev}) - \mathbf{y}_t'\lambda_2}{\omega}\right)$$

or

$$\Phi\left(\frac{\ln(N_t+1) - \lambda_1 \ln(Q_t^{ev}) - \mathbf{y}_t'\lambda_2}{\omega}\right) - \Phi\left(\frac{\ln(N_t) - \lambda_1 \ln(Q_t^{ev}) - \mathbf{y}_t'\lambda_2}{\omega}\right). \tag{27}$$

Using these probabilities, we can easily construct the conditional log-likelihood function

$$\ell(\lambda) = \sum_m \sum_t \ln\left[\Phi\left(\frac{\ln(N_{mt}+1) - \lambda_1 \ln(Q_{mt}^{ev}) - \mathbf{y}_{mt}'\lambda_2}{\omega}\right) - \Phi\left(\frac{\ln(N_{mt}) - \lambda_1 \ln(Q_{mt}^{ev}) - \mathbf{y}_{mt}'\lambda_2}{\omega}\right)\right]. \tag{28}$$

D. Derivation of the elasticities

In this section, I show how to reach a closed form solution for the elasticities that arise in this model. Using chain rule, the partial derivative of s_j with respect to p_k is

$$\frac{\partial s_j(p, N(p))}{\partial p_k} = \underbrace{\frac{\partial s_j}{\partial p_k}}_{\text{Nested logit}} + \underbrace{\frac{\partial s_j}{\partial N} \cdot \frac{\partial N}{\partial Q^{\text{ev}}} \cdot \frac{\partial Q^{\text{ev}}}{\partial p_k}}_{\text{Network effects}}, \tag{29}$$

where the first term has the classical nested-logit form (see Berry, 1994) and the second term arise from network externalities which affect both sales of electric and non-electric vehicles (see Springel, 2017). I derive each term in turn.

a) Recall that

$$s_j(\delta, \mu, \sigma) = s_{j|g}(\delta, \mu, \sigma) \cdot s_g(\delta, \mu, \sigma) = \frac{e^{(\delta_j+\mu_j)/(1-\sigma)}}{D_g^{\sigma} \cdot \sum_{g'} D_{g'}^{1-\sigma}}, \tag{30}$$

$$D_g = \sum_{k \in \mathcal{J}_g} e^{(\delta_k+\mu_k)/(1-\sigma)}. \tag{31}$$

Consider first the case where product j has an electric engine. The partial derivative of s_j with respect to N is then

$$\frac{\partial s_j}{\partial N} = \frac{\partial}{\partial N} \left(\frac{e^{(\delta_j+\mu_j)/(1-\sigma)}}{D_g^{\sigma} \cdot \sum_{g'} D_{g'}^{(1-\sigma)}} \right) \tag{32}$$

$$= \frac{\gamma_j}{1-\sigma} \cdot \frac{1}{1+N} \cdot \frac{e^{(\delta_j+\mu_j)/(1-\sigma)}}{D_g^{\sigma} \cdot \sum_{g'} D_{g'}^{(1-\sigma)}} \tag{33}$$

$$- \frac{\gamma_j}{1-\sigma} \cdot \frac{1}{1+N} \cdot \frac{e^{(\delta_j+\mu_j)/(1-\sigma)} \cdot \sigma D_g^{\sigma-1} \left(\sum_{\ell \in \mathcal{J}_g} \mathbb{1}(\ell \in EV) e^{(\delta_\ell+\mu_\ell)/(1-\sigma)} \right) \cdot \sum_{g'} D_{g'}^{1-\sigma}}{\left(D_g^{\sigma} \cdot \sum_{g'} D_{g'}^{1-\sigma} \right)^2} \tag{34}$$

$$- \frac{\gamma_j}{1-\sigma} \cdot \frac{1}{1+N} \cdot \frac{e^{(\delta_j+\mu_j)/(1-\sigma)} \cdot D_g^{\sigma} \cdot (1-\sigma) \sum_{g'} \left(D_{g'}^{-\sigma} \cdot \sum_{\ell \in \mathcal{J}_g'} \mathbb{1}(\ell \in EV) e^{(\delta_\ell+\mu_\ell)/(1-\sigma)} \right)}{\left(D_g^{\sigma} \cdot \sum_{g'} D_{g'}^{1-\sigma} \right)^2}, \tag{35}$$

$$\frac{\partial s_j}{\partial N} = \frac{\gamma_j}{1-\sigma} \cdot \frac{1}{1+N} \cdot s_j \left(1 - \sigma \sum_{\ell \in \mathcal{J}_g} \cdot \frac{\mathbb{1}(\ell \in EV)\; e^{(\delta_\ell + \mu_\ell)/(1-\sigma)}}{D_g} - (1-\sigma) \sum_{g'} \sum_{\ell \in \mathcal{J}_{g'}} \frac{\mathbb{1}(\ell \in EV) e^{(\delta_\ell + \mu_\ell)/(1-\sigma)}}{D_{g'}^{\sigma} \cdot \sum_{g''} D_{g''}^{1-\sigma}} \right), \tag{36}$$

$$= \frac{\gamma_j}{1-\sigma} \cdot \frac{1}{1+N} \cdot s_j \left(1 - \sigma \sum_{\ell \in \mathcal{J}_g} \mathbb{1}(\ell \in EV) s_{\ell|g} - (1-\sigma) \sum_{\ell} \mathbb{1}(\ell \in EV) s_\ell \right), \tag{37}$$

$$= \frac{\gamma_j}{1-\sigma} \cdot \frac{1}{1+N} \left(1 - \sigma \sum_{\ell \in \mathcal{J}_g} s_{\ell|g}^{ev} - (1-\sigma) \sum_{\ell} s_\ell^{ev} \right) s_j. \tag{38}$$

where $s_j^{ev} = s_j$ if j has an electric vehicle, 0 otherwise. Whenever model j is not an electric vehicle, the term in (33) vanishes, such that the final result is

$$\frac{\partial s_j}{\partial N} = \begin{cases} \frac{\gamma_j}{1-\sigma} \cdot \frac{1}{1+N} \big(1 - \sigma \sum_{\ell \in \mathcal{J}_g} s_{\ell|g}^{\text{ev}} - (1-\sigma) \sum_\ell s_\ell^{\text{ev}} \big) s_j, & \text{if } j \in EV \\ -\frac{\gamma_j}{1-\sigma} \cdot \frac{1}{1+N} \big(\sigma \sum_{\ell \in \mathcal{J}_g} s_{\ell|g}^{\text{ev}} + (1-\sigma) \sum_\ell s_\ell^{\text{ev}} \big) s_j. & \text{if } j \notin EV \end{cases} \tag{39}$$

b) To compute the next term, $\partial N / \partial Q^{ev}$, requires a bit more work. Since N is a step function, the derivative of N is either zero or the function is not differentiable. We replace this derivative by the marginal effect of a change in the fleet of electric vehicle, which we compute as the derivative of the Average Structural Function (see Blundell and Powell, 2004). Rewrite the structural model as

$$N_{mt} = H(Q_{mt}^{ev}, \mathbf{y}_{mt}, \eta_{mt}), \tag{40}$$

where the function $H(Q^{ev}, \mathbf{y}, \eta)$ can be written as

$$H(Q^{ev},\mathbf{y},\eta)=\sum_{k=1}^{S-1}k\cdot\mathbb{1}\left(\frac{\ln(k)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2}{\omega}\leq\eta<\frac{\ln(k+1)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2}{\omega}\right)\tag{41}$$

$$+S\cdot\mathbb{1}\left(\frac{\ln(S)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2}{\omega}\leq\eta\right)\tag{42}$$

and S is the saturation point of the network in a given market. Consider the average structural function,

$$ASF=\int H(Q^{ev},\mathbf{y},\eta)dF(\eta).\tag{43}$$

Blundell and Powell (2004) show that in the case where a control function is used to correct for the endogeneity of Q^{ev}, integration also has to be taken over the nuisance parameter ν. This gives

$$ASF=\iint H(Q^{ev},\mathbf{y},\nu,\eta)dF(\nu)dF(\eta).\tag{44}$$

Substituting (42) in (44) and solving yields

$$ASF=\sum_{k=1}^{S-1}k\cdot\iint\mathbb{1}\left(\frac{\ln(k)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2-\rho\nu}{\omega}\leq\eta<\frac{\ln(k+1)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2-\rho\nu}{\omega}\right)dF(\nu)dF(\eta)\tag{45}$$

$$+S\cdot\iint\mathbb{1}\left(\frac{\ln(S)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2-\rho\nu}{\omega}\leq\eta\right)dF(\nu)dF(\eta)\tag{46}$$

$$=\sum_{k=1}^{S-1}k\cdot\int Pr\left(\frac{\ln(k)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2-\rho\nu}{\omega}\leq\eta<\frac{\ln(k+1)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2-\rho\nu}{\omega}\right)dF(\nu)\tag{47}$$

$$+S\cdot\int Pr\left(\frac{\ln(S)-\lambda_1\ln(Q^{ev})-\mathbf{y}'\lambda_2-\rho\nu}{\omega}\leq\eta\right)dF(\nu),\tag{48}$$

or

$$ASF = \sum_{k=1}^{S} k \cdot \int Pr(N = k \mid Q^{ev}, \mathbf{y}, \nu) dF(\nu). \tag{49}$$

Replacing the probabilities and simplifying yields

$$ASF = S - \sum_{k=1}^{S} \int \Phi \left(\frac{\ln(k) - \lambda_1 \ln(Q^{ev}) - \mathbf{y}'\lambda_2 - \rho\nu}{\omega} \right) dF(\nu). \tag{50}$$

The effect of a marginal change of Q^{ev} on N is then

$$\frac{\partial ASF}{\partial Q^{ev}} = \sum_{k=1}^{S} k \cdot \int \frac{\partial Pr(N = k \mid Q_t^{ev}, \mathbf{y}_t, \nu_t)}{\partial Q^{ev}} dF(\nu), \tag{51}$$

which is equal to

$$\frac{\partial ASF}{\partial Q^{ev}} = \left(\frac{\lambda_1}{Q^{ev} w} \right) \cdot \sum_{k=1}^{S} \int \phi \left(\frac{\ln(k) - \lambda_1 \ln(Q^{ev}) - \mathbf{y}'\lambda_2 - \rho\nu}{\omega} \right) dF(\nu). \tag{52}$$

The integral is taken over the estimated empirical distribution of ν,[25] i.e.

$$\int \frac{\partial Pr(N = k \mid Q^{ev}, \mathbf{y}, \nu)}{\partial Q^{ev}} dF(\nu) = \frac{1}{R} \sum_{r=1}^{R} \frac{\partial Pr(N = k \mid Q^{ev}, \mathbf{y}, \widehat{\nu}_r)}{\partial Q^{ev}}. \tag{53}$$

c) Finally, we need to compute the partial derivative of Q^{ev} with respect to the price of model k, p_k. First, notice that Q^{ev}_{mt} is the sum of the sales of electric vehicles in county m in all periods up to t, that is

$$Q^{ev}_{mt} = \sum_{s=1}^{t} q^{ev}_{ms}. \tag{54}$$

[25] I use 500 draws from the empirical distribution of ν to compute the integrals.

Because previous period sales are considered fixed from the perspective of period t, it has to be that

$$\frac{\partial Q^{ev}_{mt}}{\partial p_k} = \frac{\partial q^{ev}_{mt}}{\partial p_k} = L \cdot \sum_{\ell} \frac{\partial s^{ev}_{\ell mt}(\mathbf{p}_t, N_{mt}(\mathbf{p}_t))}{\partial p_k}, \tag{55}$$

Using chain rule yields

$$\frac{\partial Q^{ev}}{\partial p_k} = L \cdot \sum_{\ell} \left(\frac{\partial s^{ev}_{\ell}}{\partial p_k} + \frac{\partial s^{ev}_{\ell}}{\partial N} \cdot \frac{\partial N}{\partial Q^{ev}} \cdot \frac{\partial Q^{ev}}{\partial p_k} \right), \tag{56}$$

$$\frac{\partial Q^{ev}}{\partial p_k} \left(1 - L \cdot \frac{\partial N}{\partial Q^{ev}} \cdot \sum_{\ell} \frac{\partial s^{ev}_{\ell}}{\partial N} \right) = L \cdot \sum_{\ell} \frac{\partial s^{ev}_{\ell}}{\partial p_k}, \tag{57}$$

$$\frac{\partial Q^{ev}}{\partial p_k} = \frac{L \cdot \sum_{\ell} \frac{\partial s^{ev}_{\ell}}{\partial p_k}}{\left(1 - L \cdot \frac{\partial N}{\partial Q^{ev}} \cdot \sum_{\ell} \frac{\partial s^{ev}_{\ell}}{\partial N} \right)}. \tag{58}$$

E. Elasticities, and network supply curves

Demand elasticities: I report in Table 22 the average own- and cross-price elasticities in 2017 for a selection of battery electric and plug-in hybrid vehicles. In Panel A, I shut down network effects and report the standard nested logit elasticities. I report the elasticities that take network effects into account in Panel B, which I estimate using the formulae described in Appendix D. I observe a similar pattern to Springel (2017), namely that EV are substitutes (i.e. positive cross-price elasticities) ignoring network effects, but act as complements (i.e. negative cross-price elasticities) once network effects are taken into consideration. The reason behind this result is that increasing the price of one EV induces a reduction in network size which in turn affects negatively the sales of all other EVs. The fact the the sign flips in some cases is an indication that the network effect is dominating the substitution effect for those EV pairs. These complementarities tend to increase the efficiency of large scale EV subsidies as the effect of the rebate on one particular EV is amplified by the fact that all other EV are also receiving the same price reduction through network effects.

Table 22: Own- and cross-price elasticities, electric and plug-in hybrids, in 2017

PANEL A	Bolt EV	Volt	Pacifica	C-Max	Fusion	Soul	Leaf	Model S	Prius	e-Golf
Chevrolet Bolt EV	-2.711	0.00148	0.00014	0.00017	0.00022	0.00020	0.00034	0.00018	0.00039	0.00020
Chevrolet Volt	0.00059	-2.388	0.00013	0.00016	0.00021	0.00019	0.00032	0.02311	0.00037	0.00019
Chrysler Pacifica	0.00102	0.00268	-3.897	0.00019	0.00027	0.00034	0.00045	0.00023	0.00058	0.00026
Ford C-Max	0.00049	0.00121	0.00009	-2.041	0.00016	0.00016	0.00394	0.00014	0.00496	0.00238
Ford Fusion	0.00053	0.00127	0.00011	0.00013	-2.124	0.00016	0.00026	0.00014	0.00032	0.00016
Kia Soul	0.00058	0.00132	0.00010	0.00013	0.00016	-2.165	0.00029	0.00014	0.00031	0.00016
Nissan Leaf	0.00059	0.00142	0.00011	0.00231	0.00018	0.00016	-2.320	0.00016	0.00592	0.00263
Tesla Model S	0.00249	0.67120	0.00046	0.00055	0.00071	0.00070	0.00127	-10.239	0.00144	0.00073
Toyota Prius	0.00058	0.00137	0.00012	0.00264	0.00020	0.00018	0.00516	0.00016	-2.462	0.00289
Volkswagen eGolf	0.00060	0.00142	0.00010	0.00184	0.00016	0.00017	0.00499	0.00015	0.00553	-2.212
PANEL B	**Bolt EV**	**Volt**	**Pacifica**	**C-Max**	**Fusion**	**Soul**	**Leaf**	**Model S**	**Prius**	**e-Golf**
Chevrolet Bolt EV	-2.753	-0.08539	-0.00705	-0.01111	-0.01434	-0.01232	-0.02202	-0.01072	-0.02729	-0.01268
Chevrolet Volt	-0.02453	-2.440	-0.00416	-0.00669	-0.00859	-0.00744	-0.01303	0.01660	-0.01690	-0.00798
Chrysler Pacifica	-0.01633	-0.03645	-3.901	-0.00270	-0.00410	-0.00624	-0.00725	-0.00353	-0.01004	-0.00387
Ford C-Max	-0.00907	-0.02079	-0.00139	-2.044	-0.00301	-0.00284	-0.00104	-0.00244	-0.00195	-0.00056
Ford Fusion	-0.00800	-0.01691	-0.00146	-0.00206	-2.127	-0.00260	-0.00370	-0.00197	-0.00513	-0.00249
Kia Soul	-0.04028	-0.07967	-0.00694	-0.00813	-0.01098	-2.178	-0.01699	-0.00893	-0.02003	-0.01170
Nissan Leaf	-0.04161	-0.09470	-0.00732	-0.00752	-0.01276	-0.01092	-2.344	-0.01114	-0.02367	-0.00832
Tesla Model S	-0.09946	0.46155	-0.01836	-0.02273	-0.02990	-0.03014	-0.04755	-10.269	-0.05335	-0.02374
Toyota Prius	-0.00768	-0.01651	-0.00136	0.00043	-0.00242	-0.00221	0.00065	-0.00166	-2.468	0.00049
Volkswagen eGolf	-0.03733	-0.08433	-0.00539	-0.00518	-0.01016	-0.01011	-0.01187	-0.00769	-0.01955	-2.225

Panel A - Elasticities without network effects.
Panel B - Elasticities with network effects.

Charging station supply: I am also interested in the elasticity of supply of charging stations. In particular, I want to emphasize that the entry model developed in this paper produces not only flexible supply curves, but also flexible elasticities of supply that are not restricted to be fixed across region, over time, or at different states of the EV market. Figure 5 depicts charging station supply as a fonction of the fleet of EV for 12 of the 89 counties, in 2017. All of the supply curves are monotonically increasing at a decreasing rate, a consequence of the estimated parameters of the model. Moreover, they are all converging to a saturation point. This follows from the assumption that such a saturation point exists, that is a point beyond which additional sales of EV do not generate extra charging stations. This assumption can be easily relaxed, which would result in the supply curves to become unbounded above. In practice, this assumption does not affect the estimation stage or the computation of counterfactuals, since the saturation points are set to be several orders of magnitude above observed network size in each market.

The supply curves are computed as follows. Recall that the structural model can be rewritten as

$$N_{mt} = E(N|Q^{ev}_{mt}, \mathbf{y}_{mt}, \lambda) + v_{mt}. \tag{59}$$

where $E(N|Q, \mathbf{y}, \lambda)$ is the average structural function defined above. Station supply can be recovered for various levels of Q^{ev} by using the model estimates and computing

$$N_{mt}(Q^{ev}) = S_{mt} - \sum_{k=1}^{S_{mt}} \int \Phi\left(\frac{\ln(k) - \widehat{\lambda}_1 \ln(Q^{ev}) - \mathbf{y}'_{mt}\widehat{\lambda}_2 - \widehat{\rho}\nu}{\omega}\right) dF(\nu) + \widehat{v}_{mt}. \tag{60}$$

where a consistent estimator of v_{mt} can be estimated from $\widehat{v}_{mt} = N_{mt} - E(N \mid Q^{ev}_{mt}, \mathbf{y}_{mt}, \widehat{\lambda})$.

Elasticity of charging station supply: Figure 6 depicts the elasticity of supply of charging stations as a function of the fleet of EV for the same selection of counties. Interestingly, the model seems to reject the idea that the elasticity of supply of stations is fixed both across regions and over time, but also at different states of the EV market. In particular, station operators seems to be more reactive when the network and the fleet of EV are small, and become less and less reactive as the market develops. Our assumption about the existence of a saturation point forces all elasticities to converge towards zero as Q^{ev} goes to infinity. Relaxing this assumption, we would instead observe elasticities converging towards a fixed (and positive) elasticity that is different in each market.

The elasticities of supply are computed as follows. Let $\varepsilon_{mt}(Q^{ev})$ be the elasticity of supply of stations for a given level of Q^{ev}. Then using the derivative of the average structural function defined above, we have that

$$\varepsilon_{mt}(Q^{ev}) = \frac{\partial N_{mt}(Q^{ev})}{\partial Q^{ev}} \cdot \frac{Q^{ev}}{N_{mt}(Q^{ev})}, \tag{61}$$

$$= \left(\frac{\lambda_1}{N_{mt}(Q^{ev})w} \right) \cdot \sum_{k=1}^{S} \int \phi \left(\frac{\ln(k) - \lambda_1 \ln(Q^{ev}) - \mathbf{y}'\lambda_2 - \rho\nu}{\omega} \right) dF(\nu). \tag{62}$$

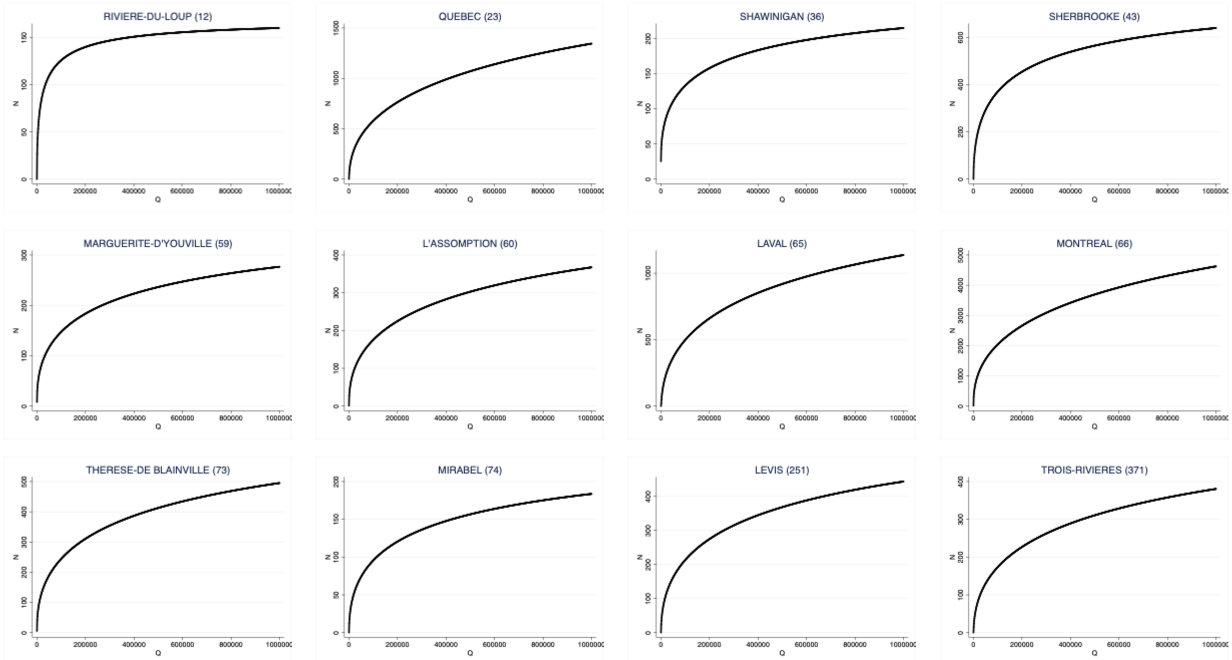

Figure 5: Station supply curves, for selected counties, in 2017

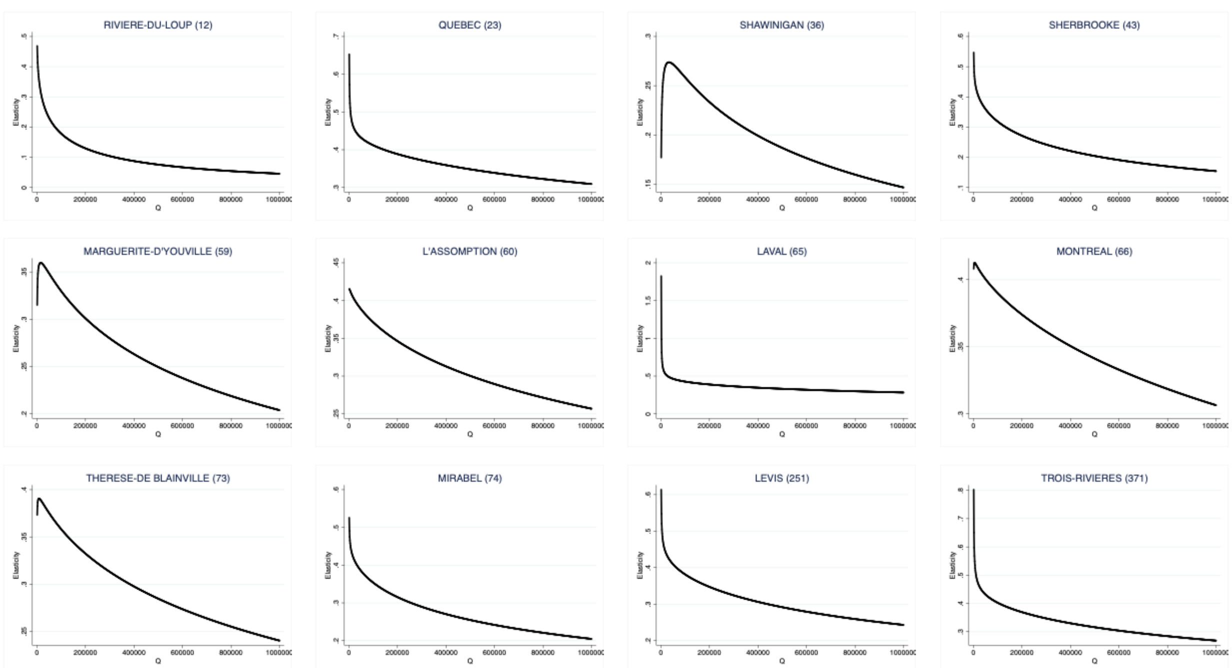

Figure 6: Station elasticity curves, for selected counties, in 2017